

T.R.
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INSTITUTE OF GRADUATE STUDIES
DEPARTMENT OF AGRICULTURAL MACHINERY AND
TECHNOLOGIES ENGINEERING



**DETECTION AND CLASSIFICATION OF BROWN
MARMORATED STINK BUG (*HALYOMORPHA HALYS*)
DAMAGE IN HAZELNUT USING IMAGE PROCESSING AND
DEEP LEARNING TECHNIQUES**

Ph.D. Thesis

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.ACCEPTANCE AND APPROVAL OF THE THESIS

The study entitled “**DETECTION AND CLASSIFICATION OF BROWN MARMORATED STINK BUG (*HALYOMORPHA HALYS*) DAMAGE IN HAZELNUT USING IMAGE PROCESSING AND DEEP LEARNING TECHNIQUES**” prepared by **Omsalma Alsadig Adam GADALLA**, and supervised by **Prof. Dr. Y. Benal ÖZTEKİN**, was found successful and unanimously accepted by committee members as Ph.D. thesis, following the examination on the date 6.2.2023.

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Omsalma Alsadig Adam GADALLA

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ÖZET

GÖRÜNTÜ İŞLEME VE DERİN ÖĞRENME TEKNİKLERİ KULLANARAK FINDIKTA KAHVERENGİ KOKARCA (*HALYOMORPHA HALYS*) ZARARININ BELİRLENMESİ VE SINIFLANDIRILMASI

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Fındığın kalite kontrolü, dünyanın birçok bölgesinde, özellikle de dünyanın en büyük fındık üreticisi olan Türkiye'de büyük bir problem kaynağıdır. Bu çalışma, görüntü işleme ve derin öğrenme tekniklerini kullanarak Kahverengi Kokarca ile enfekte olmuş ve sağlıklı fındıkları birbirinden ayırarak belirlemek ve sınıflandırmak amaçlanmıştır.

Kahverengi Kokarcalı fındık örnekleri, uzmanlar tarafından 2021 üretim döneminden elde edilmiştir. Fındık görüntülerini yakalamak için Guppy Pro CCD kamera tabanlı görüntü alma sistemi kullanılmıştır. Derin ve makine öğrenme modellerini eğitmek için toplam olarak 4540 RGB fındık görüntüsü alınmıştır.

Fındık görüntülerinin arka plandan çıkarılması için görüntü bölüntüleme işlemi Eşikleme tekniği kullanılarak gerçekleştirilmiştir. Fındık moment özellikleri, geleneksel makine öğrenme modellerini eğitmek için kullanılmak üzere RGB ve $l^*a^*b^*$ renk çıkarılmıştır. Ayrıca, Boruta seçim yöntemi kullanılarak en ayırt edici öznelik seti seçilmiştir.

Derin öğrenme modeli için, üç evrişim katmanı, üç maksimum havuzlama katmanı, bırakma ve tam bağlantılı katmandan oluşan bir Evrişimsel Sinir Ağı (ESA) modeli oluşturulmuştur. Rastgele Orman, Destek Vektör Makinesi, Lojistik Regresyon, Naive Bayes ve Karar Ağacı dâhil olmak üzere geleneksel makine öğrenme modelleri, bir kez tüm özelliklerle ve diğeri yalnızca seçilmiş özelliklerle olmak üzere iki kez eğitilmiştir. Genel doğruluk, karışıklık matrisinin istatistiksel özellikleri ve model eğitim süresinin tümü, modelin sınıflandırma performansını karşılaştırmak için hesaplanmıştır. Kahverengi Kokarcalı fındık sınıflandırmasında en verimli modeli belirlemek için geleneksel makine öğrenme modelleri, derin evrişimli sinir ağı modelinin performansı ile karşılaştırılmıştır.

Sonuç olarak 24 özellik arasından en ayırt edici özellik arasında sadece yedi tane renk özelliği belirlenmiştir. Tüm çıkartılmış özellikler kullandıktan sonra Destek Vektör Makinesi modeli kullanılarak %98.75 ile en yüksek sınıflandırma doğruluğu elde edilmiştir. Sadece seçilen özellikler kullanıldığında Rastgele Orman ve Lojistik Regresyon modellerinin performansı sırasıyla %97.5 ve %96.25'e yükselmiştir. %98.83 genel doğruluk ve 0.038 sınıflandırma hatası ESA modeli ile elde edilmiştir. Bu doğrulukla, ESA gerçek zamanlı fındık sınıflandırma sistemlerinde faydalı ve uygun olarak önerilmektedir.

Anahtar Sözcükler: GuppyPro, Evrişimsel sinir ağı, Geleneksel makine öğrenme, Destek vektör makinesi, BorutaPy

ABSTRACT

DETECTION AND CLASSIFICATION OF BROWN MARMORATED STINK BUG (*HALYOMORPHA HALYS*) DAMAGE IN HAZELNUT USING IMAGE PROCESSING AND DEEP LEARNING TECHNIQUES

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Quality control of hazelnuts is a major concern in many regions across the world, but particularly in Turkey as the world's largest hazelnut producer. Using image processing and deep learning techniques, this study intended to detect and classify healthy hazelnuts and hazelnuts infected with the Brown Marmorated Stink Bug.

Infected hazelnut samples were collected from the 2021 production period by experts. A Guppy Pro CCD camera-based image acquisition system was used to capture hazelnut images. A total of 4540 RGB hazelnut images were captured to train deep and machine learning models.

Image segmentation process was carried out to subtract hazelnut images from the background using the Threshold technique. Moment features were extracted from RGB and $l^*a^*b^*$ spaces to be used to train traditional machine learning models. Furthermore, the most relevant and discriminative feature set was selected using the Boruta feature selection method.

