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Automated Quality Control in Cashew Processing

- Machine Learning and Image Processing for Cashew Detection and Classification

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Summary

This thesis explores the development of an automated vision-based quality control system for roasted cashew processing. Traditional quality inspection methods rely heavily on manual labor, which is time-consuming, inconsistent, and prone to human error. The proposed system leverages image processing and machine learning techniques to accurately detect and classify roasted cashews into three quality categories: burnt, unroasted, and good. Using a simple hardware setup—an HD webcam and a light—the system ensures cost-effectiveness and accessibility for small to medium-sized enterprises (SMEs). The study evaluates the system's performance under various lighting conditions and assesses its adaptability to real-world challenges. The results demonstrate the potential of the system to enhance operational efficiency and product consistency, making it a viable alternative to traditional inspection methods.

Affirmation

This master's degree report, *Automated Quality Control in Cashew Processing*, was written as part of the master's degree work needed to obtain a Master of Science with specialization in Robotics degree at University West. All material in this report, that is not my own, is clearly identified and used in an appropriate and correct way. The main part of the work included in this degree project has not previously been published or used for obtaining another degree.

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Signature by the author

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1 Introduction

Food processing has experienced rapid growth in recent years, along with increasingly demanding high-quality products, which has led to innovations in manufacturing quality control processes. In particular, roasted cashews have gained significant popularity because of their nutritional value and their widespread use as snacks and ingredients in a wide variety of cuisines. It is therefore crucial to maintain consistent quality of roasted cashews to maintain customer satisfaction and the reputation of the brand. It is, however, important to note that quality control processes present unique challenges, especially for small to medium-sized enterprises (SMEs) that are typically operating with limited resources [14].

Traditionally, roasted cashews are subjected to manual quality control. Therefore, it strictly relies on human inspectors to evaluate visual attributes such as colour, texture, and size. Even though this method is flexible, it is subjective, biased, labour intensive, and prone to human errors and fatigue which result in human inconsistencies. The differences in the quality evaluation caused by the manual method have contributed to discrepancies in grading, decreased operational efficiency, as well as dissatisfaction among end consumers [20] & [48].

The use of machine vision and image processing has emerged as a viable solution for automating quality control processes. It is possible to evaluate in real time, cost effectively, consistently, and objectively using these technologies. In various industries, such as agriculture, textiles, and manufacturing, machine vision systems and image processing have been successfully applied to quality control. However, their adoption in food processing, particularly for products such as roasted cashews, is still in its infancy. However, implementing these systems involves high implementation costs, technical complexity, and the need for customized solutions tailored to specific product characteristics. As a result, widespread adoption has been slow, particularly in low-margin industries such as the food industry [11] & [14].

Quality control in the processing of roasted cashews is heavily influenced by the visual appearance of the product. Quality characteristics include uniform color, no surface defects, and proper roasting levels. Burnt or unroasted cashews do not only fail to meet customer expectations but also result in increased waste and financial losses for producers. Therefore, a vision-based quality control system that detects and classifies cashews is still an untapped market opportunity for improving operational efficiency and product reliability [48].

1.1 Problem statement

Manual quality control in roasted cashew processing, as previously highlighted, presents significant challenges for small companies such as TAAJ Food. Manual inspection is inconsistent, labour intensive, and unscalable to meet the growing demand for roasted cashews. Additionally, the owner of TAAJ Food has expressed that his greatest concern with manual quality control is that it results in several returns from customers since they sell to retailers, adding a significant amount of transportation, reprocessing, repackaging, and inspection costs. He asserts that these issues lead to product quality variability and increased operating costs, which directly affect the company's competitiveness.

There are several existing solutions available, but they are often costly, technically complex, and require significant customization to accommodate the unique visual characteristics of roasted cashews. Due to these challenges, many small- to medium-sized businesses are unable to adopt these technologies, thus continuing to rely on inefficient manual processes. There is a clear and present need for an affordable and accessible system that can detect and classify cashew quality with high accuracy and address the specific needs of SMEs in a cost-effective manner. As a result of developing such a system, we would be able to improve quality control processes in a scalable, consistent, and cost-effective manner, filling a critical gap in the industry.

1.2 Aim

The purpose of this thesis is to develop a vision-based quality control system to automatically f and categorize roasted cashews into three categories: burned, unroasted, and good quality. The system utilizes image processing techniques to assess the quality of key visual characteristics, such as color and texture.
Aiming to accomplish this overall goal, the thesis outlines a set of measurable objectives as follows:

- Detect and classify quality levels: Based on distinct color and texture variations caused by the roasting process, image processing can be used to identify cashews as burnt, unroasted, or of good quality.
- Evaluate system performance: Ensure the system's accuracy and consistency with manual quality inspection methods, ensuring its reliability for industrial applications.
- Adapt to variability: Design the system to handle variations in visual appearance due to different roasting levels, lighting conditions, and surface irregularities.

1.3 Research questions

- How accurately can the developed vision-based system detect and classify roasted cashews into three quality categories—burned, unroasted, and good—using image processing techniques focused on colour and texture?
- How effectively does the system perform in live detection and classification scenarios, considering variability in cashew shapes, orientations, and environmental conditions (e.g., lighting)?
- How effectively can a combination of image processing techniques and machine learning models trained on manually labelled cashew images enhance the system's ability to detect and classify quality levels across different batches of cashews?
- How practical and cost-effective is the system for implementation in small- to medium-sized enterprises like TAAJ Food, particularly in comparison to traditional manual quality control methods?
- What are the key limitations of the developed system, such as false positives, missed detections, or reliance on specific preprocessing steps, and how can these be addressed to improve its robustness and scalability?

1.4 Scope and limitations

The scope of this thesis focuses on the development of an automated vision-based quality control system for roasted cashews, which addresses the inefficiencies associated with manual inspections. Using image processing techniques and machine learning models, the system classifies cashews into three categories: burnt, unroasted, and good. The project includes all phases of the classification process, including data collection and preprocessing, as well as training and validation of the classification system. Through the use of a simple hardware setup, such as a webcam and a ring light, it serves as a perfect demonstration of what can be achieved with a real-world system that is affordable and accessible to small and medium businesses. Furthermore, the study evaluates the system's real-time performance and adaptability under varying conditions, including changes in lighting and cashew orientation.

There are several limitations to the development and performance of the system. While carefully labelled, the dataset used for training and validation is limited by its size and diversity. Due to this, the system may not be capable of generalizing to all possible variations in roasted cashews, such as extreme roasting conditions or defects not represented in the dataset. Furthermore, the system's reliance on controlled lighting conditions may affect its robustness when deployed in environments with uneven illumination. Moreover, preprocessing steps such as edge detection and region analysis may introduce errors in cases where cashews are flipped, partially obscured or outside the field of view. In addition to the quality of the labelled training data, the classification accuracy may also be affected by human bias during the manual labelling process. Finally, the system's performance is evaluated at a relatively small scale and may still require further testing and refinement prior to being deployed in a full industrial setting.

2 Literature review

This chapter explores key studies and theoretical frameworks related to quality control in food processing, with a focus on machine learning and image processing applications. It synthesises current methodologies, identifies gaps in research specific to cashew processing, and sets the foundation for understanding the potential of integrated quality control systems.

2.1 Vision systems

"*A machine vision recovers useful information about a scene from its two-dimensional projections*" according to [28]. The inputs of the vision systems are 2D projections of the 3D reality. Thus, knowledge about the objects in the scene and the projection geometry is required. A vision system, also known as a machine vision system, is a set of sophisticated technologies that capture, analyse, and interpret visual information obtained from the environment using imaging devices and algorithms [10]. As a result of their real-time image processing capabilities, these systems are capable of performing a variety of tasks, including object recognition, measurement, and inspection. The traditional image processing techniques employed by vision systems include edge detection, pattern recognition, and feature extraction, according to [10]. In general, the algorithms that are built into these methods are able to identify and classify objects within an image on the basis of grayscale or colour image analysis. Classical methods laid the foundation for more sophisticated techniques such as machine learning and neural networks that enhanced the capabilities of vision systems and resulted in robust systems that are capable of adapting to a wide range of complex environments [23]. Furthermore, [10] argues that classical image processing methods in vision systems constitute the foundation upon which more sophisticated technologies like machine learning are developed, making these systems more applicable across many industries as a result. He acknowledges, however, that earlier methods, such as classical image processing, continue to be used in various applications, especially in industries such as food sorting and woodworking.

2.2 Vision systems in quality control

The fast-paced industrial landscape along with the increasing requirement of high-quality products have put substantial pressure on industrial players to provide reliable products that maintain high quality standards while keeping the delivery time down. To respond to the demand for high quality and high speed, vision systems have emerged as one of the revolutionary technologies in quality control [39]. According to [10] Adopting vision systems in quality control applications is one of the big steps in modern manufacturing, this step has been driven partly by the nature of the new markets that require reliable, accurate, efficient processes and partly by the nature of vision systems. The basic ground that vision systems are built upon which is advanced sensing and algorithms is indeed the one that facilitates real-time data which renders it as a perfect fit for modern quality control systems [39]. [10] highlights that real-time monitoring and assessment of product quality during manufacturing is the most appreciated aspect in vision systems.

Yet, another important aspect of vision systems is adaptability and compatibility with other quality control systems. According to [10], vision systems can be integrated seamlessly into existing quality systems such as Total Quality Management (TQM) frameworks and Manufacturing Execution Systems (MES), facilitating a comprehensive approach to quality control. Therefore, continuous monitoring and rapid response facilitated by this integration which not only enhance product quality but operational efficiency as well [10]. Moreover, this integration reduces reliance on manual checks, which can be prone to human error [15]. The features of adaptability and real-time monitoring position vision systems are vital components to achieve high quality in pursuing operational excellence products and processes.

2.2.1 Application of vision systems in various industries

The following examples showcase the implementation of vision systems in quality control across various industries, offering insights for their application in our roasted cashew processing quality control.

Textile industry: Vision systems play a crucial role in monitoring key quality parameters in the textile yarn industry [36]. Parameters such as size, colour, and surface defects are fundamental to ensuring high-quality yarns that meet industry standards. Size uniformity, colour consistency, and minimal surface defects not only impact the final product but also affect operational efficiency during production. Similarly, in roasted cashew processing, size, colour, and surface defects are crucial quality parameters. Just as in yarn production, size uniformity is important for consumer appeal. Discoloration and surface cracks, particularly in cashews, signal quality issues, with discoloration potentially raising concerns about product safety [38]. According to [36], vision systems are widely used in the textile industry for their ability to provide real-time monitoring of defects, enabling immediate corrective actions during production and preventing defects from exaggerating as they move along the production line.

As previously mentioned, vision systems are integrated with automated production processes, the same applies in the textile industry, allowing for real-time adjustments in response to any emerging quality issues [36]. This successful integration demonstrates the feasibility of applying similar systems in other industries, such as roasted cashew processing. Additionally, surface defects in the textile industry are often very precise, involving micro-level deviations [36]. The precision and specificity required in the textile industry suggest that this system can be adapted to the food industry—particularly roasted cashew processing—by training the system to detect cashew-specific defects using a comprehensive dataset of cashew images that include such quality issues.

Transportation industry: For logistics and supply chain management, pallets are of utmost importance since they serve as means for the transportation and storage of goods. A high level of quality must be maintained during the production of these pallets in order to prevent significant disruptions and safety hazards [35]. Based on observations made by [35], several quality parameters are considered when manufacturing pallets, including size, surface integrity, load bearing capacity, and material quality. It is important to note that, although both the process of roasting cashews and the manufacturing of pallets share key quality parameters such as size and surface defects, there are differences in load-bearing capacity, which is irrelevant in cashew cases, and material quality, which could be determined prior to roasting. Ensure the size of pallets is as accurate as possible to ensure that they are compatible when being transported using forklifts, for example, or when placed in storage with other pallets. Moreover, the pallet's surface should be free from defects that compromise the pallet's safety and durability [35]. According to [35], vision systems are increasingly being used in the quality control processes of pallet manufacturing due to their ability to provide real-time monitoring and enable immediate detection of defects, which facilitates corrective actions during production, reducing the risk that these defected pallets enter the supply chain.

Moreover, [35] highlight that the adaptability of vision systems is positioning them as one of the first choices in quality control for a variety of applications and environments due to their flexibility, which allows them to be programmed to meet the requirements of a variety of production lines and product specifications. Additionally, the authors state vision systems are highly automated, which reduces labour costs, and early detections can prevent costly rework or returns for pallets. Furthermore, these systems achieve higher accuracy than humans because they are not susceptible to external factors like fatigue or inattention, they always apply the same criteria. Lastly, they mention the ability to collect and analyse data over time on defects and production quality, which could result in improved production processes and better predictive quality.

Food industry: As a result of the need for improved quality control and efficiency in food processing, vision systems have gained significant traction in the food industry in recent years [8]. A number of quality parameters of food products are assessed using these systems, making sure they comply with both industry standards and the expectations of consumers. As the purpose of this thesis is to investigate the use of vision systems in roasted cashew processing, various applications within food processing will be discussed to offer insight and ideas.

- Oyster Mushrooms: In the case of oyster mushrooms, vision systems are particularly useful due to the perishable nature of oyster mushrooms and the difficulty in manually assessing their quality [8]. The authors identify several key quality parameters for mushrooms that are monitored by vision systems, including freshness, colour, texture, and surface defects. In light of the fact that colour and texture are indicators of freshness, freshness is closely associated with colour and texture. Fresh mushrooms are usually white while unfresh ones tend to be brown. Fresh mushrooms have firm textures, while those with soft textures are considered unfresh [53]. Due to the limited shelf life of these mushrooms of 3-4 days [8], freshness is a key factor. Vision systems are increasingly used for oyster mushroom quality control as a result of their powerful capabilities [8]. Vision systems provide a reliable and consistent method for quality control that is not susceptible to the errors associated with human assessment [8]. Additionally, automated vision systems are able to process large amounts of mushrooms, thereby improving the efficiency of quality control operations, and leading to higher throughput, which is crucial for these mushrooms, given their short shelf lives [53]. It has been found that vision systems can be seamlessly integrated with machine learning systems that allow them to learn more from the data over time, resulting in higher accuracy over time [22]. Hence, operations are again made more efficient as minor defects would have been overlooked by human inspectors. Despite the initial investment being substantial, the long-term savings resulting from reduced labour costs and reduced waste make these technologies financially attractive for producers [8].

