Data-driven Implementations for Enhanced Healthcare Internet-of-Things Systems

Amleset Kelati

Data-driven Implementations for Enhanced Healthcare Internet-of-Things Systems

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This thesis is dedicated to the loving memory of my mother,
Abrehet Bahta Tekle

Whom is my first teacher and a model of my life, your personality and determination helps me to start this Ph.D and to finish it. Without your unconditional love, encouragement and support this would not be happening. Emaye, these few comments can not communicate my profoundest gratitude and love for your constant encouragement and what you have given to me is more than you ever know.

"I DO NOT CEASE TO GIVE THANKS FOR YOU" Ephesians 1:16

Abstract

Healthcare monitoring systems based on the Internet of Things (IoT) are emerging as a potential solution for reducing healthcare costs by impacting and improving the quality of health care delivery. The rising number of elderly and chronic patient population in the world and the associated healthcare costs urges the application of IoT technology to improve and support the health care services. This thesis develops and integrates two IoT-based healthcare systems aiming to support elderly independent living at home. The first one involves using IoT-based remote monitoring for pain detection, while the second one detects behavioral changes caused by illness via profiling the appliances' energy usage.

In the first approach, an Electromyography (EMG)sensor node with a Wireless Fidelity (Wi-Fi) radio module is designed for monitoring the pain of patients living at home. An appropriate feature-extraction and classification algorithm is applied to the EMG signal. The classification algorithm achieves 98.5% accuracy for the experimental data collected from the developed EMG sensor node, while it achieves 99.4% classification accuracy for the clinically approved pain intensity dataset. Moreover, the experimental results clearly show the relevance of the proposed approaches and prove their suitability for real-life applications. The developed sensor node for the pain level classification method is beneficial for continuous pain assessment to the smart home-care community.

As a complement to the first approach, in the second approach, an IoT-based smart meter and a set of appliance-level load profiling methods are developed to detect the electricity usage of users' daily living at home, which indirectly provides information about the subject's health status. The thesis has formulated a novel methodology by integrating Non-intrusive Appliance Load Monitoring (NIALM) analysis with Machine Learning- (ML) based classification at the fog layer. The developed method allows the detection of a single appliance with high accuracy by associating the user's Activities of Daily Living (ADL). The appliances detection is performed by employing a k-Nearest Neighbors (k-NN) classification algorithm. It achieves 97.4% accuracy, demonstrating its high detection performance. Due to the low cost and reusability advantages of Field Programmable Gate Arrays (FPGA), the execution of k-NN for appliances classification model is performed on an FPGA. Its classification performance was comparable with other computing platforms, making it a cost-effective alternative for IoT-based health care assessment of daily living at home. The developed methods have has practical application in assisting real-time e-health monitoring of any individual who can remain in the comfort of their normal living environment.

Sammanfattning

System för monitorering av hälso- och sjukvård baserade på IoT (internet of things) erbjuder idag kostnadseffektiva lösningar som många gånger kan utgöra bättre alternativ än traditionell övervakning inom vård och omsorg. Kostnader för sjukvård stiger brant, mycket på grund av en ökande andel äldre i befolkningen, och kraven på sjukhus och vårdinstanser att tillhandahålla högkvalitativa tjänster stiger därmed och blir alltmer utmanande. Denna avhandling presenterar två olika integrerade IoT-system, som utvecklats för att monitorera hälsotillståndet hos vårdbehövande och äldre personer i deras hemmiljö. Det första systemet bygger på en fjärransluten IoT-lösning för smärta, medan det andra upptäcker förändrade levnadsmönster som orsakas av sjukdom genom att monitorera el-användningen för den vårdbehövande.

I den första varianten har en elektromyografi (EMG) sensor med en wifi-modul designats för att övervaka smärtkänningar hos hemmaboende patienter. En algoritm extraherar relevanta data ur EMG signalen och utvärderar dessa för att kunna ange den smärtnivå som patienten upplever. Denna process ger 98.5% rätt angivna smärtnivåer hos den uppmätta signalen från EMG-sensorn, men hela 99.4% rättbestämda smärtnivåer från det kliniskt godkända testet av smärtnivå Bio Vid. De experimentella resultaten visar tydligt att den föreslagna metoden lämpar sig utmärkt för fortsatta försök på människor.

I den andra IoT-lösningen, som ska ses som ett komplement till den första, används en IoT-baserad smart mätare tillsammans med en uppsättning metoder för att bestämma belastningsprofilen för elanvändningen i den vårdbehövandes bostad och därigenom indirekt upptäcka avvikelser som indikerar att hälsotillståndet hos den inneboende har förändrats. I avhandlingen har en ny metodologi införts kallad "non-intrusive appliance load monitoring (NIALM), som baseras på maskininlärd klassificering av "fog layer". Metoden gör det möjligt att urskilja enskilda el-konsumenter med stor noggrannhet genom att jämföra mätdata med hushållets "activities of daily living", (ADL). Detektionen av olika el-konsumenter i hushållet görs genom klassificeringsalgoritmen "k-nearest neighbour's" (k-NN), vilken

har uppnått hela 97.4% träffsäkerhet och tydligt demonstrerar metodens användbarhet. Tack vare de låga kostnaderna och möjligheten till återanvändning hos "field programmable gate arrays" (FPGA), har den k-NN-baserade modellen implementerats i FPGA. Prestandan för detta system visar sig, vid jämförelse med andra beräkningsplattformar, vara ett kostnadseffektivt sätt att använda IoT-baserade lösningar för monitorering av personers hälsostatus i hemmiljö.

Sammanfattningsvis visar avhandlingen på två integrerade IoT-lösningar för patientövervakning i hemmiljö, som kombinerar smärtupplevelser med ADL och därigenom kan erbjuda trygg och kostnadseffektiv assistans till vården av sjuka och äldre personer och möjliggöra för individer att leva längre i sina egna hem.

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Amleset Kelati
Sundbyberg, November, 2021

Abbreviations

AAL: Ambient Assisted Living
ADB: Adaptive classifiers Boosting
ADL: Activities of Daily Living.
ADS: Analog-to-Digital Signal
AFE: Analog Front End
ANN: Artificial Neural Network
CCS: Computer and Communications Security.
CDE: Challenge Driven Education
CERID: Challenge,Education, Research,Innovation, and Deployment
CNN: Convolution Neural Network Things
DBCAN: Density-Based Clustering of Applications with Noise
DT: Decision Tree
ECG: Electrocardiogram
EEG: Electrocorticography
EMG: Electromyography
EOG: Electrooculography
fEMG: Facial Electrmoyography
FPGA: Field Programmable Gate Arrays
GNB: Gussian Naive Bayes,
GSM: Global System for Mobile Communications
GUI: Graphic User Interface
HAN: Home Area Networks
HEMS: Home Energy Management System
HLS: High Level Synthesis
HW: Hardware
IHH : IoT Home Healthcare
IALM: Intrusive Appliances Load Monitoring
ICT: Information and Communication Technology (ICT)
ICU: Intensive Care Unit
k-NN: K-Nearest Neighbors
LDA: Linear Discriminant Analysis,
LRC: Logistic Regression Classifier

MAP: Maximum A Posterior
ML: Machine Learning
NIALM: Non-Intrusive Appliances Load Monitoring
PLAID: Plug Load Appliance Identification Dataset
PQD: Power Quality Disturbance
PS: Processing System
PSO: Particle Swarm Optimization
QDA: Quadratic discriminant analysis
QoS: Quality of Service
REED: Residential Energy Efficiency Database
RF: Random Forest
ROC: Receiver operating characteristic
RSP: Respiration
sEMG: Surface Electrocardiogram
SpO2: Pulse Oximetry
SG: Smart Grid
SM: Smart Meter
SSE: Sum of Square Error
SVM: Support Vector Machine
SW: Software
VB: Visual Basic
VI-Trajectory: Voltage+current Trajectory
VLSI: Very Large Scale Integrated Circuit
Wi-Fi: Wireless Fidelity
WHITED Worldwide House hold and industry Transient Energy Dataset
WSN: Wireless Sensor Network
ZIP: Constant Impedance Constant Current Constant Power

List of Appended Papers

The work discussed in this dissertation is upon the original publications listed below:

Paper I

Kelati, Amleset, H. Maziku, J. Plosila, N. H. Mvungi and H. Tenhunen."Challenge Driven Education in using Emerging Technology to Narrow the Gap between the Ageing Population and the Health Caregivers," Proceedings of EDULEARN20, Conference, Palma de Mallorca, Spain, July 2020, pp, 5104-5113, doi: 10.21125/edulearn.2020.1327.

Paper II

Kelati, Amleset and H. Tenhunen. "Wearable in Cloud." in 2018 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE 2018), Washington DC, USA, Sep. 2018, pp. 7–8, doi: 10.1145/3278576.3278579

Paper III

Kelati, Amleset, I. Dhaou and H. Tenhunen. "Biosignal Monitoring Platform Using Wearable IoT." in Proceedings of the 22nd IEEE FRUCT Association / ACM Conference, Jyvaskyla, Finland, May 2018, pp. 332-337.

Paper IV

Amleset Kelati, J. Plosila och H. Tenhunen, "Machine Learning for sEMG Facial Feature Characterization," in 2019 IEEE Signal Processing Algorithms, Architectures, Arrangements and Applications (SPA), Conference, Poznan, Poland, Sep. 2019, pp.169-174, doi: 10.23919/SPA.2019.8936732.

Paper V

Amleset Kelati, E. Nigussie, J. Plosila, and H. Tenhunen, "Classification of Pain level using Zygomaticus and Corrugator EMG Features: Machine Learning Approach" Sensors, Vol. 21, issue. 19, p 254, 2021 (Submitted)

Paper VI

Kelati, Amleset, J. Plosila and H. Tenhunen. "Smart Meter Load Profiling for e-Health Monitoring System." in 2019 IEEE 7th International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada, Aug. 2019, pp. 97-102, dio: 10.1109/SEGE.2019.8859936.

Paper VII

Kelati, Amleset, I. Dhaou, A.Kondoro, D. Rwegasira and H. Tenhunen. "IoT based Appliances Identification Techniques with Fog Computing for e-Health." in 2019 IST Africa Week Conference (IST-Africa), Narobi, Kenya, May 2019, pp. 1-11, dio: 10.23919/ISTAFRICA.2019.8764818.

Paper VIII

Kelati Amleset, Gaber, H., Plosila, J., Tenhunen, H. "Implementation of non-intrusive appliances load monitoring (NIALM) on k-nearest neighbors (k-NN) classifier" AIMS Electronics and Electrical Engineering, vol. 4, no. 3, pp. 326-344, doi: 10.3934/ElectrEng.2020.3.326

Paper IX

Kelati Amleset, Gaber, H., Plosila, J., Tenhunen, H. "Implementation of K-nearest Neighbor on Field Programmable Gate Arrays for Appliance Classification." in 2020 IEEE 8th International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada, Aug. 2020, PP. 51-57 dio:10.1109/SEGE49949.2020.9181975.

List of not Appended Papers

Paper I

Kelati, Amleset, , Gaber, H., ”IoT for Home Energy Management (HEM) Using FPGA.” in 2021 IEEE 8th International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada, 2021, pp 54-57, dio: 10.1109/SEGE52446.2021.9534986

Paper II

M. Ebrahimi, **A. Kelati,** E. Nkonoki, A. Kondoro, D. Rwegasira, I. B. Dhaou, V.Taajamaa, and H. Tenhunen, ‘Creation of CERID: Challenge, Education, Research, Innovation, and Deployment “In the Context of Smart MicroGrid”’, in 2019 IEEE ISTAfrica Week Conference (IST-Africa), Nairobi, Kenya, May 2019, pp. 1–8, doi: 10.23919/ISTAFRICA.2019.8764845.

Paper III

Kelati, Amleset, I. Dhaou, Ville Taajamaa, D. Rwegasira, Aron Kondoro, H. Tenhunen and N. H. Mvungi. “Challenges for Teaching and Learning Activities (TLA) at Engineering Education.” in Proceedings. of the 12TH INTERNATIONAL TECHNOLOGY, EDUCATION AND DEVELOPMENT CONFERENCE (INTED2018), March, 2018, Valencia, Spain , PP. 9093-9098, doi: 10.21125/inted.2018.2220.

Paper IV

Amleset Kelati, J. Plosila, H. Tenhunen, “Analysis of smart Meter Design for e-Health monitoring on the Smart Grid System”, (ID SIW18-272) , Digital Proceedings of the 8th International Workshop on Integration of

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Paper V

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Paper VII

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Paper VIII

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Paper IX

A. Kelati, H. Tenhunen och F. Johansson, "Deep Breath - Wearable IoT sensor node to Monitor and Detect cough," in Proceedings 13th International Summer School on Advanced Computer Architecture and Compilation for High-Performance and Embedded Systems, Fiuggi, Italy, july 2016.

Paper X

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Paper XI

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Paper XII

Naiman Shililiandumi, Diana Severine Rwegasira, Ellen Kalinga, Aron Kondoro, Imed Ben Dhaou, Kwame Ibwe, **Amleset Kelati**, Nerey Mvungi, Hannu Tenhunen: "Adopting renewable energy in Tanzania: Opportunities and challenges". Proceedings of the 11th IFIP International Conference on Research and Practical Issues of Enterprise Information Systems (Confenis 2017), Oct. 18-20th, 2017, Shanghai, China.

Paper XIII

Aron Kondoro, Imed Ben Dhaou, Diana Severine Rwegasira, **Amleset Kelati**, Naiman Shililiandumi, Nerey Mvungi, Hannu Tenhunen: "Simulation Tools for a Smart Micro- Grid: Comparison and Outlook". In 21st Conference of Open Innovations Association (FRUCT), 6-10 November 2017, Helsinki, Finland.

Paper XIV

Diana Severine Rwegasira, Imed Ben Dhaou, Anastasia Anagnostou, Aron Kondoro, Naiman Shililiandumi, **Amleset Kelati**, Simon Je Taylor, Nerey Mvungi and Hannu Tenhunen, "A Framework for Load Shedding and Demand Response in DC Microgrid using Multi Agent System". in proceedings the 21st Conference of Open Innovations Association (FRUCT),ISSN 2305-7254, pp. 284–289, 6-10 November 2017, Helsinki, Finland.

Paper XV

Ville Taajamaa, Diana Severine Rwegasira **Amleset Kelati,** Aron Kondoro, Nerey Mvungi, Hannu Tenhunen, Imed Ben Dhaou, Naiman Shililiandumi: "Challenge Driven Education in the Context of Internet of Things", in proceedings of the 9th International Conference on Education and New Learning Technologies, July,2017, pp. 2490-2495, doi: 10.21125/edulearn.2017.1420.

Paper XVI

Diana Severine Rwegasira, Imed Ben Dhaou, Aron Kondoro, **Amleset Kelati** , Anastasia Anagnostou, Naiman Shililiandum, Simon Je Taylor, Nerey Mvungi, Hannu Tenhunen "A Demand-Response Scheme using Multi-Agent System for Smart DC Microgrid". International Journal of Embedded and Real-Time Communication Systems, vol, 10(1), pp. 48-68, 2-19 (250118-013311)

Paper XVII

Aron Kondoro, Diana Severine Rwegasira, Imed Ben Dhaou, **Amleset Kelati**, Naiman Shililiandumi, Hannu Tenhunen, Nerey Mvungi, Ville Taajamaa: "Training the Future ICT Innovators on Open Science Platform", in proceedings of EDULEARN17 Conference, Barcelona, Spain, Mar. 2017, pp. 1988–1994, doi: 10.21125/edulearn.2017.1420.

Paper XVIII

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Paper XIX

A. Kondoro, I. Ben Dhaou, D. Rwegasira, **A. Kelati,** N. Shililiandumi, N. Mvungi and H. Tenhunen, 'Simulation Tools for a Smart Micro-Grid: Comparison and Out-look', Simulation Tools for a Smart Micro-Grid: Comparison and Outlook', in in proceedings the 22nd Conference of Open Innovations Association (FRUCT), Helsinki, Finland, Nov. 2017, p. 7.

Paper XX

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Paper XXI

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Paper XXII

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List of Tables

List of Figures

Contents

Chapter 1

Introduction

Communication technology is now in the evolution era of "IoT." IoT has enabled the connection of around 26 billion devices over the last few years, and by 2025, around 75 billion devices are expected to be connected to the internet. Today, everything around us, lights, appliances, and cars, can connect to the internet. IoT enables physical devices to interact with the internet by employing sensors, micro-controllers, and network connectivity that facilitates these items to receive and transfer information. IoT for healthcare application is a new technology that aims to link sensory-related devices and humans to the internet to develop wearable appliances and healthcare supplies [18].

The IoT application in a healthcare system follows the same procedure of combining devices such as sensors and micro-controllers to analyze and send the sensor data to the cloud and then to the caregivers (doctors). The IoT-based sensor needs to be tiny, but at the same time, it should be able to integrate its necessary parts such as energy storage components, communication, and signal collection units into a single kit.[19]. The recently evolved technology of integration and miniaturization of sensors, micro-controllers, wireless networks designed in a single chip has opened up opportunities for wireless sensor networks to be applied to many sectors. Integrating the IoT application for medical services promotes healthcare services for the elderly and patients in ICUs. Real-time data for patients and their health status is stored and analyzed for doctors and caregivers to monitor them using handheld computers.

The current healthcare systems are facing a crisis due to the following (i) a quickly increasing elderly population, (ii) an increase in chronic ailments, and (ii) rising healthcare spending. The traditional health monitoring systems had online applications for gathering inpatient's information, and they did the analysis and processing offline. This system prevented real-time patient monitoring that can aid in early detection of diagnosis of sickness.

However, the exciting application domains of IoT-based health monitoring help collect long-term data for quantitative analysis and recognize underlying patterns in addition to enabling the use of wearable sensors and wireless technology for continuous health monitoring in a real-time environment and for subsequent transition to affordable healthcare. The pioneering technologies of Smart Health combined with methods of ML and innovative signal processing for bio-signals can add to the quality to healthcare systems [20]. Wearable devices can monitor bio-signals such as ECG, EEG, EMG, and EOG with innovative real-time signal processing, feature extraction, and classification applications. The ML-supervised learning methods applicable for bio-signals for classification and regression, are similar to those in which unsupervised learning is used for clustering and reinforcement learning. From the previous studies in this field, we learn that each algorithm developed by using these methods relates to the objective and goal and can lead to both weak and strong results [21]. For instance, for classification, an EMG signal that depends on facial emotional expression can be better used in the supervised ML method with a deep learning algorithm. Many researchers have been studying the application of facial expression identification for diagnosis in the field of medicine.

Similarly, future buildings will offer new opportunities, a relaxed environment, and effective prospects to their residents vis-a-vis a better health monitoring system. Intelligent buildings could facilitate, for instance, an analysis of behavioral changes while using advanced technology adaptations in an entire day's events. An important anticipation concerning smart buildings is that they would contain facilities that make the residents' living as relaxed and easy as possible. Smart Grid (SG) is an aspect of a smart building or smart city that can deliver enormous data that is based on the appliances' electricity usage. The application of load consumption monitoring can remotely recognize the activities of the elderly in their homes. This study is a part of the efforts toward SG technology advancement by using SM capabilities for appliance load measurements. These devices can have vital information that can be extracted to simplify appropriate arrangements and improve choice-making. ML and big data analytics will undoubtedly have a serious role in the provisioning of such intelligent facilities. Despite the significant existing studies concerning advanced methodologies for healthcare IoT operations, a considerable gap remains in this field. Our research focuses on the SM data about measurement of electricity usage to be analyzed with the help of advanced ML and big data analytics to identify apt appliances. The method to be used is the same as the one used for wearable devices that uses sensors, algorithms, and communication networks for e-health follow-up techniques. SM data able facilitating independent living of the elderly drawing on the electricity usage of their appliances for simultaneously monitoring their health status remotely.

In this thesis, our discussion is also focused on proposing an advanced system for ambient intelligence-assisted healthcare monitoring in association with the ML approaches that can be functional for data-driven analytics and IoT applications. To the best of our knowledge, this thesis is the first study that covers the SG and the presentation of SM data analytics associated with ML. In parallel, given that it covers wearable technology, there is ongoing advancement toward smart energy management systems using SG technology. It has various components, including SM, that generates real-time energy management data of the consumers. This data can be applied to discuss issues not only related to electricity services but also concerning indirect monitoring of one's health status. This application enables detecting sudden and abnormal changes in the occupant's daily living behavior through intelligent analysis of data pertaining to their energy usage. By integrating wearable sensors with the daily living behavioral change detection system based on evaluating the measured data from SMs, a better functioning ambient assisted living system can be realized. Our thesis can be a significant input for ML scientists to further explore this recently developed technology-inspired ML-based IoT functions.

This research thesis has been introduced along with a mention of the motivation and aims and objectives of this work. Further, we have also discussed our contributions to knowledge in this area, the methodology we have used, and the overall organization of this thesis.

1.1 Research Problem

The current structures of healthcare systems are facing a crisis due to a fast-increasing population of the elderly, an increase in chronic ailments, and rising healthcare spending [22]. At the same time, an aging population is getting exposed to suffering multiple health issues and illnesses. This group of patients often relies on a wide variety of support, including that from family, friends, social care, and third-party organizations. The value of smart technologies for immediate care distribution is growing to meet these challenges [23]. Of late, there has been swift progress in monitoring technologies for independent living, immediate mediation services, and in-patient condition handling. However, there is a knowledge gap between personalizing and behavioral pattern recognition for the home care elderly and patients with limited health resources. Still, the existing mobile and e-health solutions fail to include and exploit the use of clinical knowledge in their approaches. As a result, one of our research motivations is to find an approach that can include both clinical knowledge and patient prioritization into a solution. Being able to identify and forecast variations in activities requires a thorough knowledge of the symptoms and attitudes that are supposed to have a bearing on each of the conditions. Given the shortage of health caregivers, there is a demand for automatic pain assessment for quality care. Any patient monitoring system's capacity can be dramatically enhanced by the inclusion of medical insight [24]. Therefore, one of this thesis's motivations is to emphasize the need for a low-cost and less intrusive health status monitoring solution by proposing an approach where the elderly can live independently with assisted care. Usually, particular health observing methods have been used only to gather data from hospitalized patients. Sometimes data processing and analysis are implemented individually. They are disconnected and end up creating an unrealistic process for the recurrent follow-up of the health status and/or for not discovering of medical sicknesses. The health monitoring system's main challenges are formulating its various features and on-boarding the pattern extraction and characterization methods, which would allow the system to accurately and quickly distinguish the vital information about a patient's status within reasonable time are needed. Providing such classification and the requisite translation methodologies for profiling patients is essential. In summary, the motivation for carrying out this thesis falls into the following two categories:

1. Development of a self-reporting method is essential for patients who are using on-line-care (home health care) who are experiencing pain but are not able to communicate.

2. Need for a low cost, intrusive, less time-consuming and an accurate system for patients and the elderly that is also enhanced by behavioral change detection technology to assist them while they are located in their premises.

1.2 Objectives

1.2.1 General Objective

The primary objective of this thesis is to develop an architecture and algorithm and implement a IoT technology for supporting independent living through real-time and health status detection and monitoring system for Ambient Assisted Living (AAL).

1.2.2 Specific Objectives

The existing systems are evaluated, discussed, and inspected to find out what needs to be improved about them even as the present challenges are effectively dealt with:

- To develop an accurate pain rate monitoring and detection system.
- To develop an accurate and cost-effective behavioral change monitoring and detection system.

1.3 Research Questions

The following research questions (RQs)are addressed to achieve the objective of supporting independent living in health care IoT systems.

RQ1: How to implement an efficient pain motoring system with IoT-based health monitoring system?

RQ2: How to classify EMG signals accurately for pain detection?

RQ3: How to monitor patients' behavioral change remotely using household energy consumption data?

RQ4: How to detect and classify behavioral changes from the household energy consumption data?

1.4 Research Methodology

This research study has used the Challenge Driven Education (CDE) methodology [25] for problem identification. Further, this research has adapted the challenges [12] of the technology gap of the IoT health monitoring system for elderly and critical patients to support online care or AAL.

1.4.1 Area of Study

One of this thesis's aims is to solve the main challenges of the developed world associated with the increase in the elderly population and the difficulties faced because of the deficiency of caregivers. The findings of this study reveal that both the aging population and the caregivers have shown their willingness to become accustomed to the use of modern technology for healthcare purposes as this technology is expected to solve the present important associated problem of lack of caregivers. The fundamental reason why the elderly should opt to live in such healthcare facilities is that it establishes their independence by only receiving minor help from caregivers. IoT for health care application is expected to creates an optimistic environment for the elders, and the caregivers could also help eliminate some of their difficulties. The study evaluate the possibilities of IoT technologies to support healthcare of elderly while supporting their independent living on side and supporting their communication capabilities to assess pain on them selves with might be critical for patient using online care. Thus, we need to produce a reasonably priced, less intrusive, and proper system for behavioral change detection or identifying the routine for daily living at online care for the elderly while they are located in their premises. The thesis scope lies on the IoT technology to health care for the elderly while supporting independent living is linked with research tasks. One of the tasks is to design and implement low-cost surface EMG sensor nodes for facial expression recognition for the proposed remote monitoring system. The system supports the automated detection of pain and communication capabilities for critical patients through online care. The other task is to learn the signature and the pattern of the appliance usage at home, identifying patterns by the load consumption of the appliances and their specific time usage of electricity for supporting independent living for elderly. In particular, SM can deliver a solution by collecting individual appliances' energy consumption by determining the characteristics of the appliances from the pattern and signature of the measured data. The data set is taken to achieve and permit rapid acquisition of the appliances' signature's overall general behavioral leanings. The proposed system uses SM to collect electricity usage from homes by taking into account a detection method for typical and exceptional electricity consumption. The study on this aspect is also beneficial for reducing home energy usage based on knowledge of sensing and monitoring of the existing system that depends on overall consumer energy.

The new proposal of this thesis is developing a methodology for the consumer's energy usage dataset collected with SM to be used for health monitoring applications. A novel approach is obtained in this thesis. (i) Analysis of energy usage data obtained from smart meters for the remote chronic patient or elderly monitoring and healthcare applications. (ii) The collected SM data set can offer a quick pattern on the appliances' signatures with the deployment of wide-ranging behavioral predilections. (iii) A deep study on the relation SM dataset from appliance's usage based on their classification of the type of electrical devices; on / off, multi-state, and continuously variable using only smart meter data. Including a methodology is investigated and for classifications of the appliances, and cost-effective remote health monitoring solution.

1.4.2 Conceptual Framework

The research methodology, as implemented, of this thesis is illustrated, in-depth, in Figure 1.1. Each of the phases' yields is mentioned in the author's published conference papers and journal articles. The outline demonstration is the focus area for answering the existing challenges of health care monitoring systems.

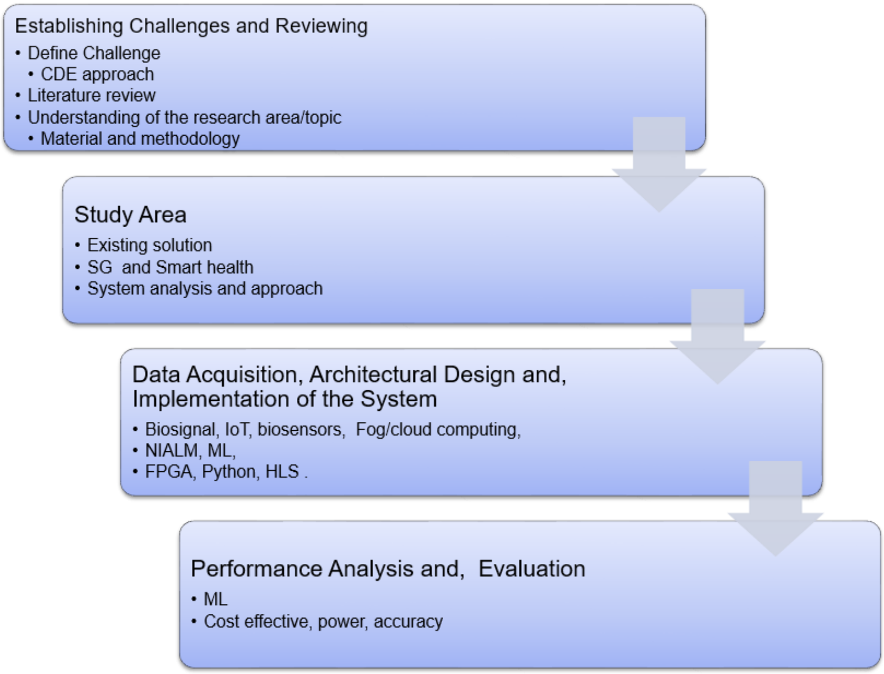

Figure 1.1: Conceptual framework

1.5 Significance and Scope

This methodological research study uses the Challenge Driven Education (CDE) methodology [25] for approaching the problem to be able to reach its objective. For our first objective, the focus was the following: (i) Reviewing relevant bio-sensors and existing pain monitoring systems. (ii) Analyzing the sensor node, wearable devices, and bio-potential acquisition design for continuous pain monitoring with low power consumption. (iii) Designing and implementing low-cost surface EMG sensor nodes for facial expression recognition with the integration of Hardware (HW) and Software (SW) components. For the proposed remote monitoring system, the first step was to design a pain monitoring node. The designed system is a low-power and eight-channel wearable bio-sensor node for collecting emotional facial expressions to be used for the pain monitoring application. The system is IoT-based and used for facial muscle movement monitoring. It has a cloud computing architecture for ample data storage and applying intelligent data processing for it to be adaptable to high data rate running and harmonizing data on the web network application. We performed the facial expressions and measurement processes by locating the muscles and placing the electrodes using our module, Wi-Fi EMG sensor prototype. The experiment was done by testing ourselves since it was significantly challenging to get actual patients' data measured using the module. However, we assumed the accuracy is acceptable even though working with accurate data, when possible, is our recommendation for better evaluation and greater accuracy.