For deep learning, a Convolutional Neural Network (CNN) model of three convolutional layers, three max-pooling layers, drop out, and a fully connected layer was constructed using RGB and Grayscale hazelnut images with different DL parameters. Traditional machine learning models including Random Forest, Support Vector Machine, Logistic Regression, Naive Bayes, and Decision Tree were trained twice, once with all features and another with the select feature set only. The overall accuracy, statistical characteristics of the confusion matrix, and model training time were all calculated to compare the model's performance. Traditional machine learning models performances were compared to the performance of CNN model to determine the most efficient model in BMSB-infested hazelnut classification.

As a result, only seven moment features were identified as the most discriminative features out of 24 features. The SVM model with all feature vectors had the greatest classification accuracy of 98.75 %. When only the selected features were employed, the performance of Random Forest and Logistic Regression models improved to 97.5 and 96.25 %, respectively. With an overall accuracy of 98.83 % and a classification error of 0.038, the CNN model was able to classify hazelnut images, which could be a useful performance in real-time hazelnut classification systems.

Keywords: GuppyPro, CNN, Traditional machine learning, Support vector machine, BorutaPy.

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SYMBOLS AND ABBREVIATIONS

BMSB	: Brown Marmorated Stink Bug
CCD	: Charge Couple Device
RF	: Random Forest
LR	: Logistic Regression
NB	: Naive Bayes
DT	: Decision Tree
PUFA	: Poly Unsaturated Fatty Acids
GAP	: Global Average Pooling
MLP	: Muti-layer Perceptron
FC	: Fully Connected
ROI	: Regions of Interest
ERR	: Error Rate
CCV	: Color Coherence Vector
CVS	: Computer Vision Systems
MVS	: Machine Vision System
GRU	: Gated recurrent units
DOF	: Degree of Freedom

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1. INTRODUCTION

Hazelnut (*Corylus avellana* L.) is a seasonal fruit belonging to the family of Betulaceae of Fagales order (Aydinoglu, 2010). Hazelnut grows in various places of the world such as USA, Italy, China, and Spain, while Turkey produces the majority of commercial hazelnuts (FAOSTAT, 2019). Hazelnuts are extensively utilized in the confectionery industry due to their flavor and taste. They have a great nutritional value because they contain a variety of constituents, primarily lipids, carbohydrates, proteins, sugar, and dietary fibers (Memoli et al., 2017). However, many factors influence hazelnut production and quality around the world. Temperature, humidity, mold, and pests all have a significant impact on hazelnut quality and yield.

Multiple guidelines have been characterized by providing countries and regions to ensure an appropriate standard of quality. They specify the minimum fruit quality requirements in terms of area, aspect, and hidden flaws. Other specifications, such as those associated with hazelnut quality and production location can be found. The much more recent international standard has been established by the Organization of Economic Cooperation and Development (OECD, 2011). It specifies the standards for the quality of in-shell hazelnuts and hazelnut kernels intended to consume directly or as food. For hazelnuts shells, only minor surface damages are permitted, have to be free of foreign material, and free of dark spots and stains influencing more than 25% of the shell's surface. On the other hand, the minimum requirements for the hazelnut kernel are; hazelnut kernels have to be free from molds, kernels should fill at least 50% of the shell cavity or be sufficiently developed, and free from blemishes and stains affecting more than 25% of the surface of the shell. Additionally, the entire nut must be free of mold, living insects, insect infestation damage, and any foreign odor or taste.

One of the most serious and recent defects facing Turkish hazelnut productions is hazelnut defection generated by the Brown Marmorated Stink Bug (BMSB). During the development period, the BMSB penetrates hazelnut and feeds on the nuts. The damage that occurs inside hazelnut rises as the pest grows, and even a minor attack might jeopardize hazelnut quality. When the insect feeds, saliva is sent down one maxillary stylet while food is sucked up via another (Mitchell, 2018). Through the feeding process, the fruit's skin is damaged, and enclosing tissue is removed, resulting in serious injuries (Short, 2010). Depending on where the insect

feeds on the fruits, they can produce blanks, shrink or corking incidents, or injuries on the kernels (Wiman, 2021). Hazelnut kernel infected with the BMSB varies in their infection severity level. Due to the pest's different behaviors, the external symptoms could appear as very clear dark skin injuries or corking damage and discoloration or very small entry points resulting from the insertion of the mouthpart (Short, 2010). Figure 1.1 illustrates the primary damage symptoms associated with kernel feeding by BMSB on hazelnut kernels. The insect has not been sufficiently managed yet, and the consequent loss from this insect is sometimes hidden or not visually detectable on the fruit surface (Saruhan, 2010).



Figure 1.1. Primary damage symptoms associated with kernel feeding by BMSB : a. healthy kernel (in shell); b. blank nut (empty shell); c. shriveled kernel; d. corking damage (Hedstorm et al., 2014)

BMSB as a polyphagous species also threatens many agricultural products such as apple, pear, peach, kiwi, corn, tomato, pepper, and cereals which are widely grown in Turkey. Moreover, the pest is generally seen in the Black Sea Region; but it can be distributed in other regions. Indeed, the distribution of the pest in other countries has been examined and the results showed that in a short time the pest spread across the entire region (Tuncer et al., 2018). According to the pest distribution areas and ecological demands, the risk map of the pest shows that the pest can spread to other parts of the country, especially the Black Sea Region due to the favorable climatic conditions (Haye et al. 2015; Kistner et al., 2017).