- Rice: Based on [13], vision systems can be applied to rice processing with great efficiency because they can be used to conduct quality control without damaging the grain, as opposed to human assessment, which frequently involves the waste of grains through the quality control process that is conducted by humans, which results in a reduction in costs. It has been established that size, colour, shape, and texture are the key quality parameters for rice grains when using vision systems [34]. The price and customer acceptance are directly affected by these parameters [28]. A grain's size uniformity and shape are often considered determinants of high-quality grains, while its colour indicates freshness and proper processing [13]. As a result of implementing vision systems in this context, accuracy is improved, human error is reduced, and quality assessment is more efficient. On the other hand, manual inspection is typically subjective and time-consuming, resulting in inconsistent quality evaluations [49].

- Fruits and vegetables: According to [50], Automation of inspection procedures is facilitated by vision systems, especially in the area of quality control of fruits and vegetables. Highlighting particularly the case of using vision systems in apples' quality control, [50] highlight that detection and grading of apples requires the use of vision systems due to their ability to detect various quality parameters in order to ensure that only high-quality apples are placed on the market. Based on the authors' findings, the key quality parameters in the case of apples are their size, shape, colour, gloss, and surface defects, these parameters are according to [7], indicators of freshness and overall product quality amongst fruits and vegetables in general. Vision systems are not limited to the measurement of external parameters, as they can also monitor internal parameters such as nutritional value, sweetness, and firmness [50]. In comparison to traditional human assessment methods, vision systems have proven to be reliable and consistent [57] & [50]. The prime motive of the adoption of vision systems in the food industry is enhancing efficiency in operation as they reduce costs, waste, improve quality, and eliminate inefficiencies

[50] & [57]. Furthermore, vision systems align with modern consumers' preference for safe and high-quality foods, helping to promote the sustainability of the food industry [7] & [50].

2.3 Image processing

The field of image processing is defined by [41] as one in which both the inputs and outputs are images. It simply receives an image, processes it, and returns it in a format ready for analysis. According to [41], researchers have discussed the overlap between image processing, image analysis, and computer vision. All three fields have common techniques; however, they differ in their focus; image processing involves enhancing or restoring images in order to prepare them for analysis. In image analysis, information is extracted from images, while in computer vision, information is interpreted in a manner that mimics the perception of human vision. There is no consensus as to the exact boundaries of operations, however the authors provide a paradigm that categories operations on three levels.

- Low-Level processing (Preprocessing): Techniques at this level aim to enhance the quality of the image in preparation for further processing. Therefore, noise reduction, contrast enhancement, and sharpening are included at this level. The use of these techniques improves clarity and reduces artefacts. Thus, ensuring the next processing can be performed on clear images. It is essential that this level be adhered to in order to ensure the reliability of both analysis and interpretation.

- Mid-Level processing (Image Analysis): The purpose of this level of processing is to extract information from the prepared images. It should be noted that the output of this level of processing is not an entire image, rather specific attributes such as edges, contours, and identifying individual objects within the image. Different algorithms exist for detecting edges, such as Sobel and Canny. These algorithms identify significant changes in intensity in the image, revealing boundaries between different objects or regions within the image. Based on the output of this processing level represented by the extracted features, we can analyse the relationships between the different objects within the image. An analysis of this kind is conducted at the next processing level

- High-Level processing (Interpretation): Based on the results of the previous processing level as represented by the identified features and structures. By using this level of processing, images will be interpreted in a way that replicates human cognitive processes, enabling the system to comprehend the image. In the case of an apple and a hand identified at the mid-level, the system will have the capability of understanding that the hand is about to grasp the apple. In all applications that require automated decision making, high-level processing is essential, since it transforms the extracted information into meaningful conclusions.

[41] define digital image processing as the process of improving, detecting, and interpreting images using computers including the three levels mentioned above.

Building on this paradigm, [41] outline a series of key techniques within each processing level that enable a systematic approach to refining and analysing image data. These techniques provide a versatile toolkit for applications ranging from medical diagnostics to industrial quality control.

- Preprocessing techniques:
  - Noise Reduction: Techniques such as Gaussian and median filtering mitigate unwanted variations in pixel intensity caused by sensor noise or environmental factors.
  - Contrast Enhancement: Techniques like histogram equalisation adjust the brightness and contrast to reveal subtle details in an image, making specific features more distinguishable.

- Thresholding: Thresholding separates regions of interest by intensity values, creating binary images that simplify analysis in subsequent stages.
- Image Resizing: Standardising image dimensions is critical for ensuring that the images are uniform in size, which can improve the efficiency and accuracy of processing.

- Feature extraction techniques in Mid-Level processing:
  - Edge Detection: Sobel, Canny, and other edge detection algorithms identify sharp changes in intensity, creating an edge map that highlights boundaries within the image.
  - Segmentation: Techniques like region-based and threshold-based segmentation divide the image into distinct regions, enabling focused analysis on areas of interest.
  - Morphological processing: Operations such as dilation, erosion, opening, and closing refine the shapes and structures within an image, improving feature clarity and reducing noise.
- Interpretation Techniques in High-Level processing:
  - Feature Extraction for Interpretation: This includes identifying attributes like colour, texture, and shape, which are fundamental in classifying objects or regions.
  - Object Recognition: Using pattern recognition, object recognition techniques allow the system to identify and label distinct entities within an image, such as classifying various objects or determining the nature of specific patterns.

The authors of [41] emphasise that digital image processing, including the three levels of processing as well as the inclusion of related techniques, is widely applied to a variety of applications ranging from medical imaging and surveillance to industrial automation and remote sensing. In each of these fields, different imaging techniques are used at each level of processing to address the specific needs of the field. Because of the diversity of image processing techniques, they are flexible and can be adapted to a variety of applications and data types. Ultimately, [41] presents a framework for refining, analysing, and interpreting visual data that results in the transformation of images into actionable insights, making it suitable for applications requiring precise and detailed analysis.

2.4 Image processing in quality control

The introduction of image processing into Industry 4.0 has significantly changed the rules of the game in quality control by facilitating the detection of defects in real-time and reducing the reliance on human factors. With the ability to integrate with different technologies such as IoT and data analytics, automated image processing systems can provide accurate and continuous quality monitoring, resulting in enhanced accuracy and consistency [29].

Through the development of algorithms for various image processing techniques coupled with machine learning, these systems are able to identify and adapt to a wide range of environments and defect types, creating a proactive approach that is entirely opposite to the reactive approach previously employed. Thus, waste was reduced, operational efficiency was improved, and high-quality products were delivered, resulting in an increase in competitiveness and customer satisfaction [30].

2.4.1 Defect detection and quality control in manufacturing

Recent studies have highlighted a variety of techniques used in automated detection, including edge detection, texture analysis, image segmentation, and machine learning, each with its unique strengths and limitations. When these techniques are applied to quality control, they yield robust and adoptable defect detection that meets and exceeds industry standards.

In order to detect sudden changes in pixel intensity that cause structural defects, edge detection is one of the primary techniques. Therefore, it is particularly useful for detecting clear-cut defects, such as holes and tears, where the border between the defect and the surrounding region is abrupt and sharp. The authors of [1] describe the use of edge detection algorithms to detect discontinuities in dyed fabrics using the Sobel and Canny algorithms. Edge detection is not as effective as other techniques when it comes to the detection of subtle surface deviations, such as stains or dye inconsistencies that are not as obvious or prominent. Consequently, image segmentation is employed in this case, as described by [1], it enables a focused analysis of potential defects by separating the fabric from the background. It should be noted that image segmentation is sensitive to the surrounding environment conditions, such as the lighting, and that any variation could result in a decrease in its efficiency. Meanwhile, texture analysis is an important technique for detecting surface-level anomalies in applications. Texture analysis differs from image segmentation since it is intended to detect tiny differences in surface patterns without defining boundaries between them. According to [1], techniques such as Local Binary Patterns (LBP) and grey-level co-occurrence matrices (GLCM) can identify minor inconsistencies in dyed fabrics that are considered defects in the textile industry. Due to the fact that image analysis identifies the most subtle deviations in patterns from the surface at a pixel level, it requires both high resolution images and high computing power, which results in high costs and complexity in quality control processes, which might limit the use of real-time applications in high-speed environments [32].

Image processing can also be enhanced by the addition of adaptability and precision through technologies outside the realm of image processing [32], especially convolutional neural networks (CNNs) and support vector machines (SVMs). The main difference between machine learning and traditional methods is that machine learning can continuously improve its accuracy by adapting to new defect types and patterns, making it a viable option for dynamic production environments. CNNs were integrated into a factual defect detection system by [32] and the number of defects detected increased by 95%. However, [32] emphasise the importance of incorporating machine learning techniques with image processing techniques, especially those that can be used during preprocessing or low-level processing. Noise reduction, contrast enhancement, and normalisation of images using software such as NumPy and OpenCV are essential steps in improving the quality of images before they are analysed. By doing so, external factors such as lighting inconsistencies that could result in missed defects can be eliminated or minimised.

Fine inspection is not applicable to all situations, however. The use of techniques such as geometric shape detection and morphological operations can be very useful in the inspection of structured and rigid objects such as printed circuit boards (PCBs) [31]. According to the authors, Otsu thresholding is an effective image segmentation technique that separates PCB components from background images. Additionally, a Hough transformation is helpful in detecting geometrical and precise shapes, such as circles, which can help pinpoint missing PCB components [31]. Furthermore, to improve the efficiency of edge detection, morphological operations aim to refine the edge detection results and by doing so enhance the clarity of the features. When used on well-defined geometric shapes, these techniques are highly effective. However, when applied to irregular shapes such as those found in fabric inspection, they are not as effective.

2.4.2 Image processing in food quality analysis and agricultural

Since the industry has long struggled to promote a method which is neither destructive nor time-consuming, image processing has gained considerable attention in the assessment of the quality of agricultural products like rice grains [45].

A number of studies have demonstrated that the whole process begins with the capture of images and then proceeds through preprocessing where the images are enhanced by noise reduction and filtering which results in improved quality [45]. Accordingly, Morphological operations such as dilation and erosion are used to separate and identify the grains, particularly when they are captured in clusters. It thus facilitates a more accurate analysis [45]. Having prepared the images for analysis, edge detection is applied to identify the boundary of rice grains, which enables precise segmentation and classification [16]. Furthermore, advanced segmentation algorithms such as Shrinkage Morphological Algorithm are applied to isolate rice kernels from the background in order to facilitate more accurate measurement of rice grains' dimensions [45]. Several texture features can be used to enhance classification, such as edge-to-ratio, allowing brown and milled rice to be distinguished even in grayscale images, according to [17]. This is more cost efficient, as brown grains tend to have a greater number of edge pixels because of their roughness, as compared to the smoother milled grains. Last but not least, classification techniques such as SVMs and CNNs facilitate quality control and prevent false labelling of rice grains. To ensure an effective quality assessment, [17] emphasise the importance of controlling external factors such as lightning in conjunction with these techniques. By combining these image processing techniques, we can improve the accuracy and reliability of a non-destructive quality assessment that is consistent with industry standards.

Once the features have been extracted, machine learning can take over. Models such as SVMs, CNN, and Random Forest classifiers are employed to categorise food products based on quality. By learning patterns from labelled training data sets, these models can distinguish various quality grades or defects [45]. A machine learning model can, for example, be used to classify rice grains into categories such as whole, broken, or damaged, thereby improving the efficiency of quality control processes [45]. Furthermore, advanced object detection algorithms such as YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector) have been implemented in applications where real-time data is important, like food production. Due to this, it is possible to identify and grade food items in both an accurate and a timely manner [46]. This is particularly important in industrial settings where large quantities of food need to be controlled quickly for quality.

For even greater precision in quality analysis, hyperspectral imaging (HSI) can be integrated with machine learning [46]. As opposed to conventional RGB imaging, which only captures red, green, and blue light, HSI captures a wide range of wavelengths, which often includes infrared or ultraviolet light. Thus, it can detect the most subtle differences in colour, texture and composition that are not visible in traditional RGB images. As a result, HSI has proven to be exceptionally accurate in many applications, including those in the food industry such as the detection of bruises in apples [46], and in many other industries. It has been discussed earlier that the main reason for using image processing or vision systems in general for the purpose of quality control is to obtain real-time monitoring. To contribute to this, machine learning is increasingly integrated with Internet of Things devices [33]. The result is the creation of a framework for real-time analysis. This enables IoT systems to monitor food conditions throughout the supply chain from production to distribution. By doing so, they ensure the safety of food and maintain the quality of food by providing real-time information.

The use of machine learning and image processing has transformed the analysis of food quality, making it more accurate, faster, and less reliant on subjective judgement. The innovation is extraordinarily useful for agriculture and food production, enabling producers to consistently meet high quality standards and deliver safer, higher quality products to consumers.

2.5 Machine learning

The field of machine learning is part of artificial intelligence, which allows systems to learn from data, recognize patterns, and make decisions without human intervention [55]. Furthermore, Due to its ability to analyze data from production processes, catch anomalies, predict potential failures, and ensure that products meet the required standards, machine learning has gained tremendous attention in quality control. According to [56], machine learning is widely adopted by quality control organizations due to the responsive decisions it makes when deviations occur in real time. Machine learning has been widely implemented in industrial environments for tasks such as defect detection

[2]. Moreover, machine learning has the potential to increase operational efficiency and reduce costs. These systems are not only faster and more accurate than manual inspection methods, which makes them an invaluable tool in mass production environments [6].

2.5.1 Deep learning

Deep learning, however, is a more advanced branch of machine learning utilizing what is known as neural networks, which consist of multiple layers of interconnected nodes [52]. Consequently, it is able to handle complex data, especially unstructured data, such as images and audio, where traditional Machine Learning would have difficulty. The following example illustrates the differences between machine learning and deep learning in the area of image processing. By using traditional machine learning for image processing, images need to be preprocessed, and features extracted by humans in order for the machine learning to learn from them. However, deep learning can extract features independently and utilize them to handle the data. Deep learning architectures, such as CNNs, are particularly good at detecting spatial patterns in images, making them ideal for tasks such as image classification and object detection [3]. These models are also highly effective at working with large datasets, which is increasingly important as industries produce more and more visual data [21].