The second focus was on designing the daily living activity of behavioral change monitoring system comprising: (i) Reviewing how energy consumption data serves health status monitoring.

(ii) Studying abnormality detection change from SM load profiling for home-based e-health services.

(iii) Proposing a new architecture for SM load profiling for normal or abnormal energy usage to determine the health status monitoring of elderly persons at home.

The aim is to connect the abnormality detection and behavioral change from SM load profiling for home-based e-health services. For the proof of our concept, a dataset was collected from the Swedish energy sector on the energy usage of 13 homes in Stockholm, at hourly interval, for one month (May 2018), and this dataset contained around 9300 measurements. Each of the homes covered had a 65 + year old person was living alone in it. We managed to discover the household's abnormality indications, and the data classification of the cluster showed unusual power usage during one or some of the 24 hours of the day, depended on the energy consumption of the consumer in the household. The result fulfilled our expectations; however, appliance-level energy consumption and load profiling analysis were needed to connect and relate the daily living changes of the consumers with their real-time health status.

Our third focus was also to improve the electrical load performance recognition by NIALM classification methodology for health status monitoring, and it entailed the following:

(i) Evaluating various classification algorithms and SM reading data features, as discussed. Further, better ML algorithms were used for greater accuracy of classification and reorganization tasks

(ii) Implementing and evaluating the classification's accuracy using K-NN, and the appliances using recognition could monitor human activity. ML algorithm analysis can classify the appliances.

For evaluating our concept, we used the NIALM and the Plug Load Appliance Identification Dataset (PLAID) dataset by splitting it into a training dataset and a testing dataset, and the normalized confusion matrix verified the result. The appliances' level energy supervision was known by forecasting behavioral sequences from the customs and routines of the individuals being studied. This method aimed to decrease the demand by conserving power and with the help of the load profiling methods used to check the user's health situation from the house itself. Our further analysis will focused on solving the current NIALM issue on overlap transients, slow transient, and the inability to classify the transient state appliances. It involved the current steps that:

(i) We proposed a HW-based FPGA implementation to detect the classification.

(ii) In the thesis, we used FPGA implementation of the ML (K-NN) algorithm and analyzed the appliance identification's performance. This includes making it a cost-effective alternative for wide-scale deployments of NIALM-based individual appliance detection for human activity daily living detection or indirect real-time health assessments.

Thus, this thesis contributes a novel approach for assessing both physical and tracking daily living activity through monitoring the use of appliances accurately can be use a indicator for potential changes in emotional and/or mental state. It indicated a well-being of a person by analyzing only the electricity readings obtained from their SM and its implementation for the ML algorithm's appliances' recognition.

The solution is in the category of: 1) Addressing the current limitations that are associated with existing technologies to facilitate a non-intrusive and personalized monitoring system;

2) Identifying ADLs to facilitate early intervention while applying medical knowledge to the obtained results;

3) Indicating specific behavioral indicators, such as prolonged and reoccurring instances of activity or inactivity, to assess the patients' ability to undertake normal ADLs and monitor their state of health.

4) Suggesting a clinical trial to evaluate whether the approach can support vulnerable people with ongoing healthcare needs who are living independently.

The results are for deploying aggregated load monitoring techniques to classify individual device interactions to aid in a home care patient's overall assessment. The method that we have used to identify individual devices is an imperative requirement for determining and identifying a patient's ADLs with a cost-effective solution. The appliances' classification is to be used for a novel method, i.e., to identify concerning behavior and routine alteration and adjust to the mis-classifications to reduce future false alarms and adequately adapt to disease progression.

1.6 Research Gap

This study focused on developing IoT technology supporting health care for the elderly while supporting their independent living. It fills the gap by proposing an IoT technology to support self-reporting methods development in home health care systems. The proposed system also uses a low-cost, less intrusive, and accurate IoT-based system that can easily be implemented for elderly daily living routine detection methodology in their own homes. The comparison of the work in this thesis with similar previous work is summarize in the Tables 1.1, 1.2, 1.3.

Table 1.1: State of art automatic pain assessment using machine learning on bio-sensor application

Author	**Dataset**	**Classifier method**	**Type of Signal**	**Accuracy** (%)
[26]	Bio Vid	RBF Neural Network	ECG, EDA, EMG (trapezius)	80
[27]	Experimental	Neural Network	EDA, Facial EMG, HR, RSP	70.6
[28]	BP4D+	Random Forest	DBP,EDA, Pulse, RSP	84.6
[29]	Bio Vid	Random Forest	EMG, ECG, EDA	98
[30]	Bio Vid	SVM	EMG, ECG, EDA	91
[31]	Experimental	Naive Bayes	HR	85
[13]	Experimental	SVM	EMG	98
This work	BioVid	SVM	EMG (Corrugator & Zygomaticus)	99.4

Table 1.2: State of the art for appliance identification

Work	**Data source**	**Sampling rate**	**Features**	**Identification**	**Application**	**Contribution**
[32]	PLAID and WHITED	High and Very High	Trajectory Image	Siamese ANNs, followed by DBSCAN	Detects Unidentified Appliances	
[33]	PLAID and WHITED	High and Very High	P, Q, D Trajectories	PQD-PCA	AAL	Excellent classifier performance compared with other approaches
[34]	PLAID	Very High	Current WS, P and Q, harmonics, Quantized waveforms, V-I binary image	K-NN, Gussian Naive Bayes, Logistic regression classifier, SVM, Linear discriminant analysis, QDA DT, RF, Adaptive classifiers Boosting		Compares the discriminatory power of different features and the performance of different classifiers
[35]	PLAID	Very High	55 Steady-state and 23 transient features	Random Forest		Proposes a feature selection algorithm
[36]		Very High Extremely High	V-I Trajectories	CNN		CNN applied to load identification
[37]	TRACEBASE and REED	Low	P trace and usage Pattern profiles	MAP Criterion	HEMS	Incorporates appliances' usage pattern for load identification and forecasting
[38]	Laboratory data	Medium	Features obtained from the PSD of the power signal	Gussian Process Classifier	HEMS	Use of multiple models in a committee voting mechanism
[39]		High	P and D	CNN design with PSO	HEMS	Integrated of NIALM into a demand side management
[40]	Private data	Extremely High	EMI signal	k-NN		Able to differentiate similar switching/ mode power supplies
This Work	**Private data** **PLAID**	**High** **Very High**	**V-I Trajectory images**	**k-NN**	**AAL e-Health**	**Activity recognition by load profiling NIALM for home appliances for real-time assistance of health condition of the inhabitants**

Table 1.3: State of the art on K-NN on FPGA implementation

Work	Architecture	Throughput, worst case	Resources usage
[41]	**Acquisition** **FPGA (LabVIEW based)**	**3.925 ls** **(255 kHz**	**1106 FFs (3.1%)** **672 LUTs (3.8%)**
[42]	Pre-processing (P, Q + Harmonic Computing) 1 ARM Cortex A9 667 MHz (LabVIEW RT)– FPGA (LabVIEW based	188 ls+k / 333 ls a 250 ns (per token)	16.8 kBs RAM – 808 FFs (2.3%) 735 LUTs (4.2%
[43]	Event Detection 1 ARM Cortex A9 667 MHz (LabVIEW RT) FPGA (LabVIEW based)	91 ls 40 MHz (25 ns)	16.54 kBs RAM – 938 FFs (2.6%) 826 LUTs (4.7%
[44]	FPGA (Manual coding)	14 MHz (71 ns	126 FFs (0.4%) 568LUTs (3.2%
[45]	FPGA (System Generator based)	12.9 MHz (76 ns)	3016 FFs (8.6%) 3924 LUTs (22.3%
[46]	Disaggregation Computer Intel core i5-2410M 4CPUs 2.3 GHz 1 ARM Cortex A9 667 MHz (LabVIEW RT)	4 ms 953 ls	847 FFs RAM 8.03 kBs RAM –
This work	Classification Xilinx Zynq-7000, programmable System on Chip (SoC), in Dual ARM Cortex-A9 MPCore (System Generator based)	138MHz 7.5ls	79 kBs RAM – 21647 FFs (20.3%) 19784 LUTs (37.2%

1.7 Thesis Contributions

1.7.1 Summary of Contributions

The main scientific contributions of this thesis are as follows: (i) Investigation of the possibility of ML-based situation-aware techniques to provide smart health services with NIALM data-driven analytics; (ii) Documentation of research challenges and trends for smart health and how ML designs can aid in dealing with such demands; (iii)Description of smart health applications, including happiness, confidence, efficiency, and satisfaction, and the role of ML in such operations. Our project's focus is to develop an architecture for the IoT platform to be used in the development of health technology devices and their applications. The target is to develop the architecture and bio-medical signals monitoring prototype for determining the health conditions of patients. Different bio-signals can be collected using wearable sensors. The recognition of the pattern can be demonstrated with signal analysis. Practical algorithms are required to extract and interpret the sensed data in the proper context of the disease or health conditions. By measuring the appliances' energy usage, it is feasible to monitor personal activity and profile the change in behavior using an intelligent data analysis technique. To use the associated data for the detection of behavioral change, a detailed understanding of a person's condition and expected behavior is essential. Long-term periodical energy data with high resolution needs to be collected to detect a patient's behavioral changes. To the best of our knowledge, there is still a gap in terms of developing an effective ML algorithm and implementing it in HW form for better appliance classification performance and accuracy. Therefore, in our research, after we investigated the implementation of appliances' energy usage with ML, we also implemented the algorithm in HW and gained better performance accuracy by making it a cost-effective alternative for indirect behavioral change assessments. The SM analysis for health condition prediction threw up accurate results with the NIALM approach by predicting the human activity patterns based on the appliances' electricity consumption. K-Means algorithm together with the time and frequency of the appliances' usage improved the pattern information about the electricity consumption of several appliances at a given time. The algorithm for the selected appliance identification implemented using FPGA improved the classification accuracy by gaining less processing run time and low power consumption, thus, making it a cost-effective solution.

In this dissertation, we recognize and deliver research-based results and proposals for the challenges associated with two IoT based health monitoring system to serve people. We initialize the system to raise the requirements for developing an accurate pain rate monitoring, and the second one is to target for an accurate cost effective behavioral change monitoring and detection system. In both cases, we model a system to produce real-time condition and that replies concerning the situation for health monitoring system. A hybrid design of lightweight, well operable, compact, cost efficient system is the requirement of space in order to monitor patients or elders without affecting their everyday activities. The expected results and the contributions is illustrated by addressing research question as described in section 1.3. Figure 3.1 summarizes the research contributions:

1.7.2 Overview of Original Publications

This thesis is a compilation of nine innovative publications. In this section, we offer a summary of each of these publications by introducing the authors' contributions to each publication.

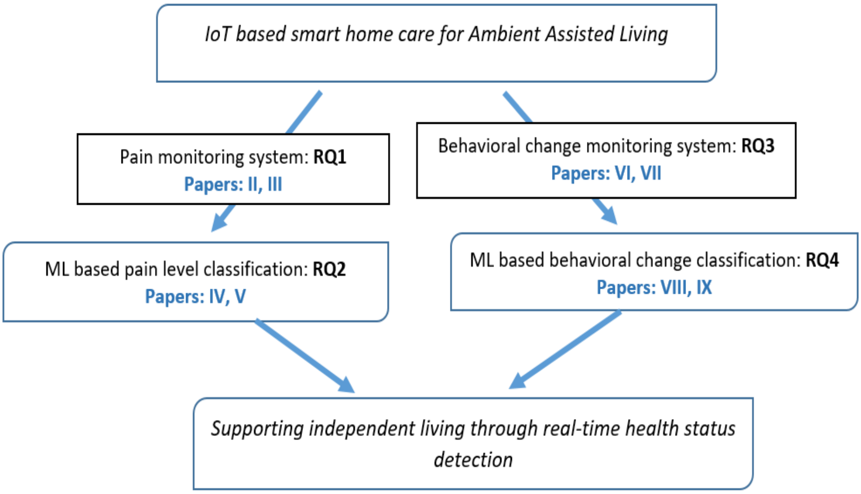

Figure 1.2: Summary of research contributions.

Paper I : Challenge Driven Education (CDE) in Using Emerging Technology to Narrow the Gap Between the Aging Population and the Healthcare Givers

The problem associated with the growth of the elderly population on the structural systems of pension, social security, and healthcare. It shows how CDE is an enhanced problem-solving approach by analyzing the existing research on this topic that has explored the challenges for elderly caregivers. The central areas recognized in this study are partly supported by previous research, particularly, in the area of well-being of the elderly. The fundamental reason why the elders have access to proper healthcare facilities has to do with establishing their independence with only minor assistance needed from their caregivers. This paper uses a challenge-driven approach to discuss the complex dynamics of elderly-caregiver relationships and how technology can be leveraged to enhance healthcare and promote independent living. Emerging technology leads to internet-dependent humanity; associative devices like sensors, wearable devices, and unique technology accessible on mobile phones and touch-pads will ensure that the elderly can stay safely in their own homes. We summarize, based on existing research, by pointing to the acceptance of this technology by both the elderly and the caregivers. On a positive note, the results generally show that the desire and acceptance of e-Health devices and technology is higher among both the elderly and the caregivers. The increase in the population of the elderly with a proportional decrease of caregivers suggests that technology usage in healthcare systems can contribute by offering cost-effective healthcare to the elderly. However, this technology is still the critical target for solving the associated problems of the lack of caregivers given the senior citizens' disproportionate growth. Finally, the design and development of cost-effective healthcare technology solutions that depend on activities and data-driven monitoring and technology systems are required.

Author's Contribution:The author of this thesis is the first and primary author of this publication. The author lead the wiring preparing the first draft and complied all the comments from the co-authors. The author is also responsible for leading the writing, compilation, and (virtually) presentation of the work in the conference venue.

Paper II: Wearable in a Cloud

The importance of health care facilities at home and how they become more and more critical. It describes a design approach and system architecture of IoT-based wearable remote monitoring systems for healthcare applications. The IoT-based wearable device performance is checked for real-time monitoring of the surface EMG (sEMG) signal. Improved design of bio-sensors that can measure the ECG and EMG with a wearable device due to the used similar devices, but are the shortage of diagnostic accuracy due to their low sample rate, and minor channels are connected to the body. In this paper, we present our design of a wearable system with 8-channel AFE and use a Wi-Fi module to transfer the data to the cloud to measure the ECG or EMG more accurately at home, almost at the same sample rate and channels at the hospital. The cloud is then built for receiving the data and for a real-time display and helps the doctors monitor the patients' condition remotely—the prototype design is that of a 2-layer PCB board, flexible and reliable with a thickness of 1.6mm. The board is developed using the Eagle PCB design SW tool for schematic and layout. The board size is small (60mm x 32mm x 4mm). So, a small capacitor by increasing the wire width template is essential with some standard steps.

Author's Contribution: The author of this thesis is the main author of this publication. The author proposed a bio-sensor-based remote health monitoring system and shouldered the responsibility for the general description, feasibility study of the prototype designing with circuit-level PCB design, soldering of the parts, and sending to the manufacturer. Furthermore, and testing and verifying the HW and the SW communication part of the implementation. The author of this thesis was also responsible for writing, compiling, and presenting this work at the conference venue.

Paper III: Bio-signal Monitoring Platform Using Wearable IoT

In this publication, a design methodology and system architecture of the IoT based wearable sensor node was proposed for real-time monitoring of the sEMG signal. The presentation of the suggested system was also related to the current e-health system. The basic aim of this system's implementation is remote patient monitoring. The system is composed of IEEE 802.11 WLAN, wireless sensor network to receive the bio-signal from patients and send it to a remote server on real-time basis to update the database concerned. The related architectures were investigated by means of an in-depth study to identify their advantages and disadvantages including the appropriateness of wireless communication technology's suitability for healthcare applications. The system server node gathers the information of the medical status from numerous client nodes and updates the remote database and web page that can be accessed remotely. In summary, we deliver a Wi-Fi and battery-powered wearable IoT unit to monitor a patient's bio-signal for their health control from anywhere and at any time through an IP-based network. The system is composed of up to 8 channel electrodes to measure the bio-signal. The article also presents in much detail the specifications and demonstrations of the prototype's performance by comparing it with state of the art systems.

Author's Contribution: The author of this thesis is the primary author of this publication. The design idea is one of the author's contributions, and he has developed and implemented a remote healthcare monitoring IoT-based architecture based on IEEE 802.11 WLAN. The author was also responsible for writing, compiling, and presenting to the conference venue.

Paper IV: Machine learning for sEMG Facial Feature Characterization

The essential application of a wearable e-health system is related to monitoring bio-medical signals and their applicable techniques for feature selection and classifications for real-time applications. The analysis of the data that comprised the muscle activity of the face, which formed upon emotional expressions. The main task was to find a specific classification technique for the collected facial sEMG signal and investigates the ML algorithm as a suitable method for the recognition and classification of EMG signals. The article also reveals how the SVM classifier was processed for classification of facial sEMG signal related to the pain intensity dataset. The result obtained from the assessment effects and approaches is able to show that the pattern recognition and facial EMG signal classification are based on emotional expression. The classification result is 99% accurate using the SVM technique that enhances the classification algorithms for sEMG signals. The publication shows that SVM is an effective classification technique for a dataset related to facial emotion expression. This paper presents a summary of the main contributions involving a comparison of various classifiers and proposes future research to compare the results with commercially available systems.

Author's Contribution: This author is the primary author of this publication and has designed, implemented, and proposed the model, including collecting the data, analyzing the collected data, and suggesting the possible use of facial sEMG signal for pain assessment. The author also led the writing process by requested the co-authors for their comments, compiled the final version for publication, and presented the work at the conference venue.

Paper V: Classification of Pain level using Zygomaticus and Corrugator EMG Features: Machine Learning Approach

A real-time recognition of facial expressions is required to certify the accurate pain assessment of patients in ICU, infants, and other patients who may not be able to communicate verbally or even express the sensation of pain. Facial expression is a key pain-related behavior that may unlock the answer to objective pain measurement tool. In this work, a machine learning based pain level classification using data collected from facial electromyograms (EMG) is presented. The dataset is acquired from part of Bio Vid Heat Pain database [1] to evaluated facial expression from emg corrugator and emg zygomaticus and an EMG signal processing and data analysis flow is adapted for continuous pain estimation. The extracted pain-associated facial electromyography (fEMG) features classification is performed by a supervised ML algorithm, on the KNN by choosing the value of k and that depends on the nonlinear models. The presentation of the accuracy estimation is performed with and considerable growth in classification accuracy is noticed when the subject matter from the features is omitted from the analysis. The ML algorithm for classification of the amount of pain in patients could deliver valuable evidence for the health care providers and aid the treatment assessment. Performances of 99.4% shown on the binary classification for the discrimination between the baseline and the pain tolerance level (P0 verse P4) without the influence of on a subject bias. Moreover, the result of the classification accuracy is clearly showing the relevance of the proposed approach.

Author's Contribution: This author is the primary author of this

Article. In this paper, she has emphasized and demonstrated the ML K-NN method to be an accurate classifier for a fEMG signal related to emotional facial expression. The author has led the writing process by requested the co-authors for their comments, compiled the final version for publication, and submitted the article to the MDPI Sensors journal and being the article's main correspondence.

Paper VI: Smart Meter Load Profiling for e-Health Monitoring System

To enhance the basic health-monitoring process, which is expected to solve the problems caused by the fast-rising population of the elderly and the consequent healthcare mandate. The customer's power consumption readings using SM to deliver healthcare by analyzing load profiling. The article shows the matrix-based analysis and classifier with the K-Means data mining and clustering algorithm method. In summary, this publication comprises: (1) a discussion on the SG foundation related to the different opportunities of health monitoring produced by the SM technology innovations. It includes SM load profiling integration at home to control the patient's significant conditions. (2) an examination of the load consumption at homes by combining the report on life and electricity consumption to determine and monitor the ordinary or abnormal actions. (3) a representation of using data mining for load profiling of power consumption that appears to identify the ordinary and exceptional management of the users based on normal or abnormal performances. Finally, the article offered a glimpse of the future work to be related to the activity of elderly home appliances to be connected with such criteria as user frequency and usage period to figure out an effective healthcare monitoring system.

Author's Contribution: The author of this thesis is the prime author of this paper. The author was the principal investigator of the proposal of SM load profiling method to apply for e-health monitoring. The author also produced and set up the complete model electricity usage report to identify the consumers' normal and abnormal load consumption based on expected or unexpected behaviors. The author led the writing process, compiled the final version for publication, and presented the work conference venue.

Paper VII: IoT-based Appliances Identification Techniques with Fog Computing for e-Health

Improving the living standard of urban societies and making healthcare benefits maintainable and effective. The proposed e-health system deals with a model transformation as sufferers of mental inconsistencies can be supervised and detected through an analysis of their home appliances' electricity usage. The developments in home-based e-health functions by considering the electricity usage data and involves the modeling of Constant Impedance and Constant Current and Constant Power (ZIP) that is approached along with the non-intrusive and intrusive techniques. The implementation of a simulation for the ZIP model on Fog-assisted healthcare IoT system to handle energy data-sets is used the GirdLAB-D simulation platform to perform accurate representations of household appliances and implementation of the ML algorithm to detect abnormal behavior. The pillars of the smart-city design uses along with a collection of the symbols for the assimilation and expansion of upgraded health benefits availed of through the regular monitoring of the end-user tasks. It is reports here on ADL, which is the preeminent method for defining a person's well-being using methods for appliances' identification. The load modeling approach on the dynamic ZIP model and advanced appliance parameters related to active power and reactive power, current, and impedance is discussed. Eventually, this work discovers a fog-based architecture for the e-health system. In this publication, we communicate our dedication to our future work creating a method for appliance identification using ML approaches and the algorithm implementation on FPGA to achieve adequate recognition of HW architecture.

Author's Contribution: The author of this thesis is the main author of this paper. In this paper, the author discusses the IoT systems for appliance identification and analyzes important. The author designed and built the complete Fog-based architecture for the health motoring system based on appliance identification. The simulation on the GirdLAB-D tool for the ZIP model's implementation to construct accurate models of household's appliances is also part of the author's contributions. The author also led the writing and compilation of the final version for publication and presented this work at conference venue.

Paper VIII: Implementation of Non-intrusive Appliances Load Monitoring (NIALM) on K-Nearest Neighbors(K-NN) Classifier

NIALM investigates an individual's house energy usage considering the characteristic deviations in voltage and current appliances in a home. The system classifies the energy usage of each appliance from the aggregated home energy usage. NIALM, as presented here, shows each appliance's load consumption by indirectly identifying the abnormal changes in appliance usage. The proposed NIALM approach is based on feature extraction from load consummations measurements of the electricity usage measurement signals to classify the appliance's state of activity. In this work, we have developed the recognition accuracy and the detection of appliances based on their applicable state using the ML approach, i.e., the K-NN algorithm classifier. The dataset used to achieve this handling is from the publicly accessible PLAID of power, voltage, and current signals of appliances from several households. In summary, this article presented an approach to classify appliances with NIALM techniques by distinguishing the signature of different appliances and their behavioral pattern based on disaggregated total energy consumption data to individual appliance specific energy load. Comparing different classification algorithms has demonstrated that K-NN is the most suitable classifier for most appliances used in the household. This analysis summarizes that the identification performance can be done based on the operational states of the appliances. Finally, the implementation of the K-NN algorithm for PLAID dataset appliance classification is potentially scalable for detecting the activity of the occupant and for monitoring their daily routines. This article then points to how future research work could discuss facilitating effective behavioral detection using NIALM on the HW implementation of NIALM with K-NN that can be more suitable for cost effective approach.

Author's Contribution: The author of this thesis is the primary and principal author of this article and has proposed and implemented the complete NIALM technique to distinguish the signature of different appliances and their behavioral patterns and further, the author has developed the ML algorithm and implementation and performance verifications of the classification accuracy. The author led the writing of the paper, compiled its final version for publication, and sent the article to the AIMS journal and the article's main correspondence.

Paper IX: Implementation of K-Nearest Neighbor on Field Programmable Gate Arrays for Appliance Classification

Appliance electricity consumption dataset produced by using the NIALM technique for faster and improved appliance classification, efficiency can be increased by implementing the k-NN classifier in HW. An FPGA HW implementation can advance the handling time with a high standard of efficiency performance. The HLS-based result has decreased design complexity and time for achieving cost efficiency. PLAID is used as a benchmark for the implementation. The selected appliance recognition is implemented using Xilinx Zynq-7000, and the HLS-based solution has used resources of 37.1 percent for LUT and 21 percent for FF from the available chip. Thus, the paper explained the comparison of the K-NN algorithm for PLAID appliance classification that had reached the novelty method and a possible efficiency in identifying the activity of elders monitoring their everyday habits. We discussed the future dataset to be carried out in the FPGA PS unit, and we hope the communication bandwidth will be cut down tremendously.

Including the K-NN algorithm implementation using HLS is practical for implementing the NIALM system for all state appliance classification.

Author's Contribution: The author is the primary author of this paper. The delivery of the methodology proposal and modeling algorithm implementation techniques is the author's contributions. The author led the writing of this paper, compiled the final version for publication, and presented it at the conference (virtual).

1.8 Thesis Organization

This thesis has been divided into two parts. Part I presents a research summary, and Part II delivers the original publications. Part I consists of the following chapters as described in Figure 1.2 of the thesis navigation Framework:

- *Chapter 1* introduces the motivation, presents the research questions, and a brief overview of the research contributions.
- *Chapter 2* provides the background and discusses important topics related to the works.
- *Chapter 3,4,5* present the main contributions to the research topic in each chapter separately by solving the research question and the result analysis described on that original publication while focusing on the challenges that address.
- *Chapter 6* presents our approach and our conclusions. Further, it answers and validates the research questions, and finally, it proposes questions to provide directions for future research.

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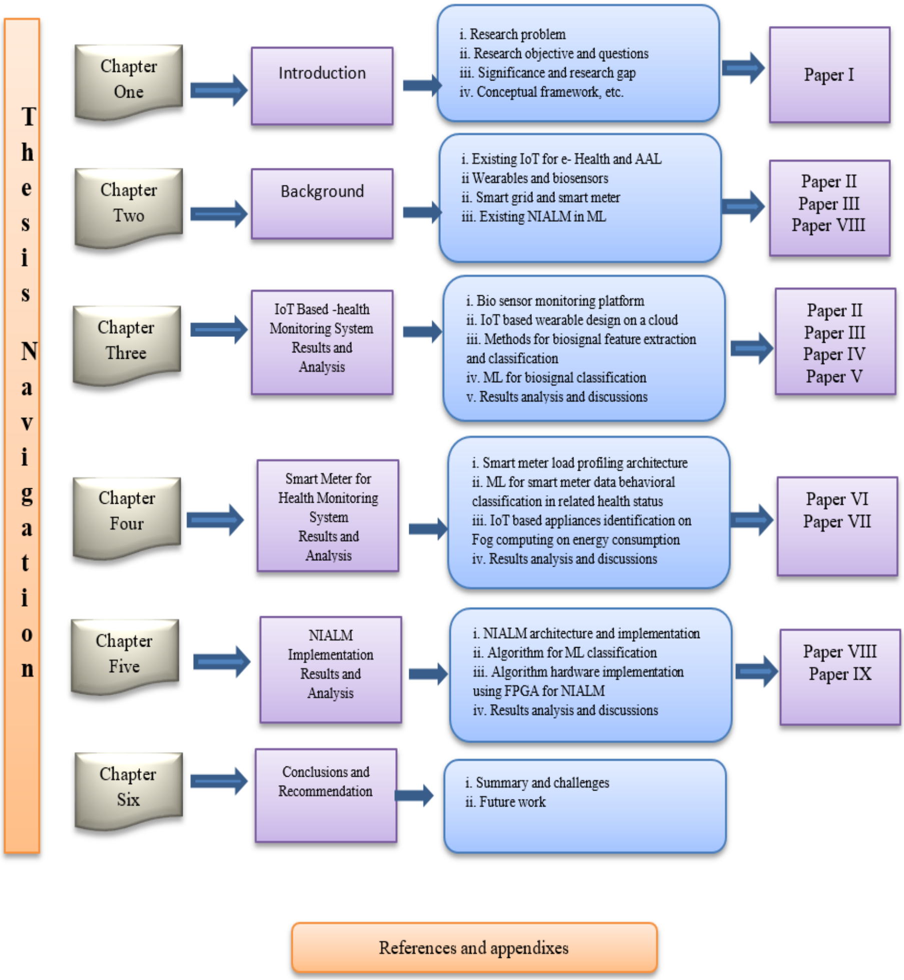

Figure 1.3: Thesis organization.