To control this pest, multiple management processes have been applied such as mechanical, chemical, and biological. However, sufficient results have not been achieved yet. On the other hand, to control this pest with the classical biological method, numerous studies have been carried out and an accepted base has been created. A study carried out in China (the homeland of the pest) identified that the egg parasitoid *Trissolcus japonicus* (Ashmead) is the most effective way to control the pest (Zhu and ark., 2016). Considering the economic importance of the pest, controlling the pest population using the available methods is very important. Moreover, while the short-term control methods (chemical, mechanical, and biotechnical) are applied, working on long-term classical biological control methods is necessary to improve the final value and quality of the product.

Economically, in the last few years; the pest caused damages of 200 Million Dollars in 2017, 300 Million in 2018, and about 500 Million in 2019 for the total hazelnut production in Turkey which negatively affected the hazelnut export value (Anonymous, 2019) (Figure 1.2). Emin (2020), stated that 20% of hazelnut damage was due to brown skunk infestation and this percentage is expected to reduce hazelnut quality and productivity by 50%. To come over these challenges, post-harvest quality control operations represent an important issue that can significantly improve hazelnut quality (Anonymous, 2020).

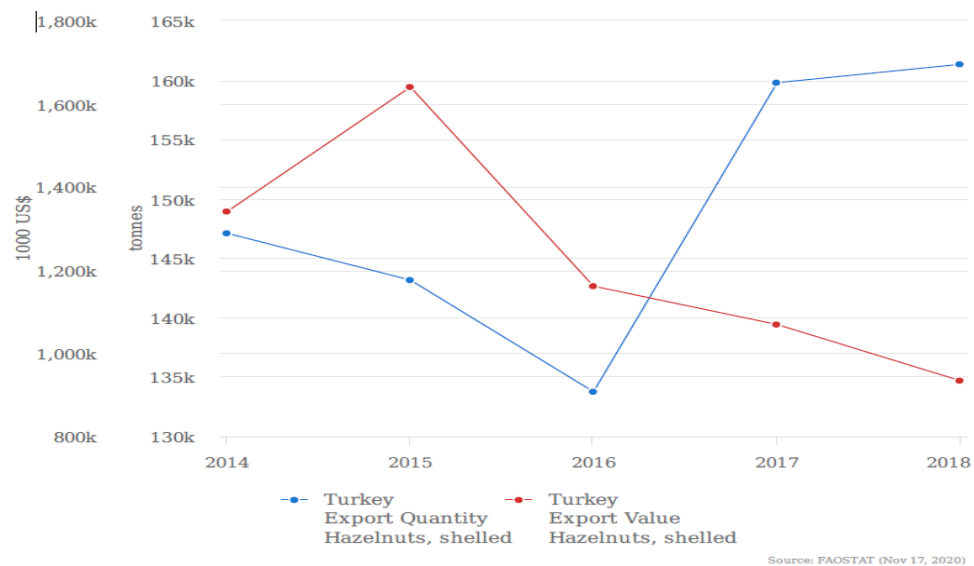


Figure 1.2. Hazelnut quantity and export value, Turkey (2014-2018) (FAOSTAT, 2018)

The process of classifying hazelnut into hazelnut infected by a brown skunk and healthy as a post-harvest operation is a very important quality control factor and affects the quality of hazelnut significantly. But it is surprising that in most hazelnut processing factories the process of hazelnut quality estimation is still mostly performed manually by trained workers. Generally, the method is time-consuming, costly, unhealthy, destructive, and subjective (Delila, 2017). The mechanical systems that used for hazelnut classification, classify hazelnut depending on the hazelnut's external properties such as; shape, and size. In addition, today the machines that classify hazelnut operate based on the properties that have already been identified before. This means they may fail to detect new diseases and defects, defect with similar characteristics, visually unseen and internal defects.

Post-harvest processing operations are commonly used to overcome these concerns. Due to the highly perishable nature of hazelnut fruit, hazelnut processing industries face significant postharvest challenges (Moscetti et al., 2014). During post-harvest processing operations the primary method for detecting defects in the fruits is visual inspection, which includes sample preparation, consecutive sampling methods, visual and sensory characteristics examination, and dismisses nut classification. This technique, which is focused on visual and organoleptic evaluation takes time and trained workers for accurate nuts classification. Other methods have been studied to develop smart inspection techniques for inspecting hazelnut quality characteristics. Machines supported by mechanical approaches such as calibrator devices are used to characterize the dimensions of the shell and empty nuts. These machines are advantageous for the pre-treatment of the products, but they are not quality management mechanisms. A unique approach for detecting blank hazelnuts has been proposed, depending on an examination of the acoustic signal generated by the nut's action on a steel surface (Onaran et al., 2005).

There is no satisfactory technique for detecting insect pests in hazelnuts rapidly after harvest. Under existing production procedures, the most common technique for detecting defected hazelnuts involves manual selection, which is time-consuming, subjective, labor-intensive, and does not recognize hazelnut with very low severity levels. As a result, there is a need to raise the level of subjectivity, stability and effectiveness in assessing hazelnut quality. The digital image processing approaches and artificial intelligence methods can play a significant role in this

endeavor as the method offers the potential for high speed, non-destructive classification of hazelnut (Yadhunath et al., 2022). Machine vision systems are suitable for inspecting rigid and predefined objects. However, visual characteristic of agricultural products such as color, shape, texture are difficult for machine vision system to discern. Artificial intelligence algorithms such as artificial neural network have presented to be powerful in dealing with the type of problems that require interpolation of huge amount of data.

Applying machine vision with pattern recognition techniques, machine learning, and deep learning algorithms to identify hazelnuts has numerous advantages over traditional sorting methods. The essential information can be acquired from the hazelnut using several types of sensors and sent to a computer, where it can be decoded and classified. Multiple image processing methods can be employed to capture informative properties and information from input data for enhanced categorization and recognition performance in image processing.