2.5.2 Transfer learning

A transfer learning approach uses a pre-trained model for one task as a basis for solving a second one [43]. Transfer learning is of particular value in deep learning, where training models from scratch is both time-consuming and resource-intensive. By transferring the knowledge previously obtained to another related task, training will be more efficient and will result in increased performance. According to [25], transfer learning involves using a pre-trained model that has been trained on a large and diverse dataset to ultimately fine-tune it on a smaller, more task-specific dataset. One of the most appreciated benefits of transfer learning is the ability to reduce the dependence on large datasets for training [44]. The fine-tuning of transfer learning maximizes its adaptability since it allows for the freezing or retraining of some layers [25]. Additionally, pre-trained models have been exposed to a significant amount of data. Therefore, robust features that can be generalized to a variety of tasks have been extracted [44]. This is particularly useful in industrial environments in which the collection and annotation of large datasets can be very costly and difficult. Hence, transfer learning is the most effective method for training in scenarios that have limited data [44]. Moreover, since transfer learning utilizes pre-trained models, it is not necessary to invest in high computational costs in training models from scratch. Consequently, it is accessible to organizations with limited technical capabilities [19].

According to [43]. Despite these advantages, there are several challenges to consider when applying transfer learning to specific tasks such as defect detection. The primary challenge is domain shift, which occurs when the source domain (the dataset used for pre-training) differs significantly from the target domain (the dataset for defect detection). This can lead to suboptimal performance if the model fails to generalize effectively [43]. Furthermore, the features learned by a pre-trained model may not be closely related to those required for the task at hand [25]. Thus, choosing a pre-trained model trained on a dataset with similar characteristics is crucial to ensuring relevance. A fine-tuning process can also be difficult, as practitioners must determine which layers to freeze, how to adjust learning rates, and other factors to avoid overfitting [44]. Further, in specialized domains, there may be a limited number of suitable pre-trained models, which makes it necessary to develop task-specific models [19]. Therefore, to maximize transfer learning potential in a variety of machine learning applications, these challenges must be addressed.

According to [43], the integration of transfer learning and image processing techniques has shown considerable potential for improving classification accuracy. As an example, fine-tuning pre-trained models like AlexNet and ResNet50 on well-processed images has resulted in high accuracy rates in applications such as tea quality identification [55]. The use of image processing techniques such as noise reduction and feature enhancement can further improve the quality of input data, allowing models to focus on the most significant aspects of images [18]. However, the success of this integration can be hampered by inappropriate preprossesing models that could obscure critical features [26]. Once again, similarity between the source and target domains is essential. It is therefore possible that large differences could cause poor generalization [4]. In addition, these differences are exacerbated by inappropriate fine-tuning processes as reflected by improper learning rates or training epochs [9], or by incompatible alterations to input size which may reduce classification accuracy [55]. It is therefore important to take careful consideration of the preprocessing methods, the relevance of the models, and the alignment of the domains in order to avoid adverse results when using the combination of transfer learning and image processing.

2.5.3 Advances in Deep Learning Architectures for Quality Control: ResNet, CNNs, SVM, and YOLO

Recently, advances in deep learning architectures and machine learning techniques have been widely applied in quality control systems across a wide range of industries [56]. Residual Neural Networks (ResNet), CNNs, SVMs and YOLO have been demonstrated to be effective tools for automating defect detection, improving operational efficiency, and meeting product quality standards. Nevertheless, every method has unique advantages when it comes to image analysis, classification, and real-time monitoring [54].

2.5.3.1 Convolutional Neural Networks (CNNs)

CNNs are a widely adopted deep learning architecture specifically designed to process grid-based data, such as images. CNNs comprise an input layer, hidden layers, and output layer. The input layer is responsible for passing raw data to hidden layers. Typically, hidden layers include convolutional layers that extract features such as edges, textures, and patterns from input images and produce feature maps as outputs. When pooling layers are present, they reduce the size of the feature maps by summarizing important information. When fully connected layers are included, they take the features learned by the convolutional and pooling layers and perform the final classification or prediction, which is then passed on to the output layer. While all CNNs contain convolutional layers, the use of pooling and fully connected layers depends on the specific application of the CNNs.

During the training process of a CNN, neurons in each hidden layer are connected with neurons in the previous and next layers. To determine its output, each neuron computes a weighted sum of its inputs, adds a bias, and applies an activation function. At the beginning of training, the weights are assigned random values, but during the training process, the weights are adjusted based on gradients corresponding to the amount of learning required to minimize the error. The vanishing gradient problem occurs when gradients become too small, which means that the network cannot efficiently learn.

In defect detection, CNNs are highly effective because they automatically learn features without the need for manual feature engineering. This capability has made CNNs a popular choice for tasks such as fruit quality assessment, where they distinguish between ripe and unripe fruits or detect surface defects. Furthermore, CNNs have been applied to quality control of cashews and to the automated inspection of meat products to ensure that only high-quality products are available to consumers. Based on their ability to withstand variations in lighting, orientation, and scale, they can be used in real-world applications [5] & [40].

2.5.3.2 ResNet

ResNet is a deep learning architecture designed to address some of the key challenges encountered in training CNNs, in particular the vanishing gradient problem. ResNet, developed by [27], is a breakthrough solution that introduces skip connections (or residual connections). As a result of these connections, input data can bypass certain layers and be added directly to the output of subsequent layers. Through this bypassing mechanism, the network can learn residual functions instead of learning the entire mapping from scratch. ResNet mitigates the vanishing gradient problem often encountered by CNNs when training very deep networks by preserving the original input and preventing the cumulative loss of information over many layers. ResNet is therefore capable of supporting architectures with hundreds or even thousands of layers without compromising performance.

ResNet also improves the performance of CNNs in various applications, particularly defect detection and quality control. As an example, it has been successfully utilized to identify quality issues in fruit, such as bruises and discoloration. It has also been used to identify packaging defects such as mislabeling or damaged materials. Its ability to capture intricate patterns while maintaining computational efficiency makes it an ideal tool for industrial applications. Furthermore, ResNet's architecture is highly compatible with transfer learning, which allows pre-trained models to be fine-tuned for specific quality control tasks. ResNet is therefore an ideal solution for real-world defect detection and classification challenges because it reduces the need for large labeled datasets and minimizes computational costs [27].

2.5.3.3 Support Vector Machines (SVMs)

While SVMs are not deep learning architectures, they remain highly effective methods for performing supervised learning tasks such as classification and regression. Due to their ability to handle non-linear data through kernel functions, they are particularly well suited for defect detection in quality control, where the relationship between features and output may not be straightforward. As an example, SVMs have been used to classify cashew nuts based on quality metrics such as their color, shape, and surface texture. Similarly, they have been applied to the detection of defects in fruits and vegetables, categorizing images as fresh or spoiled based on visual characteristics. Due to their robustness to overfitting and their ability to handle high-dimensional datasets, SVMs are a practical choice for various classification tasks in quality control [47].

2.5.3.4 You Only Look Once (YOLO)

YOLO represents a paradigm shift in object detection by treating the problem as a single regression problem. Unlike traditional methods of object detection, which involve a region proposal followed by classification, YOLO processes the entire image in a single pass through a neural network and predicts bounding boxes and class probabilities at the same time. With this unified approach, YOLO is able to detect in real-time up to 45 frames per second. In crowded scenes, YOLO's ability to consider the global context of an image significantly reduces false positives and improves detection accuracy. The use of YOLO in industrial quality control has included the identification of defects in real time in fruit, meat, and packaging products. Its speed and efficiency make it ideal for high-speed production lines where immediate feedback is essential. The grid-based architecture of YOLO, however, may cause it to have difficulties localizing small objects or defects that are closely packed, requiring careful tuning for specific applications [24].

2.6 Quality control in roasted cashew processing

Quality control of roasted cashew nuts is essential for customer satisfaction and maintaining competitiveness. The traditional method of quality control relies heavily on manual inspection, which is both time consuming and prone to human error. The demand for high quality cashew continues to grow, which has led to the development of increasingly effective and reliable methods for quality control. The use of image processing has enabled automated grading and quality inspection of products by evaluating factors such as size, colour, texture, and shape. Several studies have demonstrated that machine vision systems can improve both the accuracy and efficiency of cashew classification based on texture features [48] & [11]. Moreover, a variety of machine learning techniques such as Back Propagation Neural Networks (BPNN) and SVMs offer the possibility of more advanced and enhanced classification processes based on a large database [20] & [14]. The combination of these technologies not only improves efficiency in the cashew industry, but it also ensures that customers receive high quality products. Before delving into the details of image processing for quality control, a number of factors that contribute to cashew quality will be discussed.

2.6.1 Key quality parameters for roasted cashews

To determine the level of quality among cashews, quality parameters have to be defined. According to [37] & [38], key quality parameters for cashews are the following:

- Physical properties: Dimensions such as length, width, thickness, geometric mean diameter, and sphericity are essential for determining nuts' uniformity and quality. Based on these measurements, nuts can be classified for processing and packaging in accordance with market standards. Furthermore, uniformity in size has a profound effect on the roasting efficiency as well as the appearance of the final product.

- Density: is generally defined as the mass per unit volume of the nut. It is possible to understand the behaviour of nuts during processing and storage based on their density. A more specific density is vital for nuts, which is the bulk density. Bulk density is the mass of the nuts per unit volume, including the spaces between them. When the bulk density is higher, the nuts are packed more tightly and there are fewer voids or air spaces, indicating better quality nuts that are less likely to break during transportation and storage. As a result, determining the storage requirements and maximising packaging efficiency requires an understanding of bulk density.

- Porosity: refers to the amount of void space within a cashew nut. A roasted cashew's texture and crunchiness are affected by this factor. Higher porosity nuts have a lighter texture and a better capacity to absorb flavours and oils during roasting, resulting in a better taste and quality of the final product. As a result, the final product should have a lower porosity.

- Moisture Content: Cashew nuts require appropriate moisture content before and after roasting, for different reasons. During roasting, nuts with a high moisture content will steam rather than roast, which will result in uneven roasting and affect the taste adversely. The ideal moisture level for roasting is 7%. In contrast, the moisture level of the final product should be lower and lower than before roasting to ensure quality and a long shelf life.

- Mass: Both cashew nuts processing and marketing are influenced by their mass. Prior to roasting, it is important to determine the mass of the nuts. A higher mass indicates batches that contain whole nuts, while a lower mass indicates batches that contain broken or damaged nuts. Additionally, mass is used to calculate the moisture content of the nuts. After roasting, it is important since it contributes to determining weight loss due to roasting, which in turn affects flavour concentration. When mass is lost as a result of moisture loss, the final product will have an increased taste and will be more crushable.

- Flavour and Aroma: To achieve high quality and consumer acceptance, it is essential to balance aroma and flavour. As a result of the roasting process, the natural flavours of nuts can be enhanced and different flavours can be imparted based on the choice of roasting mediums, such as groundnut oil or palm seed oil.

- Colour: The colour of roasted cashew nuts is a crucial indicator of their quality, as it directly impacts consumer preference. The visual appeal of nuts can be enhanced by a uniform, appealing colour, whereas uneven or darkened nuts may appear over roasted or burnt to the consumer.

2.6.2 Existing techniques in raw cashews quality inspection

An image-based grading system for raw cashew kernels is presented by [11]. Images are captured by the Raspberry Pi camera setup, and they are pre-processed by several steps including grayscale conversion, thresholding, and noise reduction in order to increase their clarity. By incorporating morphological operations, further clarity is enhanced and key features such as size, shape, and texture are identified. The process is concluded by using a decision tree classification mechanism. However, even though this system demonstrates significant potential for real-time grading, it has some limitations, primarily lighting conditions that can impair colour and texture analysis. Furthermore, relying solely on visual features restricts the ability to assess other key quality factors such as flavour and aroma, as well as scale the system for high volume operations.

[48] present a portable quality inspection prototype that addresses the inefficiencies associated with manual inspection of raw cashews. Using image processing and sensors, this system is capable of assessing and evaluating quality parameters such as colour, shape, and size. Although the primary objective of the system is to assess the quality of raw cashews, the study notes that it is possible to adapt the system to roasted cashews as well. This can be accomplished by incorporating colour thresholds for roast level and enhanced texture analysis for detecting surface changes caused by roasting. Moreover, the inclusion of moisture sensors demonstrates how important it is to maintain an ideal moisture level for raw and roasted cashews, which results in reduced spoilage and, therefore, improved quality. In summary, this prototype presents a promising portable solution, however it highlights the need for further research into more sophisticated algorithms that take into account texture complexity.

It is discussed by [29] in their study that machine vision can be used to inspect roasted cashews. Nonetheless, the roasting process results in a change in both colour and texture. When cashew kernels are roasted, they undergo a significant colour change ranging from a light tan to a dark brown colour. Because of the broad spectrum of colours, there is often overlap between quality grades, which causes complications for classification algorithms whose efficiency is solely based on colour differentiation. When colours overlap, machine vision systems have difficulty assigning quality grades to cashews since similar colours may represent cashews of different roasting stages or levels of defect. Moreover, roasting results in cracks, splits, and irregularities on the surface, which are responsible for altering the texture of the product. The inconsistencies in textural characteristics vary even within kernels of the same grade, adding to the complexity of the image analysis phase and increasing the risk of a misclassification. Further, [29] point out that machine vision systems are often unable to capture subtle variations in texture and colour, contributing to the complexity of the classification process. They indicate that the decreased capability of the system is caused by several factors, including external factors such as lighting conditions, which can vary during image capture, resulting in different classifications for the same kernel depending on the lighting conditions. Also, the volume and diversity of the training dataset play a significant role in determining the quality of the output.