Chapter 2

Background and Related Work

A smart city integrates smart health, smart grid, and other smart technologies that have emerged in our world to offer new capabilities in terms of using IoT application. This chapter describes the health monitoring system's status with reference to two developed smart applications by identifying the improvements depending on our proposal and approach. We look at the previous research efforts in integrating IoT-based health monitoring systems and the SG application for the possibility of a health status monitoring system. Finally, this study analyzes the previous research that has been conducted and analyzes the remaining knowledge gaps.

2.1 IoT and Ambient Assisted Living

IoT is a fast-growing technology that makes our surroundings smarter by enabling things to be connected anytime, anywhere with anyone using a network router for any service or application. It is a network that connects sensors or devices to the internet, including digital technologies such as wireless systems, a computing system, low power technology, big data, analytical, and AI to accumulate, interconnect, and share intelligence without human intervention. Information from IoT supports researchers who are investigating environmental situations to forecast and avoid equipment failures, industrial interruption, and restricted access to logistics. Technological developments lead us into smart things by recognizing, discovering, detecting, linking, and guiding innovative communication methods among persons and things as they relate to each other. Smart devices operated by the hyper-connected IoT are becoming ever more dominant and universal in our personal lives. Nowadays, some or the other IoT application is linked with our daily routines and assists us in almost all social and business activities, including e-health [47] traditional inheritance services[48],

[49],[50],[51], including authorized area [52], [53], [54], community management area [55],[56],[57], and into the more related socioeconomic development area [54], [58] in addition to home-based robotics, self-directed and attached vehicles [59], and wearable technology. IoT is dedicated to bring about a real-life revolution to make our lives more relaxed, more effective, and "smart." IoT's potential uses are numerous and valid in the everyday life of persons, organizations, and humanity. IoT application involves being "smart" vis-a-vis the operating environment in sectors such as agriculture, transportation, healthcare, emergency building, smart city, manufacturing, tourism, and energy, and it is also connected to our routines. IoT has diverse application areas, and some of its uses are summarized in Figure 2.1 [60].

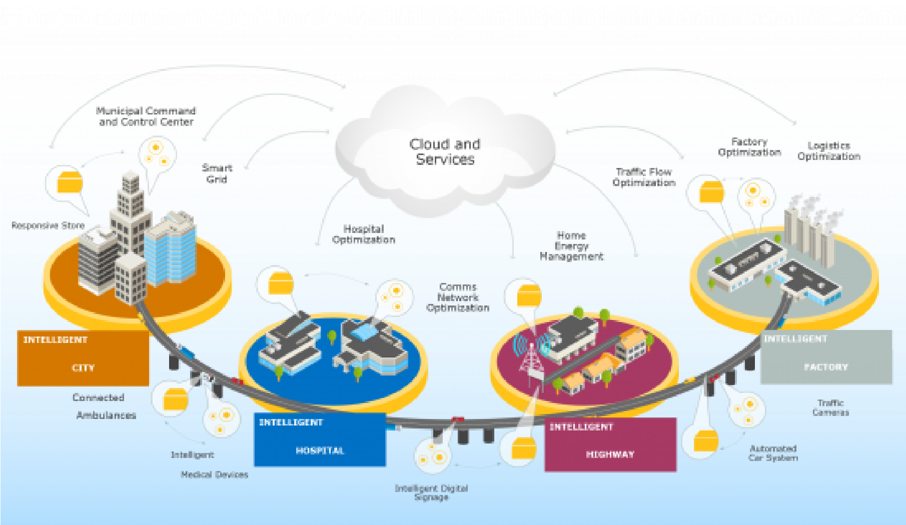

Figure 2.1: IoT application domains [4].

Sensors are rather omnipresent now, and their development will continue. Today, sensor-equipped industrial apparatus is driven by AI. Medical devices can self-diagnose and send alarms to patients and clinicians to monitor the health status of the former remotely. Health monitoring systems are looking to use sensors and actuators to develop our lifestyle with health technologies. Many tools explore the openings for the application of IoT to reform manufacturing and humanities. Mainly, IoT refers to connected physical and digital mechanisms [61]. IoT mechanisms can communicate data without the help, interference, or initiative of the people. On the other hand, by the end of 2019, there were 27 billion connected components globally, and this number is expected to increase to 76 billion in 2025. As many of the connected devices' roll-out, which is predicted to be more than 30 billion by 2020, connecting with or employing IoT will enhance the capacities across the researchers and medical professionals to advance their procedures. The research of IoT is extensive and is increasing in extent without restrictions [62]. IoT's key deliverable is to certify accessible equip-

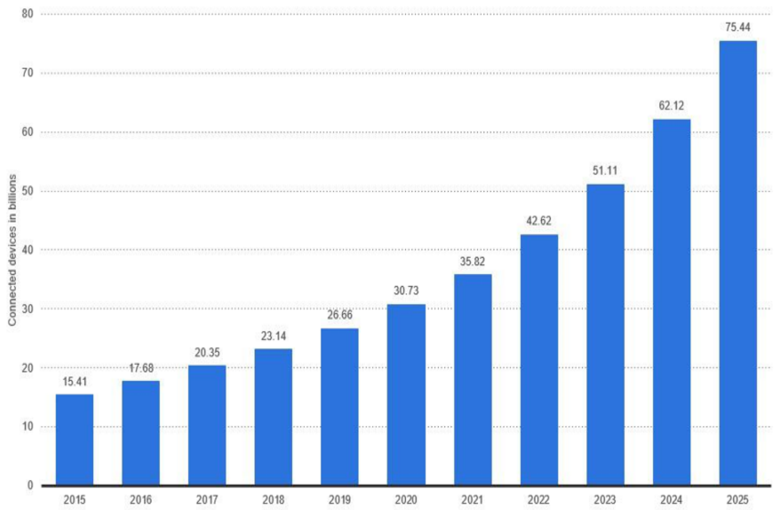

Figure 2.2: Estimated healthcare IoT device installations world wide 2015 -2025 (in billions) [5].

ment, devices, sensors, and networking components for data communication capabilities over the internet. IoT refers to connected physical and digital mechanisms. [61]. The continuing growth of IoT-connected components and devices during the present century is because of the progression of wireless technology and innovative findings in the area. The wearable devices are small in size and can sense, gather, and save data for offering support in several application areas, such as healthcare education and industries. At present, consumers are devoting much of their time to developing smart devices and smartphones as one of the factors associated with these smart devices for IoT-based health care monitoring system. Smart and wearable devices can record user's data such as heart rate, breath rate, sleep patterns, blood pressure, number of steps, and location [63] continuously. IoT-based e-health monitoring system for the elderly establishes a home care monitoring system by offering enormous opportunities to revolutionize healthcare and is an enabler to achieve an improved care system for both patients and care providers. At the same time, it can help with better asset utilization, new sources of revenues, and reduced healthcare costs. Also, the IoT-based e-health system can change the existing approach to how healthcare is delivered. Figure 2.3 illustrates IoT-based e-Health monitoring for the elderly.

Figure 2.3: IoT-based Healthcare - elderly monitoring.

A structural IoT-based e-Health monitoring system platform has four stages as far as the solution architecture. Figure 2.4 below depicts these 4 stages of IoT solution architecture.

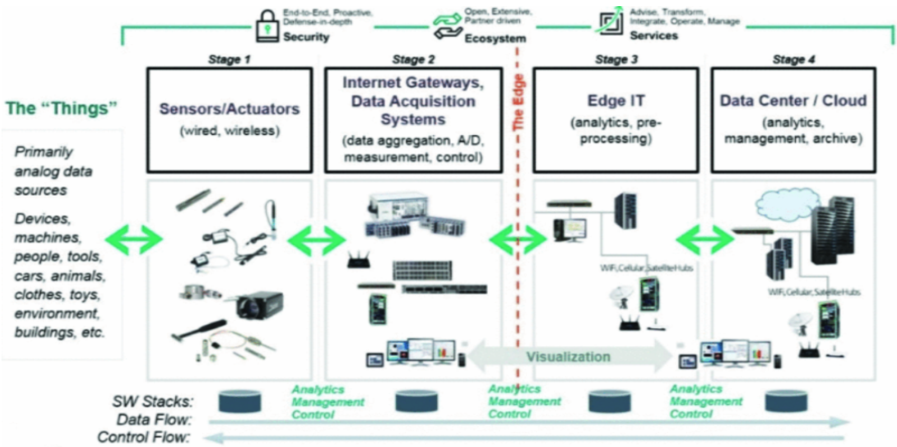

Figure 2.4: Four stages of IoT solution architecture [6].

Stage 1: Connecting things for receiving the principal data that could be analyzed. Usually, it involves a number of sensors that are either wired or wireless.

Stage 2: Connecting the collected data to the internet and data processing in terms of analog to digital conversion (ADC).

Stage 3: Executing pre-processing of the rest of the data through IT systems.

Stage 4: Saving the preprocessed data in a cloud server.

An alternative to a health monitoring system is related to AAL that incorporates methodological systems to care for older adults in their daily routine to permit a self-determining and secure lifestyle as long as possible. Smart technology can simplify the remote health care monitoring ability for AAL. Mobile communication and emerging technologies can process significant data and launch communication networks to cover older adults, their surroundings, and their caregivers.

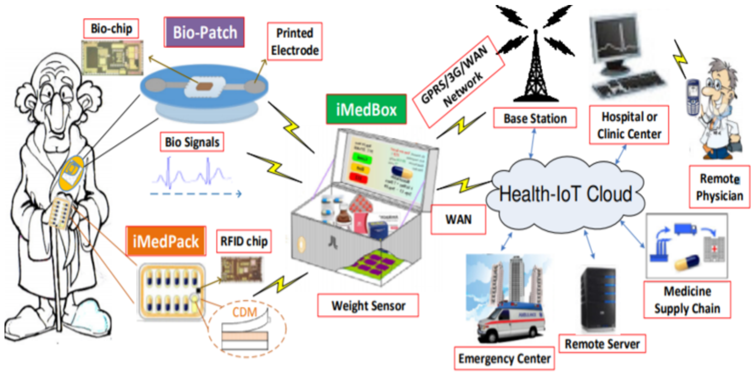

Figure 2.5: IoT and AAL for elders' health monitoring application [7].

The provisioning of healthcare with smart objects and consequences in the form of a practical IoT structure for Ambient Assisted Living (AAL) developments has become acceptable to both the elderly and their caregivers [12]. This advanced set-up allows individual communication between older adults, their surroundings, and caregivers to lead to the dominant feature in AAL, which aids the elderly to live in their homes using smart objects as facilities. AAL is a technology associated with behavior analysis in the home-based situation for health status monitoring systems. These monitoring systems have to recognize temporary dangers, including extensive health conditions [5]. AAL comprises elderly care systems by permitting independent and secure privileges in their daily routine. AAL needs a channel or communication to facilitate older adults and their caregivers' services.

Individual communication between older people and their caregivers is a significant feature in AAL. The AAL standard tends to be recognized with IoT as a facilitator for the elderly to stay inside their premises and communicate well with their caregivers using smart and intelligent devices. AAL involves a practical structure to care for older people and patients with distinct needs throughout their day-to-day routine. The key aim for AAL is to provide an adoptive independence solution by promoting a secure lifestyle for the elderly and special care patients in their own homes or surroundings. The initial need for AAL solicitations comes from a change in the population composition in the advanced countries where life-cycle anticipation is increasing while the birth rate is dropping. This situation has forced these countries to seek a new method and economical solution to keep healthcare possibilities within the limited plan of a cost-effective solution [64]. Application of AAL entails facilitating increase in the quality of life, comfort, and protection of the elderly by enabling them to live independently. The focal point of AAL is to gain help for people's well-being and healthcare facilities with restricted incomes to attain a well-developed standard of life [65] [66]. IoT for AAL has a vital role in enabling the health, safety, and well-being of an individual home equipped with smart appliances. The setting for AAL is categorized by the IoT capability associated with individual features needed for an ambient assisted setting for older people. Monitoring of the health status, safety, peace of mind, and the social aspect is performed without knowing the system behind it by enabling a local setting for a typical application of AAL on IoT. The European Union Commission commends the AAL on IoT theory in its following observation: "The scope of IoT applications is expected to contribute to addressing today's societal challenges." [67].

2.2 IoT-based Healthcare System

IoT-based e-health system is growing fast with the installation of devices to deploy an essential technology in the healthcare setting. IoT-based e-health devices can collect data from the patients, doctors, nurses, and caregivers to send information on the emergency case, need for medication or therapies, to remind doctors or patients of medical visits. Introducing IoT leads to a radical revolution concerning [68] sharing of the health information associated with the body sensor to help the health professionals to analyze and monitor the patient's diagnosis. The significant advantage of IoT for healthcare applications is that they help develop a high-quality and low-cost healthcare system. A combination of personal health care systems network and the internet has been intensely researched, and [69] it has been shown that mobile data and other technologies involved in healthcare system facilities are to be delivered at the cloud level. This method brings an early warning of health disorders by reducing the spending on curing the sickness. Cloud service development and IoT-based healthcare methods for the elderly can provide a cost-effective communication platform between the patients and doctors. For instance, the measurement results of body parameters such as EMG, heartbeat (ECG), and temperature can quickly be delivered from the cloud to the doctors so that they can suggest treatment. Also, it is easy to locate the patient by detecting the patient's body conditions remotely. Using mobile applications has a straightforward Graphic User Interface (GUI) with the help of which patients and doctors can read parameters so that the readings can be easily accessible using the internet connection from mobile anywhere in the world. Thus, IoT plays an essential part in the rationalization of healthcare applications meant for detection and supervision of chronic diseases on every level of the global stage [70] These applications even can help in avoiding the spread of diseases to others. Some examples of IoT's role in healthcare delivery are listed below:

1. Clinical care: Patients that require staying at the hospital and are known to have a physiological condition need to be monitored constantly with an IoT-driven, non-invasive monitoring system. This kind of method works by using sensors to gather wide-ranging physiological data, storing the information, analyzing the data, and transmitting it to caregivers with wireless technology for review and further analysis whenever needed. The method tends to advance quality health care systems by employing continuous dedication, including minimization of the costs incurred on participating in data collection and exploration.

2. Remote monitoring: Globally, many people have severe and chronic health problems since there is a massive lack of access to health monitoring systems. However, minor but dominant wireless connectivity solutions associated with IoT are presently being established as potential monitoring systems to serve patients by offering them suitable health recommendations. Besides, having many connected sensors and units on the IoT system that can execute different utilities can have an enormous impact on the health monitoring system.

3. Cloud service: This is used for sorting data and delivering security and capability for retrieving all the constraints at all times. It is beneficial for prompt treatment advice by the clinician. An IoT system produces an awareness when such advice is essential during acute situations and notices about the medicines, location change, and health conditions are to be shared. [71].

One of our main research aspects lies in presenting IOT's integration with healthcare monitoring devices such as sensors to a focal point using Cloud computing interfaces. The nature of information and real-time data about a patient's health condition to be transmitted to the doctors has improved thanks to the Cloud computing concept. An IoT-based e-Health system has three covered architectural layers as shown in figure 2.3. The patient's data is duly collected and saved for it to be accessible to healthcare facilities that are associated with its monitoring and other events.

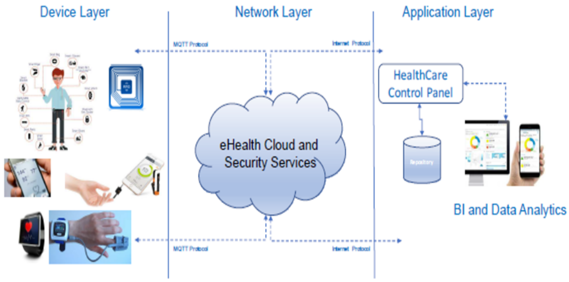

Figure 2.6: IoT Healthcare layered architecture [8].

2.2.1 Bio-sensors and Wearable Devices

The European Commission's study on healthcare systems shows that, worldwide, the population over the age of 65 years is expected to more than double from 357 million in 1990 to 761 million in 2025. The same study also shows that Europe's total healthcare expenses have increased from almost 7.5% in 2007 to around 14.9 % by 2060. The Swedish Ministry's Office of Health and Social Affairs that is responsible for the country's budget analysis has predicted that elderly healthcare expenses are expected to rise from 13 % in 2010 to 16.6 %t of GDP in 2050 [72]. Altogether these figures suggest that healthcare solutions require a significant modification in terms of becoming accessible and affordable. Rearrangement of healthcare systems should help them to evolve to deliver well-being rather than just defeat sickness. The healthcare system's main focus should be on prevention of diseases and, to this end, the immediate recognition of illness to obtain the best answers for the related issues. Recent technology advances in the integration of and size reduction of sensors, wireless networking interfaces, embedded micro-controllers, microprocessors, and radio interfaces have enabled and prepared the devices concerned to help herald a new epoch of many advanced and appropriate applications [73]. The effect produced on human lives by the use of IoT is considered to be a tremendous change akin to the impact that the internet has caused during the past periods. As such, IoT is known as "the next of internet" that uses supporting methodological devices along with sensors and Wireless Sensor Network (WSN), including actuators. For the future, the healthcare structure is shifting from today's hospital-centric one to the hospital-home-balanced one starting 2020, and the home-centric model will be complete by 2030. The IoT technology will enable IoT Home Healthcare (IHH) or Health IoT facilities by combining and customizing the Information and Communication Technology (ICT). This e-Health-IoT service is going global and will be adapted such that it will speed up health-care transformation from being career-centric to being patient-centric [74] [75]. Recently, the IoT industry is customized with low-power Wi-Fi as the devices can collect a tremendous amount of data with high bandwidth and a lower operating power. Low-power Wi-Fi sensors have the benefit of incorporating any network structure based on IP-protocols without a need for an additional gateway. Healthcare seekers can profit from the procedure of continually monitoring it so that they can attain the best recovery from a long-lasting health issue such as recovering from a severe event or surgical process[75]. Traditionally, these e-Health monitoring devices were used for data collection while the data processing and analysis task used to be done offline. This procedure is complex and unrealistic and lacks recognition of real-time medical conditions. Nowadays, various devices and technologies have been devised for being used to facilitate IoT healthcare systems using WSN. Among the standardized systems are included low energy Bluetooth [76], IEEE802.15.6 [77], ZigBee [78]. WirelessHART [79], WIA-PA [80], and 6LoWPAN [81]. The ZigBee, WirelessHART, ISA100, and WIA-PA are all utilizing the IEEE802.15.4 [30]. Systems like ZWave [82] are used very often in some industries, but they are not openly standardized yet.

Table 2.1: Comparison of wireless network standard [1], [2] [3]

Standard	Bluetooth	UWB	ZigBee	Wi-Fi
IEEE spec	802.15.1	802.15.3a	802.15.4	802.11a/b/g
Frequency band (GHz)	2.4	3.1-10.6	868/915 MHz; 2.4 GHz	2.4 GHz; 5 GHz
Maximum signal rate	1 Mb/s	110 Mb/s	250 Mb/s	54 Mb/s
Nominal range (m)	10	10	10/100	100 m
Nominal TX power	0 - 10 dBm	-41.3 dBm /MHz	(-25) - 0 dBm	15 - 20 dBm
Channel bandwidth	1 MHz	500 MHz - 7.5 GHz	0.3/0.6; 2 MHz	22 MHz
Number of RF channels	79	(1-15)	1/10; 16	22
Coexistence mechanism	Dynamic frequency selection	Periodic sleep aware routing low overhead	Dynamic frequency selection	Dynamic frequency selection
Modulation type	GFSK	BPSK, QPSK	BPSK (+ ASK), O-QPSK	BPSK, QPSK COFDM, CCK, M-QAM
Basic cell	Piconet	Piconet	Star	BSS
Encryption	RCS, WEP, AES	SES/CCM	AES	AES

The IEEE 802.11 WLAN [1] as designed and obtained from WSN is often used for optimization. The key topographies that are compulsory for wearable sensors and bio-sensors, including WSN in their design, are meant to gain a high data rate and solve the power issue by offering long battery life than the other standard batteries. The fundamental requirements for Wireless Medical Sensors (WMNs) are the following:

1. Accessibility - To accomplish non-invasive and discreet uninterrupted health checking and monitoring, wireless medical sensors need to be

standardized as lightweight and tiny. The dimension and mass of sensors mainly depends on the size and assembly of the battery.

2. Reliable communication - Wi-Fi sensors' communication is of the highest significance when it comes to their use in the healthcare sector. Various medical sensors' communication requests diverge with the actual sample rates that range between 1 Hz and 1000 Hz. The best method to progress reliability is to carry out the signal processing task on the sensor itself.

3. Security – Most IoT devices can be associated with spreading on public networks that operate with two-way communication data flow. It becomes very easy, then, for these devices to be highly exposed to susceptible spasms. IoT devices are exposed to kinks even with naïve methods.

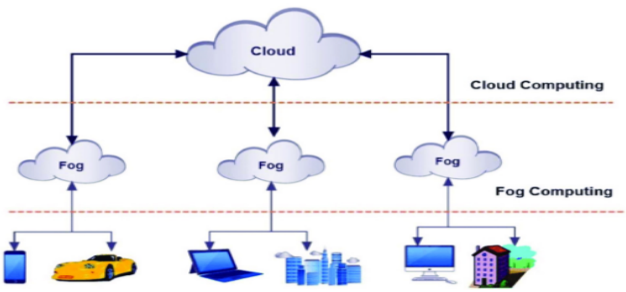

Figure 2.7: Fog and cloud computing for IoT e-Health system.

Using wearable and bio-sensor devices in a healthcare system can reduce treatment costs and increase in-home care opportunities. An essential step in providing adequate home care is to obtain safe and cost-effective monitoring systems. These devices can detect and analyse different bio-medical signals while patients stay in their homes. Previous studies on this topic have shown that those patients who have chronic health conditions have proved that home-care systems can assist patients better [83]. The solution to tackling this challenge to expand the remote and home healthcare system's opportunities is to use a safe and cost-effective monitoring system. Bio-signal is a user-friendly, flexible, and easily accessible method that can measure human physiological signals. Bio-sensors (sensors) and wearables are an essential part of IoT e-Health applications. They can obtain medical information from patients and transmit that data with the use of diverse wireless technologies to the Internet or smartphones and gateways. Patient monitoring system and sensors are the parameters that depend on the patient's status; however, being small and simply wearable to be able to be operated on low power consumption only make the wearables/sensors more advantageous[84]. IoT-based e-Health monitoring using bio- signals and wearables have promoted the doctors to get an extensive amount of data from their patients in real-time using Fog and Cloud computing architecture. Figure 2.7 shows the architecture for Fog and Cloud computing:

2.2.2 Bio-signal Processing

IoT application in healthcare system uses wearable technology for real-time and continuous healthcare systems along with the application of sensors [85]. In many cases bio-signals have a mixture of signal and noise that needs to be pre-processed before the use of further analysis. Typical bio-signal presentations and the usage of signal processing algorithms need feature extraction. It is also understandable that once the signals are gained, the challenging procedure lies in choosing a suitable signal analysis method. Bio-signals are similar to ECG, Electrocorticography (EEG), EMG, Pulse Oximetry (SpO2), Electrooculography (EOG), and Respiration (RSP), and they are used for IoT health applications. Their measurements help healthcare applications for implementing healthcare schemes after the signal pre-processing, feature extraction, and classifications.

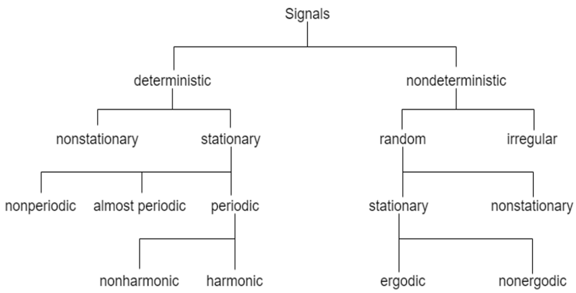

Figure 2.8: Types of bio signals characteristics.

Bio-signals are recorded in space-time events such as the heartbeat or muscle contraction activities of a biological event. Bio-signals can also communicate behavioral information from the understanding and transformation of signals. Like all kinds of signals, bio-signals have been categorized as signals supported with some energy and measured directly from their biological source's external power. These external energies are mainly measurable by indicating the characteristics of the physiological system. A bio-transducer is a device used for transferring the bio-signals to an electrical signal. Usually, a PC or laptop is used to convert the measured analog signal to a digital one with a discrete time-signal processing method. Figure 4 shows the basic properties and characteristics of bio-signals: stationary or non-stationary, linear or nonlinear, and deterministic or stochastic (random). The measured raw bio-signals are usually combined with noise and other associated unwanted signal components. The measured signal gives useful information after different stages of the procedure that analyses the signal are completed. Straight forward signal analysis approaches, such as amplification, filtering, digitization, processing, and saving, using digital circuits or copters are also a part of the bio-signal analysis. Such procedures are believed to increase the value of the collected bio-signal data. Bio-signals have a different stage of signal analysis in which the vital aim of signal analysis is to extract valuable facts from collected data by carrying out signal phases described in the subsection below and as shown in Figure 2.9:

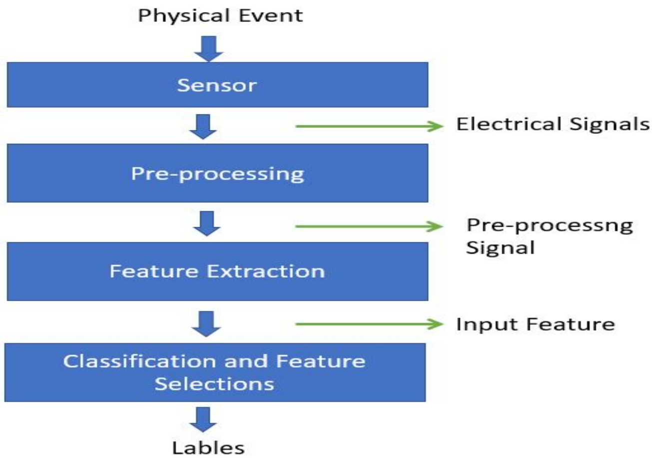

Figure 2.9: Stages of bio signal analysis.