No pattern recognition deep learning or machine learning-based system has been employed for BMSB-defected hazelnut categorization, according to literature searches and direct conversation with hazelnut processing facilities. For accurate hazelnut categorization, research must be undertaken to find appropriate image features and proper classification algorithms.

The primary goal of this research was to determine the feasibility of separating healthy hazelnut from BMSB-defected hazelnut using image processing and deep learning techniques. The specific objectives of this study were:

- To investigate the feasibility of classifying hazelnut into it is two classes by designing a suitable convolution neural network deep learning-based classifier.
- To investigate the classification performance of the convolutional neural network under RGB and Gray-scale color spaces of hazelnut images, using different combinations of deep learning parameters.
- To investigate the potential of different image-extracted features for the classification of hazelnut using traditional machine learning classifiers.
- To select an appropriate pattern of features and investigate the feasibility of the selected features in hazelnut classification.

- To compare the performance of the developed models and determine an efficient classification technique.

1.1. Organization of the Other Research Chapters

The second chapter includes a review of the literature on hazelnut production in the world and Turkey. Hazelnut infestation with BMSB and the symptoms related are also presented in the chapter. As well as part of the post-harvest processes of hazelnuts and the challenges related to the operation are also included in this chapter. In the last part of the chapter, Computer Vision and Image Processing, Deep and Machine Learning concepts and their application in evaluating the quality of agricultural products are presented.

Chapter three of this work deals with the materials used and the implementation of the Computer Vision system, as well as the methodologies and the equipment utilized in this study. Chapter four is about the results of the research experiment and also includes discussions and results evaluation. Chapter five, on the other hand, generalizes the research through conclusions and recommendations. Chapter six contains a list of references. Finally, the scripts for programming are included as appendices.

2. LITERATURE REVIEW

2.1. Hazelnut

The hazelnut (*Corylus avellana* L.) is one of the world's most important food sources, with an annual production of 1125178 tons of in-shell hazelnuts. Turkey provides 776046 tons of the whole production (70%), whereas Italy provides 98530 tons of the global hazelnut production. Azerbaijan (53793 tons), the United States of America, China, Georgia, Iran, and Spain are the other minor hazelnut producers (FAOSTAT, 2019). The world hazelnut production and the main producing countries are illustrated in Figure 2.1. Hazelnuts have risen in importance over the years due to their high nutritional value as an excellent source of fats. As well as the lipid fraction that makes up the majority of hazelnuts is made up of non-polar and polar constituents (Koyuncu et al., 2005). Triacylglycerols are the most important nonpolar lipids in hazelnut oil, accounting for about all of the total nonpolar lipids. Furthermore, hazelnuts are a significant source of monounsaturated and polyunsaturated fatty acids (PUFA) (Gunes et al., 2010). These factors directly alter the plasma lipid profile in the body (Orem et al., 2008). As a result, hazelnut can be investigated further for the treatment and prevention of heart disease. Hazelnuts are commonly utilized in the confectionery sector to make baked and chocolate-based items like ice cream, as well as dairy products, and may be found in everything from cereals and bread to yogurts, soups, salads, and main courses, as well as confections (Webber, 2019).

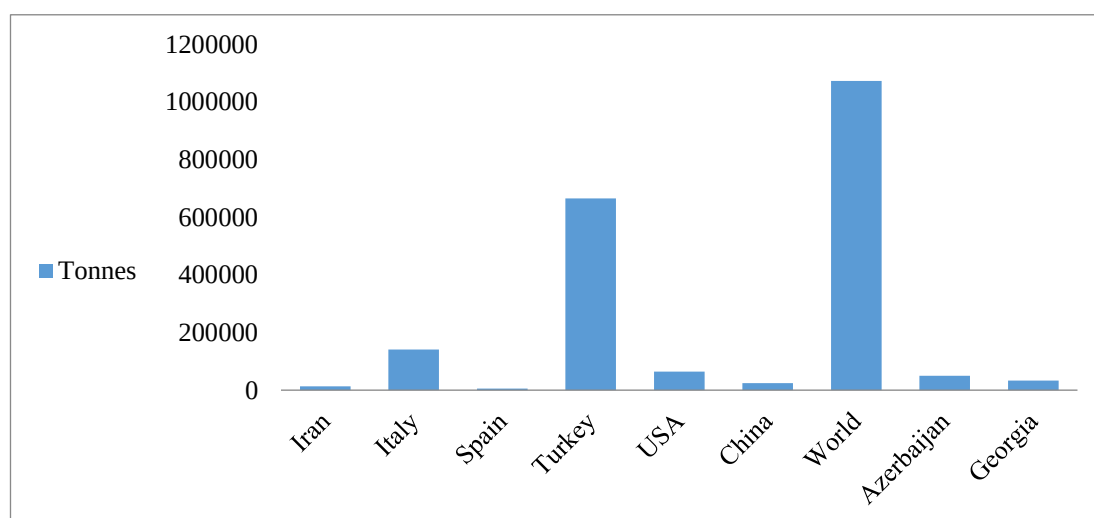


Figure 2.1. Hazelnut production (in shell) in the world and the main producing countries (FAOSTAT, 2019)

2.2. Hazelnut Production in Turkey

Turkey is thought to be the birthplace of hazelnut culture. Hazelnuts are grown in two different regions in Turkey: old and modern. The zones of Ordu, Giresun, Trabzon, Rize, and Artvin are located in the Eastern Black Sea Region. The new region covers the provinces of Samsun, Sinop, Düzce, Sakarya, Zonguldak, and Kocaeli in the Central and Western Black Sea Region (Islam, 2018) (Figure 2.2). Because of the ecosystem of the area, the Eastern Black Sea Region is ideal for hazelnut cultivation. In addition, the soil in these places is unsuited for other crops and the land is steeply sloped. Because two to three million growers (5 percent of the population) rely on hazelnut production for their livelihood, it is simple to see how important hazelnut cultivation is to the region's social and economic framework (Marti, 2004). In certain places, traditional hazelnut growing practices with intensive labor are popular. Lately, there has been a rise in knowledge of the employ of agricultural practices, as well as the establishment of new orchards.