2.6.3 Challenges in image-based quality control for roasted cashews

The following are a list of the challenges in applying image-based quality control for roasted cashews:

- Variability in visual appearance due to roasting methods: Cashews' physical appearance is greatly influenced by the roasting method used [12]. Each roasting method affects the physical properties of cashews differently, resulting in a distinctive visual appearance. Thus, image-based quality assessment is complicated [12]. Traditional image processing techniques often rely on uniform shapes and sizes, roasted cashews can however vary significantly in both respects. [38] highlight that this variability complicates the ability to differentiate between whole nuts and fragments. Thus, the effectiveness of standard image-based classification systems is reduced. Compared to conventional ovens, Halogen-oven roasting produces cashews with a lower moisture content (3.23 %) and an improved appearance thus ranking higher in crispness and appearance. However, these visual differences are not always consistent enough to serve as a reliable indicator of the quality based solely on the appearance [12]. Therefore, for a reliable quality assessment of roasted cashews, additional indicators that are not image-based are necessary, not only for visual aspects, but also for other key parameters that cannot be captured in images alone for the assessment of the roasted cashews' quality. This emphasises the importance of a combination of chemical and sensory evaluations in conjunction with image analysis [12].

- Limitations of texture analysis techniques for roasted cashews: It has been demonstrated that textural analysis methods can accurately classify raw cashew kernels with up to 90% accuracy [51]. The grey level co-occurrence matrix (GLCM) has, however, proven problematic when applied to the classification of roasted cashews. These methods are unable to accurately classify roasted cashews due to their high variability in colour shifts and surface changes as a result of roasting. Accordingly, [51] suggest that in order to improve the accuracy of these methods, they should be trained on datasets that cover a greater range of roasted grades and incorporate additional colour features.

- Impact of lighting conditions and colour variability: Image segmentation algorithms struggle significantly in dealing with roasted cashews, as roasted cashews tend to have darker and more heterogeneous colour profiles [38]. The difficulties are compounded by variations in light conditions which can cause drastic shifts in colours perceived by the system, which in turn complicates further segmentation accuracy [38]. A reliable colour segmentation is important for quality assessment in a variety of applications, but traditional methods have difficulty maintaining accuracy under varied lighting settings.

- How can these obstacles be overcome? Although these challenges pose significant challenges, [38] suggest that machine learning holds promise for improving image-based quality control. As opposed to traditional methods, these models are trained using extensive datasets containing a wide range of roasting methods, colours, textures and sizes, which results in improved adaptability to the visual complexity of roasted cashews [38]. Also, combining traditional image-based quality control with chemical or sensory evaluations could improve the reliability of image-based quality control in roasted cashews [12].

2.7 Overview of reviewed studies

Techniques for image processing have found wide application in a number of industries, including the food industry, in which evaluation of key quality parameters is vital to both the safety of the product and the competitiveness of the organisation. The use of image-based quality assessment techniques for products such as rice, mushrooms, and cashews include processes such as edge detection, noise reduction, and segmentation. The use of these techniques has proved essential for identifying the visual characteristics of food products, which play an important role in product quality and customer satisfaction. Many cases have shown that the use of these techniques in machine vision systems has resulted in an efficient and accurate classification system that requires little human intervention. Furthermore, integrating machine learning models such as SVMs and neural networks has further improved the precision of defect detection and classification. Consequently, systems could adapt more readily to variations in appearance and texture. Specifically, machine vision systems improve sorting and grading accuracy of cashew nuts by detecting subtle changes in texture and colour, streamlining operations and reducing human error. Therefore, these systems have gained popularity as an efficient solution for the high-throughput, real-time quality control in the food industry.

Even though these technologies have proven successful in raw food processing, their application to roasted cashews presents several challenges. Variability in visual appearance is a result of different roasting methods, the inability to capture certain key quality parameters through images, limitations in texture analysis, and the influence of lighting conditions. The challenges mentioned above create significant gaps in existing research, since they limit the reliability and adaptability of current image-based quality control systems for assessing the quality of roasted cashews.

In order to address this gap, this research aims to develop a simple, cost-effective prototype for image processing designed specifically for the quality control of roasted cashew nuts. This system will be based on a combination of the image processing techniques suitable for the case of the roasted cashews and a robust machine learning model trained on an extensive and diverse dataset of roasted cashew images in order to capture the wide range of visual characteristics across differing roasting levels. As a result of this combination, the system will be able to identify and detect the most subtle variations in colours and textures within each quality grade. Hence, improving the adaptability of the classification model to cope with roasting's complexities. Further, to obtain more stable colour and texture analyses, preprocessing techniques designed for lighting normalisation will be used, such as contrast enhancement and histogram equalisation. To reduce the lighting factor to the minimum, controlled lighting will be applied to all images. Furthermore, this system will include advanced texture analysis methods, such as Local Binary Patterns (LBPs) and machine learning-driven segmentation, in order to better account for the unique irregularities of roasting surfaces. As a result of applying machine learning algorithms such as CNNs and SVMs, the system is able to recognize nuanced variations in texture and colour specific to each roasting level. Thus, detection and classification will be more accurate. As a result, this method addresses not only the existing challenges associated with traditional colour- and texture-based techniques, but also helps to enable a scalable, high-throughput inspection process that is aligned with the operational requirements of companies such as TAAJ Food.

3 Methodology

This research employs a systematic methodology grounded in experimental design, iterative testing, and the integration of image processing and machine learning techniques. The methodology is structured to address the research questions comprehensively and ensure the development of an effective and scalable vision-based quality control system for roasted cashews.

3.1 Literature review and gap identification

The study began with an extensive review of existing literature on vision systems, their applications in quality control, and image processing techniques used in food quality assessment. Special attention was given to roasted cashews, where gaps in the current body of research became evident. Existing methods were found to be either too costly, technically complex, or ill-suited for SMEs. This review established the necessity for a cost-effective, automated system tailored to the unique visual characteristics of roasted cashews.

3.2 Experimental approach

The experimental design was chosen to explore cause-and-effect relationships between critical variables—such as lighting conditions, preprocessing techniques, and visual characteristics—and their impact on system performance, see Figure 1. This approach ensures the methodology is robust for industrial applications, where accuracy, efficiency, and scalability are key. The following are the key variables:

- Lighting condition: It is intended that lighting conditions be standardized and optimized in order to minimize or eliminate their adverse effects on image processing and, consequently, on classification.
- Image preprocessing and processing Techniques: Different techniques are tested in order to determine the most effective means of detecting defects in cashews.
- Visual characteristics: Due to roasting in contrast to the first two variables, this one is uncontrollable since it is subject to the natural changes in appearance caused by roasting.

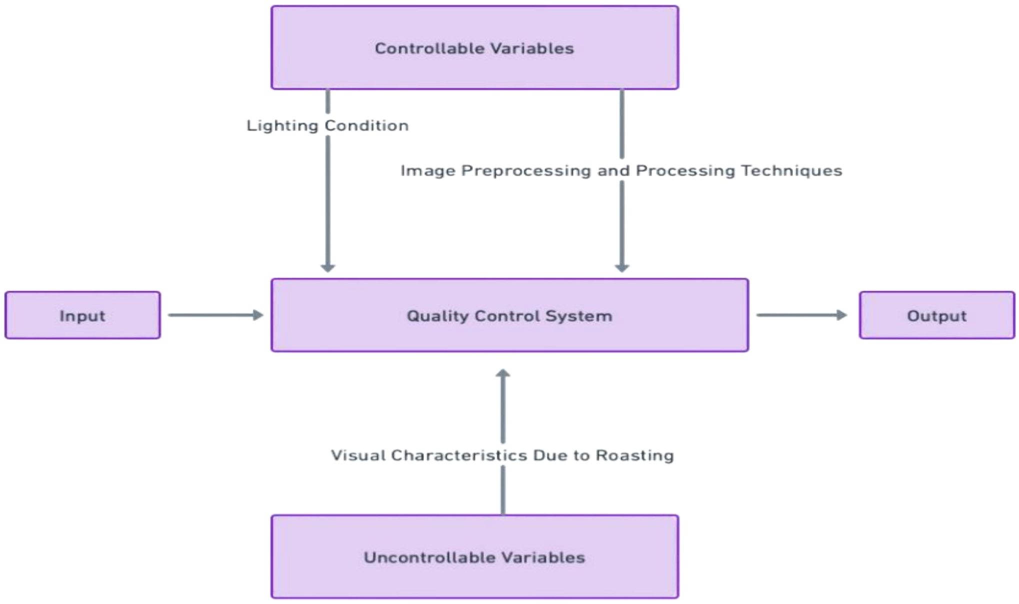

Figure 1. Visualization of controllable and uncontrollable variables

3.3 Alignment with research questions

The methodology aligns with the research questions by addressing several key aspects that evaluate the system's effectiveness and applicability.

- Detection and classification accuracy: The methodology integrates advanced image processing techniques and machine learning models to classify roasted cashews into three categories—burned, unroasted, and good. This directly addresses the first research question by assessing the system's ability to achieve high accuracy using color and texture analysis.
- Performance in variable conditions: The iterative testing process evaluates how the system handles variability in cashew shapes, orientations, and environmental factors, such as lighting, answering the second research question about its real-world applicability.
- Enhancement through machine learning: By training models like ResNet-50 on manually labeled datasets, the methodology explores the synergistic effects of combining machine learning with image processing. This directly addresses the third research question regarding the system's enhancement capabilities.
- Cost-effectiveness and practicality: A simple hardware setup (HD webcam and ring light) ensures affordability and accessibility for SMEs like TAAJ Food. Comparative analysis with manual methods evaluates the system's practicality, addressing the fourth research question.
- Limitations and scalability: The methodology explicitly identifies and addresses limitations such as false positives and dependency on controlled environments. Iterative refinement and augmentation techniques ensure the system’s robustness and scalability, answering the fifth research question.

3.4 Expected outcomes

By grounding the research in a methodical and iterative process, this study aims to deliver a robust, cost-effective, and adaptable quality control system that addresses the unique challenges of roasted cashew classification. The methodology not only answers the research questions but also sets a foundation for future work in this domain.

3.5 Evaluation methods

In order to evaluate the performance of the system, specific metrics were used to assess its accuracy, reliability, and efficiency:

- Detection accuracy: It was determined by comparing the classifications generated by the system with those generated from a manual labeled test set of cashew images. It indicates the accuracy with which the system can identify defective cashews.
- Processing speed: Processing speed was measured by recording the time taken to process and classify images. This metric is essential for industrial applications, where efficient, high-throughput processing is required.
- Robustness to variability: The system's capacity to manage variations in lighting and roasting levels was assessed through targeted experiments. Tests were conducted to determine the system's consistency and reliability in detecting defects in diverse imaging conditions, thereby ensuring dependable performance in real-life situations.
- Error analysis: The fail rate of the system across different classification categories was analysed to identify potential areas of improvement. This includes a breakdown of false positives and missed detections.

To be considered successful, the system must have three features: high detection accuracy, commercial viability, and resilience to variations in cashew appearance. These results will provide a basis for further recommendations on improving automated quality control in cashew processing.

4 Development of the cashew classification system

This section explains the development and evaluation of an automated vision-based quality control system for classifying roasted cashews. The project aims to address the inefficiencies of manual inspection by providing a solution that is cost-effective, scalable, and suitable for SMEs. The system categorizes cashews into three distinct classes: burnt, unroasted, and good quality, based on visual characteristics such as color and texture.

The development process builds on insights from the literature review and incorporates technical tools to overcome challenges. These include issues such as variations in lighting, limitations in the dataset, and the complexity of texture analysis. To achieve robust classification, the system utilizes MATLAB and ResNet-50 with transfer learning. The section provides a detailed account of the processes involved, which include data collection in controlled lighting environments, image preprocessing to improve quality, and the training and evaluation of the classification model.

Furthermore, this section highlights the challenges encountered during development, such as inconsistencies in lighting and dataset representation, and explains the measures taken to address these issues. It also presents the outcomes of iterative experiments, which refined both the hardware setup and the software implementation. The final solution offers two practical application options: a pick-and-place robotic system for large-scale operations and a Boolean-based approach for smaller-scale businesses. Both options aim to ensure reliable and efficient quality control for roasted cashews. The section concludes by discussing the system's potential for broader applications in industries requiring high-precision visual inspection.

4.1 Addressing aims

The primary aim of this project was to develop a system capable of categorizing roasted cashews into three quality grades—burned, unroasted, and good—based on visual attributes such as color and texture. To achieve this, the work focused on designing an adaptable and affordable hardware setup that would ensure compatibility with the constraints faced by SMEs. Advanced image processing techniques and machine learning were employed to enhance classification accuracy, while systematic experiments were conducted to ensure the system's robustness under varying conditions, such as changes in lighting and cashew orientation. The iterative development process was critical in aligning the final solution with the specific needs of the application and in overcoming the challenges identified in the literature.

The literature review provided a strong foundation for the methodology by highlighting critical gaps and opportunities in existing systems. Current quality control methods were found to lack affordability and adaptability for SMEs, which influenced the selection of a simple hardware setup, including an HD webcam and a ring light, alongside efficient preprocessing techniques to optimize cost and reliability. Additionally, studies pointed out technical challenges such as lighting variability and the complexity of texture analysis in roasted cashews, which were addressed through preprocessing techniques like contrast enhancement and controlled lighting. The review also emphasized the potential of machine learning for improving defect detection and classification. This insight guided the integration of the ResNet-50 model, enhanced with transfer learning and trained on a diverse dataset, to effectively handle the visual complexities of roasted cashew quality assessment.

4.2 Data collection

The data represented in the images was collected using an HD webcam and a ring light. In controlled lighting conditions, these tools were used to capture cashew images. At first, this setup was used to create the training model, and then it was used to create the live detection and classification model. Ultimately, this setup was chosen after many experiments and setbacks from which it was realised in practice the importance of having an effective and controlled lighting environment. This is, however, highlighted in theory as well. A MATLAB script was used to automate the process of capturing images, detecting cashews, and classifying them. To filter out non-cashew shapes, edge detection (Canny method) and region property analysis were combined. When a cashew region is identified by the software, the user is prompted to confirm detection and categorize the cropped cashew as either burned, unroasted, or good. This manual classification ensures accurate labeling. Subsequently, each labeled image was saved in a corresponding folder for use in training the deep learning model. Through this method of data collection, a robust categorized dataset was produced which served as the basis for training the model in order to detect and classify cashew quality levels effectively.

4.3 Model training

During the training process, various technologies were utilized to maximize the model's capabilities, including the sophisticated pre-trained ResNet-50 model, CNN, a convolutional neural network widely known for its robust image classification capabilities, and transfer learning, see Appendix A. The latter was employed to adapt the model particularly for the task of cashew quality classification into three categories: burned, unroasted, and good. Additionally, the final layers of the ResNet-50 architecture were replaced with customized layers specifically designed for cashew classification. These layers include a fully connected layer, a SoftMax layer, and a classification layer.