1. *Pre-processing* The information of a bio-signal is devalued frequently by a disruption of noise. Hence, these signals should be processed and filtered to get vital information for the further stage of signal processing. Bio-signal data processing that is implemented with different algorithms depends upon the challenges intended to solve. In general, the signal pre-processing step can improve the signal quality for better diagnosis and monitoring results. For instance, noise removal is a critical analysis and smoothing part of the EMG signal. Raw EMG dataset package delivers valuable

and accurate information after a pre-processing comment is made to succeed. The EMG signal processing steps include data acquisition, analog to digital conversion, and amplification, which lie at the first stage of the signal [86]. The EMG signal acquisitions are done with sensors and gathered by putting electrodes on the skin surface. Thus, the measurements taken change to an electrical quantity output by the sensors. The electrodes also deliver a connection between the electrical measuring tool and the biological interaction with the method. The signals gained from the electrode need to go through the signal pre-processing steps such as amplification, filtering, and conversion of the analog-to-digital signal. The description for the QoS requirements, amplitude, and frequency range of the common bio-signal are listed in Table 2.2

Table 2.2: Amplitude, and frequency range requirements of bio-signal

Bio-signal	QoS Requirement				Frequency and Amplitude		
	Data rate (bps)	**Latency**	**Battery life**	**Bit error rate (ms)**	**Frequency range (HZ)**	**Amplitude range (mv)**	**Quantization (bits)**
EGG	320k	<10-10	>1week	<250	0.1	0.001-0.8	4-6
EEG	86.4k	<10-10	>1week	<250	0.1-100	0.01-1	4-6
EOG		<10-10	>1week	<250	0.1-10	0.01-0.3	4-8
ECG	72k	<10-10	>1week	<250	0.01-300	0.05-3	10-12
EMG	1.536M	<10-10	>1week	<250	50-3000	0.001-100	4-6
RSP	320k	<10-10	>3years	<250	0.1-1	2-50 breath/min	8-10

2. *Feature Extraction and Feature Selection;* Bio-signal data representation for pattern analysis is the principal part of feature extraction. It is the procedure of extracting and adapting information into a feature vector. and it decreases the pattern to a helpful demonstration of the data. The actual signal processing happens at the feature extraction stage to get important information from the bio-signal. The feature extraction's common strategies are the following: (1) Feature discrimination that each pattern of the feature in unique classes should have meaningfully unique values. (2) Feature reliability depends on the pattern for the same class that has similar values. (3) Autonomous features are not associated with each other. (4) The optimal characteristics of features are to remove unnecessary features. The task is to extract features to get helpful information from the input data for the further classification task that depends on the input signal's application and type. (5) Feature selection and pattern identification need typical features for the features to apply and be used to discriminate among patterns. Classification accuracy depends on the selected features. Also, for actual classification, it is vital to use features that are equipped with the best discriminatory control among the classes [87]. Thus diverse approaches have been advanced for making the best input feature set for classifiers. Importantly, feature selection also depends on the advance information available on training data.

3. *Feature Training and Classifications Method* The bio-signal classification of bio-signals depends on the signal, and it is continuous or discrete and

deterministic or random signals as shown in Figure 2.6. Stationary signals do not change any time in terms of the properties of the signal. The ML method is the most recognized classification method for reliable bio-signal analysis, enabling the measured signal to be identified. Several typical methods for bio-signals' feature extraction and classification are used. Usually, these methods have some redundancy on the input data, and the pattern recognition cannot be efficient and accurate. Nowadays, researchers have a problem finding or measuring and then feature extraction and classification of bio-signals received from actual patients. There is limited access to it because of the regulations imposed on the healthcare centers that can access patients to perform this action. In that case, meaning in the case of not having reliable samples to use, it will also be difficult to investigate a suitable signal analysis method or procedure. The other technical issue faced in detailed bio-signal analysis is whether the signals are weak, i.e., in mVolts range and whether the associated noise and common-mode signals range between -5 and +5V)[88]. The Bio-signal amplification process is carried out to get a high common-mode rejection ratio, including for the signal filtration that is needed before the signal undergoes feature extraction and classification using different methods. Table 2.3 lists some bio-signal processing and analysis methods such as Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT), Discrete Wavelet Packet Transform (DWPT), Artificial Neural Networks (ANN), Wavelets Transform (WT), Fuzzy Logic, and SVM, that have been used in the past. DWT is the known method for EMG feature analysis. [89].

Table 2.3: Bio-signal processing and analysis methods

Bio-signal	**Methods**		
	Feature Extraction)	Classification	Disease
ECG	Karhunen Lo'eve Transform (KLT), Wavelet Transform	Neuro Fuzzy, Artificial Neutral Networks	Heart Disease, Coronary Syndrome,
EEG	Wavelet Transform	Artificial Neutral Network, Fuzzy	Epileptiform brain sleep disorders
EGG	Wavelet Transform, FFT	Artificial Neutral Network, LDA	Gastric abnormalities
EMG	Detrended Fluctuation Analysis, Wavelets	Neural Networks, Fuzzy Logic, SVM Learning	Muscle Response, Nerve Injury
SpO2	Neural Networks,	Neural Networks,	Obstructive sleep apnea (OSA) Background
RSP	autoregressive modeling (AR)	LDA, Neural Network	OSA Body activity
EOG	autoregressive modeling Wavelets, ICA	Linear filter	Eye movement or blink

To summarize, the EMG is a method for assessing and acquiring the electrical activity created by skeletal muscles to diagnose over 100 neuromuscular diseases. Researchers have focused on obtaining more accurate results on the classification of EMG signals. The signal is one of the standard methods used for acquiring the emotional state of the human signal using the applied signal processing method[90]. Emotion classification is established on developing and analyzing the facial-expression recognition dataset. Sensors and cameras or microphones are used to collect and analyze facial expression images. [91] [92]. The video analysis signals have an interface with the device signal and, they tend to amplify the proper expressions that often do not match with the definite emotions. Thus, better quality and accuracy of recognition for emotions is obtained by investigation facilitated by the use of sensors [93]. Classification of the bio-signals achieved a better result with proper ML algorithms to ensure the classification results. Emotion recognition using ML techniques such as SVM, ANN, K-NN on bio-signal can classify the associated expression of emotions and state of identification [10]. Many researchers have found a relationship between facial expression identification and medical issue diagnosis in the past. EMG signal delivers information about the muscles' act by measuring the voltage level's variation on the skin's surface. Measured signals depend on muscle contraction and relaxation by detecting surface voltage from muscle activity[94]. Inter-muscular measurement of EMG can be achieved using a monopolar needle electrode on the activity, personality, and psychopathology measurement of a person [95]. Facial expression is an intense presence of sensitivity that can show an individual's emotional state and alter the emotional conditions during stimulation [96]. Our thesis will focus on facial activity pattern recognition with the help of EMG signals for pain assessment application. In the coming section, we will show our approach using ML for emotional feature characterization.

2.3 Data-Driven Health Status Monitoring

Currently, smart home creation is in the process of revolution with interaction of communication system to exchange information. The smart homes model has undergone an essential revolution that has hugely improved the way many systems communicate, cooperate, and interchange valuable dataset for analysis. The change is advanced by integrating IoT technologies that have permitted the design of native systems to be cost-effective regarding power consumption by allowing many components to operate by batteries [97]. The IoT translation method has fundamental issues and faces several challenges. It tends to the various facilities that are operating autonomously on their own data communication protocols on multi-service platforms for data intercommunication. Smart homes use various fields that are integrated with sensors, data extraction, and ML to combine critical behavior sensing tools with accurate human sensor data. The accomplishment of data sets during earlier research [98] recommends further the studies on whether a building's energy consumption can be simulated by gathering the data sets from each user.

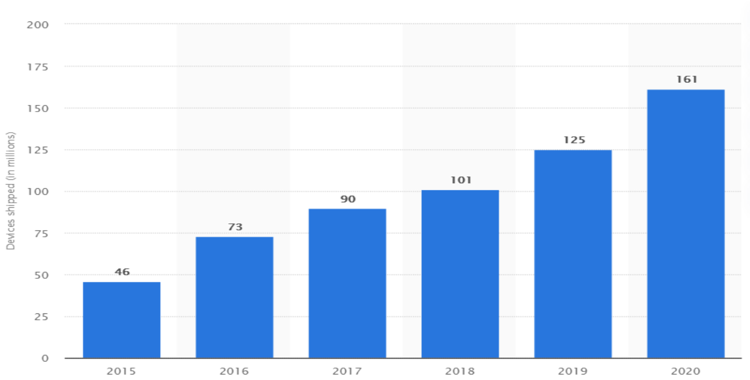

Figure 2.10: SM roll-out program [9].

The collection of automated data set on the building's energy usage has developed progressively using a high-resolution sensor. Many utilities and government sectors are engaged in rolling out a SM program to develop an SG. By the year 2024, SM's installation in the US will reach 81% of the total electricity meters[9].The data set collected by SM is aimed for the understanding of the building energy further being aware of each home's and their appliances' electricity load. SMs can send the electricity usage readings of every second, minute, or hour to the consumers and utility sectors. The data set report can be available for the analysis to improve and optimize the building or home energy control. The utility sectors can control each home's smart meter data to identify electricity usage and plan appropriately and quickly.

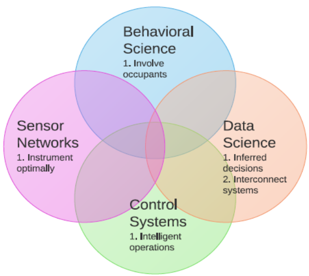

Figure 2.11: Data-driven building energy efficiency and its intersection with behavioral science, data science, control systems, and sensor networks [10].

The data-driven building energy efficiency interaction of previous research on sensor networks, behavioral sciences, data science, and control science is shown in the figure above. Solving these problems is mostly associated with intelligent systems, and algorithms for data extrapolation of the associated users at home is crucial as studies on the energy consumption data set that is available have shown. [99] [100] [101]. Many researchers have developed algorithms for understanding behavioral characteristics of inhabitants according to their electricity usage. [102] [101]. Further, the energy consumption data to solve the problem(s) associated with the physiological and behavioral data analysis and modeling for health and well-being of the occupants must deal with the usage of the appliances' energy consumption in detail. NIALM can be used by dividing the energy reading perceived at a single point of the appliance's energy consumption [103]. A researcher [104] recommended complete electricity information to reduce their electricity usage by 5-15 percent with the help of behavior modification. Another researcher [105] achieved a mean reduction of 15 people on user electricity consumption by analyzing the disaggregated information from 300 users in California. Introducing Advanced Smart Metering Infrastructure (AMI), NIALM has had a lot of changed behavior. Recently, several researchers have gained results by analyzing the data set collected on an user's electricity consumption and by storing it on the cloud-based services. Thus, using cloud-based data sets too has gained tremendous interest in NIALM research. Some of the data sets that applied NIALM research are: are REDD [99], BLUED [100], AMPds, [41] and UK-DALE [106]. In addition to the NIALM application, many researchers have collected datasets for many kinds of applications for buildings such as HES [107], SMART, [102] and PLAID [108]. An interference problem concerning NIALM was recently studied using sound processing to separate the useful information [109]. The outcome of this study was based on edge detection for NIALM algorithm. However, many NIALM methodologies have been recommended in the current and earlier studies, [110], [111], [10], [112], [113] and a wide-ranging summary has been learned and employed by many researchers [114] ,[115]. All the results have shown to use the supervised approaches with a central offline focal point. The consumer's usage of electricity on the real-time electricity dis-aggregated information needs an appliance level data collection for an optimal algorithm that can be used for classification. Data-driven approaches using supervised NIALM are needed to create a model for each appliance. In this thesis, we discuss the NIALM approach on the PLAID dataset as a benchmark. The analyzed dataset with the NIALM system for appliance characterization can also analyze the physiological and behavioral data. We will discuss our data-driven health status monitoring approach using SM data within the SG system categories in the next sections. We further show by extracting relevant information from the collected energy

Table 2.4: Difference between traditional power grid and SG

Characteristics	Traditional Power grid	SG
Technology	Electromechanical	Digital
Distribution	One-Way Distribution	Two-Way Distribution
Generation	Centralized	Distributed
Sensors	Few Sensors	Sensors Througout
Monitoring	Manual	Self
Restoration	Manual	Self-Healing
Equipment	Failure & Blackout	Adaptive & Islanding
Control	Limited	Pervasive
Customer Choices	Fewer	Many

usage data on NIALM to understand people's behaviors.

2.3.1 Smart Grid and Smart Meter

The shortage of consistent and maintainable energy foundations is one of the next generation's foremost global challenges. It targets the advancement of the near future Smart Grid (SG) for decreasing household energy consumption by on-boarding the data mining approach and intelligence technologies. It also has been proved as [116] the energy disaggregation approach that separates the energy signal into the electrical usage of the appliance at home by encouraging consumers to save their energy usage. The recent version of this operation improved with SG facilitating the two-way flows of electricity and information between the electricity grid's operation. Table 4 summarizes the contrast between a traditional grid and SG.

The International Energy Agency (IEA) [117] is dedicated to bringing current energy technology facilities including the SG technology to make buildings secure and uncontaminated. IoT-based SG technology's fundamental aspect is to manage and monitor any attacks of environmental situations remotely by adapting such information as would be available on SM, transmission lines, sensors, and substations. For better use of IoT-deployed SG systems, the system's security, compatibility, interoperability, and reliability should be standardized. The research on the standardization aspect is ongoing separately on IoT technology [118] [119] and SG [120], but it is not started at the IoT-based SG systems. Smart meters (SMs) can store enormous amounts of data that is beneficial for energy consumption prediction and beyond real-time extractions and apply deep learning to the collected data. To the best of our knowledge, not much work has been done on big data analytics and cloud for IoT-based sg systems using ml, which expressly progresses the routine. Our thesis deliverS the advantage of delivering an

IoT-based SG with complete development of the SM technology to be used for bringing about behavioral changes in routine lifestyles using ML. The SG's principal component, the AMI, delivers advantages by having bidirectional communication capabilities as a core part of the SG's advancement. AMI provides an attractive opportunity for service providers and other vendors, particularly concerning the SM we have considered for our research approach by measuring the appliances' energy usage. The SM's core purpose is to show real-time energy usage of the users within the SG utility sector [121]. For successfully achieving the cost objective, the electricity usage data set acquired from electricity user appliances is obtained by assessing the household aggregated energy consumption. The SM employment has been determined as per the European Union's Energy Efficiency (EE) Directive (2012/27/EU), which was issued on 25 October 2012 [122]. The cost-effective deployment is based on SM delivery on user-based electricity usage vis-a-vis real-time energy consumption information and advice. In Sweden, Eltel's Power Business Smart Grids [123] have contracted with the Vattenfall Electricity Distribution AB. The aim is to substitute 236,000 electricity meters throughout the country with SM, and the signed agreement costs around EUR 22 million. The company have the authority for the implementation and roll-out of the complete SM technology, including the installing the infrastructure of SM, planning, and installing SM[123]. SM is the main apparatus for achieving sustainability by improving energy consumption on the daily activities at homes. SM's advantages in giving faster and more precise information on electricity usage to customers can apply to energy efficiency. The consumers' behavioral change can easily be detected with analysis based on the pattern of electricity usage. Previous researchers have discussed the advantages of SM for keeping a relaxed home environment[124][125], for saving energy [126]], for providing information from user energy consumption data on their emotional reactions,[127] and for exploring AAL on the visualization the residential energy use [128]. The previous studies have revealed the importance of and searched for energy usage awareness that relies on using real-time statistics for cost-effectiveness for keeping a relaxed and suitable home environment. SM is a valuable tool to maintain energy efficiency on the single-user level and delivers a challenge for researchers to monitor its usage information. However, our unique approach to this thesis lies in the context of the application of IoT-based SG with SM system for remote controlling and managing home appliances by including the NIALM system.

2.3.2 Non Intrusive Appliance Monitoring

NIALM is intended to give appliance identification by the turning on/off of a particular appliance. The initial idea of the Non Intrusive Appliance Monitoring (NIALM) system, as stated by Hart, [129] was introduced as energy desegregation [130]. The contest in NIALM for the profiling of individual appliances has difficulties in separating each of the load signatures unless very accurate and high purpose meters similar to SMs are used. Consequently, this study's space has been systematically discovered, [131] and this is still is an ongoing research area—previous studies employed SM data by developing behavioral data from the appliance usage pattern on the household. The result is beneficial for estimating the electrical usage on the household [132], [133], [134]. However, given the requirement for decreasing the energy consumption and facts of the many appliances available at home, a novel way of analysis to manage electricity usage for consumers is needed. The appliance's real-time energy consumption information can assist the event of energy consumption by simultaneously monitoring the consumers' abnormal usage of appliances. We consider, in our thesis, the real-time energy consumption information that will support the elderly living independently by ultimately monitoring the health conditions and the status of safety of the consumers within the NIALM system.

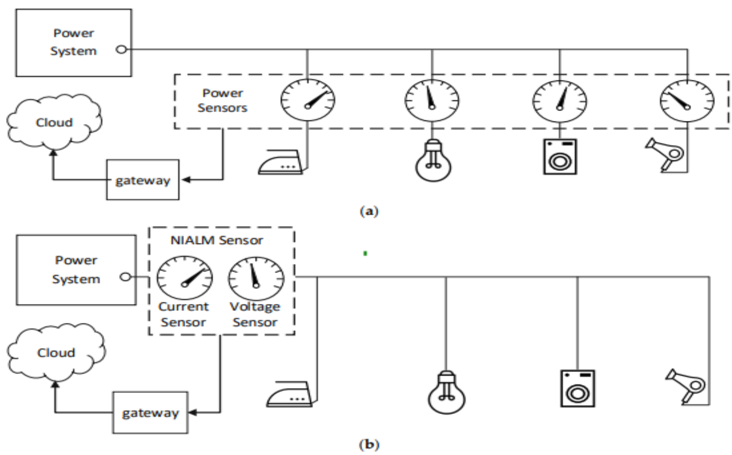

Figure 2.12: Appliance load monitoring systems: (a) intrusive appliance load monitoring (IALM); (b) non-intrusive appliance load monitoring (NIALM) [11].

The Appliance Load Monitoring (ALM) system can deliver comprehensive appliance identification. The idea of ALM is from the 80th-century, where [135] the methods fall into two classes: NIALM and Intrusive Load Monitoring (IALM), which is primarily conventional. NIALM is generally defined as a one socket detecting technique that needs an SM or a sensor device. It is a single-point sensing system for the characterization of household appliance's aggregated energy usage measurements. The ILM system, on the other hand, needs the usage of several sensors [132] with a scattered sensing scheme that each sensor is connected to for the monitoring of each appliance. There are various benefits and drawbacks of each technique. IALM is viewed as the correct technique as its measurements are gotten straight from the device [[136]. However, this approach is both expensive and challenging. IALM also has the threat of sensors for dividing the aggregate power consumption to the different appliances. The research gap is in terms of solving the requirement for decreasing energy consumption tracking. The growing of appliances at home needs a novel way of analysis for consumers to manage their electricity usage. On the other hand, an appliance's real-time power consumption data can assist the event of power utilization by monitoring the consumers' possible abnormal use of appliances. With this in mind, we have considered, in our thesis, the real-time energy consumption information to support independent living of the elderly by ultimately monitoring the health conditions and the status of safety of the consumers within the NIALM system. NIALM is also seen as a method that can expose or detect a consumer's information [137]. Additionally, abnormality electrical usage in the electrical devices [138], including our contribution [16] can used for Home Energy Monitoring systems (HEMS) and AAL [139] technologies. Mainly, AAL tools are helpful for treatment and recovery of the health status of the elderly [140]. This system works by compiling data for the events and abnormality of the appliance usage and informing medical or ambulance services. Our contributions on NIALM have delivered the basic key information from the on/off or alteration of the appliances' usage information for the AAL systems, which is applied to the vital steps [16]. Even though the AAL systems aid the consumer in terms of awareness of their electricity usage for lowering their cost, it also encourages elders to live confidently in their homes.

2.3.3 Appliances' Identification Approach using NIALM

NIALM is an approach for analyzing alteration in the voltage and current on the household and identifying the active appliance's energy usage measurements. The appliance identification is upon analyzing the whole electricity consumption of a house or a building to recognize each appliance. Defining a load of the respective appliance in NIALM method depends on using certain procedures and tools. We describe and highlights the NIALM appliances' identification process of consideration stages in Figure 2.13. *Data*

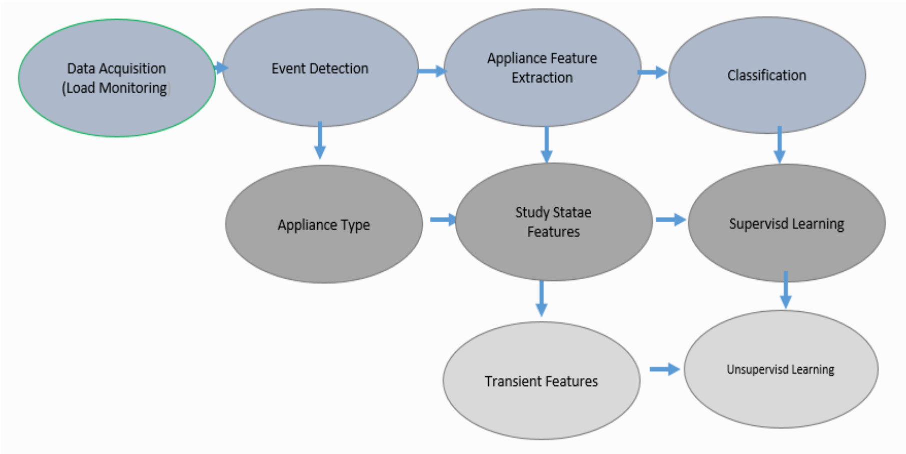

Figure 2.13: NIALM process and considerations.

Acquisition: The current sensor and voltage images/ devices or SM are used to collect the input concerning the essential measurement of the whole NIALM system upon a direct connection of the central node point. Individual energy consumption patterns are available from aggregated energy consumption measurements. NIALM, which frequently involves in-load disaggregation, focuses on the development of an algorithm to disaggregate specific devices that are utilized on a metered power line [141],[142]. NIALM was first proposed [129], as a method for identifying the power signature of appliances by taking in to account the measurement of the aggregated load, by detecting the ON/OFF states of the appliance.

The total load that is measured from SM is calculated as:

$$P(t) = \sum_{i=1}^{n} a_i(t) P_i(t) + e(t)$$

Where P(t) is power consumption by the aggregated measurement, e(t) is a noise of the signal or error. The overall amount depends on whether appliances are turned on at indicated time. a(t) = 1, if the appliance is turned on at t, or 0, if the appliance is turned off at time t NIALM can achieve the corrosion of P (t) on the specific appliance's power signal to accomplish the disaggregated energy-sensing. Electrical measurements can show the pattern as the load consumption signature of the appliances by implementing a disaggregation algorithm. The algorithm can identify each appliance's activity that depends on the measurements taken on the aggregated load.

Table 2.5: Appliances' state-based models

Model	Sample Appliances
ON/OFF	Toaster, Light, Bulb, Water-pump, Coffee-machine, etc.
FSM	Processor-controlled appliances, Washing machine, Dish-washer, Refrigerator, etc.
Continuously variable	Light, Dimmers, Variable-speed drive, Heat- pumps, etc.

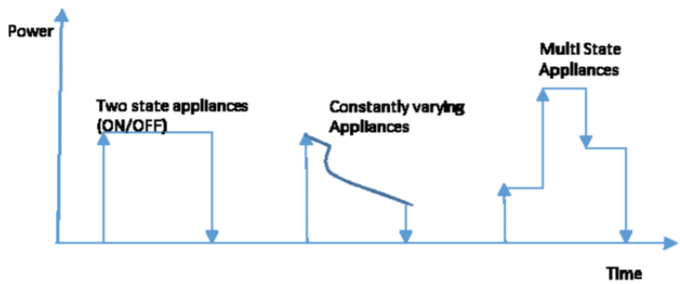

Figure 2.14: Appliances' states and their energy consumption pattern. [129]

For measuring the aggregated load consumption, different kind of measurement devices can be used, which are as follows: [131]. (1) Low-Frequency Energy Meters: Mostly, are the SMs in the market that can propose different sampling frequencies based upon the need of information [143] that can be taken out from the electrical signals. However, the Nyquist–Shannon sampling criteria should be considered for getting the fundamental frequencies in multiples of 60 Hz for higher order harmonic electrical signals [144]. (2) High-Frequency Energy Meters: The frequency is between 10 to 100 MHz that is needed to get the transient events produced by the electrical signal. Studies show that the available meters show different data measurements within 10% to 20% [145], [146]. Including imperfect functionality is seen with cheap SMs as they are made of low resolution ADC and trivial dimensions of on-chip Flash memory gotten for saving different operations in the processing unit [144]. A variety of prototypes have been developed and discussed by many researchers to get a higher rate sampling frequency on the load l signals [100], [146]. The NIALM system depends on the household learned from a single meter. Some types of appliances in the e-household have drawbacks because of the limitations that exist on the identification of low-power and variable appliances. Another method has been suggested by [147] to create use of circuit-level loads for high-power appliances to have a committed circuit within the household *Event Detection* Event detection is one of the most considerable processes for appliance classification or identification. [148]. But the method is complex as many appliances at home activate in different ways and states for the mode of operations. More analysis is required for considering the classification of the appliance types based on their electrical usage. Type 1 appliances: These operate in their on/off states (Two-state appliances). Examples of such devices consist of lighting, boilers, and toasters. Type 2 appliances: These are appliances that operate in multiple states (i.e., Multi-State Devices (MSD) or Finite State Appliances (FSA)). Their examples include dryers, washing machines, and dishwashers. As these appliances can operate in multiple states, they add to the difficulties faced in appliance classification. Type 3 appliances: These appliances are the ones that operate in a non-fixed state (i.e., Continuously Variable Devices (CVDs)). Normally, these appliances are not constant, and their examples are smoke detectors and intruder alarms. Knowing the diverse appliance types is important for NIALM as they offer facts on the load consumption vis-a-vis the appliances' characteristics.

Feature Extraction: Raw data handling is meant to help identify the events of the appliances' state alteration from On to OFF and the corresponding power load measurements. An event detection unit identifies the ON/OFF change of appliances by exploring the variations in the level of power classified as the steady-state or transient states. In the previous studies, numerous event detection approaches are suggested [149], [150], [151] for describing the identification bases of the steady-state and transient state. The operational state is associated with the establishment of event-based feature extraction approaches. Steady-state approaches can distinguish appliances by the apparatus-based on the differences of their steady-state signatures by recognizing if the appliance is on the ON/OFF state. For the case of the transient approach, the transient signatures describe the appliance state changes by shape, size, and duration of energy consumption by extracting features bases of the transient wave-forms. The transient signatures need a higher sampling rate, normally more than 1,000 samples per second to be extracted [143]. Several other methods[152] are also suggested by escaping the event detection process from the current and voltage measurements [153] or by considering the frequency spectrum information for identifying the actively working appliances [70].

Load Identification: The load identification algorithm analyzes the appliances' extracted features to identify the state of appliance from the aggregated dataset measurement. Supervised ML methods are well known, for the NIALM method is a focused procedure of classified data to improve the classifier. Nowadays, most of the supervised learning approaches are adjusted for load disaggregation and are based on optimization or pattern recognition. The practical power measurements P(t) uses an optimization approach and the appliance power signals to decrease the identical error as stated in [154], [155]. The disadvantage is that having unknown loads in P(t) increases the optimization challenge as an approach method for the identified appliances [154]. The pattern recognition method has mainly been the chosen technique for the assignment of load identification. Today, researchers and scientists have revealed a higher curiosity in unsupervised learning methods for load disaggregation without relying on data that cannot recognize the classification events. This approach practices the unsupervised learning methods by disaggregating the aggregated (accumulated) power measurements without the execution event detection.

2.3.4 ML Algorithms for Appliance Identification Techniques

In the past, many researchers have focused on the study of appliance identification with the NIALM algorithm [156], [[155], [154],[157]. It suggests adopting ML algorithms and optimization techniques to identify power signatures of household appliances. However, most the common of the initial research studies unearthed a challenge from the viewpoint of signal processing. Their effort was to identify the device signatures, which would differentiate each of the devices one by one using the mathematical expressions methods [[158] or the classification task with temporal techniques as shown in figure 2.15. The principle underlying the ML application is to

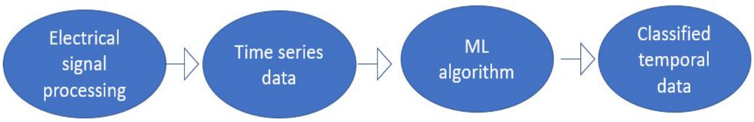

Figure 2.15: Temporal classification methodology.

achieve an effective classification outcome. Many classifiers are presented depending on the algorithms' classification that is suitable for the application and the available data-set. Most of the data processing applies ML to develop meaningful information from the collected data. Most of the ML approaches use a supervised ML method in which the training phase is based on the labeled data set [159]. Some ML approaches have been introduce here, and their applications are listed below:

*S*VM: Is used on the data set's kernel, complication, and application. However, the SVM algorithm is a dominant method for NIALM or data classification as defined in [160]. The primary stage of data classification on SVM is to create a decision plane that splits fixed items with diverse membership in a class. It assures by differentiating among the class members by magnifying the margin among them using hyper-planes. The highest margin of the hyper-planes can show the capability of distinguishing the classification of the training data set presentations as seen in figure 2.16.

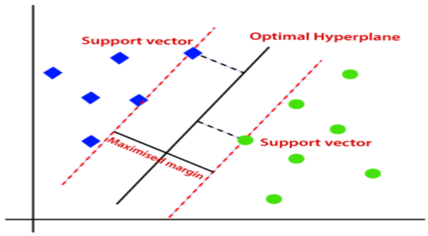

Figure 2.16: SVM with hyperplane.