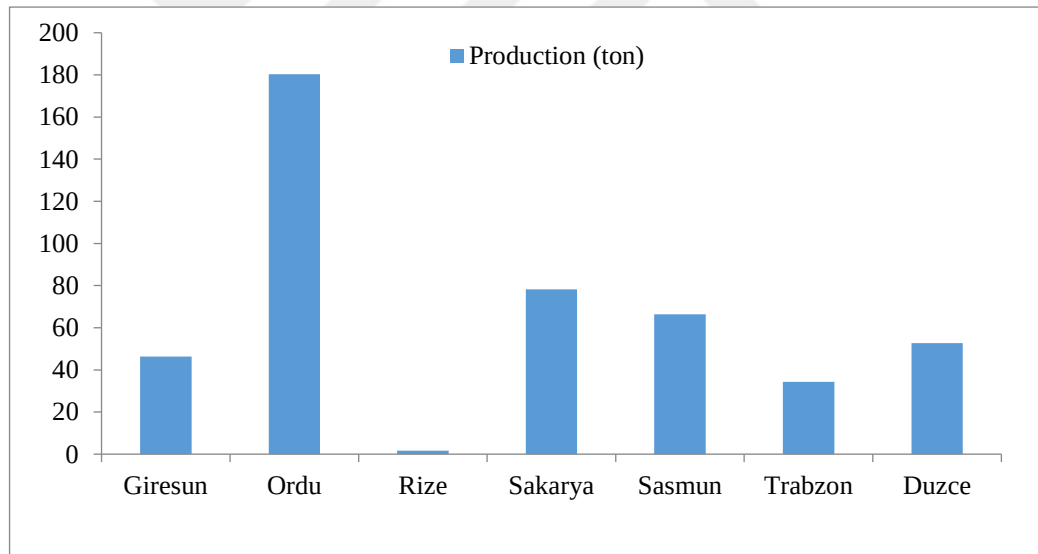


Figure 2.2. Hazelnut production in Turkey (TÜİK, 2022)

Turkey's hazelnut production areas are a mix of cultivars, but the most important is the Tombul variety (Islam and Ozgüven, 2000). As a result, Turkey has 18 conventional hazelnut types. There are 15 old registered varieties and three new registered types among these varieties. In Turkey, hazelnut cultivars are divided into three categories: round group: Allahverdi, Cavcava, Çakıldak, Foşa, Giresun melezi, Kalinkara, Kan, Kara, Kargalak, Mincane, Okay 28, Palaz, Tombul, Uzunmusa,

pointed group: Sivri, İncekara, and long group: Yuvarlak badem, Yassı badem (Islam, 2018).

2.3. Site of Orchard and Plantation

Numerous elements influence the location of the hazelnuts. Location and orientation, soil, and climate conditions are the most critical ones. A proper environment and consistent rainfall or irrigation is essential for high-quality nut production and healthy hazelnut tree growth. A pleasant summer and chilly winter constitute the ideal climate for hazelnut production. Exposed places that will be dried off by the summer wind should be addressed. Hazelnuts require a consistent temperature for fruit growth and production. Temperatures below -8°C and over $+36^{\circ}\text{C}$ are detrimental to hazelnut production and should be avoided. For optimal production, more than 700 mm of annual precipitation is necessary, dispersed throughout the year, notably in June and July. Supplemental watering may be beneficial during the establishment period. The hazelnut climate may be found in the Black Sea Region, where the relative humidity of 60% is ideal and temperatures range from 8 to 21°C (Islam et al., 2004).

2.3.1. Reproduction System of Hazelnuts

Hazelnut cultivars have a significant genetic sucking capacity. Suckers are the bottom shoots of the hazelnut tree. In Turkey, sucker (rooted plant) is the most common method of vegetative reproduction. The use of rooted suckers for reproduction is a traditional approach and they are employed as a seedling taken from hazelnut orchards with plentiful rooted stools (Tonkaz et al., 2017). The difficulty of harvesting suckers, the suckers' poor root status, varied diameter and length, and the lack of disease and pest testing are all downsides of this technique (with suckers). Producers, on the other hand, prefer to obtain seedlings due to the lower labor and cost (Islam, 2018).

2.3.2. Orchard Management

2.3.2.1. Pruning

The hazelnut plant has several stems in nature. For the production of hazelnuts, it is preferable to cut the tree so that only one main stem emerges. The major goals of hazelnut tree trimming are to increase the tree's yield and productivity, improve its health by improving vitality and producing a robust and solid structure, and make nut

harvesting easier (Vlahova, 2020). Pruning will be done over the following 2–5 years to create an enhanced leader tree with 3–5 branches. Pruning is not essential in the subsequent years until vigor begins to wane. Inadequate pruning can reduce shoot vigor and cropping capability in mature trees. Flower bud development, fruit set, productivity, and nut fruit size are all affected by excessive shadowing (Me et al., 2004).