In preparation for training, preprocessing techniques were employed to resize and enhance the collected images to match the input dimensions demanded by ResNet-50. Thus, ensuring compatibility and enhancing generalizability of the model. The dataset was then divided into two subsets for performance evaluation: training (80%) and validation (20%). Various methods of data augmentation, including random rotations and flips, were employed to simulate variability and enhance robustness of the model.

Using the Adam optimization algorithm, the model was fine-tuned with a small learning rate of 0.0001 over 10 complete passes through the dataset (epochs), see appendix A. Performance was monitored throughout the training process based on validation data. Thus, minimizing overfitting and guaranteeing the model's adaptability to overlooked data. As a result, the system was capable of accurately detecting and classifying cashew quality levels.

4.4 Sources of error

During both the development and testing of the automated quality control system, several potential sources of error were identified. Although ring light has substantially enhanced the experiment, there have been inconsistencies in image capture, which has affected both training and classification accuracy. Furthermore, the datasets used for training were sourced from available products on the market, so it is possible that some of the roasted cashews purchased could actually be unroasted or burnt. This could have potentially affected the model's ability to generalize to unseen data. Since the dataset used for training is relatively small, not all possible roasting levels have been adequately represented. Therefore, the model's performance may be limited in real-world applications. Further, there may have been slight distortions in the captured images as the result of environmental factors such as vibrations or irregularities in the setup of the webcam. Finally, the algorithm's use of edge detection and region properties has led to missed detection when cashews are concealed, flipped, or partially outside the detection area.

4.5 Experiments and iterations

System development and improvement was achieved through a series of experiments and iterations regarding both hardware setup and software enhancements. For the hardware setup, we used the room lighting, then the flashlight, and finally a ring light. Various hyperparameters, such as the learning rate and batch size, were tested during training to optimize the accuracy of the ResNet-50 model. By using techniques such as random rotations and flips, the dataset's diversity was thus increased, and the robustness of the model was improved. Also, experiments were conducted to evaluate the accuracy of the trained model in real-time classification and the speed of the processing. Prior to choosing ResNet-50, many different approaches and combinations of approaches were tested among others SVMs, CNNs, YOLO.

These experiments revealed areas for further improvement, which suggested excluding the enhancement of edge detection thresholds and the enhancement of preprocessing techniques when coupled with transfer learning. We tested the same model equipped with ResNet-50 with and without image processing techniques such as edge detection, contrast enhancement, and noise reduction. It was found, however, that the model's performance was worsened when transfer learning was combined with image processing techniques, likely due to overprocessing, which led to the loss of features. In every iteration, the system has been directing toward its objectives of high detection accuracy, efficacy, and adaptability. A tree of image processing techniques on different levels was considered at the outset of the project, see Figure 2. Ultimately, the classification model was limited to high-level processing represented by machine learning, deep learning, optimization techniques and performance monitoring techniques.

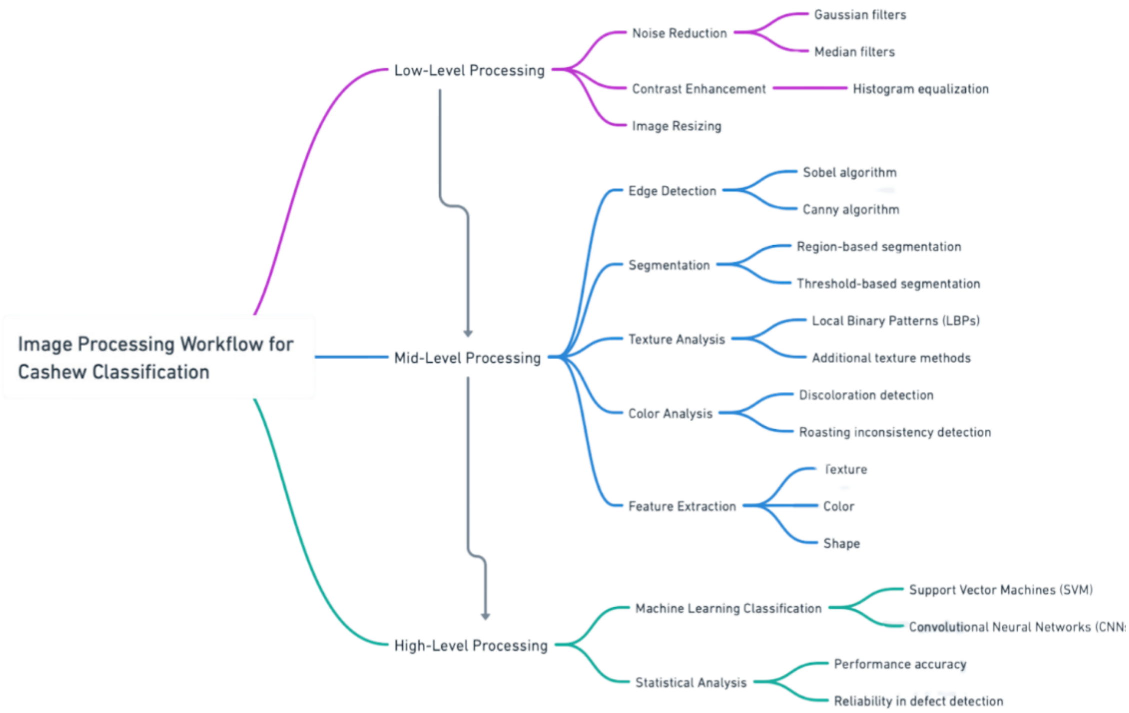

Figure 2. Illustration of the different image processing techniques at different levels

4.6 Final solution and application

Our classification system leverages image processing and machine learning to detect and classify roasted cashews in real time, which can be seen in Figure 3. By combining hardware simplicity with software sophistication, it offers SMEs, including businesses like TAAJ Food, a cost-effective, scalable, and reliable solution for quality control. The system is designed to provide instant classification of cashews, thereby enhancing operational efficiency.

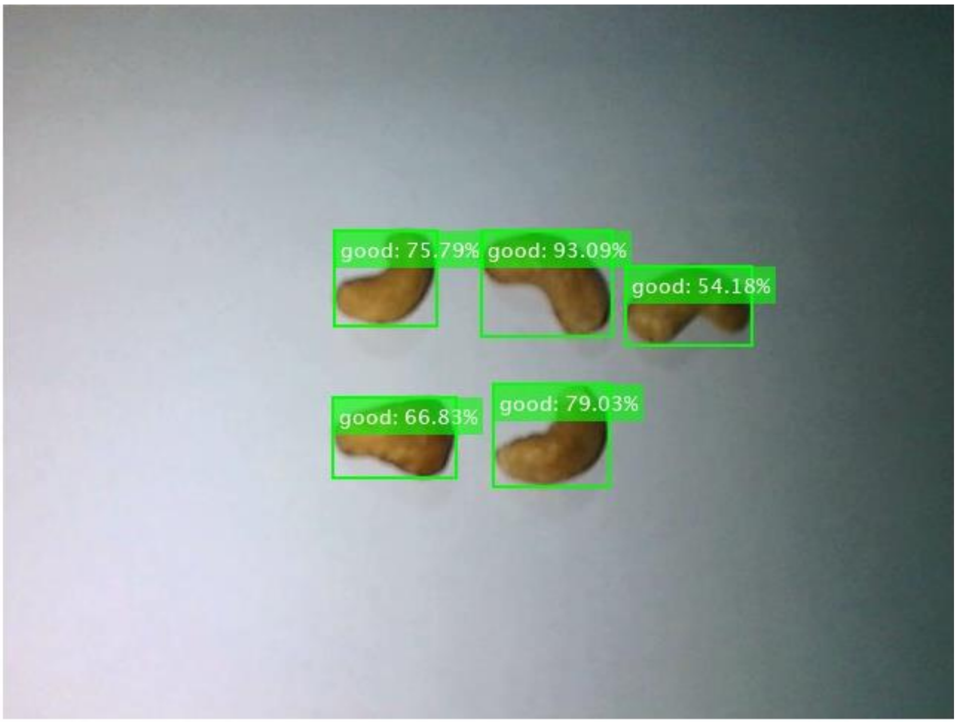

Figure 3. Visualization of the system's detection and classification functions.

In response to the identified need for a reliable and cost-effective quality control system, two implementation approaches are presented. Both approaches utilize the same classification model but differ in how they process and act upon the information. To demonstrate the system's functionality, we developed a classifier that outputs the coordinates of unroasted or burnt cashews, see Appendix B, allowing for precise identification of defective items. This output can serve as an input for a pick-and-place robot, enabling automated sorting if the SME can accommodate such equipment within their budget.

Alternatively, for businesses unable to budget for robotic systems, the output is configured as three Boolean signals, which can be sent to external machinery to facilitate cashew sorting, see Appendix B. The following is a simplified illustration of this setup.

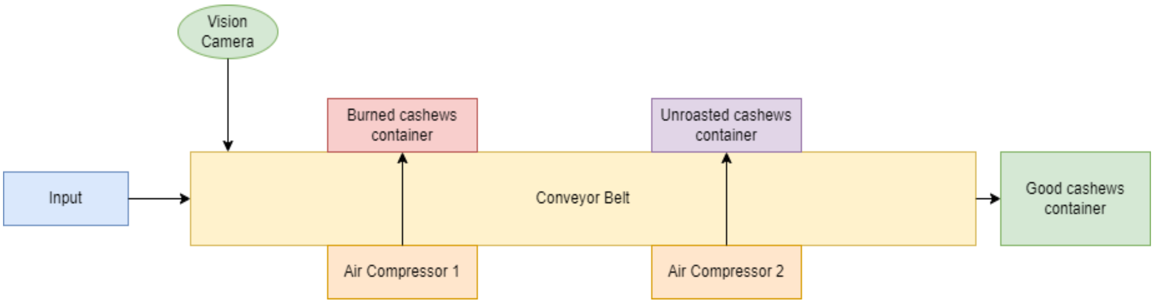

Figure 4. Illustration of the quality control system in Alternative 2, utilizing air compressors.

To demonstrate the results, we implemented an Ardiuno-based circuit that visualizes the classification outputs.

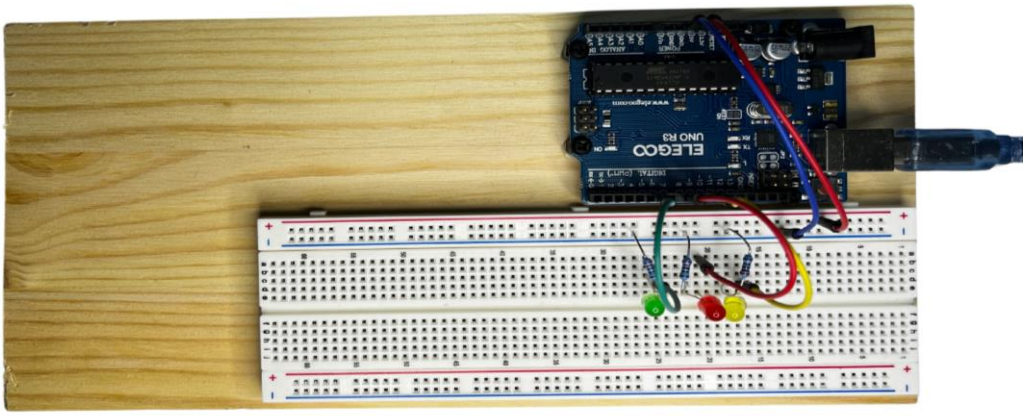

Figure 5. A prototype of Alternative 2 where LED lights represent different air compressors in reality.

In this setup, a green LED represents good-quality cashew classification, a red LED indicates a burned cashew classification, and an orange LED corresponds to an unroasted cashew classification.

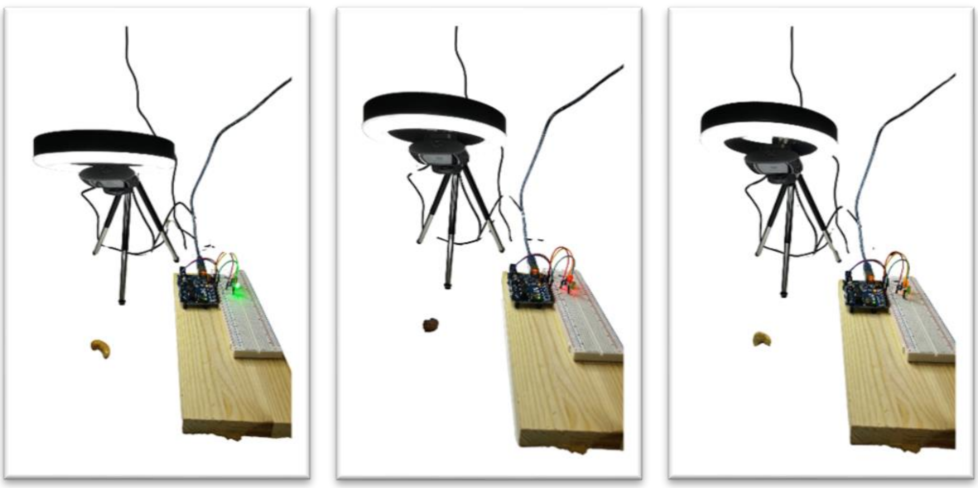

Figure 6. Demonstration of the system operating across all quality levels.

The primary distinction between these two approaches lies in their suitability for different scales of production. The pick-and-place robot system is ideal for high-volume operations, such as large-scale cashew processing. In contrast, the Boolean-based approach is more suited for smaller-scale applications, processing cashews one at a time. However, with the integration of a fast conveyor system, this approach can also be adapted for higher production rates. Finally, the use of this system in roasted cashew quality control demonstrates its broader potential for application in industries requiring high levels of visual quality inspection. Its ability to adapt to diverse conditions and manage complex classifications makes it a valuable tool for improving both operational efficiency and product reliability across various domains.