The SVM algorithm has used a process to find the kernel function by expression and using a mathematical expression tool [161] for grid exploration and optimization on the training sets. The algorithm applies to regression, classification, and outline detection.

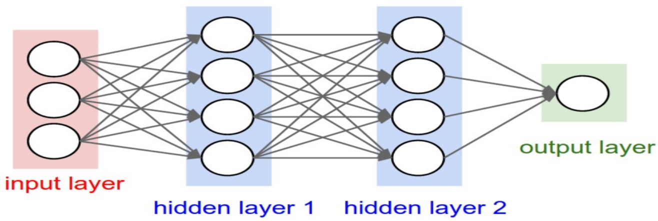

Figure 2.17: A Multi-layer ANN.

*A*NN: It is one of the ML technologies that has a unique approach designed upon the human brain functions. It can resolve arduous tasks by analyzing the connected processing features (neurons) of the brain. ANN extract patterns and detect trends by using the existing and former training from the collected data. The two methods of ANN are classified as Feed Forward and Feedback Networks.For common neural networks, the layer type is the fully-connected layer in which neurons among two neighboring layers are entirely pairwise connected, then neurons inside a single layer share no contacts. Figure 17, shows an example Feed Forward Neural Network of fully-connected layers.Most ANNs are competent in identifying complex nonlinear interactions among dependent and independent elements by the functions that detect all possible connections among the forecaster elements and by developing training algorithms [162]. There are drawbacks of ANNs that depend on the network operation as black boxes, so they do not offer an exact type of information for a specific solution [162].

K-NN: The K-NN classifier defined on [163] use processes for labeling testing instances from a majority selects the nearest neighbors of each point and mentions items of neighboring unknown values. The Euclidean distance is required for the K-NN algorithm corresponding to the value of the classified K-NN algorithm. Thus, if d is the distance and K-NN deals with continuous and discrete attributes, while negotiating with the discrete attributes, the distance between the two instances is equal. The (x1, x2, x3 ... xn) are the first instance values, and (y1, y2, y3 ... yn) are the second instance values. Figure 2.18 shows the flowchart of our implementation of

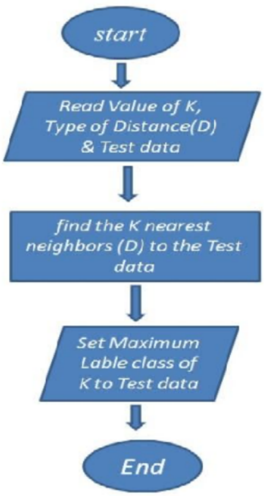

Figure 2.18: Flow chart of K-NN.

the K-NN steps of the algorithm to be used for appliance identification considering the training and testing dataset from PLAID data of the appliances in the house. It is critical to have the correct distance metric for the K-NN algorithm. The steps used on the algorithm are to be made steady by determining the value of k, which is upon the distance calculation to select the closest neighbor to test the data. Its maximum use is for the classification of data. On the other side, some of the authors who used the ML algorithm in [164] were inclined to use SMs based on unsupervised ML techniques. They showed that the Decision tree (DT) and K-NN are able to implement it and able to solve the identification problem when compared to other ML algorithms for NIALM analysis [163], [165].

2.3.5 Summary of Literature Review

The literature review carried out for this research focused on the areas shown in Figure 1.1 and Figure 2.19. The focus is on IoT-based health monitoring systems and the implementation of the ML algorithm. This thesis also proposes a future extension of this research. The application of the Health monitoring system has four aspects to be studied. These are the following: (i) SG (NIALM and SM), (ii) ML algorithms for (feature extraction and classifications), (iii) IoT system development on Fog and Cloud computing communication, and the study of (iv) Smart-health with the application of bio-signal processing by means of wearables, Wi-Fi sensors and, biosensors. Besides, the processes reviewed for this study focus much on the part data-driven approach for a health monitoring system using the EMG signal, and the NIALM system.

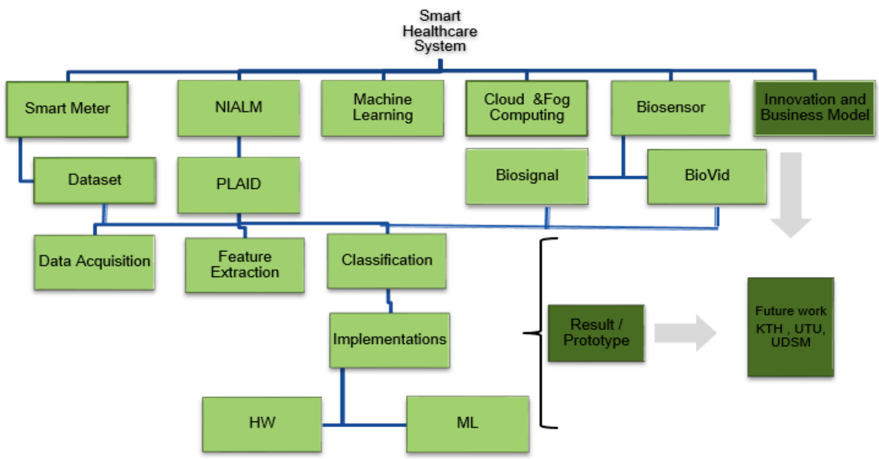

Figure 2.19: Focus areas of the research.

Chapter 3

IoT Based Healthcare System

An advanced health monitoring system needs to minimize the costs involved in accessing it by solving the problems associated with the proliferating population of the elderly who require/demand fast and reliable healthcare services. We expect a remote health monitoring system to improve patients' quality of treatment as they can be treated in their own homes from where the vital signs of their health conditions can be tracked. A Health monitoring system needs to solve the problem associated with long-term monitoring of patients with limited health status and on-board real-time reporting methods. Smart wearable devices can bring about valuable results in enhancing the healthcare system. Remote monitoring of the bio-signals using IoT-enabled units is suitable for the current healthcare system to improve an individual's life. Our research develops two methods to solve the health monitoring solution for the health care system. The first method involves wearables, where as the second one relies on energy usage profiling.

IoT Based bio-sensor for health monitoring:

In this approach, we have designed an sEMG sensor node using off-the-shelf components to assess and monitor the pain intensity of ICU patients or patients with verbal difficulties. The sensor node communicates its data using the integrated Wi-Fi module. An appropriate feature extraction algorithm is applied to the EMG signal and SVM algorithm to classify the monitored data for assessing the level of pain. The prototype tested for the use of fEMG for pain assessment on the experiment setup. In second approach we use clinically approve data set to prove the sustainability of fEMG signal for pain level detection. In both cases the classification achieves high accuracy, which proves its suitability for real-life pain communication for supporting independent living through real time health detection for assisting daily living .

SM load profiling for health monitoring: On the other hand we developed a system using a SM and appliance load profiling methods to de-

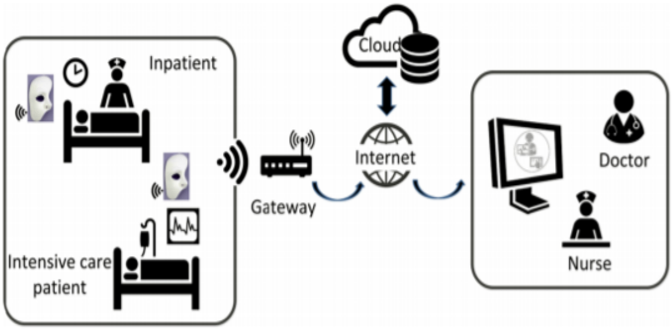

Figure 3.1: Example for remote pain monitoring system [12].

tect the occupant's behavioral change, which indirectly provides information about the occupant's health conditions. The behavioral change detection is performed by employing the ML classification algorithm. This classification's results show high-level accuracy which also be used for supporting independent living for real-time or online health detection. We will explain our findings in greater detail in Chapter 4 of this thesis.

Further, this particular chapter presents the novel approach of high data rate and low power bio-sensor design using accurate and friendly Printed Circuit Board (PCB) or Flexible Printed Circuit (FPC). This procedure enhances a health monitoring and health care system and, in our particular case, for pain assessment for those who have difficulty communicating about their pain intensity or pain level. The sensor used in this case is a Wi-Fi optimized IoT-based healthcare system that consists of a HW and SW system for receiving different vital signs via bio-signals such as ECG and EMG. We describe the architecture and protocol of the bio-sensor module design for a real-time communication-based health monitoring system. Besides, we discuss our contributions to the facial emotion expression using EMG signals' analysis, features extraction, and the characterizations approach to enhance an accurate emotion state recognition for pain assessment. Further, this chapter demonstrate the implemented fEMG signal classification by means of ML algorithm clinically approved on Bio-Vid pain intensity dataset [166]. It also achieved high performance of classification accuracy that confirms our prototype functionality and Bio-Vid dataset usefulness for pain detection. Our contribution to the proposed design for IoT-based remote pain assessment sEMG sensor node is that it uses facial expression for pain assessment application. The Wi-Fi sensor that has eight-channels, and its size is small because of which it integrates mobile web applications is experimented for sEMG data accruing, processing, and feature extraction as well as characterization of the bio-signal data. dataset.

3.1 IoT-based Healthcare System on Experimental fEMG

Facial expressions can be potentially be use as means of instantaneously detecting pain signals that can facilitate spontaneous pain monitoring mechanisms for individuals. Certain assessment devices can, thus, be recognized/used as replacement and alert mechanisms for comprehensive care of the elderly and minors, and of those individuals who cannot inform about their pain severity or health status. We propose a Wi-Fi bio-sensor node to monitor the pain assessment using the facial sEMG signal. The sEMG wireless sensor is incorporated within an IoT system for remotely monitoring the level of pain. The sensor node has eight-channels of the sEMG node, and each channel has a 1,000 Hz sampling frequency, which is enough to cover the data communication to the cloud server over the gateway in real-time. The design does consider low energy consumption and the ability of the device to assure accurate time monitoring for an extended period. The device has remotely demonstrated that it can deliver real-time pain information to the doctors and the caregivers by employing a web application established for transmitting a large amount of sEMG data. Further, signal processing of the dataset, feature extraction, and cauterization were also real-time. Our contribution here focuses on proposing an IoT-based sEMG bio-sensor node designed for real-time monitoring of pain intensity and its assessment through facial expression in real-time.

The fEMG pain assessment sensor node is implemented on the cloud computing system technology by using the IoT technology. The system considers helping the patients in ICU and/or the elderly/ minors to detect their pain levels and to estimate their pain using their expressions as observed from their facial sEMG signals. The sensor node comprises a cloud-computing remote monitoring system for data analysis, big data processing, and it implements an ML classification algorithm.

Our contribution can be summarized as follows: (1) the proposal of facial expression for pain assessment application, (2) the design of an eight-channel, small-sized Wi-Fi bio-sensor (3) its integration with a mobile web application to perform sEMG data collection, processing, feature extraction, and characterization, and (4) implementation of a classification algorithm on an IoT-based platform on a cloud for pain assessment using the facial sEMG signal.(5) showed the algorithm of pain detection with a fEMG signal using a clinically approved dataset. The architecture for the SEMG remote pain monitoring system based on the IoT application is shown in Figure 3.2: A wireless sensor protocol is applied to the sensor node to collect and transmit data based on the category of IoT-based e-health monitoring systems. Wi-Fi is a wireless communication protocol that can gather and transfer enormous data on the sEMG monitoring system.

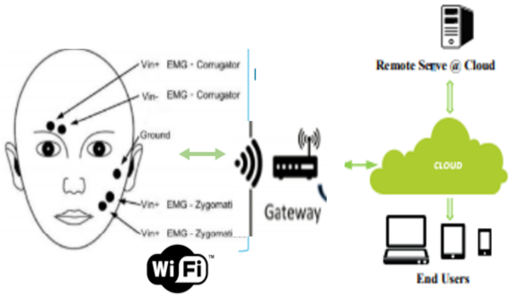

Figure 3.2: Architecture for IoT-based sEMG sensor node [13].

We used a wireless LAN (IEEE 802.11 WLAN) protocol-based bio-sensor node to collect the ICU patients' pain intensity information through a WLAN access point or gateway. The sEMG or bio-sensor nodes were composed of an Analog Front-End (AFE) and a module from RTX4140 (IEEE 802.11 WLAN). A complete SW operating system was delivered with the RTX module. The Wi-Fi sensor prototype architecture has the following four units : 1) Wireless Sensor Node: The sEMG sensor interface and the processing hardware unit are applied through the AFE module to record information from the bio-sensors further to execute the ADC conversion function. The discrete numerical dataset comes via AFE and is run on RTX4140 over SPI. The design is user-friendly for collecting the bio-signal using the electrode connected to the face, digital signal processing, and data transmission. 2) Gateway: The UDP client request operating on the RTX4140 refers to the UDP packet of information to send to a remote server using the Wi-Fi communication protocol. The gateway can be an access point or a router cellphone located on the bio-sensor node and cloud. A smart gateway is intended to facilitate the features of reliability, heterogeneity, and scalability of the communication of the data in a remote healthcare monitoring system. 3) Cloud-computing Server: The UDP and TCP protocol uses cloud-based servers to receive data from the Wi-Fi bio-sensor. This involves processing of the database on the UDP server's submission by operating on the remote system using python script to communicate with the UDP port, accumulate the received information, and keep the remote database up-to-date. The data will be viewed using an HTML5-enabled web browser after the transmission to the database server for storage and further signal processing and data classification. (4) Web server application: A mobile-based application based on HTML5 acts as a communicating interface between the system and the caregivers. The web-server's implementation uses Hypertext Pre-processor (PHP) scripting language that can authenticate the data and the more significant data flow in situations that demand monitoring and evaluation of the health status on the web page in real-time. The patient's helpers and doctors can remotely access the information on the web page through smartphones or PCs. The web app's application is associated with the possibility of using many terminal devices including those with different operating systems, such as MS Windows, Mac OS, and Android. Thus, the web page information can be used remotely by the patients' helpers and doctors by employing smartphones and PCs.

Our system has the capacity to operate even when the data flow that demands the monitoring and evaluation of health status is large. The bio-sensor is composed of an 8-channel AFE with MCU. The Wi-Fi module can integrate the SW and HW components, and a cloud server receives and processes the bio-signals. The module is small; it has a rechargeable battery and operates on very low power consumption.

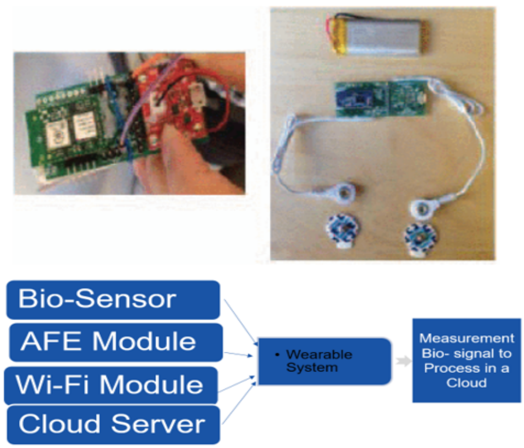

Figure 3.3: Bio-sensor module units [14].

We also show that the sEMG sensor node does not limit operation on a single bio-signal but has a multi-function applications based on the IoT technology to monitor a person's health in a real-time environment. This health monitoring module can collect and transmit the bio-signals in real time and perform signal processing, feature extraction, and classification.

The following subsection will discuss in detail the processing mechanisms that we investigated for the bio-signal characterization.

3.1.1 EMG Sensor and Bio-signal Processing

The sensor node is connected with the electrode using EMG to measure the activity of muscle electrical signals. sEMG is a process of detecting and recording the available data of muscle activity. For facial expression recognition, the sEMG signal's classification accuracy is the main issue. Accurate classification of sEMG depends on applying acceptable placement of the electrode and signal processing. Two facial expressions have been defined in the lab environment using the emotional experience expressed with the statistical parameters. A frown expression indicates the emotion of pain, and a smiley face suggests no pain. These two expressions can be defined as happiness and sadness. The first approach for the EMG signal's collection is to be aware of and solve the problem associated with the high signal-to-noise ratio and distortion of the signal. The raw sEMG data about the face was collected with the sampling rate of 1 kHz using an IoT-based remote Wi-Fi sEMG sensor prototype as we have discussed in the above paragraphs. [167]. Electrodes connected to the zygomatic major and corrugator supercilli tissue on the face, as shown in Figure 3.1, arbitrarily collect sEMG measures from the frown and smiley actions of the tissue or muscles. Further, the signal interpretation starts pre-processing for dealing with the artifact and this is followed by filtering, rectification, and polishing of the compiled data. i. e., having it correspond with or without pain (pleasure and sorrow).

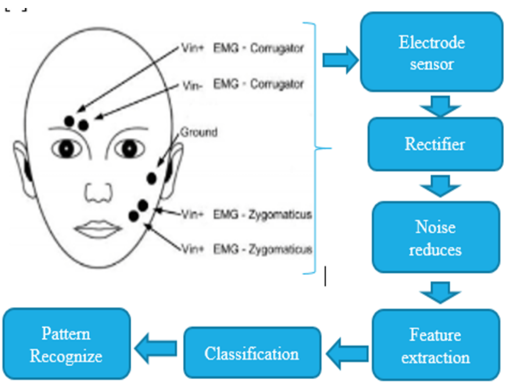

Figure 3.4: Facial EMG measurement using electrodes and signal analysis for pain detection [13].

We captured the emotion data from the muscle activity or movement of a part of the face at the forehead, eyelid (corrugator), and cheek (corrugator). The pain-associated signal measurement was considered along with the muscle activity tension. A gap was taken between the measuring sessions of the happy and sad emotions. We considered the relaxed facial expression to eliminate the previous emotional stimuli. We used statistical signal processing for analyzing and extracting information from signals. The statistical feature extraction method is used in many applications and has produced excellent bio-signal processing and analysis results. In our test, the initial proposal was as follows: (i) sEMG data is processed by updating it in the second interval, and butter-worth notch and high-pass filters are applied in each channel. (ii) Each filtered sample has 2,000 discrete points of one track. (iii) We consider two activities that correspond to the two expressions: happy and sad. (iv) Each channel has 12 features: 8 time, and 4 frequency domain statistical analyses of the signal. Diagnosing the onset of action on the EMG signal is particularly demanding, and the progress of the signal classification process depends on it. During the experiment, the detection algorithm to onset detection of 20 Hz high-pass filter and 50 Hz low pass filter was checked, and the threshold was over 25 samples with a 1 kHz sampling rate.

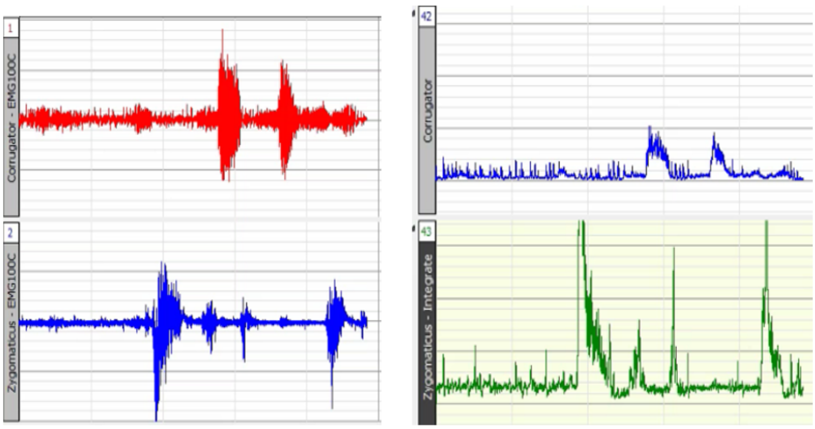

Figure 3.5: sEMG signal from the zygomatic and corrugator and the corresponding normalized signal.

The figure below shows the time domain and the frequency spectra of the EMG signal from the Zygomatic muscle.

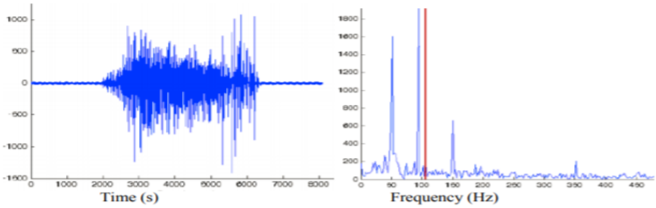

Figure 3.6: Time domain, frequency spectra of the EMG signal from the zygomatic muscle [13].

For effective pattern recognition and classification, a well-established signal processing method for feature extraction is needed. So, we extracted 12 statistical features from two-channel based on the time and frequency domain corresponding the frequency band of 20 features. The statistical features were calculated as per the equations shown in the table 3.1.

Table 3.1: EMG features and their descriptions

Feature	*Mathematical description*	*Description*
IEMG	$IEMG = \sum_{i=1}^{N} \lvert x_i \rvert$	Signal power estimator: calculating the summation of the absolute values of EMG signals.
VAR	$VAR = \frac{1}{N}\sum_{i=1}^{N} (x_i - \bar{x})^2$	How far the numbers lie from the mean.
MAV	$MAV = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i \rvert$	Adding the absolute values of all of the values and dividing it by the length.
Median		Median value of the sequence.
SSI	$SSI = \sum_{i=1}^{N} \lvert x_i^2 \rvert$	Energy of EMGs.
MDV	$MDV = \frac{1}{L}\sum_{j=1}^{L-1} (x(j+1) - x_j)$	Mean value of the differential value of all the peak value of EMGs.
RMS	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	It is modeled as amplitude modulated Gaussian random process whose RMS is related to the constant force and non-fatiguing contraction.
WL	$WL = \sum_{i=1}^{N-1} \lvert x_{i+1} - x_i \rvert$	It is the cumulative length of the waveform. The resultant values indicate a measure of waveform amplitude, frequency and duration all within a single parameter.
FMD	$F_{MD} = \frac{1}{2}\sum_{i=1}^{M} PSD_i$	The frequency median splits the power spectrum density into two equal parts.
FMN	$F_{MN} = \frac{\sum_{i=1}^{M} f_i PSD_i}{\sum_{i=1}^{M} PSD_i}$	The frequency mean.
MFMD	$MFMD = \frac{1}{2}\sum_{j=1}^{M} A_j$	It is the frequency at which the spectrum is divided into two regions with equal amplitude.
MFMN	$MFMN = \frac{\sum_{j=1}^{M} f_j A_j}{\sum_{j=1}^{M} A_j}$	It is the average of the frequency.

After detecting the features from the above calculations and on each channel, 12 features for each emotion of feature expression and classes for the feature sets are defined.

3.1.2 ML for fEMG Classifications

The frequency domain and statistical features of the classification are based on the SVM algorithm. SVM was selected because we realized that it handles the noisy sEMG signals better by classifying them in well-identified clusters. SVM is a binary classifier that estimates data as follows:

$$(((X_1, Y_1), ..(X_m, Y_m)) + R)^N x + / - 1 \tag{3.1}$$

For the discriminate of the two classes, the basic principle for SVM is that a hyperplane should be determined to distinguish the two classes with maximal margin, and we deployed the architecture process of SVM algorithms as shown in the figure below: . We improved the onset movement identification

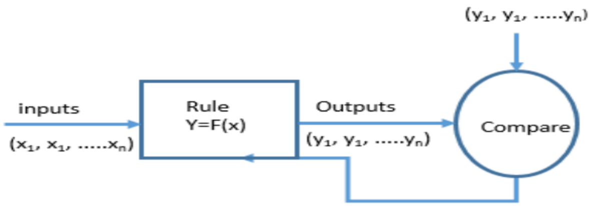

Figure 3.7: The architecture of SVM algorithm [13].

method on the EMG during the experiment by discovering a recognition algorithm. This algorithm can express the onset detection on the 20 Hz high pass filter and 50 Hz low pass filter. In that case, it determined the on/off time filter, and the threshold was more than 25 samples with a 1 kHz sampling rate. The extracted statistical features were fed to different classifiers to classify the pain or no pain features. The sEMG for the EMG signal classification employed the Classifier Learner app of the Matlab tool. Some tested classifiers from the Learner app are Decision Tree, Linear Discriminant Analysis, MG-SVM, K-NN, and Bagged Tree Ensemble classifiers. Including validation schemes in Classifier Learner was considered.

Results Analysis

The SVM classifier that corresponds to (happiness) (without pain) and (sadness) obtained high accuracy result of 97.89%. The experiment compared with 2,040 features to gain the desired accuracy and the following result was obtained:

Accuracy - 97.89%
Prediction speed Around 2,700 obs/sec
Training time 138.18 sec

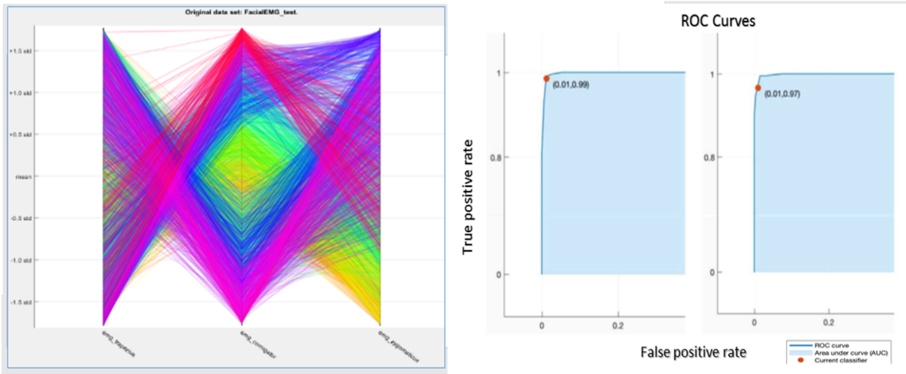

Figure 3.8: fEMG raw dataset and its ROC curve figures which generated from the SVM classifier [13].

The classification accuracy validated for the two kinds of kernel functions on SVM were applied: These are the Cubic SVM and Gaussian SVM.

Gaussian SVM

Facial Expressions	SAD	Happy
SAD	1.00	0.00
Happy	0.03	0.97

Cubic SVM

Facial Expressions	SAD	Happy
SAD	1.00	0.00
Happy	0.02	0.98

Figure 3.9: Classification accuracy validation.

The confusion matrices for the two different classifiers are shown, and the level of accuracy for each of the cases of the classification is also shown. Cubic SVM and Gaussian SVM with an overall accuracy of 98% percent and 97% percent were had as shown in figure 3.9.

3.2 Pain Detection using fEMG

In our research we also use the the Bio Vid Heat Pain Database, [15] where the study was conducted in accordance with the ethical guideline to show the application of fEMG for pain assessment and detection. Facial expressions can be potentially be use as means of instantaneously detecting pain signals that can facilitate spontaneous pain monitoring mechanisms for individuals. The monitoring of facial expressions to assess pain intensity provides a way to determine the need for pain medication in patients who are not able to communicate verbally. This part of our research considers the fEMG from emg corrugator and emg zygomaticus for investigation of pain level detection by means of ML approach to be useful for nonstop monitoring of patients using on line system [168]. The target task and application is focus on describing the method on the assessment of acute pain, which results changes in the facial electrical activity of skeletal muscles employing the measurement from fEMG signal. The previous studies also have been indicating that activity of EMG signals as shown in figure 3.10 that in particular the zygomatic and corrugator muscles, could provide information on pain intensity [169] [170].

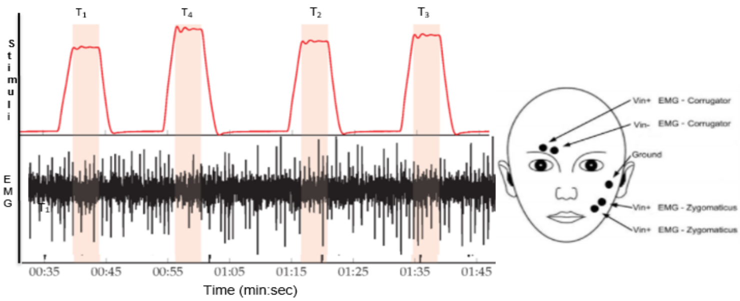

Figure 3.10: Pain intensity level of heat T_o to T_4(a)Orginal fEMG signal; (b)facial expression of pain tolerance according emg corrugator and emg zygomaticus [15].

3.2.1 Data Exploration and Processing of Bio Vid dataset

EMG signals were measured on the zygomaticus and on the corrugator. The signals were recorded with a sampling rate of 512 Hz and were initially filtered with a butter worth band pass filter (20-250 Hz). For further noise reduction, a signal separation method (decomposition analysis) was subsequently applied [171]. Characteristics describing the amplitude, variability, stationary, entropy and frequency characteristics of the respect signal were extracted from the processed signals [171]. On the other hand, the database involves of a healthy people subjects. Heat stimuli were practiced to the people in 4 altered pain stages ((P_1, P_2, P_3, P_4). The standard (no pain) was 32°C. T_1 is the threshold temperature stage.The maximum temperature which was used for tolerance heat pain stimulus (T_4) is 50.50 C.