2.3.2.2. Irrigation

Hazelnut is mainly farmed in the Eastern Black Sea part, where the climate is appropriate. Hazelnut plants required between 800-1000 mm of yearly rainfall, based on evaporation and transpiration (Ellena et al., 2012). Nevertheless, due to recent changes in numerous temperature variables and global climate change conditions, "irrigation" or "support irrigation" in hazelnut cultivation in Turkey has become unavoidable. Drought typically affects hazelnut orchards on south-facing slopes, which have low water accumulation potential and soil depth, and that significantly reduces output and component quality (Tonkaz et al., 2017).

2.3.2.3. Fertilization

Because the hazelnut plant grows well in a wide range of soil types, soil quality should not be an issue for plant development. A soil investigation or leaf analysis to identify soil quality is highly recommended before proceeding. The biological and chemical equilibrium of the soil might be harmed by incorrect fertilizer recommendations. Furthermore, sufficient nutrition is critical for both stool growth and nut establishment and growth. The main fertilizers N, P, K, and other soil elements must all be available in appropriate amounts. Nitrogen is an essential ingredient that should be added to the soil every year. The growth of the plant's branches and stools will be stunted if there is inadequate nitrogen applied (Özenc and Caliskan, 2000). Nut formation and productivity will be diminished as a result of the short and thin stool development. Some nutrients, such as Phosphorus (P), Potassium (K), Magnesium (Mg), and Zinc are useful elements (Szczypiński and Zapotoczny, 2012). A lack of these nutrients can lead to a reduction in; the establishment of buds, growth of the shoot, and hazelnut final productivity (Özkutlu et al., 2016).

2.3.2.4. Diseases and Pests

Many pests attack hazelnuts in the field and during storage operations. The nut weevil (*Balaninus nucum*) is a pest that bores into the nutshell and presents the eggs inside the kernels. The filbert weevil (*Curculio uniformis*) and the green stink bug (*Acrosternum hilare*) pests attack nuts during the developing period, while the filbert bud mite (*Phytocoptella avellanae*) destroys buds and attacks developing fruits. However, the new BMSB insect has recently become a major issue in Turkey's hazelnut industry. Because of higher temperatures and a lack of natural predators, the BMSB, which is native to Northeast Asia, has been spreading around the world in shipping containers and breeding freely (Moscetti et al., 2014).

2.4. Hazelnut Quality and Brown Marmorated Stink Bug Infestation

The most prevalent hazelnut faults, which impact the color of the kernels as well as other quality characteristics, are rotten and pest-affected kernels. Pest-defected kernels are caused immediately in the field by plant pest bites, which then become a source of microbial spoilage (Moscetti et al., 2014). Because of extremely high temperatures and a lack of natural predators, the BMSB, which is native to Northeast Asia, has been spreading around the world in shipping crates. The stink bug, which gets its name from the unpleasant chemicals it produces as a defense-first appeared in Turkey in 2017, after wreaking havoc in Georgia. The insect has since spread to at least eight Turkish cities, largely in the Black Sea Region, which provides over 70% of the total hazelnut production (Wiman, 2021).

The pest is a member of the Hemiptera order, or true insects such as aphids, cicadas, leafhoppers, and others. Adult of BMSBs are mainly 15 to 17 mm long and they are distinguished by their "shield-shaped body" and distinctive dark brown and white marbled coloration. BMSB feeds on vegetative parts like leaves and husks at first, but in later phases, they can eat the nuts directly. Regardless of the hardness or thickness of the shell, the insect's mouthparts can penetrate it and enable it to eat the kernel within (Özdemir and Tuncer, 2021). Managing BMSB has shown to be a challenging task in general. Pyrethroid treatments are most commonly employed in orchards and the effects are quite temporary. Backlight trapping and pheromone pyramid traps have had inconsistent outcomes in experiments, and no appropriate and acceptable control methods have yet been established (Nielsen, 2009).

The insect can produce blights, shrivel, or corking damage to the kernels depending on when it feeds on them (Wiman, 2021). Their mouthparts suck up material and pump saliva down one maxillary stylet when feeding (Mitchell, 2018). When feeding, the breakdown of the fruit's skin, as well as the removal of the surrounding skin, causes damage and injuries (Short., 2010). Moisture and germs such as fungal spores can enter through the lesions formed by the entrance of the mouthparts, leading to kernel or fruit mold and other problems (Mitchell, 2018).

2.4.1. Pest Monitoring

To detect BMSB, pheromone traps, visual samples, or beating trays are good detection techniques. To monitor the vegetation in the orchard it is preferred to place the traps on orchard borders, rather than in orchard interiors. Although management thresholds based on trap captures or other sampling techniques have not yet been thoroughly established, any trap captures call for a survey of the orchard to look for populations that could be harmful. Nymphs in hazelnut can serve as a warning sign of potential damage. Stink Bugs are extremely cryptic and can be challenging to find in a crop. Slow movement when scouting can be crucial for identifying nymphs without triggering a hiding or flight response. Looking for egg masses and young nymphs on the underside of leaf surfaces is important. To make a comparison of samples from different times of the season or positions, standardizing the duration of time spent visually searching for stink bugs is necessary (for instance, ten minutes). The highest pressure from the BMSB is usually appear late in the season (Aug thru Oct), and damaging levels can sometimes build much sooner. The population level at the end of the previous season, winter survival, and weather during spring are all factors affecting current season population levels (Ak et al. 2019).

2.4.2. Management

2.4.2.1. Short-Term Control Methods

Cultural and Mechanical Control

Only when there are very few trees, hand-collecting and killing egg masses, nymphs, and adults can be a successful management method; however, this approach is not feasible commercially. Exclusion netting may also be an option for home orchardists. For commercial growers and backyard orchardists, removing or

excluding adult aggregations from overwintering locations like farmhouses and outhouses may assist in decreasing local populations.