5 Results and discussion

This section presents the results of the classification model based on the performance parameters outlined in the methodology section. These parameters include detection accuracy, robustness to variability, processing speed, and failure rates. However, processing speed will be excluded from the analysis, as its evaluation requires measuring the time for the entire process—such as the time taken for a robot to pick up a cashew and place it in the appropriate container, or the influence of conveyor belt speed in the alternative with air compressors. Unfortunately, such measurements were not feasible in the scope of this study. Therefore, the results will focus on the remaining three parameters: detection accuracy, robustness to variability, and failure rates. Following this, the outcomes of TAAJ Food's current quality control approach will be presented. The section concludes with a comparison between the two approaches.

5.1 Classification accuracy in different lighting conditions

To evaluate the importance of the lighting environment, the classification model was tested under various lighting conditions to assess its impact on detection and classification accuracy, as well as to analyse the failure rates. These insights can serve as a foundation for further improvements to the model.

5.1.1 Room lighting

We found that the classification system was 100% accurate for burnt and unroasted cashews when it was applied to the same trained set without any light directed at the camera, see Figure 7. Although the classification accuracy was highest for burnt and unroasted cashews, it was only 16% for good cashews, and 84% were misclassified as burnt cashews.

Conversely, when the system was applied to a new set of cashews not used for training, the results were 100% accuracy for burnt cashews, 21% accuracy for good cashews and 100% accuracy for unroasted cashews.

There was, however, a failure in the detection process that results in 17% of all detection cases, and 33% of misdetection cases involved burnt cashews, with the remainder involving unroasted cashews. Misdetection cases were resolved by moving the cashew to a brighter area. The misclassification of good cashews was divided between 64% misclassified as burned and 15% misclassified as unroasted. The following is an image of the setup used.

Figure 7. The setup used to detect and classify cashews in room lighting

5.1.2 Flashlight

By using a flashlight directed at the direction of the camera as it can be seen in Figure 8, the classification model has become more accurate. Starting with the cashews used for training, the accuracy was as follows: 100% for burnt cashews, 100% for unroasted cashews, and 84% for good cashews, with 16% misclassified as unroasted. Nevertheless, there was no failure of detection in any case. Furthermore, when the classification model was applied to new cashews, the accuracy was as follows: 100% for burnt cashews, 87% for unroasted cashews with 13% misclassified as good and 93% for good cashews with the remaining 7% misclassified as unroasted. Again, misdetection cases were none for those new cashews as well. Here an image of the setup with flashlight.

Figure 8. The setup used to detect and classify cashews with the support of a flashlight.

5.1.3 Ring light

To ensure a balanced and robust lighting system, the ring light has been implemented, see Figure 9. During the testing of the classification model equipped with ring light on a set of cashews that were used for training, 100% accuracy was obtained for burned cashews, 96% accuracy was obtained for good cashews, while 4% were actually misclassified as unroasted, but the classifier instantly changed the classification to good, and 100% accuracy was achieved for unroasted cashews. Approximately 5% of cases are misdetected.

The classification results for new cashews were unexpected. The prediction was that accuracy would skyrocket and surpass the former lighting environments. The model's accuracy for burnt cashews was 100% with no misdetection cases, 84% for good cashews with 16% misclassified as unroasted, the misdetection cases account for 8%, the accuracy of the model for unroasted cashews was the worst, with just 63%, and the remaining 37% were misclassified as good cashews. Misdetection cases accounted for 32%, which is the highest of all environments and categories tested. Here is an image of the setup with ring light.

Figure 9. The setup used to detect and classify cashews with the support of a ring light.

5.1.4 Effect of lighting conditions on classification performance

The classification accuracy for the training set varied across lighting conditions as highlighted in Figure 10. Under room lighting, while burnt and unroasted cashews achieved 100% accuracy, good cashews were classified with an accuracy of only 16%, showing significant room for improvement. Introducing a flashlight improved the accuracy for good cashews to 84%, and the ring light further increased it to 96%, while maintaining 100% accuracy for burnt and unroasted cashews. These results highlight the effectiveness of controlled lighting in enhancing the model's training accuracy.

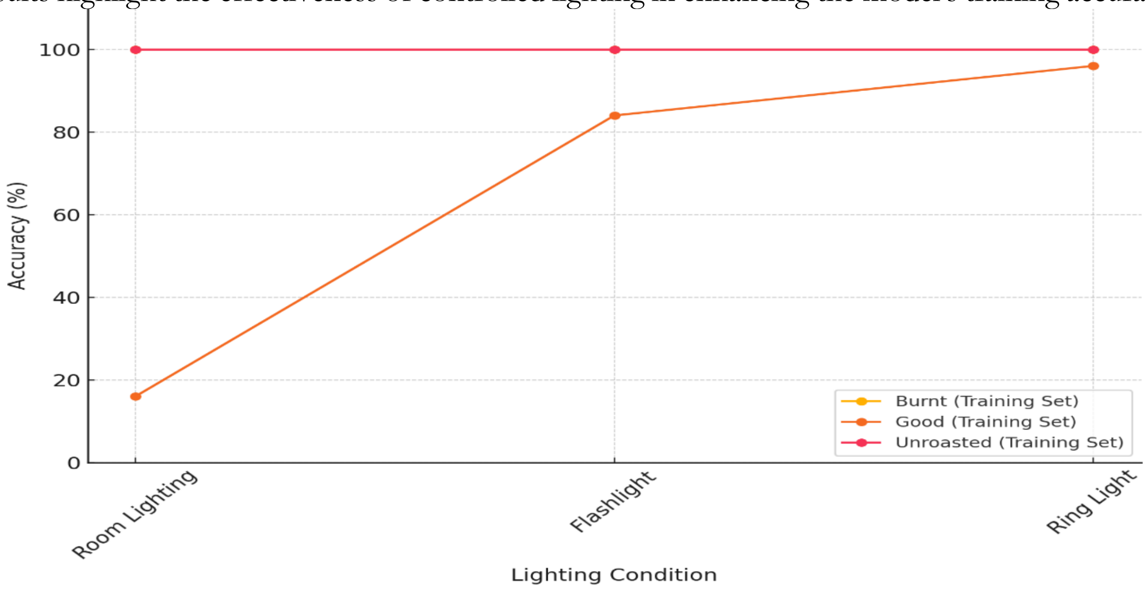

Figure 10. Classification accuracy by lighting condition for the training set.

For unseen data, the accuracy trends showed improvements under better lighting conditions, but challenges persisted as presented in Figure 11. Room lighting achieved 100% accuracy for burnt and unroasted cashews but fell short with good cashews, where accuracy dropped to 21%. Flashlight lighting raised accuracy for good cashews to 93% and 87% for unroasted, with no detection failures. Surprisingly, under the ring light, while burnt cashews maintained 100% accuracy, accuracy for good cashews decreased to 84%, and unroasted cashews saw a significant drop to 63%. These results suggest that while advanced lighting like a ring light can help in some scenarios, calibration and adjustments are needed for better performance with new data.

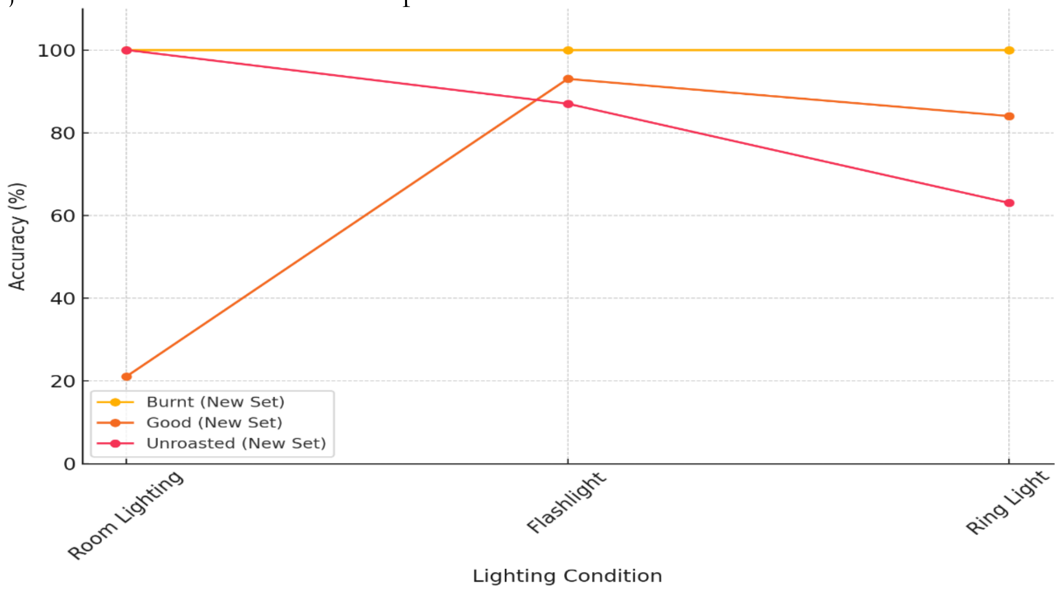

Figure 11. Classification accuracy by lighting condition for unseen data.

The rate of misdetection, defined as the failure of the system to detect any cashew type, varied widely across lighting conditions which is visualised in the Figure 12. Room lighting showed a 17% misdetection rate, which dropped to 0% under flashlight conditions. Thus, demonstrating the flashlight's efficiency in minimizing detection failures. However, the ring light exhibited the highest misdetection rate at 32%, indicating potential issues in balancing light intensity and uniformity. These findings emphasize the need for fine-tuning lighting systems to reduce detection failures.

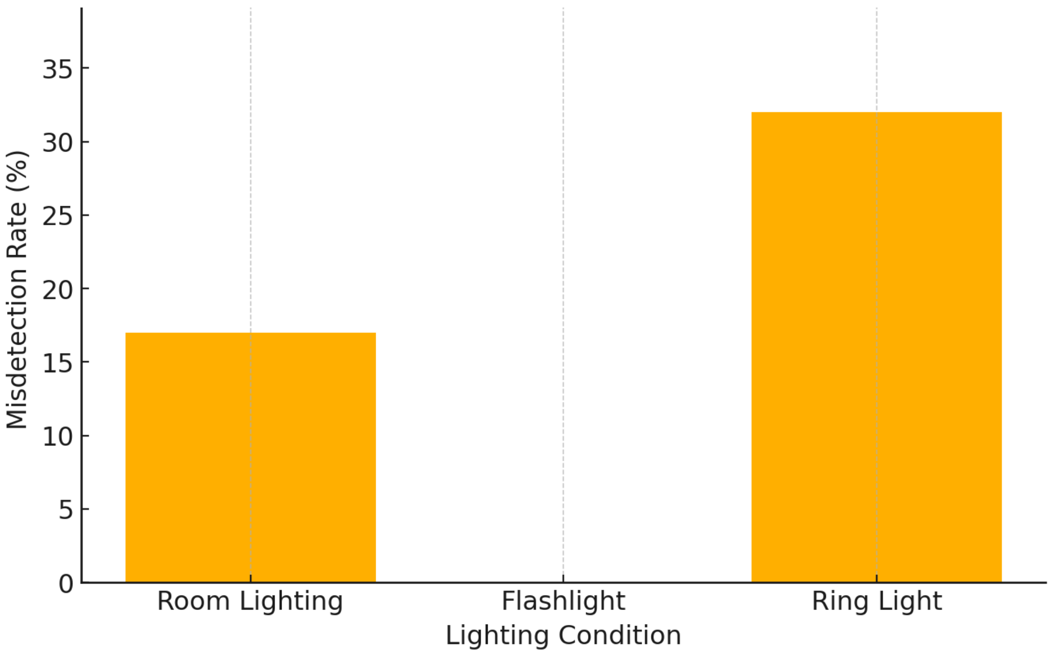

Figure 12. Misdetection rate by lighting condition.

The training set was created under standard room lighting conditions. When the lighting was enhanced using a flashlight, the system's accuracy and detection rates improved significantly. However, when a ring light was introduced, the distance between the camera and the subject was altered. Moreover, the brighter and more uniform lighting of the ring light differed from the setup involving the flashlight, thereby causing a drop in accuracy and detection rates.

Nevertheless, the training set were expanded to include data collected with the ring light, the system's performance was significantly improved in this lighting condition as well, just as it did with the flashlight. However, the accuracy levels for unseen data were 92% for good cashews, 100% for burnt cashews, and 86% for unroasted cashews. Hence, the results highlight the importance of lighting consistency during both training and testing. The goal of using varied environments was to demonstrate how different lighting conditions impact accuracy and detection rates.

Thus, for optimal performance, the system should be trained and deployed under consistent and balanced lighting conditions that are neither too bright nor too dark. This approach would ensure the training program is well-suited for real-world applications.

5.2 The quality control approach adopted by TAAJ Food

The quality control approach adopted by TAAJ Food is not strictly regulated, primarily because the company operates on a mass production scale. In the absence of an automated quality control system. Thus, the inspection process depends heavily on the ability of operators to identify defective cashews or nuts generally by sight. However, this method is inherently unreliable and insufficient for ensuring consistent quality across all products. The nuts are transported from the oven to the packaging machine via a conveyor belt in a continuous stream, which makes it exceptionally challenging for inspectors to examine every nut individually.

Moreover, instead of conducting thorough visual inspections, operators rely on specific parameters within the roasting oven, such as temperature and humidity, to monitor the quality of the production process. Nevertheless, this approach does not adequately address the issue of identifying defective nuts, thereby highlighting a significant limitation in the quality control system.

TAAJ Food quantifies quality issues by analysing the volume of returned goods from customers. These returns serve as an indirect measure of production inconsistencies and defects. Furthermore, since the company sells its products in bulk to wholesalers rather than directly to consumers, the returns are recorded in terms of the number of 5-kilogram bags returned. Below is a table presenting the total production, the volume of returned goods, and the corresponding percentage of returns for their three main product variants—mixed nuts in salty, sour, and smoked flavours—for the period of January to September 2024.

Table 1. Detailed data on production and returns at TAAJ Food collected over nine months.