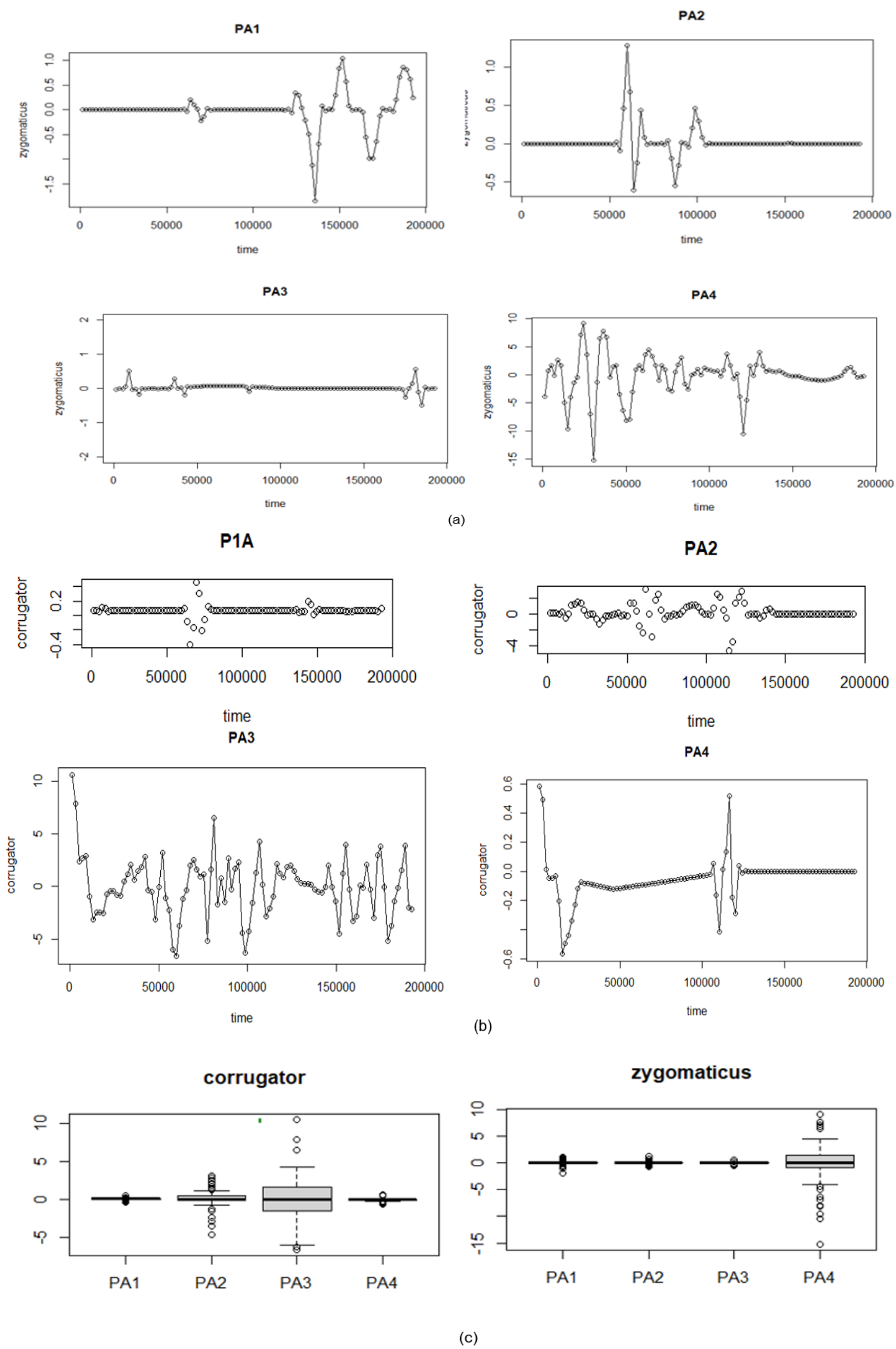

Figure 3.11: Four altered pain stages (P_1, P_2, P_3, P_4 as: (a) EMG zygomatic muscles; (b) EMG corrugator muscle; c) Comparing of (P_1, P_2, P_3, P_4 for EMG corrugator and EMG zygomatic muscle.

EMG signals were measured on the zygomaticus and on the corrugator. The signals were recorded with a sampling rate of 512 Hz and were initially filtered with a butter worth band pass filter (20-250 Hz). For further noise reduction, a signal separation method (decomposition analysis) was subsequently applied [171]. Characteristics describing the amplitude, variability, stationary, entropy and frequency characteristics of the respect signal were extracted from the processed signals [171]. On the other hand, the database involves of a healthy people subjects. Heat stimuli were practiced to the people in 4 altered pain stages ((P_1, P_2, P_3, P_4). The standard (no pain) was 32°C. T_1 is the threshold temperature stage.The maximum temperature which was used for tolerance heat pain stimulus (T_4) is 50.50 C. To summarize the preprocessing of the EMG signal is performed using the steps: (1) Visualization of all the raw to quantify the noise intensity and the movement that corresponds to the stimulation of the pain.(2)The EMG signals is filter between 20-250 HZ using Butterworth filter (3) The level of pain is measured practically by heat using four pain thresholds T_1 – T_4 with each 5.5s “pain window” that corresponds to the base with regard to the baseline during the “non-pain window”. (4) The eruptions of EMG activity is distinguished by using the Hilbert Spectrum[171]. However, our consideration focused on the facial expression analysis as a tool for measuring pain from emg corrugator and emg zygomaticus to serve for continuous pain estimation by comparing the pain levels as shown in figure 3.9.

The model for figure 3.11 was constructed using the fEMG features as the input and periods P_1 – P_4as the labelled output for each emg zygomaticus and emg corrugator.

3.2.2 Feature Extraction

Time domain of the sEMG features lies into four groups in accordance to the mathematical specifications[172]:

- Calculations that depend on the amplitude amount of the sEMG signal, which consist features energy information of the signal; Coefficients of the prediction model (e.g., AR); and
- The Features frequency information (e.g., ZC and SSC) where a threshold parameter needs to be pre-defined;
- Coefficients of the prediction model (e.g., AR); and
- Features extracted from two adjacent or several segments of an sEMG signal (e.g., MAVS).

Including frequency domain features extracted from power spectral density. Time domain features are more commonly found in sEMG pattern recognition studies and reveled that the frequency domain features did not show better performance compared to the time domain ones[173].

The considered EMG feature are based according to the previous studies [58] and the listed features are as below.

- A_peak as amplitude peak of the EMG signal
- A_RMS as amplitude quadratic mean of the EMG signal
- V_range as variation width of the EMG signal
- V_std as standard deviation of the EMG signal
- F_zc as number of zero crossings of the EMG signal (frequency measurement)
- S_sd as standard deviation of EMG signal components (degree of stationary;
- $E_Shannon$ as entropy of the EMG signal according to Shannon

The features were extracted for each of the EMG signals, i.e., for the EMG -zygomaticus and EMG-corrugator. Then the features have been independently standardized (z-transformation). Further, as we mentioned earlier the features were computed on the preprocessed windows of 5.5 seconds. A total of 159 features were analysed, [58] and the selected feature for the two EMG signal characterization is summarize on figure 3.11.

3.2.3 Classification

The contribution this thesis proposed ML based algorithm implementation for pain level classification for supporting independent living through real time status. We applied the K-NN algorithm since it shows an improved and promising effect for classification of signals and images [163]. We observed that the feature selection algorithm achieved by pre-selection of all the extracted 159 features using statistical analyses by checking and verification checks. The initial steps is to eliminate out-liners of the features that include either zero or static number for all conditions. Therefore, our evaluation is based on the relationship of among the pain threshold (0 vs. 1 vs. vs 3 vs.4) and EMG signal characteristic's is illustrated in Figure 3.12.

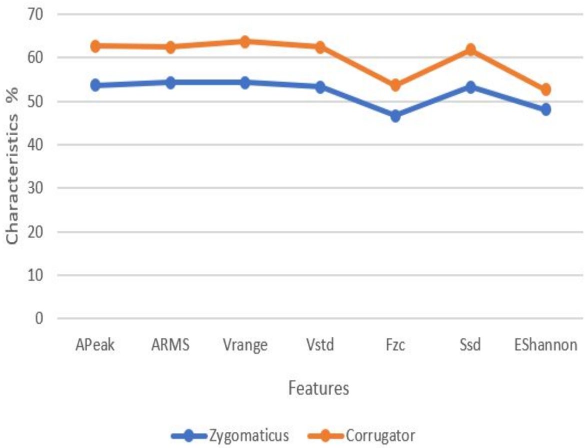

Figure 3.12: Relationship among the pain threshold 0 vs 1 vs2 vs3 vs 4 and EMG signal characterization for zygomaticus and corrugator.

Moreover, we noted that the amplitude feature $_P2_P$ and the entropy feature E$_S hannon$ are previously investigated as the features for an accurate classification of the pain intensity on both Zygomaticus and Corrugator signal by using K-NN classifier. [168] [15].

We showed an improved method for better classification accuracy by deploying the fEMG feature as independence of the subject. The classification is performed on the K-NN algorithm by choosing the value of k and that depends on the majority voting. One of the reason of using K-NN is because of is less sensitive to out liners[163]. Further the presentation of the accuracy estimation has shown considerable increase of classification accuracy upon our deployment. The application of ML to classify the amount of pain in patients could deliver valuable evidence for the health care providers and aid the treatment assessment. The analysis with respective average performances of 99.4%. The process for the classifications of the features consisting of the discrimination between the base-line and the pain tolerance level (P_1 verse P_4 upon analysis with out subject bias. Three of the K-NN classifiers: Fine, Medium and Coarse K-NN are considered for the classification. The procedure also later included the Principal Component Analysis (PCA) algorithm to reduce the computing and to faster characterization..Moreover, the experimental results clearly show the relevance of the pain assessment for health care facilities and approaches.

The figure 3.13 shows the K-NN classifiers (K-NN Fine, Medium and Coarse K-NN) that are compared with 8501 and accuracy of five-fold cross validations techniques and the clip of the obtained classification accuracy.

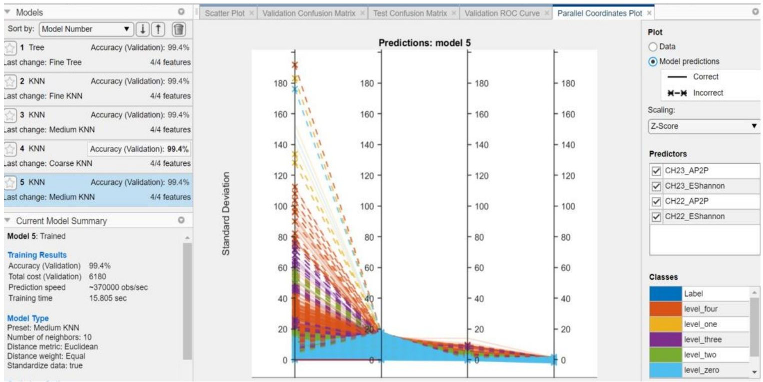

Figure 3.13: Classification result depending on the amplitude feature $_P2_P$ and the entropy feature $E_{shannon}$.

3.2.4 Discussions and Results Analysis

The result achieved for this part of the research is the combination of our prototype experimental data analysis and its validation on the Bio Vid Heat Pain Database. For Bio Vid data analysis the experiment is compared with 159 features to gain the desired accuracy[174]. In this result analysis section, we discussed the performance of the classification accuracy. The best performance is obtained from the k-NN classifiers: Fine, Medium, and Coarse k-NN [175], and part of the confusion matrix and ROC are demonstrated. The classification performance can be accessed by the area under the ROC curve (AUC)[176] parameter as indicated in Figure 3.14. In this work, the value of K=10 gives the higher classification rate on most of the pain level emotions compared to other K values [175]. The maximum classification rate of 99.4 % is obtained on pain levels using the K-N classifier. The classification performance can also be accessed by the area under the ROC curve (AUC)[176] as seen in figure 3.14.

The activity of fEMG signals from the zygomaticus and the corrugator muscle is able to communicate the level of pain intensity. In our analysis, the subject type is omitted and to the best of our knowledge, this has not yet been analyzed previously according to the relationship of EMG and pain level intensity. Further, the use of EMG seems to enable continuous pain level communication and supporting individuals for independent living through real-time health status detection[175].

In summary, this section, showed how smart wearable devices for e-health is an effective solution to improve health care services. Wireless monitoring of biosignals using IoT enabled devices are vital for today's

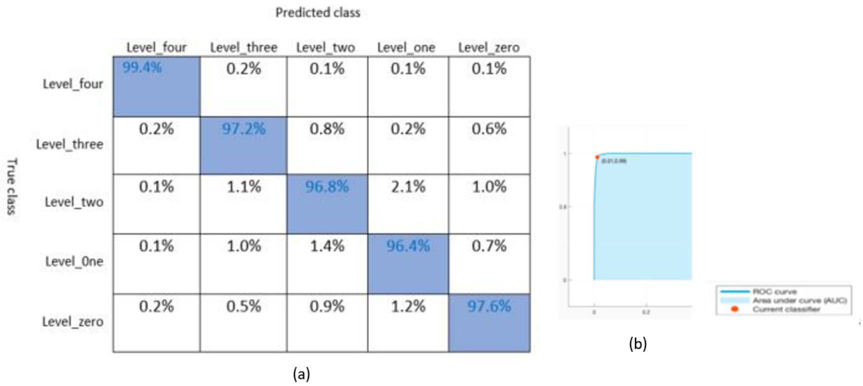

Figure 3.14: (a)K-NN classifier accuracy validation in percentage (b)The ROC curve generated from K-NN classifier.

health care system in order to save the vulnerable life of people. We present a design methodology and system architecture of IoT based wearable remote monitoring system for healthcare applications. The IoT-enabled wearable device is tested for real-time monitoring of the sEMG signal. Our recommended remote monitoring proposed system performance has also been compared with the existing e-health platforms [167]. The platform supports encryption standards and supports 16 ADC channels which makes it the lowest power consumption per channel. On the other hand, our study also shows that EMG analysis is a cost-effective and robust alternative way that supports the health care system by the classifications of the pain intensity and facial expressions. The accurate sEMG signal acquisition needs gaining a radical and suitable classification result that starts with the location of the electrode in the clean face and has its own specific position for better sEMG signal recording. However, the disadvantages to the use of this technique come from the issue that the same muscle may be involved in different emotions. For example, both angry and sad facial expressions can produce from corrugator muscle activity. This also applies to the rest of some of the facial muscles for emotional expressions. We could test the effectiveness of the prototype module in this study by testing [167][14] on a volunteer for facial emotion identification and identifying of sEMG facial movement (frowning and smiling). We observed that sufficient EMG recording devices with better performance than ours are in the market. However, in this work, we proved that the prototype, IoT-based remote pain monitoring, and multi-channel recording system has the capability of our expectations for recording EMG and another related biosignal and the ability to use for related health solutions. Furthermore, it can be obtained for healthy individuals and beyond use for disabling and elders. In this study, the measured signal is analyzed, and the feature extraction is done using a statically time-domain approach. The study has compared various classifiers and tested on different ML models and, the result showed K-NN / SVM performed the best classification accuracy for facial emotion identification. Thus, the approach has a unique methodology for pain assessment based on emotion recognition of fEMG signal, and the suitable classification algorithm is depend on the amount of the generated dataset. .

Chapter 4

Data Driven Healthcare Using Smart Meter Data

This section of the thesis will discuss one of our contributions to the novel approach of implementing the health monitoring system with two types of data-driven architectures by using SM. SG reports better information than the executed current energy generation and distribution structure. It permits complete monitoring of customer energy consumption by load profiling, including better energy consumption and management of fault tolerance detection. SM can accumulate the energy consumption data, and further analysis can recognize operating patterns and routine usage. Our thesis investigates the energy consumption reading from the SM dataset to help researchers and energy providers to identify and classify consumers according to their electricity usage behavior. A novel approach of the consumer's electricity usage data, collected by SM, and the load profiling supports the healthcare sector based on the pattern of normal or abnormal consumers' energy consumption.

Our contribution of the two data-driven approaches for health monitoring systems on SM load profiling is based on the voltage, current, and power measurement, and the results of our data-driven approach based on :

- the SM energy consumption measurements can identify and investigate the pattern for abnormal changes and further detect the person's behavior change.
- a proposal of the architecture for IoT-based SM dataset processing for the appliances' identification. (We investigated SM load profiling analysis at the appliances' level to yield more accurate results than the consumer's total energy consumption analysis.)

showed a ZIP model for appliances' load profiling. The proposed architecture for IoT-based fog computing can analyze the identifications of the appliances on the fog computing structures. This structure of using the consumer's appliances, if measured, can generate big data from those measurements.

4.1 Smart Meter Load Profiling for Healthcare System

SG is applied in the healthcare monitoring service through optimization. The indirect approach for SG technology to be adopted for humans' monitoring systems has a different method than that of the wearable devices used for health monitoring. SM is a component that enables the consumer's valuable information to be collected and stored through the dataset of their electrical consumption. This method permits the elderly or patients who desire special health care to live in their homes in a very very relaxed and happy way even as they receive help from their caregivers and doctors with the use of real-time monitoring services. In this thesis, we have presented and investigated the application of SM being cost-effective and, at the same time, being able to monitor the consumer's energy usage by forecasting behavioral patterns from the behaviors and routines of the consumers. This method minimizes the problem of health care systems. It delivers the monitoring facility that can be recognized immediately about normal or unusual behavior for those cases who wish to live without the caregiver's innervation daily. This approach depends on the big data produced by SM devices that are considered for supporting healthcare facilities. The objective is to decrease the costs involved by saving energy consumption, and the load profiling analysis also helps in monitoring the consumer's health status while the latter are in their homes. Therefore, the contribution of this thesis also part of our paper [177]can be said to be the following:

- Discussion on the SM standard for the novel opportunities of health status monitoring delivered by the SG technology. It contains SM load profiling through the incorporation of a home-based monitoring system to capture the patient's health situations.
- Implementation of the investigated household energy consumption data along with providing additional information about the usage period for getting more accurate determination of the usage, i.e., whether it is normal or abnormal behavior.
- Application of data classification techniques for load profiling to model energy consumption and describe the users' routine and unexpected usage based on regular or random performance.

- Delivery of an architecture for the health monitoring system meant for patients and the elderly who have recognized their health status and want to stay in their home for an extended time based on each one's necessity and state of health. We found the suggestion to investigate electricity consumption, SM data exploration such as data extracting, clustering, and classification methods to be an approach that recognizes the typical or atypical of the habitat's energy usage.

This thesis has delivered a monitoring system for patients and the elderly who have recognized health-limited status to live in their homes for lengthier periods based on their necessity and state of health. Due to the enormous amount of data-sets that get generated, SM exploration methods such as data mining, clustering, and classification are vital in recognizing the users' normal or abnormal energy consumption. The SG and SM set-up is crucial for ensuring adequate energy consumption uses that aids customers to be alert of their energy consumption of a particular appliance's day-to-day usage. Figure 4.1 illustrates the vital components of SM data analysis for e-Health monitoring.

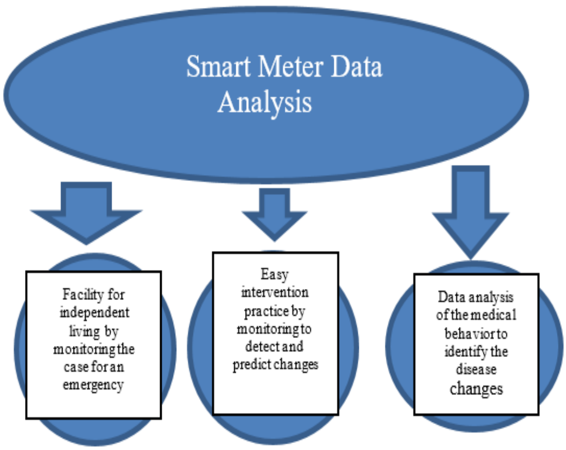

Figure 4.1: Proposed SM load profiling architecture [13].

Developing an efficient methodology for SM load profiling establishes a connection between electricity usage and consumers' behavioral change. We can access the energy usage dataset gained through SM in real time for the data to be shared with designated third parties for load profiling. We can analyze the dataset with the support of ML algorithms to recognize the usage patterns. We can use the usage patterns for investigating the normal and abnormal health status of the consumers who are at home.

Figure 4.2 is the proposed SM load profiling architecture for the health monitoring system. The architecture is presented based on the principle of the measurement of appliances' energy consumption using SM application for health status monitoring on the smart grid system, as shown in figure 4.1. [177] The collected measurement of appliances can distinguish a trend

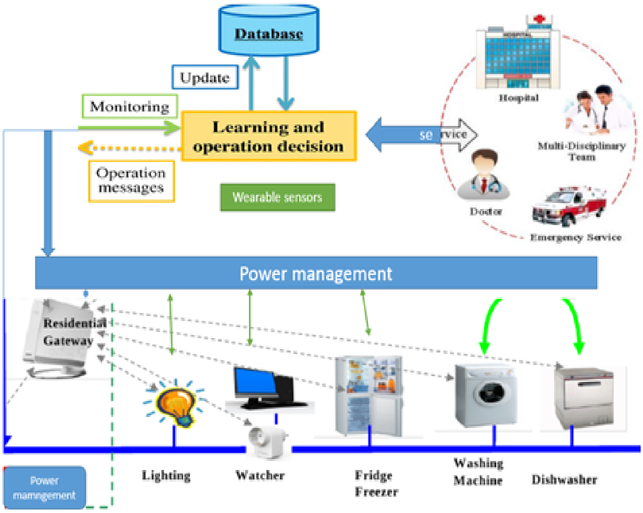

Figure 4.2: Smart meter application for healthcare system [13].

or pattern of each user's electricity consumption. Our principle is to check if there is a shift in the user-health condition that leads to a difference in the behavior related to the appliance's usage and, therefore, a change in the appliances' energy usage pattern and vice-versa. To prove this concept, we have done an experiment and come up with certain results that we have to discuss in detail in our publication [177]. The experiment can be summarized in the following paragraphs:

4.1.1 Dataset and Load Profiling Implementation

The load profiling implementation that we have shown [177], the dataset that was collected concerning the energy usage in the 13 houses from "Energyimyndigheten" (Swedish energy sector) for one month during October 2017 for one hour (sixty minutes). The houses were analyzed with regard to their use of electrical appliances such as heating and cooling systems and lighting. This led to the collection of 8,940 SM dataset measurements from the of the 12 houses. One of these houses was not considered as it remained unoccupied for an extended period. Figure 4.3 shows an example of the measures used in this study that represent the hourly readings over 24 hours.

$$\mathbf{M} = \begin{vmatrix} A_{1\,1} & A_{1\,2} & \cdots\cdots\cdots\cdots\cdots\cdots\cdots . A_{1\,12} \\ : & : & : \\ A_{744\,1} & A_{744\,2} & \cdots\cdots\cdots\cdots\cdots\cdots\cdots . A_{744\,12} \end{vmatrix}$$

$$\mathbf{M}' = \begin{vmatrix} A_{1\,1} & A_{1\,2} & \cdots\cdots\cdots\cdots\cdots\cdots\cdots . A_{1\,744} \\ : & : & : \\ A_{12\,1} & A_{12\,2} & \cdots\cdots\cdots\cdots\cdots\cdots\cdots . A_{12\,744} \end{vmatrix}$$

$$\mathbf{M}new_{reduced} = \begin{vmatrix} A_{1\,1} & A_{1\,2} & A_{1\,3} & A_{1\,4} & A_{1\,1} \\ : & : & & & : \\ A_{12\,1} & A_{12\,2} & A_{12\,3} & A_{12\,4\,1} & A_{12\,5} \end{vmatrix}$$

Figure 4.3: 24-hour energy usage of the houses.

We compared and investigated a unique method for analyzing this extensive energy dataset and adopted the K-means clustering to proceed with our approach of clustering techniques to attain electricity consumption patterns within a definite time. Further, the K-Means clustering algorithm was used to identify the patterns within a definite time-based electricity consumption dataset to identify the users' health status. This is the main contribution of our work. We have proposed a new electricity usage analysis by employing the k-means clustering approach [177]. Figure 4.4 shows the case-by-case matrix-based data dimension technique used to diminish the big energy consumption data and to facilitate the the use of the data clustering technique.

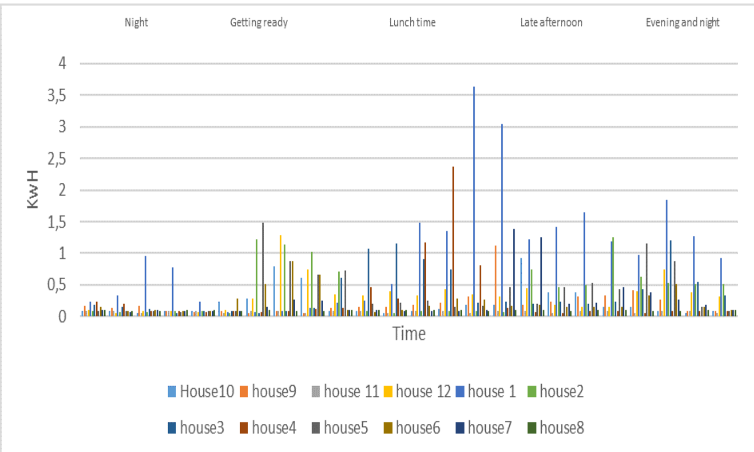

Figure 4.4: Dataset used for visualization and clustering.

The reduced dataset is plotted to show the similarity of the specific time during the day as shown in Figure 4.5.

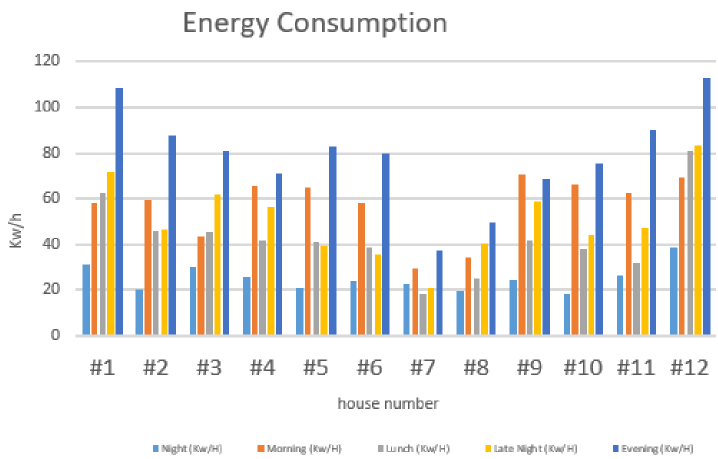

Figure 4.5: Comparison of the total energy consumption between the five time periods during 24 hours.

4.1.2 K-means Clustering Algorithm

K-NN is essential for the clustering and classification of large datasets. K-Means algorithm was selected given its ease of implementation and commonly appropriate energy consumption data sets. It has been established as one of the 10 best data mining algorithms [178] that are relevant to the data similarity classifications and also suitable for a dataset's load profiling implementation. The pattern analysis was performed by using clustering techniques to check the similarity of the electricity usage at a given time. The similarity of electricity usage patterns was identified with the help of the K-means algorithms and evaluated as per the SSE analysis. Larger SSE indicated that the rate of data similarity in the cluster was small. Therefore, the SSE is the total of the squared variations among each reflection and its group's mean. It also uses a measurement of the differences in the cluster.

$$\Delta(x, y) = \sum_{i=1}^{n} (x_i + y_i)^2 \tag{4.1}$$

$$SSE = \sum_{i=1}^{\infty} \sum_{i=1}^{\infty} dist_2(m_i, x) \tag{4.2}$$

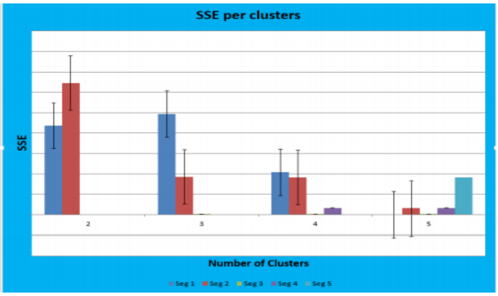

Figure 4.6: Comparison of SSE according to clustering of houses based on energy use.