H. halys varies according to regions and they start to travel to their wintering places with the cooling of the weather (it is generally starting from October). While some of the adults overwinter in the gardens, some of them overwinter in houses, hangers, and etc. They move collectively towards places. As some of the adults enter the houses, some of them are hibernating by hiding in places such as the cracks in the walls of buildings and roofs. In such places, adults can be vacuumed or clean with an electrical vacuum, collected and destroyed.

Chemical Control

In the short term, the spread of the brown skunk in many countries mainly carried out using chemicals. However, chemical control can cause serious problems in the short and long terms. The biggest risks encountered in chemical control are the resistance of the pest, and the problems that created by pesticides in the food chain. In addition, due to the deterioration of the natural balance, some insect species that were not harmful before will transfer to harmful species. To date, many chemical preparations from different groups have been tested on *H. halys* and some of them are applied to control the insect in the field. However, in many countries despite the intensive use of chemicals, no significant success is achieved. The brown skunk in nature shows activity for a long time (8-9 months) and in agricultural areas for 5-6 months. Hence, chemicals materials (pesticides) found to be effective only for short duration which requires many spraying process in the same year (Özdemir and Tuncer, 2021).

2.4.2.2. Long-Term Control Methods

Biological Control

At the Black Sea Agricultural Research Institute in Samsun, a biological control laboratory was established. After samurai beekeeping is placed in brown skunk eggs that damage 200 agricultural products in the facility where production is started, biological control will be started in the regions where the pest is concentrated. Chinese origin samurai bees, which will be produced in a laboratory environment, will be released into nature to biologically control brown skunk. There are numerous predators (spiders, katydids, lacewing larvae) that attack the eggs and

early nymphs. Adults and mature nymphs have fewer natural enemies, but birds and spiders occasionally hunt them. A highly specialized predator known as a crabronid wasp (*Astata bicolor*) paralyzes the nymphs with stings before carrying the paralyzed stink bugs to their underground nests, where the stink bugs serve as food for the nest's young. Because most chemical BMSB treatments are broad-spectrum, they may have an adverse effect on biological control and trigger outbreaks of secondary pests like scale and aphids (Anonymous, 2022). Various methods are applied to control BMSB. However, it is known that the most effective control method is biological control. BMSB threaten many agricultural products in Turkey especially hazelnuts. Although many studies have been carried out to control the pest, sufficient results have not been achieved yet and significant amount of the product is harvested as low quality product (Ak et al., 2019).

2.5. Harvest and Post-Harvest Processing of Hazelnuts

Effective harvest and post-harvest methods are critical for producing a high-quality product, which determines commercialization and producer profitability (Turan and Karaosmanoglu, 2019). Hazelnuts are often collected in August when they are fully grown and have fallen to the ground in Turkey. Because of the variety and the environment, it may vary. In the old area, harvest is mainly done manually. When hazelnuts are fully grown and have fallen to the ground, they should be collected. One can gently shake hazelnut branches to encourage nuts to fall or wait for them to fall naturally (Hudson and Degenhardt, 2020). If possible, all dropped nuts have to be collected before the rainy season arrives. Harvesting the crop while it is still damp will cause storage issues and impair the quality of the nuts. Harvesting operation has grown increasingly popular on the ground in flat places in recent years, as mechanized harvest enables better crop production and lower operating costs (Bernardi et al., 2017). In most cases, automated harvesting systems rely on the absence of weeds in the area surrounding the trees (Islam, 2018).

Sweeping is a simple method of collecting hazelnuts. The nuts are collected in a thin window in the middle of the tree line, which is cleaned with air blast or mechanical fingers. Sweep simply fast enough to stay ahead of the pickup machines to ensure efficiency. Mechanical harvesting is used to collect most commercially cultivated hazelnuts. The harvesting machine usually follows the sweeper, which removes and isolates the nuts from the leaves, twigs, and other debris and dumps

them in a tote box or trailer. Some hazelnut farmers utilize bottom-drop trailers that they open over drop pits. The nuts are then removed from the pit and loaded into bulk trucks for transport to the cleaning and drying factories. If totes are utilized, a third-person rides a forklift tractor out of the orchard to carry the tote boxes.

Hazelnuts, like many other agricultural products, require a considerable amount of post-harvest processing. The main steps for post-harvest handling of hazelnuts are given in Figure 2.3.