Month	Total Production (Tonnes)	Total Returns (Bags)	Returned Salty (Bags)	Returned Sour (Bags)	Returned Smoked (Bags)	Total Production (Bags)	Return Percentage (%)
January	88.69	63	32	12	19	17738	0.36
February	89.35	240	120	48	72	17870	1.34
March	86.07	211	106	42	63	17214	1.23
April	86.63	52	26	10	16	17326	0.30
May	81.14	126	63	25	38	16228	0.78
June	87.75	92	46	18	28	17550	0.52
July	88.90	134	67	27	40	17780	0.75
August	86.88	211	106	42	63	17376	1.22
September	87.20	73	37	15	21	17440	0.42

5.3 Comparison of classification model with TAAJ Food's current approach

There are approximately 134 bags returned per month on average for TAAJ Food according to the previous table, and the average return percentage is 0.77%. Based on the confined training set available within the limited timeframe of this project, the flashlight scenario represents the best-case results for implementing the classification model. As a result of testing on unseen data, specifically new cashews under flashlight lighting conditions, the classifier achieved 100% accuracy for identifying burnt cashews, 87% accuracy for identifying unroasted cashews (with 13% misclassified as good), and 93% accuracy for identifying good cashews (with 7% misclassified as unroasted).Unroasted cashews misclassified as good by 13% represent an important issue, since these defective cashews would be packaged and transported incorrectly. By contrast, there is no cause for concern regarding the 7% of good cashews misclassified as unroasted since these nuts are redirected to the unroasted container and can be manually inspected and corrected.

Even though this does not reflect the conditions at TAAJ Food, assuming that all returned goods are solely caused by unroasted cashews would result in a reduction of up to 87% in returned goods when applied under flashlight conditions. According to TAAJ Food, in practice, the primary reason for returned goods is burnt or in other words overroasted cashews. Considering that the classifier was able to detect burnt cashews with 100% accuracy, it can be concluded that at least 87% of returned goods could be avoided. On a monthly basis, this reduction would result in 116 bags if the lighting environment applied in quality control is similar to the lighting environment applied in the flashlight test.

Additionally, the cost savings associated with this improvement extend beyond the value of the goods themselves. These savings are reflected both in direct costs, such as rework labor, packaging waste, and transportation expenses, as well as indirect costs related to customer dissatisfaction and possible brand damage. By replicating flashlight lighting conditions in the production process, TAAJ Food will be able to achieve significant operational efficiency while improving customer satisfaction.

6 Conclusion

6.1 Future Work and Research

It is crucial to expand the dataset to include a broader spectrum of roasting levels and diverse lighting conditions, which would enhance the model's ability to generalize and perform robustly in real-world applications. Studies on advanced preprocessing methods, such as hyperspectral imaging, may provide new insights into subtle differences in colour and texture that traditional RGB imaging techniques may not be able to detect. Moreover, research into the integration of real-time IoT technologies could lead to the development of dynamic quality control systems capable of adapting to environmental changes and providing continuous monitoring. Finally, studying the processing time of such systems when implemented is essential to productivity and operational efficiency, both of which are essential components in all industrial environments. Hence, automated quality control systems could be widely adopted in the food processing industry, which may result in widespread industrial adoption.

6.2 Critical Discussion

In this thesis, a vision-based quality control system is developed that utilizes machine learning and, in particular, transfer learning. Earlier in the thesis, we defined the problem of finding an automated alternative for the current manual quality inspection method in cashew processing. The classification model developed here addresses this problem. The development process resulted in two solutions based on the company's budget to replace the manual quality inspection system for cashew processors such as TAAJ Food. The first one is relatively cost-effective since it does not require substantial initial investments, and the classification model provides three distinct Boolean outputs based on whether the cashew is burned, good, or unroasted. A signal triggers an air compressor to send the cashews into the appropriate container as they are conveyed along a conveyor belt. In this approach, each item must be processed individually, however, this disadvantage can be mitigated by adjusting the conveyor belt's speed. Alternatively, a pick-and-place robot can be used. The classification model would be adjusted in order to send a result, which is a coordination of the defective cashew to the robot for pick-up. This method can process cashews in batches, but it is somewhat costly.

[38] has stated that variations in lighting lead to drastic colour shifts for roasted cashews, which stands as a major challenge for the application of vision-based quality systems. Due to their wide range of colours, roasted cashews can be difficult to distinguish. During the experiment, images were captured in room light for unroasted cashews, which led to low accuracy and relatively high levels of misdetection. By applying the flashlight, light was enhanced, and no detection failure was observed in any category, while accuracy increased for all categories for unseen data, reaching 100% for burnt cashews, 87% for unroasted cashews, and 93% for good cashews. Further lighting enhancements led to a decline in both detection rates and accuracy as ring light were applied, which was unexpected. The accuracy and detection were restored to some extent after the classifier was trained and tested in the ring light environment, which is consistent with the recommendation of [29] that capturing and classification should take place under identical lighting conditions.

Moreover, [19] emphasize that transfer learning is ideal for organisations with limited technical infrastructure. [44] states that it is beneficial in scenarios with limited data, as it is in this thesis. According to [43], integrating machine learning and image processing techniques produces better accuracy results, which was not the case in the experiments conducted. A considerable loss was observed in both the accuracy and detection rates of the classifier when they were combined. In contrast, according to [26] image processing methods can obscure important features, and [9] indicate that it is imperative to choose the appropriate learning rates and training epochs for this integration. Despite this, high accuracy was not achieved when transfer learning and image processing were combined. However, this issue was ignored due to the fact that high accuracy and detection rates were already achieved with only ResNet-50, which is considered to represent transfer learning.

The results of the thesis demonstrate that TAAJ Food could save as much as 87% of their returned goods if this classification model was implemented in their production line. This significant amount of savings in direct and indirect costs can justify the investment in such a cost-effective solution. It is, however, up to TAAJ Food to decide which approach they will take based on their budget and the balance between the initial investment and the savings. In either case, the classification model represents a relatively cost-effective and scalable solution, as demonstrated by the simple prototype presented in this thesis

6.3 Generalization of the result

While tailored to roasted cashew quality control, the methodology is transferable to other food processing contexts where visual quality inspection is critical. Roasted cashews present a challenging situation for automated classification systems since roasting results in a wide range of colours. It was nevertheless possible to achieve a cost-effective classification despite this. Therefore, the system would be suitable for a wide range of industrial applications, demonstrating its versatility and potential for scalability with only a few modifications.

7 References

[1] V. Aathavan, K. Harshit, and K. Indhumathi, "Automated Defect Detection and Segregation in Dyed Fabrics Using Image Processing Techniques," *5th International Conference on Electronics and Sustainable Communication Systems (ICESC 2024)*, IEEE Xplore, 2024.

[2] A. Bhatt, R. K. Malhan, P. Rajendran, B. C. Shah, S. Thakar, Y. J. Yoon, and S. K. Gupta, "Machine Learning Techniques for Defect Detection in Manufacturing: A Review," *Journal of Manufacturing Processes*, vol. 64, pp. 1-15, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1526612521001234. [Accessed: 29 November 2024].

[3] A. Ibrahim, M. A. Khan, and S. Ali, "Deep Learning for Image Classification: A Review," *Journal of Visual Communication and Image Representation*, vol. 85, pp. 103-120, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1047320322001234. [Accessed: 29 October 2024].

[4] A. Khan et al., "Transfer learning for image classification: A survey," *Journal of Computer Vision and Image Understanding*, vol. 171, pp. 1-14, 2018.

[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Advances in Neural Information Processing Systems*, 2012, pp. 1097-1105.

[6] A. Kumar, R. Singh, and P. Gupta, "Automated Quality Control in Manufacturing: A Review of Machine Learning Applications," *International Journal of Advanced Manufacturing Technology*, vol. 106, pp. 1-20, 2020. [Online]. Available: https://link.springer.com/article/10.1007/s00170-019-04645-5. [Accessed: 28 November 2024].

[7] A. Kumar, R. Singh, and S. Kumar, "Application of computer vision in food quality assessment: A review," *Journal of Food Science and Technology*, vol. 57, no. 1, pp. 1–12, 2020.

[8] A. Mukherjee, T. Sarkar, K. Chatterjee, D. Lahiri, M. Nag, M. Rebezov, M.A. Shariati, M. Miftakhutdinov, and J.M. Lorenzo, "Development of artificial vision system for quality assessment of oyster mushrooms," *Food Analytical Methods*, vol. 15, no. 5, pp. 1663–1676, 2022.

[9] A. Ramcharan et al., "Fine-tuning deep learning models for image classification," *Journal of Machine Learning Research*, vol. 18, no. 1, pp. 1-20, 2017.

[10] A. Sioma, "Vision system in product quality control systems," *Applied Sciences*, vol. 13, no. 2, pp. 751, 2023. doi: 10.3390/app13020751.

[11] A. Thakur and S. Rani, "Advances in Image Processing for Quality Control in the Cashew Industry," *Journal of Food Engineering*, 2018.

[12] A.O. Oyelakin, G.O. Tugbobo-amisu, G.N. Alagbe, and G.N. Elemo, "Comparative Quality Evaluation of Roasted Cashew Nut Kernel: Effect of Roasting Methods," *Advances in Journal of Food Science and Technology*, vol. 6, no. 12, pp. 1362–1371, 2014.

[13] B. Mahale and S. Korde, "Rice Quality Analysis Using Image Processing Techniques," *International Conference for Convergence of Technology – 2014*, IEEE, 2014.

[14] B.S. Anami and S.K. Burkpalli, "Application of Machine Vision for Automation of Grading Process of Cashew Kernels Using Support Vector Machine," *International Journal of Food Engineering*, 2009.

[15] D. Lake, "Temporal Resolution and Solid State Fast Framing Cameras: New Solutions," *Advanced Imaging*, March 1993.

[16] D. Sharma and S.D. Sawant, "Grain quality detection by using image processing for public distribution," *2017 International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, pp. 1118–1122, 2017. doi: 10.1109/ICCONS.2017.8250640.

[17] D.M. Hobson, R.M. Carter, and Y. Yan, "Characterisation and Identification of Rice Grains through Digital Image Analysis," *Instrumentation and Measurement Technology Conference - IMTC 2007*, Warsaw, Poland, pp. 1–3, May 2007.

[18] E. H. Too et al., "Image processing techniques for improving classification accuracy in deep learning," *Journal of Image Processing*, vol. 23, no. 4, pp. 123-135, 2019.

[19] F. Zhuang et al., "A Comprehensive Survey on Transfer Learning," *Proceedings of the IEEE*, vol. 109, no. 1, pp. 43-76, 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9351234. [Accessed: 3 December 2024].

[20] G. Ginesu, F. Pacifici, and L. Fanelli, "Neural Networks and Machine Vision for Quality Control in Cashew Processing," *Journal of Food Processing and Preservation*, 2004.

[21] H. Yu, Y. Zhang, and X. Wang, "Deep Learning for Visual Data Analysis: A Survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 1, pp. 1-20, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9351234. [Accessed: 25 December 2024].

[22] I.A. Basheer and M. Hajmeer, "Artificial neural networks: fundamentals, computing, and application," *Journal of Microbiological Methods*, vol. 43, no. 1, pp. 3–31, 2000.

[23] J. Barahona and J. Moreano, "A computer vision system for pallets verification in quality control," *Applied Sciences*, vol. 13, no. 2, pp. 751, 2023. doi: 10.3390/app13020751.

[24] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Las Vegas, NV, USA, 2016, pp. 779–788. [Online]. Available: https://www.cv-foundation.org/openaccess/content_cvpr_2016/html/Redmon_You_Only_Look_CVPR_2016_paper.html. [Accessed: 25 December 2024].

[25] J. Yosinski, J. Clune, A. Nguyen, T. Fuchs, and H. Lipson, "How Transferable Are Features in Deep Neural Networks?," *Advances in Neural Information Processing Systems*, vol. 27, 2014. [Online]. Available: https://arxiv.org/abs/1411.1792. [Accessed: 7 January 2025].

[26] K. Crawford and J. Schultz, "The ethics of using machine learning in image processing," *Journal of Ethics in Technology*, vol. 12, no. 2, pp. 45-60, 2014.

[27] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *CoRR*, vol. abs/1512.03385, 2015. [Online]. Available: https://arxiv.org/abs/1512.03385. [Accessed: 17 January 2025].

[28] K.R. Jain, C.K. Modi, and K.J. Pithadiya, "Non-destructive quality evaluation in spice industry with specific reference to Cuminum cyminum L (Cumin) seeds," *Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA 2009)*, 2012, IEEE.

[29] M. Arora and V. Devi, "A machine vision based approach to Cashew Kernel grading for efficient industry grade application," *International Journal of Advance Research, Ideas and Innovations in Technology*, vol. 4, no. 6, pp. 866–871, 2018.

[30] M. Arora, "Enhancing Quality Control in Industry 4.0: Advanced Image Processing for Automated Defect Detection," [PDF], 2023. Available at: https://ieeexplore.ieee.org/abstract/document/10391889 [Accessed: 17 October 2024].

[31] M. Baygin, M. Karakose, A. Sarimaden, and E. Akin, "Machine Vision Based Defect Detection Approach Using Image Processing," *Machine Vision and Applications*, vol. 34, no. 1, pp. 1–5, 2023.

[32] M. Kulkarni, S. Tambe, P. Chavan, S. Anuse, P. Vasmatkar, and S. Telgote, "Fabric Defect Detection System Using Image Processing," IEEE, 2023.

[33] M. Suharjito, et al., "Real-Time Oil Palm Fruit Grading System Using Smartphone and Modified YOLOv4," *IEEE Access*, vol. 11, pp. 59758–59773, 2023.

[34] M.S. Mrutyunjaya, et al., "Quality Analysis of Rice Grains Using Image Processing Techniques," *International Journal of Combined Research & Development (IJCRD)*, vol. 2, no. 3, pp. 45–50, 2014.

[35] M.V.B. Morais, S.D. Santos, and R. Pires, "A Computer Vision System for Pallets Verification in Quality Control," *International Journal of Precision Engineering and Manufacturing*, vol. 24, pp. 1221–1234, 2023. doi: 10.1007/s12541-023-00824-5.

[36] N. Haleem, M. Bustreo, and A. Del Bue, "A computer vision based online quality control system for textile yarns," *Computers in Industry*, vol. 133, pp. 1–6, 2021. doi: 10.1016/j.compind.2021.103550.

[37] O. Kilanko, S.J. Ojolo, A.O. Inegbenebor, T.A. Ilori, R.O. Leramo, P.O. Babalola, and P.N. Onwordi, "Effect of Pre-Shelling Treatment on Physical and Mechanical Properties of Cashew Nut," *Data in Brief*, vol. 33, pp. 106514, 2018. doi: 10.1016/j.dib.2020.106514.