Table 4.1: Clustering results

Clusters	1	2	3	4	5
SSE	13.352	10.827	6.801	4.225	2.462

The K-means clustering algorithm validates the cluster of the estimated household's pattern and is able to identify the abnormal behavior based on the energy consumption. We showed a mixture of matrix-based consumer energy consumption datasets' exploration and K-Means clustering data classification methods expected by SSE results. An analysis of SSE can determine the household's load consumption and its normal or abnormal electricity usage for typically related behavior. We formed one to five clusters to calculate SSE and the members or number of iterations in each. The biggest SSE was obtained from clustering it as 1 cluster (i.e., it involved all of the houses being considered). However, SSE enhanced with performance in 5 clusters, and the results are shown in Table 4.1 and Figure 4.6.

4.1.3 Results Analysis

The results indicated that the load consumption data measured by SM is implemented with an ML algorithm for the data set similarity classification. Including the K-means algorithm can relate to estimating the health situations of the consumers. The K-means clustering algorithm method is based on the partition and centroid approaches for the characterization and analysis that based on SM-generated big data. It performs quicker than the rest of the similar clustering algorithms that are applied to data for cluster analysis. The source data is refined into supervised learning classifications. The model associated with behavior identifies and detects abnormal household behavior vis-a-vis its energy consumption to predict the resident's health status. The contribution of this part of the thesis is further detailed in the following subsection and chapter 5. We have investigated the key challenges and evaluated the findings. However, to obtain accurate result of electricity usage to perform the health monitoring and and the associated task, a personal interaction of home devices such as dishwasher, TV, light, fridge, and laptop is needed.

4.2 IoT-based Appliance Identification on Fog Computing

The fast-paced growth of automation technology, embedded systems, and connectivity is advancing the development of the IoT technology. Devices joined through IoT are increasing daily and making our lives more productive and accessible. IoT can be advanced by deploying a sensor network to collect data of the surroundings for remote monitoring purposes.

Our thesis proposes an architecture based on IoT technologies to design and implement SM and a fog-computing system for processing energy datasets. We use the GirdLAB-D simulation for the implementation platform to design the correct models for appliances in the household. ML algorithm serves to identify the abnormal behavior related to energy consumption measurements. SM design for monitoring and load profiling of the appliances improves the older adults' quality of life either in the e-health center or in their homes depending on the measurement of the appliance's usage information in terms of time, duration, and energy consumption. The SM data is collected and relayed to monitor the elders' normal or abnormal behaviors and have an application with real-time monitoring ability which would automatically give results and end up assisting the caregivers in observing and monitoring the elderly.

There are many options for smart home-based health monitoring systems as proposed in the several previous studies [179]. Most of the systems are equipped with the following components: (1) sensors, (2) communication networks, and (3) processing systems. Mostly the sensors are those that substantially relate to the patient's surroundings and gather appropriate health data to be used for monitoring health conditions. Most academic or industrial or private researchers continuously develop health monitoring systems and wearable sensors to collect vital information from patients' bodies. For Home Area Networks (HANs), the processing and communication arrangement can collect the data that is to be transmitted and saved for processing. To monitor patients without any physical interaction in a cost-effective manner, we have proposes NIALM and appliance identification. NIALM is previously applied for appliance identification and load forecasting and here we proposed it as a novel approach of a health monitoring system. We investigated and analyzed the algorithms and architectures concerned for our novel approach[16] NIALM was used for ADL of the consumers for prior identification of their health status and abnormal behavior.

4.2.1 Load Modeling

We have defined the mathematical and modeling techniques and architecture for the NIALM implementation platform for IoT-based appliance identification on Fog computing using a modeling approach for NIALM for the appliances' identification based on the load modeling AC appliances in the house. The equivalent circuit of AC appliances for the k^*th*.

number of impedance as shown in figure 4.6. where;

$$Z_k = Z_k < \theta_k \tag{4.3}$$

Z is the equivalent impedance of the circuit

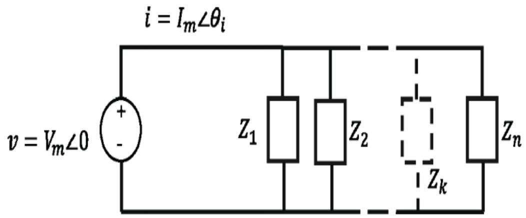

Figure 4.7: Circuit model of AC appliances in a given house [16].

The apparent power is calculated as:

$$S = V_{rms}^2 < 0/Z < \theta = P + JQ \tag{4.4}$$

The ZIP are significantly used to the model. The AC appliances and the ZIP model are represented by its polynomial and static model. The equations (3) and (4) are ZIP coefficients.

$$P = P_0[Z_p V/{V_v}^2] + I_p V V_0 P_p] \tag{4.5}$$

$$Q = Q_0[Z_q V/{V_v}^2] + [I_q V V_0 P_q] \tag{4.6}$$

The ZIP equations for the active and reactive power are given in (4) and (5) respectively.

$$P = V^2/V_0^2 Q_0 Z \sin(Z_o) + V_0^2 Q_0 I \sin(I_o) + Q_0 P \cos(P_o) \tag{4.7}$$

$$P = V^2/V_0^2(Q_0 Z)\sin(Z_o) + V_0^2 Q_0 I \sin(I_o) + Q_0 P \cos(P_o) \tag{4.8}$$

where Z is the percent of load that is constant impedance, P is the percent of load that is constant power, I is the percent of load that is constant current , $Z_\theta$is the phase angle of constant impedance fraction, $I_\theta$is the phase angle of constant current fraction and P_θ is the phase angle of constant power fraction. Our investigation for appliances' identification is based on the load modeling AC appliances. The equivalent circuit of AC appliances for the Kth number of impedance is shown in Figure 4.6. We develop a Constant, Impedance, Current Power model on the open-source GridLAB-D simulation platform for the home devices. The structures of GridLAB-D are open-source and user-friendly platform and offer a code for re-writing as desired[16]. The system has multi-state time arrangement load models that are compatible with load profiling compilation associated with the user appliance's voltage measurements. The platform can operate on a multiprocessor tool and uses multi-agent methods to permit organizing novel control algorithms.

4.2.2 System Architecture

Our implementation on load modeling is defined and uses GridLAB-D IEEE 13 node stranded for the current, voltage control, and load flow measurement of the appliance on its simulation. The system architecture that used the simulation tool is shown in Figure 4.7.

Load profiling and predicting requirements undergo a limited process to increase efficiency and decrease the associated error results. Our system's architecture is composed of a smart plug for the home appliance that is connected to acquire power. The smart plug is connected with the sensors inside the house together with the communication and DSP units. The smart plug can still switch to on/off to hold the demand response pattern and further analyze health monitoring. The household plugs are linked with numerous linked connections to the SM; then, it performs the data collections using plugs. Lastly, the SM analyzes and carries the information to a server and stores it for further applications related to healthcare services or for controlling the user's energy consumption purposes. The Fog-assisted IoT-based platform consists of HW and SW parts as listed in Table 4.8 and Table 2 to compile, simulate, and implement the stored information for our proposed application.

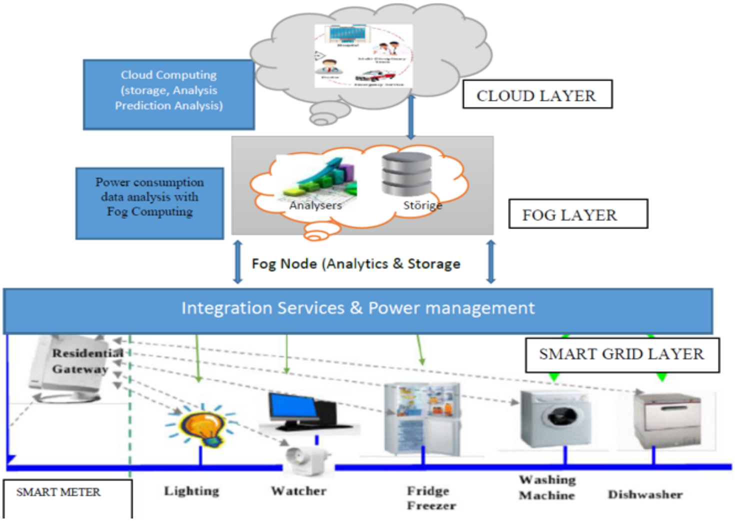

Figure 4.8: Energy consumption analysis in fog/cloud computing for Healthcare.

4.2.3 Result Analysis and Discussions

This section shows how an abnormality detection in behavior can be recognized by energy usage data obtained from SM. In other words, we showed that a consumers' energy usage data acquired from a smart meter is used to check the health status, health changes, and general well-being of a house occupant. In this case, health deterioration, especially with the prior study of consumers' electricity usage routines can predict the user's normal or abnormal health status. It includes when a person stops using the electricity or consumes low energy. The prediction leads to information if the person is in danger or has difficult health conditions. In addition, performing an immediate change from the routine of energy utilization can lead to an abnormal situation. However, this assumption is based on the historical data of deep learning of the daily energy usage to identify the daily routine and habits of the consumer. The analysis of the medical problems should be beneficial before using the power consumption information for acceptable healthcare applications. Again, related information, on how often and how long the consumer uses the appliances on a normal routine including the frequency or the duration of patterns is useful to recognize the alteration. A rapid response is initiated whenever the device is used to alert consumers when deviating from their typical energy use patterns. Still, SM collects enor-

Table 4.2: HW and SW tools to simulate the proposed prototype

Device/tool	**Functions**	**Tools / Devices**
Current sensors measure the instantaneous	Power consumption and RMS value	ASC712
Microcontrollers	Filtering calculatio (ZIP), Comunication appliances Identification SM	Atmel 89S52 AVR456 MCF51EM254 TMPM411F2
Middleware	Security, heterogeneity	AVR465,
Power system simulator	Simulation, modelling	GridLAB-D and Matlab

mously big data sets, handling and evaluating the dataset shows a technical challenge.

The load profiling method on a combination of matrix-based consumer's dataset analysis and K-Means clustering data mining techniques that is predicted by the sum-of-squared error (SSE) results are presented. From the analysis of SSE, we can determine or predict the daily load of the household and its normal and abnormal electricity usage to model the associated behavior. We also identified and detected the household abnormal behavior with the analysis of energy consumption to predict the residence health status. However, in order to improve the accuracy prior setup of a prediction algorithm of the parameter is needed. We investigated the need for modification of features according to the individual state and circumstances to be used for assisting independent living for users in the household. The primary data classification results using K-NN classifiers to recognize unusual energy usage applying electricity load automation is an encouraging tool for monitoring health status at home [177]. It is based on the concept and approach of classification of the appliances upon their kind and mode of operation with the aggregated energy measurement application. It also leads to consideration of the consumer's health status by using a redefined mode of operations of the appliances. Machine-learning processes build a map of routine behaviors and activities over time, thereafter enabling computerized detection of anomalous behavior or unexpected behavior. Our publication [16] has reviewed the currently reported algorithms for appliance identifications by analyzing the load modeling methods.

The obtained result proves that e-health using electric load intelligence is a promising technology for the home-based healthcare system. One of the ideas behind this system is to identify the type and operation mode of the electric appliance using aggregated energy measurement, then determine the health status of the occupant using a predefined mode of operation. This section presented the surveyed result of the latest published algorithms for appliances identifications and load modeling techniques. We showed the dynamic ZIP model as the most suitable candidate for load modeling. The design of the models needs prior knowledge of the appliance to measure the significant parameters as related to active power and reactive power, current, and impedance. Our fog architecture uses a smart plug through which a home appliance gets the power. The smart plug is an embedded system that houses sensors along with the communication and DSP processing blocks. The plug can also control the operation of the appliance to support the demand response scheme. The electric plugs within the house are connected through various communication links to the smart meter. The smart meter aggregates the data from all the plugs and processes and sends the data to a server. The analyzed data are used for healthcare diagnosis and other home energy management functions. Finally, the present work devised a fog-based architecture for the e-health system. We note that a dynamic ZIP model is the most proper option for prospective appliances' modeling and classification.

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Chapter 5

Non-Intrusive Appliances Load Monitoring Implementation

This section of our thesis discusses our contribution to the NIALM system used for health status monitoring applications from the state of an appliance's operation. We show our novel approach's findings on how the NIALM system together with SM data from the appliance's measurements can offer the operationalization of the AAL principle by using the ML algorithm for a remote health care monitoring approach. The main task lies in the appliance's state of operations of the feature that is extracted to classify according to the obtained power signals from the appliance's load consumption. The classification and identification of accuracy to be determined for appliance detection are implemented using the ML method, namely, the k-NN classification algorithm. For verification, a publicly available PLAID high-frequency data set is used as a benchmark. The data set is composed of power, voltage, and current signals from the appliance's measurements taken from many homes. The appliances' classification from the PLAID dataset is performed on the K-NN algorithm and obtained at high accuracy and ability to build up a cost-efficient result. Including the implementation of k-NN classifier in FPGA or HW has improved the run time by advancing the processing time with a significant standard of achievement accuracy. We have documented our findings and results in our published article. [180].

5.1 NIALM

The idea of home electrical appliances that describes the NIALM system was formerly established by George Hart through the 80s [129] to develop a non-intrusive system to monitor the energy consumption of a particular appliance from the central power control system of the electrical grid network.

Which means uses one intrusive sensor to monitor all appliances in the electrical network. NIALM offers information on individual appliances and their present state of operation by identifying individual loads from the aggregate power consumption. It is associated with the necessity of decreasing energy consumption and the growing number of appliances in the current home environment. The NIALM method, thus, proposed an inexpensive way for appliance monitoring by using SMs. This entire methodology is discussed in our work [180], and it evaluates each appliance's electricity usage from their aggregate energy consumption. Further, the overall energy usage is observed from the home's common node and can reduce electricity cost using SMs [177]. The appliances' identification and ALM techniques can be categorized as ILM and NILM as per the process described in Figure 5.1:

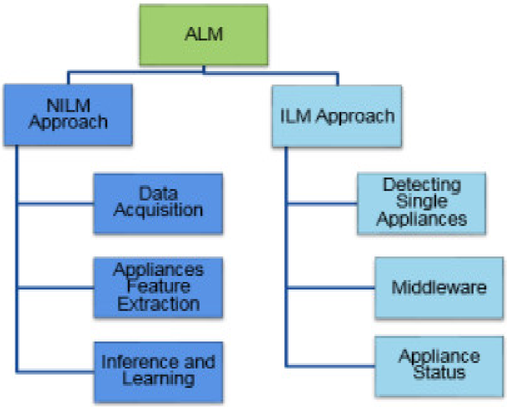


Figure 5.1: NILM and ILM Framework.

The system can explore each household's electricity usage by knowing the unique differences of the usage pattern of the appliances currently in the household. This method classifies each appliance's energy usage from the accumulated home energy consumption further by indirectly identifying the anomalous changes in the appliance's usage. Our work on the NIALM method has suggested and discussed the solution for appliance identification and characterization mechanisms to support the aging population's wish to live independently [17], [180]. The idea behind this effort is to draw on the data-driven analysis approach to monitor the occupants' safety by indirectly detecting abnormal behavior through the use of appliances. We focus here on the NIALM energy disaggregation method. For activity recognition, all electricity usage is divided into a definite load of each household's appliances.

5.1.1 Classification of NIALM Data for Activity Detection

SM's advance has driven the growth of NIALM concerning the progression of disaggregate total energy usage of the building into single electrical loads even at the appliances level. This thesis contributes to the daily living activities' monitoring through the NILAM system with the energy usage appliances having a single-phase SM or socket associated with aggregated measurements. In that case, using NIALM proves the occupant's activity such as food and drink preparation or the washing of clothes by predicting the occupant's everyday routines. We can associate this with a prior study of the household, such as the number of occupants, their daytime activities, and idleness, their time of being in the house or away, and other weekly social activities. In that case, the NIALM system can also be used as an appropriate health monitoring system other than its general and initial applications for consumers' use of energy assets for minimizing costs. The result of the appliances' identification showed that NIALM, besides being a technique for demand-side management to be used for providing effective solutions vis-a-vis AAL, can also provide information through appliances' identification about the household's activity and health status. Figure 5.2 indicates how NIALM could be used to monitor the household's health status using aware mechanized structures.

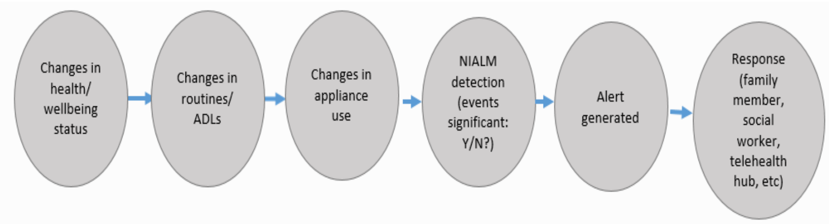


Figure 5.2: NIALM approaches for health status monitoring

Table 5.1 discusses the possible behavioural change in appliances' usage and the indication of the health status associated with activity in the NIALM category

Table 5.1: Identifying possible changes and routines using NIALM for a health monitoring system for the elderly.

	NIALM Detection	Potential Behavioral Changes	Possible health risk
Long Term Changes	Use of kettle or other appliances during night	Sleep problem disturbance	Mental health problem Pain associated illness
	Use of kettle	Sleep disorder	Pain associated illness
	Leaving appliances on oven	Memory problem	Mental health problem
Short Term Changes	Different time of appliances use other than the usual	Reducing the social relationships	Social isolation & Mental health
	Stop using appliances altogether	Inactivity	Fall Stroke
	Sudden decrease in use of appliances	Lower capacity for ADLs	Sickness Worry about falling Failure to take

Procedures for the NIALM System

Our approach is based on recognizing the appliances' usage associated with cleaning, cooking, and sleeping daily. The information from the events of the activities and the appliances' usage duration can be obtained from the user's routine to detect an abnormal situation. The novel activity monitoring is based on the mixture of appliances recognizing the on/off states of the appliances and event detection. This activity monitoring is also based on feature extraction considered from the signature of each of the appliances' load consumption one at a time during the on/off event. The feature extraction has a V-I trajectory (voltage/current) and steady-state measurements of the appliances before and after the event. It is also considered to be the feature of appliances used during the transient threshold crossing point from on to off state or vise versa. Besides, the NIALM appliance's identification and characterization method we have implemented the use of the ML algorithm that has resulted in high accuracy. The summary of our approach and steps are shown in Figure 5.3

Data Acquisition

This research uses the PLAID [101] dataset as a benchmark for NIALM and appliances' classification. After that, the NIALM system is to be an appropriate health monitoring system in addition to its initial application for measuring a consumer's use of energy assets and minimizing the costs. We have used for our analysis the 1,074 events of all the 11 appliance types based on the motivation of the appliances' events. The appliances' events have been considered at 30 kHz with 16-bit amplitude resolution. In gen-

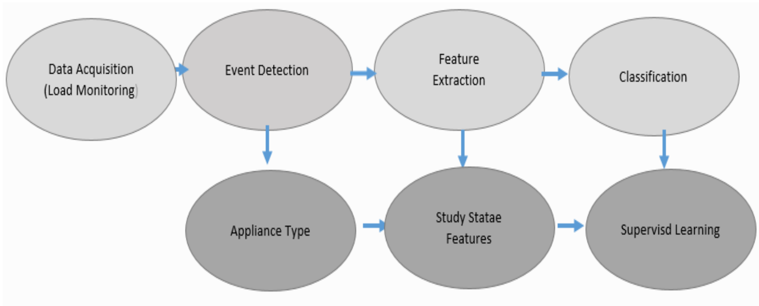


Figure 5.3: Procedures for appliances' characterization on the NIALM system.

eral, NIALM is applicable for energy data with altered level data resolution and frequency. The data set is a collection of voltage and current appliances of 60 houses in the US located in Pittsburgh, Pennsylvania. For more information on the collected appliances type such as hairdryer, compact fluorescent lamp, microwave, heater, fridge, air conditioner, washing machine, laptop, incandescent light bulb vacuum cleaner and fan, the data set and results are described in our research article. [17]. The figure below

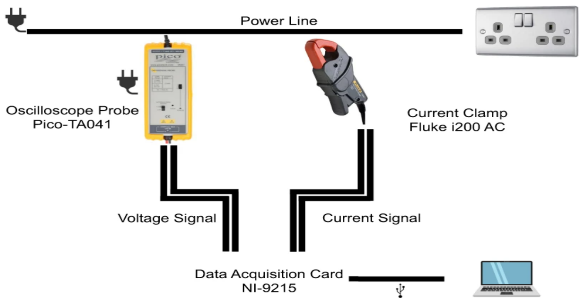


Figure 5.4: Measurement set-up for capturing data.

shows the load consumption collection by employing a National Instruments (NI-9215) data acquisition card, which has four concurrently sampled analog input channels corresponding with a 16-bit ADC capture voltage and current measurements. These are connected to a computer via a USB connection. More about the data collection and data type and prepossessing is described in the linked literature [108]. The measurement setup for capturing the PLAID dataset used current clamp can collect with a one-second or sub-second sampling rate. The monitoring devices can capture high-

Table 5.2: Number of instances of appliances and appliance types

Appliance types	**Number of jnstances**	**Appliance types**	**Number of instances**
Compact fluorescent lamp	175	Fridge	38
Vacuum cleaner	38	Incandescent light bulb 1	114
Hair dryer	156	Fan	115
Microwave	139	Washing machine	26
Air conditioner	66	Heater	35
Laptop	172	**Total**	**1074**

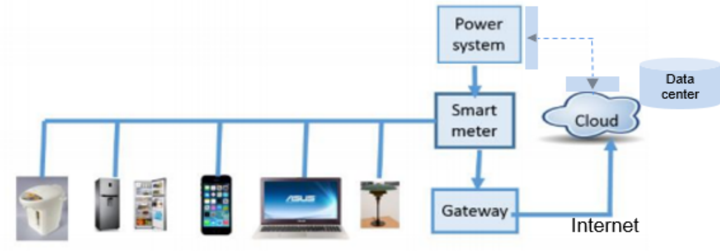
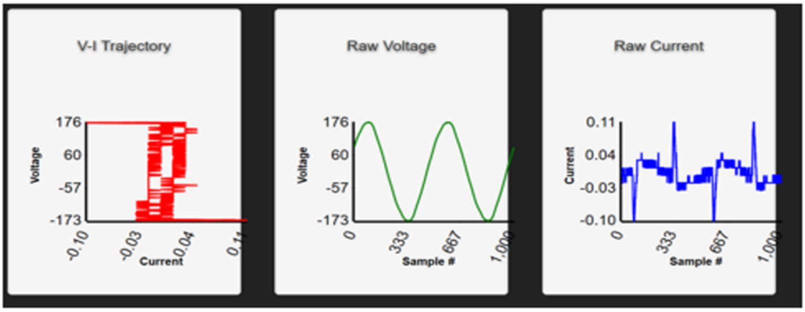


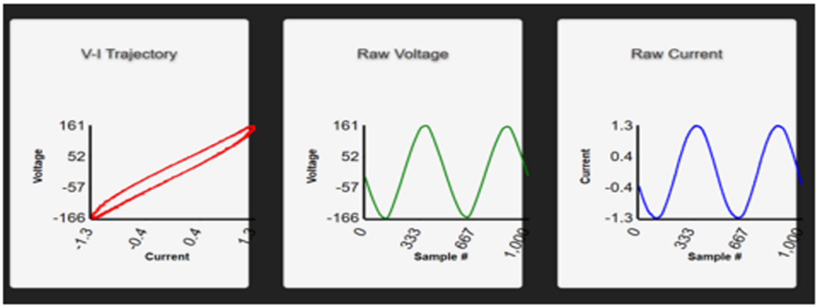
Figure 5.5: Architecture for NIALM with cloud processing.

frequency data sampling up to 1MHz (one million samples per second). It means that they can detect both high-energy and low-energy devices. Having measurements from the low-energy devices used as part of the occupant's daily routine, such as watching their favorite TV programs, could be necessary for the healthcare monitoring system. The collected data will soon undergo different stages of processing such as noise removing, filtering, harmonic component separation, and signal synchronicity to yield accurate and sensible information. Table 5.2 shows the number of appliances' instances and appliance types: Figure 5.5 depicts the architecture of data acquisitions.

Event Detection : NIALM is an electricity load analytic method that depends on ML and signal-processing systems and predicts the load consumption of the individual household appliances from the aggregated measurements of the central network of the grid. NIALM has extended its importance by using household appliance load consumption for promoting the energy-efficient home idea and working toward reducing the carbon footprint. In our thesis, NIALM will be associated with AAL by associating event-based algorithms for disaggregation mechanisms. However, NIALM generally has event-based and state-based methods that use supervised learning that relay in the previous training event detection. Event-based methods depend on detecting algorithms that rely on the switch continuity principle as switch-ON, which was initially introduced by [129]. We used the event-based approaches depending on the appiances' detection to latch the appliances' events by the switch-ON or switch-OFF buttons on it. Event-based styles are usually more effective with pre-processing of the voltage and current signals. There are several types of appliances that are existing in a household. Appliances also operate in different types of styles other than ON and OFF as we discussed in our article[17]. An event's incident is supplemented by deviations in voltage and current, which are usually detected by associating the variation on the duration with a fixed threshold, including for this approach thereby permitting the noticing of the event's detection to be considered as an anomaly detection, which is the central aspect of this study. The primary element of event-based approaches is to classify the models with the help of the extracted features due to the variations of power. However, features can be classified according to their engineered and data-driven categories. Feature extraction: The data-driven features were extracted from the raw voltage and current measurements of publicly accessible PLAID load appliance identification dataset [101]. The dataset covers energy consumption measurements from 11 appliances in 55 houses with 1,074 current and voltage measurements at a sampling frequency (fs) of 30kHz. The data in the evaluated appliance load signatures, based on V-I trajectory, schemed on the steady-state voltage and current shows the appliance's electrical features. The phase angle alteration between voltage and current and the appliance features can be gained by scheming the V–I trajectory features as defined in detail in [181]. We have also documented our findings in our article [180] by showing the voltage and current trajectory (V-I) of all the 11 appliances categorized by their steady-state signature. The figure below shows the appliances' steady-state signature based on the VI-trajectory, raw voltage, and raw current waveform. The V-I trajectory has managed to show the signature or pattern of the appliance.



(a) Air Conditioner load



(b) Bulb

Figure 5.6: Example of appliances' steady state signature [17].

5.2 Appliance Identification with the K-NN Algorithm

The PLAID dataset is achieved from the collected SM measurements of the appliances' energy use in a household. The appliance measurement dataset is extracted and is used for NIALM and appliance identification daily. The features' predictable patterns can identify each appliance based on the appliances' operating states during a fixed period operation. The appliances' classification depends on the pattern recognized by each type of appliances' operational and predictable energy consumption. We verified the accuracy of this classification by matching it with the available set of features. We found that, here, the input data quantity is not a factor for the accuracy of the appliance feature extraction. Usually, it depends on the quality of the available information [108]. For NIALM and the appliances, identification and classification are mainly obtained from the ML algorithms and related supervised methods. We studied different ML classification algorithms to come up with a suitable ML algorithm for appliance identification. Among them, k-NN, Random Forest, Decision Tree, GNB, and logistic regression classifier have been checked in the previous study[34]. The classifiers' performance has been shown with several groups of extracted input features from the measurements taken through SMs. As we stated in the last sections, the features obtained to classify the appliances have transient and steady-state features. The binary VI-trajectory is an excellent candidate to represent the feature since it has been the best-accomplished feature extracted in prior study conducted on PLAID [34]. This feature is generated by plotting a voltage verse to the current of an instance using a binary 0 or a 1 value according to the trajectory's present type. Figure 7 shows a plot comparing the various ML algorithms to find the correct and effective algorithm. We noticed that the accuracy of the classification is varied with the change sampling frequency. The result is established on the PLAID dataset as an input and application software that uses Python3 code representation and other necessary packages of R studio as explained in [108].

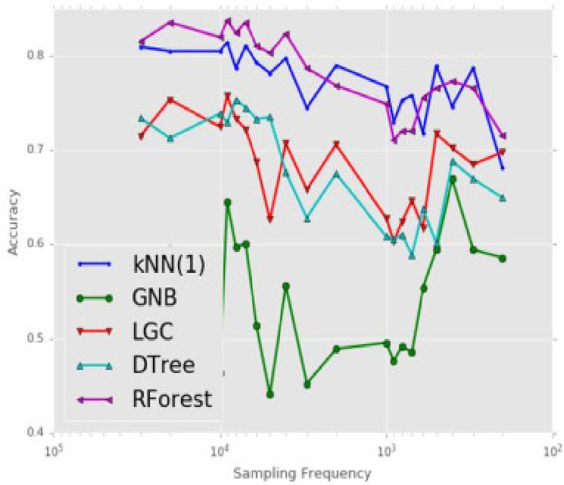


Figure 5.7: K-NN classifier accuracy comparison on PLAID dataset.