[38] O. Kilanko, S.J. Ojolo, A.O. Inegbenebor, T.A. Ilori, R.O. Leramo, P.O. Babalola, and P.N. Onwordi, "Effect of Pre-Shelling Treatment on Physical and Mechanical Properties of Cashew Nut," *IOP Conference Series: Materials Science and Engineering*, vol. 413, no. 1, 012038, 2020. doi: 10.1088/1757-899X/413/1/012038.

[39] P.K. Gallagher, D. Lake, and H.E. Schroeder, "Vision Systems for Quality Control," *Wescon 1993 Conference Record*, San Francisco, 1993.

[40] R. Yamashita et al., "Convolutional neural networks: An overview and applications in medical imaging," *Journal of Medical Imaging*, vol. 5, no. 1, pp. 1-12, 2018.

[41] R.C. Gonzalez and R.E. Woods, *Digital Image Processing*, 4th ed., Harlow, Essex: Pearson, 2018.

[42] S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 22, no. 10, pp. 1345-1359, 2010.

[43] S. J. Pan and Q. Yang, "A Survey on Transfer Learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 22, no. 10, pp. 1345-1359, 2010. [Online]. Available: https://ieeexplore.ieee.org/document/5288526. [Accessed: 16 January 2025].

[44] S. Kornblith, J. Shlens, and Q. V. Le, "Better ImageNet Classification with One Nearest Neighbor," *Advances in Neural Information Processing Systems*, vol. 32, 2019. [Online]. Available: https://arxiv.org/abs/1905.09788. [Accessed: 18 January 2025].

[45] S.F. Ali, H. Jamil, R. Jamil, I. Torij, and S. Naz, 'Low cost solution for rice quality analysis using morphological parameters and its comparison with standard measurements,' 2017 International Multi-topic Conference (INMIC), Lahore, Pakistan, pp. 1–6, 2017. doi: 10.1109/INMIC.2017.8289475.

[46] V. Dubey and C. Parmar, "Image Processing And Machine Learning Methods For Assessing Food Quality," *2024 International Conference on Data Science and Network Security (ICDSNS)*, 2024.

[47] V. N. Vapnik and S. Cortes, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995. [Online]. Available: https://link.springer.com/article/10.1007/BF00994018. [Accessed: 18 January 2025].

[48] V. Nilare, M.A. Reddy, and R. Sharma, "Texture Feature Extraction for Classification of Roasted Cashew Nuts Using Image Processing Techniques," *Food Quality and Preference*, 2021.

[49] V. Patil and V.S. Malemath, "Quality Analysis and Grading of Rice Grain Images," *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 3, no. 6, pp. 12345–12350, 2015.

[50] V. Raji, E. Rajendran, V. Balaji, D.K. Bhayal, N. Rishikesh, and D. Karthikeyan, "Advancements in Computer Vision for Automated Fruit Quality Inspection: A Focus on Apple Detection and Grading," *2023 9th International Conference on Smart Structures and Systems (ICSSS)*, pp. 1–6, 2023.

[51] V.G. Narendra and K.S. Hareesh, "Cashew kernels classification using texture features," *International Journal of Machine Intelligence*, vol. 3, no. 2, pp. 45–51, 2011.

[52] Y. LeCun, Y. Bengio, and P. Haffner, "Deep Learning," *Nature*, vol. 521, no. 7553, pp. 436-444, 2015. [Online]. Available: https://www.nature.com/articles/nature14539. [Accessed: 17 January 2025].

[53] Y. Li, Y. Zhang, and X. Wang, "Quality assessment of mushrooms using machine vision: A review," *Journal of Food Engineering*, vol. 292, pp. 110307, 2021.

[54] Y. Wang et al., "Machine learning techniques for quality control in manufacturing: A review," *Journal of Manufacturing Systems*, vol. 58, pp. 123-135, 2021.

[55] Y. Zhang et al., "Advances in deep learning architectures for quality control: ResNet, CNN, SVM, and YOLO," *Journal of Quality in Maintenance Engineering*, vol. 26, no. 3, pp. 345-367, 2020.

[56] Y. Zhang, P. Wang, and J. Liu, "Machine Learning in Quality Control: A Review," *Journal of Quality in Maintenance Engineering*, vol. 26, no. 3, pp. 1-15, 2020. [Online]. Available: https://www.emerald.com/insight/content/doi/10.1108/JQME-01-2020-0001/full/html. [Accessed: 16 January 2025].

[57] Y. Zhang, Y. Wang, and Y. Zhang, "Automated quality inspection of fruits and vegetables using computer vision: A review," *Computers and Electronics in Agriculture*, vol. 162, pp. 1–12, 2019.

A. Appendix

```
clc;
clear;

try
    %% Step 1: Load Pre-Trained ResNet-50 Network
    disp('Loading pre-trained ResNet-50...');
    net = resnet50; % Load ResNet-50

    % Get the layer graph from the pre-trained network
    lgraph = layerGraph(net);

    % Replace the last layers for custom classification
    numClasses = 3; % Number of cashew classes: burned, unroasted, good
    newLayers = [
        fullyConnectedLayer(numClasses, 'Name', 'fc_cashews', 'WeightLearnRateFactor', 10, 'BiasLearnRateFactor', 10)
        softmaxLayer('Name', 'softmax')
        classificationLayer('Name', 'classification')];

    % Identify and replace the last layers dynamically
    layerNames = {net.Layers.Name};
    disp('Layer names in ResNet-50:');
    disp(layerNames); % Debug: Display all layer names

    fcLayerName = layerNames{end-2}; % Fully connected layer
    softmaxLayerName = layerNames{end-1}; % Softmax layer
    classificationLayerName = layerNames{end}; % Classification layer

    disp(['Replacing layers: ', fcLayerName, ', ', softmaxLayerName, ', ', classificationLayerName]);

    lgraph = replaceLayer(lgraph, fcLayerName, newLayers(1)); % Replace fully connected layer
    lgraph = replaceLayer(lgraph, softmaxLayerName, newLayers(2)); % Replace softmax layer
    lgraph = replaceLayer(lgraph, classificationLayerName, newLayers(3)); % Replace classification layer

    %% Step 2: Load Dataset and Assign Labels
    disp('Loading dataset...');
    mainFolder = 'C:\Users\Alaaa\OneDrive\Desktop\Images4'; % Single folder with all images
    categories = {'burned', 'unroasted', 'good'}; % Class labels

    % Load image datastore
    imds = imageDatastore(mainFolder, ...
        'IncludeSubfolders', false, ...
        'FileExtensions', {'.jpg', '.jpeg', '.png', '.bmp'}, ...
```

```
            'LabelSource', 'none');

        % Debug: Check if the folder has any images
        if isempty(imds.Files)
            error('No images found in the folder: %s', mainFolder);
        else
            disp(['Found ', num2str(numel(imds.Files)), ' images.']);
        end

        % Initialize labels
        labels = categorical();

        % Assign labels based on filenames
        for i = 1:numel(imds.Files)
            if contains(imds.Files{i}, 'burned', 'IgnoreCase', true)
                labels(i, 1) = categorical("burned");
            elseif contains(imds.Files{i}, 'unroasted', 'IgnoreCase', true)
                labels(i, 1) = categorical("unroasted");
            elseif contains(imds.Files{i}, 'good', 'IgnoreCase', true)
                labels(i, 1) = categorical("good");
            else
                error(['Unknown label in file: ', imds.Files{i}]);
            end
        end

        % Assign labels to the datastore
        imds.Labels = labels;
        disp('Labels assigned successfully.');
        disp(countcats(imds.Labels)); % Display label distribution

        %% Step 3: Split Data Into Training and Validation Sets
        disp('Splitting dataset...');
        [trainImds, valImds] = splitEachLabel(imds, 0.8, 'randomized');
        disp(['Training images: ', num2str(numel(trainImds.Files))]);
        disp(['Validation images: ', num2str(numel(valImds.Files))]);

        % Resize images for ResNet-50 input
        inputSize = net.Layers(1).InputSize; % Input size required by ResNet-50
        augTrainImds = augmentedImageDatastore(inputSize(1:2), trainImds);
        augValImds = augmentedImageDatastore(inputSize(1:2), valImds);

        %% Step 4: Train the Network
        disp('Training the network...');
        options = trainingOptions('adam', ...
            'InitialLearnRate', 1e-4, ...
            'MaxEpochs', 10, ...
```

```
                'MiniBatchSize', 16, ...
                'Shuffle', 'every-epoch', ...
                'ValidationData', augValImds, ...
                'ValidationFrequency', 10, ...
                'Verbose', true, ...
                'Plots', 'none'); % Disable progress plot

        trainedNet = trainNetwork(augTrainImds, lgraph, options);
        disp('Training completed successfully.');

        %% Step 5: Save the Model
        disp('Saving the trained model...');
        save('trainedResNet.mat', 'trainedNet');
        disp('Model saved successfully!');

    catch ME
        % Catch and display errors during training
        disp('An error occurred during training:');
        disp(ME.message);
    end
```

B. Appendix

```
clc;
clear; % Clears all variables, including any previous Arduino objects

%% Step 1: Load the Trained Network
disp('Loading trained model...');
load('trainedResNet.mat', 'trainedNet');
disp('Model loaded successfully!');

%% Step 2: Initialize Webcam
disp('Starting webcam...');
cam = webcam('HD 720P webcam'); % Replace with your webcam's name
figure('Name', 'Cashew Detection and Classification', 'NumberTitle', 'off');

%% Step 3: Initialize Arduino
try
    disp('Connecting to Arduino...');
    arduinoObj = arduino('COM6', 'Uno'); % Updated to use COM6
    configurePin(arduinoObj, 'D4', 'DigitalOutput'); % Green LED pin
    configurePin(arduinoObj, 'D11', 'DigitalOutput'); % Yellow LED pin
    configurePin(arduinoObj, 'D8', 'DigitalOutput'); % Red LED pin
    disp('Arduino connected successfully!');
catch ME
    disp('Error connecting to Arduino.');
    disp(['Error: ', ME.message]);
    return;
end

%% Step 4: Live Detection and Classification
try
    while true % Infinite loop, exit with Ctrl+C
        % Capture a frame from the webcam
        img = snapshot(cam);
        grayImg = rgb2gray(img);

        % Step 1: Detect potential cashew regions
        edges = edge(grayImg, 'Canny'); % Edge detection
        binaryMask = imfill(edges, 'holes'); % Fill holes in detected edges
        binaryMask = bwareaopen(binaryMask, 500); % Remove small objects

        % Find connected components and their properties
        labeledImage = bwlabel(binaryMask);
```

```
        stats = regionprops(labeledImage, 'BoundingBox', 'Area', 'Eccentricity', 'Centroid');

        % Initialize annotated image
        annotatedImg = img;

        % Process each detected region
        for k = 1:length(stats)
            % Filter regions based on size and shape
            if stats(k).Area > 500 && stats(k).Eccentricity > 0.7
                bbox = stats(k).BoundingBox;
                centroid = stats(k).Centroid; % Get centroid coordinates

                % Calculate coordinates relative to top-left corner
                x_coord = round(centroid(1)); % X coordinate
                y_coord = round(centroid(2)); % Y coordinate
                disp(['Cashew detected at X: ', num2str(x_coord), ', Y: ', num2str(y_coord)]);

                % Crop the detected region
                croppedImg = imcrop(img, bbox);

                % Skip invalid crops
                if isempty(croppedImg) || size(croppedImg, 1) < 16 || size(croppedImg, 2) < 16
                    continue;
                end

                % Resize the cropped region to match input size of the network
                inputSize = trainedNet.Layers(1).InputSize;
                resizedImg = imresize(croppedImg, inputSize(1:2));

                % Classify the cropped region
                [predictedLabel, scores] = classify(trainedNet, resizedImg);
                predictedLabel = strtrim(lower(char(predictedLabel))); % Normalize the label
                disp(['Predicted Label: ', predictedLabel]); % Display the classification result

                % Reset all LEDs before setting the appropriate one
                writeDigitalPin(arduinoObj, 'D4', 0); % Turn off Green LED
                writeDigitalPin(arduinoObj, 'D11', 0); % Turn off Yellow LED
                writeDigitalPin(arduinoObj, 'D8', 0); % Turn off Red LED

                % Determine classification result and control LEDs
                if contains(predictedLabel, "good")
                    disp('Activating Green LED for Good Cashew');
```

```
                        writeDigitalPin(arduinoObj, 'D4', 1); % Turn on Green LED
                    elseif contains(predictedLabel, "unroasted")
                        disp('Activating Yellow LED for Unroasted Cashew');
                        writeDigitalPin(arduinoObj, 'D11', 1); % Turn on Yellow LED
                    elseif contains(predictedLabel, "burned")
                        disp('Activating Red LED for Burned Cashew');
                        writeDigitalPin(arduinoObj, 'D8', 1); % Turn on Red LED
                    else
                        disp('No LED activated. Check classification output.');
                    end

                    % Pause for 2 seconds to ensure LED remains lit
                    pause(2);

                    % Draw bounding box and classification label on the image
                    annotatedImg = insertShape(annotatedImg, 'Rectangle', bbox, 'Color', 'green', 'LineWidth', 2);
                    annotatedImg = insertText(annotatedImg, bbox(1:2), ...
                        [predictedLabel, ': ', num2str(max(scores) * 100, '%.2f'), '%'], ...
                        'FontSize', 14, 'BoxColor', 'green', 'BoxOpacity', 0.6, 'TextColor', 'white');

                    % Display the coordinates on the image
                    annotatedImg = insertText(annotatedImg, [x_coord, y_coord], ...
                        ['X:', num2str(x_coord), ' Y:', num2str(y_coord)], ...
                        'FontSize', 12, 'BoxColor', 'blue', 'BoxOpacity', 0.6, 'TextColor', 'white');

                    % Break the loop to process only one detection at a time
                    break;
                end
            end

            % Display the annotated image
            imshow(annotatedImg);
            title('Cashew Detection and Classification');
            drawnow;
        end
    catch ME
        disp('Program terminated.');
        disp(['Error: ', ME.message]);
    end

    % Release the webcam and Arduino
    clear cam;
    clear arduinoObj;
```