We found that K-NN and RF showed good performance when compared to the other classifier methods. Besides, we know that the K-NN classifier corresponds to the classification of active or reactive power input features. Figure 5.5 shows RF to have a better result; however, previous analysis [114] has validated and proved that K-NN has accomplished higher accuracy to high-frequency current and voltage and imbalanced and balanced datasets that are similar to PLAID. Besides, K-NN has expressed the best results. The algorithm is broadly used as the classification algorithm with accurate implementation [164]. For the unbalanced dataset in Table 1, K-NN offers improved performance by automatically identifying either linear or non-linear distributed data sets. Hence, it has achieved good results on many data points. This algorithm is used as a data-mining algorithm for feature extraction. Pattern recognition, including its classification of the features, can be implemented with a low error rate. In summary, our classification method using K-NN uses the following steps:

- Detection of events: Changes in events related to energy usage are caused by the variations in the states of an appliance. Different signal processing algorithms can identify events.

- Clustering of events: The identified event is further clustered by grouping events that may arise from a similar change of state of an appliance. The unsupervised ML, specifically, the K-NN algorithm, is used during this phase of the clustering.

- Modeling of appliances: With the clusters gained and using time series analysis, the appliance types are constructed. An appliance type regroups the clusters to express a change of state of the appliance. The supervised ML, in specific the K-means algorithm, is used in this phase.

- Tracking of appliances consumption: Once we come up with the appliance models, the behavior of each appliance is tracked using the appliances' energy usage during each time

K-NN needs to calculate the distance between the training and testing dataset of each of these datasets for knowing the K-NNs of a test point. We used the Euclidean equations as shown in equation (1) [182]. For a specific nearest number of K, and the unknown dataset x and a distance metric D, K-NN checks all over the dataset and computes D among x and every training dataset. The neighbors and near neighbors are labeled for anonymous data and the K-NN input by knowing the dataset's samples. Therefore, on the majority label, we used the same standard K-NN algorithm to characterize NIALM for appliance identification methods [183]. We will discuss our method for the K-NN algorithm classification for the implementation and the used evaluation metrics in the next section.

5.2.1 Evaluation Metrics Analysis

As mentioned earlier, the test bench PLAID dataset comprises 11 appliances such as vacuum cleaner, microwave, compact fluorescent lamp, fan, laptop, fridge, hairdryer, heater, incandescent light bulb, air conditioner, and washing machine. Their on-off states are considered for modeling. However, the washing machine was considered as an outlier because it was not compatible with our evaluation. The other modeling problem was that it was impossible to separate the testing dataset from the whole training dataset for PLAID. We considered evaluating the training and the testing on the whole dataset, and a higher training accuracy was obtained. SW analysis indicated that we should either divide the training:testing data proportion to 90 percent: 10 percent throughout or evaluate the entire procedure. The details of our result are discussed in our article [180]. In our research, we emphasis on predicting the accurate appliance at a specified instance of time. A usually considered metric is the accuracy of the classification from all likely classes.

The accuracy of the algorithm is determined on the CM [115]; Precision (P), Recall (R) and F-score (F). The metrics are derived as of True Positive(TP), True Negative(TN), False Positive(FP) and False Negative(FN). Based on TP, TN, FP and FN values, the F-Score parameter measures the classification performance for the comparison of the classifier.

The F-Score is the stability between precision and sensitivity for every appliance. For a single appliance in each house, the F-Score can be expressed as:

$$F - measure = 2\left(\frac{PPVXTPR}{PPV + TPR}\right) \tag{5.1}$$

$$Precision = PPV = \frac{TP}{TP + FP} \tag{5.2}$$

$$Sensitivity = TPR = \frac{TP}{TP + FN} \tag{5.3}$$

where TP signifies the true positives (i.e., the amount of appliances correctly labeled to the positive class), FP are the false positives (i.e., the amount of appliances incorrectly shown as labeled to any class) , and FN is the false negatives (i.e., the amount of appliance which were not labeled to the positive class).

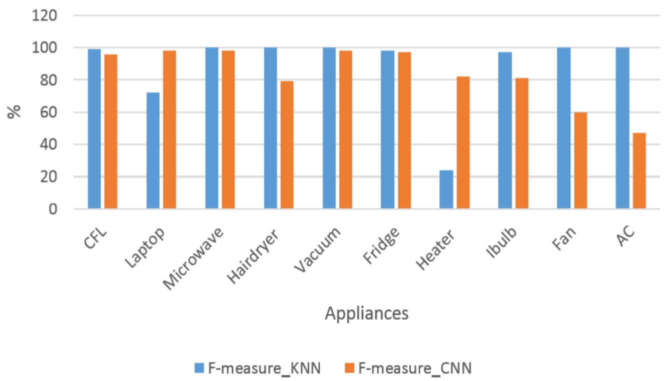


Figure 5.8: Comparison of F-measure on K-NN and CNN algorithm for appliances identification results.

The appliance performance that was indicated by the use of K-NN (as per our result) was compared with the previous result of the Convolutions Neural Network (CNN) [184], which was also based on the PLAID dataset on NIALM and the classification of appliances. Our method using K-NN was found to be better better in classifying most of the appliances than was the case with CNN.

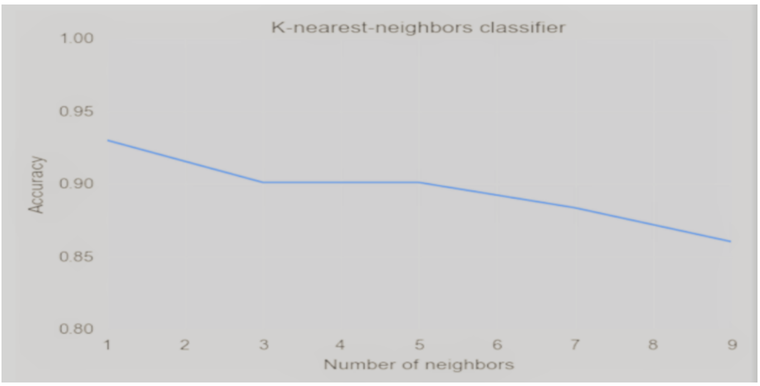


Figure 5.9: K-NN classifier and number of neighbours.

We also analysed identifying appliance type per house by testing the performance of the K-NN and RF classifiers would be to forecast or recognize the type of appliances in specific house, established on the voltage and current signals, by training the model on the data from the remaining of the houses. figure 5.9 shows the K-NN performance accuracy classification according the number of neighbors. In that case we decided to have only 1 for the K-NN classifier performance.

The characteristic of the RF classifier have shown in Figure 5.10 and shows increasing the number of trees may improves the performance when indicates are around 70-100. In that case the accuracy shows at 80 sub-trees.

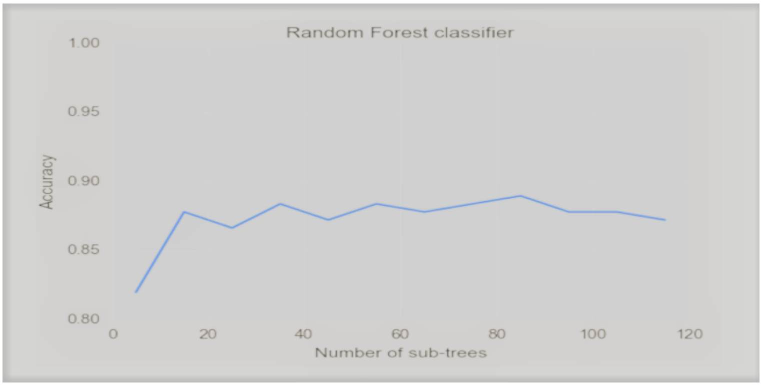


Figure 5.10: RF classifier and number of sub-trees.

Based on the analyses undertaken we are able to identify some common patterns and draw conclusions about the two best performed classifiers identified in terms of time and accuracy, K-NN and RF.

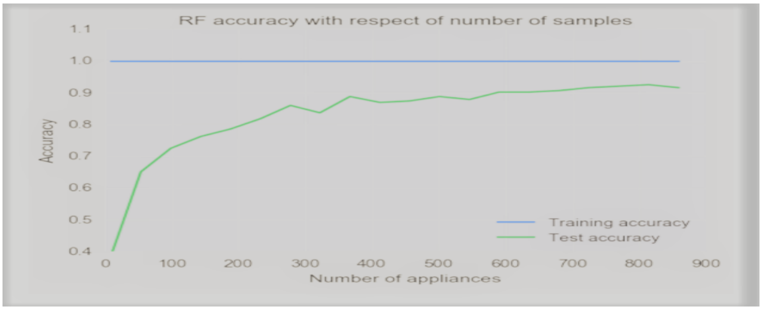


Figure 5.11: RF accuracy with respect of number of samples.

Though K-NN marks to some extend grater ac accuracy of classification than RF, the high accuracy in both classifiers by cross-validation techniques. For majority the appliances input signals of current and voltage https://www.overleaf.com/project/61855d61b0f7568c7d307a1ddo not reach steady state in different appliances. Figure 5.11 shows the training and test accuracy evolution of the RF classifier with respect to the number of samples. Incriminating the number of sample after 700-800 samples shows that the accuracy is increasing.

5.3 K-NN Implementation on FPGA

NIALM is very expensive and has to use complex communication network to transfer the data. FPGA is a low cost solution in developing specific solution, and the NIALM system requires high sampling frequency requires for processing of some appliances. In addition, the V-I shape signals are considered binary image input for data-driven features extraction. The ML method using K-NN algorithm is considered for classification. The V-I trajectories require an advance computational analysis for extracting the features. Thus, processing high-frequency current and voltage signals and extracting the features need cloud computing since it cannot be performed only on SM. However, our solution is a part of the processing to be done in the HW implementation to avoid communications overheads. However, appliance load monitoring approach with NIALM, conducted in a smart house can draw several inferences such as appliance-level energy consumption from total (circuit-level) energy consumption acquired from a smart meter.

5.3.1 Implementation of Architecture

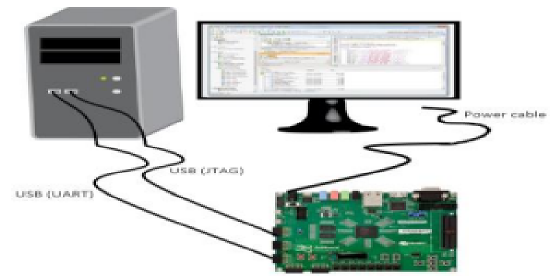


Figure 5.12: HLS implementation platform with Zynq7000XC7Z020-CLG484-1Evaluation board.

In the previous section, Figure 5.5 shows the architecture of the data acquisitions, and the V-I trajectory was shown in a plot , producing a visible pattern for measured appliance of PLAID dataset that can be used for the classification of appliances according the plot shape. The system involved a very high-bandwidth and extensive communication period to transport the high-frequency current and voltage wave forms. It is also different from the recent development on the IoT-based communications that belong to the high-throughput of lesser packages. In that case, the real-time disaggregation cannot apply to the grid quality of NIALM. The K-NN that is used in the previous section was modeled in c code for the implementation of the FPGA.

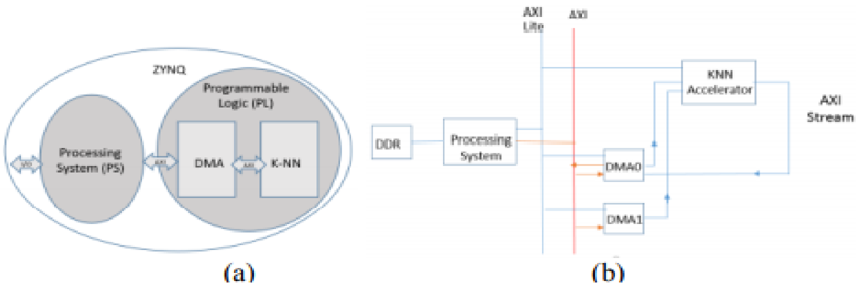


Figure 5.13: (a) K-NN system implementation using Zynq and (b) K-NN algorithm's flow.

Figure 5.13 shows the HLS platform with the Zynq7000XC7Z020-CLG484-1 Evaluation board that we suggested in our thesis as apt for implementation. FPGAs use configurable processing logic (PL) hardware which allows to be fast and reusable processing devices. Figure 3 depicts the proposed CNN architecture implemented on the IP core.This is so because of the computation for the run time being a cost-effective solution. We use hardware implementation for processing logical part of the processing by using FPGAs. In that case, the FPGA implementation will take care of the heavyweight processing to be completed locally by eliminating the communication outflows; then, the Internet's communication would be for the appliance's classification. Besides, the high-speed permitted by the hardware's implementation would allow close-to-real-time disaggregation. The K-NN system's implementation process using Zynq and the K-NN algorithm's flow is shown in Figure 5.14

Further, the K-NN was represented in the C code. Through a Register Transfer Level (RTL) model, the result was developed and transported as an intellectual property (IP) core. Thus, the IP was realized on an FPGA. The FPGAs can handle a configurable programmable logic (PL), that can accelerate a flexible processing operations. The K-NN algorithm for implementations on FPGA involves the following two steps: The procedure

Algorithm 1:

```
for each test_datasets do
   for all train_datasets do
      distances.attach(distance(test_dataset, train_dataset))
   end for
   indexes ← getKShortestDistances(distances, k)
  new_class  ←   getMoreFreqClass(indexes,  train_set)
end  for
```

Algorithm 2 is the Pseudo-Code that states the processor software program for control the DMA and achieving the final stage of the k-NN algorithm shown as below:

Algorithm 2:

```
for  int i = 0; i < N'; i =i+ 1 do
   dma Upload(test_dataset[i])
  dma Upload(train_set)
  dma Download(indexes)
  new_class[i] ← getMoretFreqClass(indexes, train_set)
end for
```

Figure 5.14: Algorithm for implementation on FPGA.

using loop unrolling was helpful in the achievement of parallelism among the loop's iterations. It generates multiple replicas of the loop section. In such a case, extra parallelism can achieve more system performance and the throughput will also be more. Optimization will offer efficient loop unrolling for applying the whole resources delivered by FPGA.

5.3.2 Performance Analysis

Table 5.3: Results of performance and power consumption for implemented K-NN algorithms

Resources	Available	Used	%
BRAM (Block of Memory)	140	39	27.8
DSP (Digital Signal Processing)	200	7	31.8
FF (Flip-Flop)	106400	21647	20.34
LUT (Look-up Table)	53200	19784	37.18
BUFG (Global Buffers)	32	1	3.12
Latency		5.9 ms	
Power		1.94 W	
Energy		4.1 mJ	

Table 5.3 shows the result that was obtained from HLS implementation. Number of LUTs required to implement an accelerator depending on the

value of k. The implementation's performance exploration is as described in Table 5.3. The results showed the unused resources are that are calculated by K-NN operation on FPGA implementation. It also has advanced performance on the power and energy and the latency as low as 5.9 ms. The HLS implementation on K-NN classifier more accurate and has sped up the processing time with improved performance. One of our thesis's contributions is solving the FPGA implementation issue on the current NIALM system's difficulty concerning comparing the transient appliances. We have showed CNN classifier with FPGA implementation to have the potential of solving this problem. Experiments on extracting the load profiling and energy usage signatures for identifying the appliance have shown that implementing the NIALM algorithms on FPGA acceleration has gained a better run-time and response time. We also compared our results with other researchers' results on Zynq-7000 FPGA implementation [17]. Table 5.4 shows an example of the comparison of the results from the comparable ML implementations on FPGA:

Table 5.4: Comparisons of results from similar ML implementations on XILINX ZYNQ-7000 FPGA

Ref	**Method**	**Processing time**	**Power**
[185]	K-NN	4.8 ms	1.78 W
[186]	ANN	5.7 ms	1.86 W
Our result	K-NN	5.9 ms	1.94 W

The K-N-N implementation achieved the higher performance and speed up processing and, have established the timing requirements of speed up processing.

5.3.3 Result Analysis and Discussions

We propose a health monitoring of the AAL framework for the effects of elderly and chronic patients increase has become harder to cope with caregivers. Table 5.3 summarizes the identification of possible changes and routines using NIALM for a health monitoring system for the elderly. These include monitoring inability, sleep disorders, memory difficulties, changes in activity patterns, inactivity, occupancy, and the identification of ADLs. The thesis identified the advantage of smart meters' delivery instead of wearable or biosensors for a cost-effective and intrusive solution for AAL. As SM rollout, programs deployment are in place now, and the application of home care has a significant impact on the progression of AAL and load disaggregation. SM load profiling can identify and recognize the sudden changes in behavior and can be used to monitor people in their homes to support independent living. NIALM can identify the energy consumption of specific appliances with low-cost power meter plugs connected to the central control system. NIALM system and appliances classification on ML approach is used for analyzing the unfamiliar pattern and the alerts to be identified by caregivers. The capability of recognizing the appliance's electricity usage assists a better understanding of the household behavioral patterns. The appliances usage pattern study, and changes in the electricity usage patterns of individual appliances offer the detection method for abnormal behavior that is associated with the condition of health status. SM and appliance level load profiling methods are developed to detect the behavioral change of the occupant, which indirectly provides information about the health status of the occupant. The behavioral change detection is performed by employing the K-nearest neighbors (k-NN) classification algorithm on the appliances. The thesis presented a novel approach of ML algorithm for appliance identification in the context of NIALM as an adequate technique for AAL. NIALM implementation in FPGA is needed for achieving the high performance of classification for all type of appliances state.

NIALM based open benchmark dataset PLAID, we have used, shows a promising result for analyzing variations between current and voltage and detecting the energy consumption of each appliance from a single point aggregated measurements. The extracted features from the voltage-current trajectory are implemented with the k-NN classifier to recognize appliances. The accuracy matrix F-score average equals 90%. The ML supervised learner bases k-NN ML algorithm implementation has a better performance of accuracy than the rest of the compared machine learning algorithm to classify and detect each appliance. The k-NN classifier shows that the classification of the accuracy rate depends on the size of the appliance's training data sets. The thesis shows, the on/off state for the appliance event detection and the k-NN classifier have acceptable accuracy rate identification of the appliances. The result of the appliances identification can show that NIALM is an effective technique for advanced demand-side management, can be operated for AAL by providing indirect information about the activity and health status of the household from the detected appliance usage. We can show this assumption further as the load consumption and the monitoring system we proposed can recognize the associated activities of the user on daily basis. Therefore, the method can rely better on the information of the event of the activities and the duration of the appliance usage.

In the section, we presented an approach to classify appliances with NIALM techniques by distinguishing the signature of the different kinds of appliances. This behavioral pattern is based on disaggregated total energy consumption data to individual appliance-specific energy loads. The comparison of different classification algorithms has demonstrated that k-NN is the most suitable classifier for most appliances used in the household. Our analysis summarizes the identification performance done based on the operational states of the appliance. The implementation of the k-NN algorithm has potential scalability for detecting the activity of the occupant, and for monitoring their daily routines. We demonstrated by using the PLAID dataset for appliance classification.

In addition, the implementation of the k-NN algorithm, hardware (HLS) improves the processing time and the performance of the accuracy to detect each appliance. NIALM K-NN algorithm implementation on FPGA has achieved the real-time classification of the appliances by showing a promising result on lowering the processing time and consumed power. The implemented the KNN algorithm using an embedded ARM Cortex-9 processor on Zynq-7000 has gained by a short response time. Furthermore, the results from the ML algorithm show the synthesis tool procedures can capture the estimated and the accurate run time and the resources area (FFs, DSPs, and LUTs). These results are used for measuring the accuracy, the processing time of the accuracy that can significantly reduce the system development cycle, and the available resources on the hardware. The proposed implementation can detect the classification, able to analyze the identification performance for all states of appliances.

To summarize, these part of the thesis has a unique approach to solve the challenges of health care systems : (1) by investigating of SG application for health monitoring systems using smart meter load profiling, (2) by showing the elderly independent living solution using remote monitoring system employing appliances load classifications, (3)by building a cost-effective (no cost) of using SM that can handle big data health monitoring system. The NIALM and appliances classification with ML approach has solved the problems associated with a smart meter and a new method to healthcare facilities for independent living elderly home-care that deliver assistance to the AAL area. In addition, comparing the k-NN algorithm for PLAID appliance classification has gained the novelty approach and potential scalability on detecting the activity of elderly monitoring in their daily routines. NIALM algorithm implementation in FPGA has shown high performance to classify the appliances. On the other hand, the thesis shows how the selected ML classifier algorithm implementation on FPGA has improved the classifications, and the appliance identification accuracy with low-cost scalability.

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Chapter 6

Conclusions and Future Work

During this dissertation, two data-driven-based, and IoT-based health monitoring systems were developed. The first one contributes to remote pain assessment through ML algorithm for facial EMG signals for emotion recognition and for pain-level classification. The second system is about devising an accurate and cost-effective behavioral change monitoring and health status detection mechanism for the elderly so that they can live in the comfort of their homes vis-a-vis the AAL approach. In both these cases, the developed systems employ ML algorithms for classification, and they are intended to provide real-time notifications to healthcare providers.

In this concluding chapter, the findings and resulting conclusions will first be presented, and then followed by the contributed highlights of the study and recommendations for future research.

6.1 Main findings

The main findings and resulting conclusions of this thesis are outlined as the summary of RQs responses;

RQ1: How to implement an efficient pain monitoring system with IoT-based health monitoring system?

This thesis has delivered the design of a prototype composed of WiFi radio module, EMG multi sensor node, analog front end, analog digital converter, digital processing cores and I/O interfaces. Besides the WiFi radio module, the prototype consists of AFE, ADC and a digital processing unit.Converter (ADC), and a digital processing core. The prototype also includes a software package that can communicate with the application through UDP and TCP protocols. The designed prototype was tested for pain monitoring by measuring the fEMG signal on the face for different emotional expressions. This IoT based unit is used for assessment and control patients' bio-signal for their health control at any time, from any where, and by any one employing an IP-based network. A data-driven pain-level monitoring system has been studied for pain-level assessment of elderly or chronic patients. We used clinically approved data in context for our proposed use of fEMG to be used as a pain level communication tool for the healthcare system.

RQ2: How to classify EMG signals accurately for pain detection?

The thesis delivers a methodological analysis for pain assessment and pain estimation by applying signals processing, pattern recognition with feature extraction, and classification methods on fEMG. We have shown that SVM algorithm for facial emotion identification of fEMG signal has better classification accuracy. We gain optimal results from fEMG after the measured signal is analyzed and performed the feature extraction, and we compared various classifiers by testing on different ML models. The results analysis confirmed that the developed approach classify fEMG signals accurately for pain detection. In addition, K-NN based classification algorithm were adopted for pain assessment of the clinically collected Bio Vid Heat Intensity dataset. The maximum classification accuracy of 99.4% is obtained. These results demonstrates that fEMG signals are meaningfully associated with individual emotional states. By applying the most appropriate feature extraction and classification methods on the fEMG signals, pain level assessment of subjects with communication difficulty can be performed. FEMG actions are meaningfully associated with individual emotional practices and having the some sort of incapacitates for communicating their level of pain. Thus, the developed sensor node and FeMG classification method is beneficial for continuous pain assessment for patients who are using home health care, and are under smart home-care community

RQ3: How to monitor patients' behavioral change remotely using household energy consumption data?

This thesis has also delivered a health monitoring system in response to the situation of the elderly in the AAL framework that is associated with an increasing number of elderly individuals needing constant monitoring and care. The system is based on single-point monitoring of household energy consumption (via SM) and identification of the individual appliances and their usage profiles. The results from our data-driven analysis indicate that this can be done for the advancement of the health monitoring and health care system. Health status identification at home allows the detection of ADLs, such as sleep patterns, changes in activity patterns, inactivity, and occupancy, which can ease the burden of the caregivers and the patients alike. In this regard, this thesis has established SM-based load profiling to enable the recognition of sudden changes in occupants' behavior. In other words, the ability to monitor patients' behavioral change remotely using household to monitor patients' behavioral change remotely using household energy consumption data. The methodology is cost-effective compared with the bio-sensor or wearables. As SM roll-out, programs are in place now and indicate a significant impact for both the progression occupant's behavioral change vis-a-vis AAL and load disaggregation in a cost-effective manner. Our novel approach related to a consumer's electricity usage data from SM is made for consumer characterization by typical load profiles. The method is applied to support the healthcare sector based on the identification of consumers' normal or abnormal energy consumption along with a combination of matrix-based analysis of consumers' dataset, k-means clustering, and data mining techniques.

This thesis has shown that IoT-based real-time load profiling of the appliances can improve the quality of life to support and provide the aging population which wishes to live independently. It offers solutions for older adults or chronic patients located either in the healthcare centers or living in their homes by depending on the measurement of appliance usage of time, duration, and energy consumption. The SM data is utilized to monitor the elderly's normal or abnormal behaviors and to apply for real-time monitoring that can automatically give results by assisting the caregivers. Appliance level load profiling using the NIALM system was developed for monitoring the health status of the elderly indirectly through detection of behavioral changes in the context of AAL. NIALM system classification for activity monitoring is achieved by providing information about the household's activity and health status through appliance identification of that household.

RQ4: How to detect and classify behavioral changes from the household energy consumption data?

This thesis has delivered the behavioral change detection devised with the help of the NIALM approach. The study also proposed the architecture for IoT-based SM dataset processing for the appliances' identification. We investigated SM load profiling analysis at the appliances' level to yield more accurate results than the consumer's total energy consumption analysis. To detect and classify behavioral changes from the household energy consumption data at appliances, we use the PLAID dataset as a benchmark and were analyzed by the k-NN classifier algorithm. The k-NN classifier achieved superior performance compared to other ML algorithms and was explored with high accuracy. The use of SM and NIALM for indirect healthcare systems is a novel approach and beneficial to AAL. FPGAs demonstrated a cost-effective alternative for wide-scale deployments, we further implemented the k-NN algorithm for NIALM based behavioral change detection for appliance identification on an FPGA. The advantage of using FPGA is the investigation to increase the run time of the process. Thus, we investigated an approach using V-I trajectory features, a k-NN algorithm, and FPGA implementation for NIALM for appliances classification. Notably, the algorithm implementation in FPGA has improved classification and appliances identification accuracy. It is based on the analysis of the results of the K-NN implementation on FPGA; the used resources, the consumed power and, time in the system development life cycle. These parameters tend to a proportional increase with the number of Ks. The FPGA implementation for k-NN is recommended to speed the processing by performing the heavy-weight processing locally and eliminating the communication outflow with the near-by real-time disaggregation.

In summary, the thesis has delivered technologies and cost-effective alternatives IoT-based real-time healthcare monitoring and healthcare assessment of daily living at home. In particular, we developed intrusive cost-effective healthcare technology solutions using biosensors, smart meters, and NIALM for the activity and data-driven approaches.

6.2 Future Work

Through this thesis, we investigated the possibility of healthcare systems using IoT technology and data-driven analytic. We presented our unique methodological approach and included future work to extend our result.

Using SMs and NIALM for intrusive health monitoring is a novel approach and beneficial for supporting the elder's wish to live independently. In the future, collecting more data would be for devising a further steps of effective behavioral detection. A combination of NIALM and other sensors that show the processing and identification events, and effective hardware implementation provide low-cost scalability for system development.

We recognized the future importance of the domains of SG and SM; however, when the generated massive amount of data becomes a challenge and future opportunity in this field of research. The main challenge will be sensor fusion for intrusive assisted living. Furthermore, developing sensor fusion methodology for combining the pain level classification with detection of behavioral changes will be among the future task. These devices can also offer more predictive information for the elderly and chronic patients and enable more relevant care providers' actions. We recommend future studies to include the reliable communication and security aspects of the proposed system.

In the future to consider IoT-based multiple different types of wearable sensors and living space monitoring sensors combined with NIALM can provide much more accurate health status information. Multi-sensory information requires more efficient processing and identification at the household level. More study is required to fulfill the real-time monitoring system requirements with communication infrastructure devices and accelerate artificial intelligence into the mobile platform. The approach can offer to reduce latency and enable physicians and clinicians to deliver real-time healthcare.

Further, the HW implementation part of our research technically suggests that the focus is on the current NIALM difficulty of the comparison issue of multiple states of appliances. The current appliance's states comparison issues of NIALM will be addressed through an updated FPGA implementation approach. In the future complete NIALM system of FPGA that requires a comparison of different approaches by evaluating the outcome on the real-time processing, the performance, the cost, and the system power consumption is needed.

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