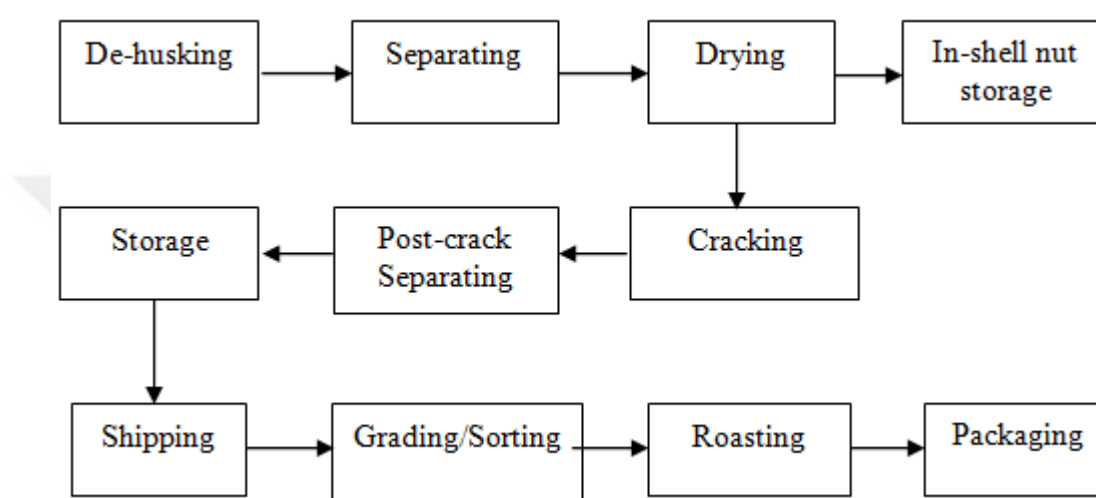


Figure 2.3. The main hazelnut post-harvest processing operations

In Turkey, hazelnut varieties typically have lengthy husks encircling the fruit. The mature fruits are hard to separate from the husks and fall in groups to the ground (Beyhan et al., 2009). Drying is required if the moisture content of the hazelnuts is higher than 8-10% after harvesting and cleaning (Ferrão et al., 2020). Drying is a vital operation and required to ensure the quality of hazelnuts during storage (Turan and Karaosmanoglu, 2019). Fruits are collected in groups from the land or plants and spread out on a level surface to dry in the sun before being husked with various huskers (Turan, 2018). Separated nuts are placed on a flat surface to dry. A grass or concrete combination is usually employed for this operation. Nuts are dried to a moisture content percentage of 7% (Turan and İslam, 2018).

Post-harvest hazelnut evaluations revealed that BMSB feeding appears to have harmed a significant proportion of nuts. The damaged kernels seem shriveled and withered, with evident feeding points consisting of a noticeable depression encircled by necrotic tissue areas that can lead to mildew and rotting (Molnar, 2010). Christopher (2014) evaluates the destruction caused by *H. halys* adults feeding on

hazelnut kernels. As a result, he claims that when stink bugs feed on ripe nuts, a higher percentage of kernels develop corky, white, rotting kernel tissue, with no statistically significant differences variation in the proportion of damaged kernels exhibiting these symptoms in field or laboratory studies.

Dried fruits are kept in volume or in jute baskets. Nuts in the shell can be kept for up to a year and cracked as needed. Compression cracking in which the nut is squeezed until the shell fractures and impact cracking, in which the nut is slammed against a hard surface to crack the shell, are the two most common methods of breaking. Whole kernels, split kernels, half-cracked nuts, and shell fragments are all produced during the cracking process. To separate the complete kernel from the shell fragments, a post-crack separation procedure is used. Separating good kernels from split, mold, internal and external degraded, shrunken, and insect-attacked or defective kernels is a huge task to ensure the quality requirements (Fischbach, 2021; OECD, 2011).

Hazelnuts are high-value products that suffer defects that are year dependent and are sometimes associated with off-flavors (Pscheidt and Ocamb, 2015). These flaws are quality issues that result in yield losses as a result of non-compliance with market quality standards. Before preparing shelled nuts, a quality check is performed regularly. Ferrão et al. (2020) accomplished work on the post-harvest categorization of the hazelnut sector intending to analyze post-harvest operations in the hazelnut industry. In the results, they discovered that the major difficulties outlined by the participants during hazelnut storage were the appearance of pests, mold growth, fruit rancidity, and color and texture change.

The identification and categorization of infected hazelnuts as post-harvest quality control processes are two topics that must be considered as separate problems in the field of artificial vision. Hazelnut quality is presently assessed using a variety of methods. As a non-destructive quality control approach, digital image processing techniques that are primarily derived from particular circumstances in which researchers seek to imitate human vision and decision-making techniques are combined with artificial methods to identify and classify objects without destructing samples or severely damaging them (Czimmermann et al., 2020).

2.6. Computer Vision and Image Processing Concepts

Generally, a computer vision system is a technology that was created by combining a camera and a computer. More specifically, machine vision systems (MVS) and computer vision systems (CVS) attempt to mimic human vision to access data information from an item without requiring physical involvement (Sandoval et al., 2018). Timmermans (1998), characterized computer vision systems as states that encompass the capture, processing, and analysis of two-dimensional pictures. Image processing techniques are used by computers and machine vision to interpret the image or object being inspected. In general, image processing algorithms take a picture as input and output a transformed image. Filters, smoothing, sharpening, and even grayscale conversion can be applied to images. Image processing is used by both computer vision and machine vision to analyze images, but the interpretation is used to reach a decision or logical conclusion as a result. This choice or logical conclusion in machine vision is frequently followed by an autonomous action in the industry (Anand and Priya, 2019). The main issue in machine vision systems is to create a machine human-like vision skill. These systems, like the human brain, should be trained not only to handle images but also to analyze and characterize them. Image processing, on the other hand, is primarily concerned with the use and mathematical and computational functions and image transformations. In computer vision, both quantitative and qualitative information from visual data is important. Similar to human vision, it is about distinguishing between objects, classifying them, sorting them according to their size, color, texture, and so on (Pinto et al., 2008). Image processing methods are used to accomplish computer vision tasks. Beyond a single image, details in computer vision can be collected from static images or moving images such as videos (Naik and Patel, 2017). Machine learning and artificial intelligence methods are widely used to understand and use images for inspection purposes. These techniques aim to mimic the unique nature of human thought.

An image sensor, a frame grabber, and a computer with appropriate software and algorithms form a conventional image processing system. The analog signal from the sensor is digitized into a series of integers and saved in the computer as an image. The object is then displayed using various image processing algorithms that extract a pattern from the image. The extracted pattern is classified by classification

algorithms, which in turn can generate a signal to animate a trigger that directs the object to the desired route. Figure 2.4 shows a schematic diagram of the software and hardware components of a typical inspection (classification) vision system.

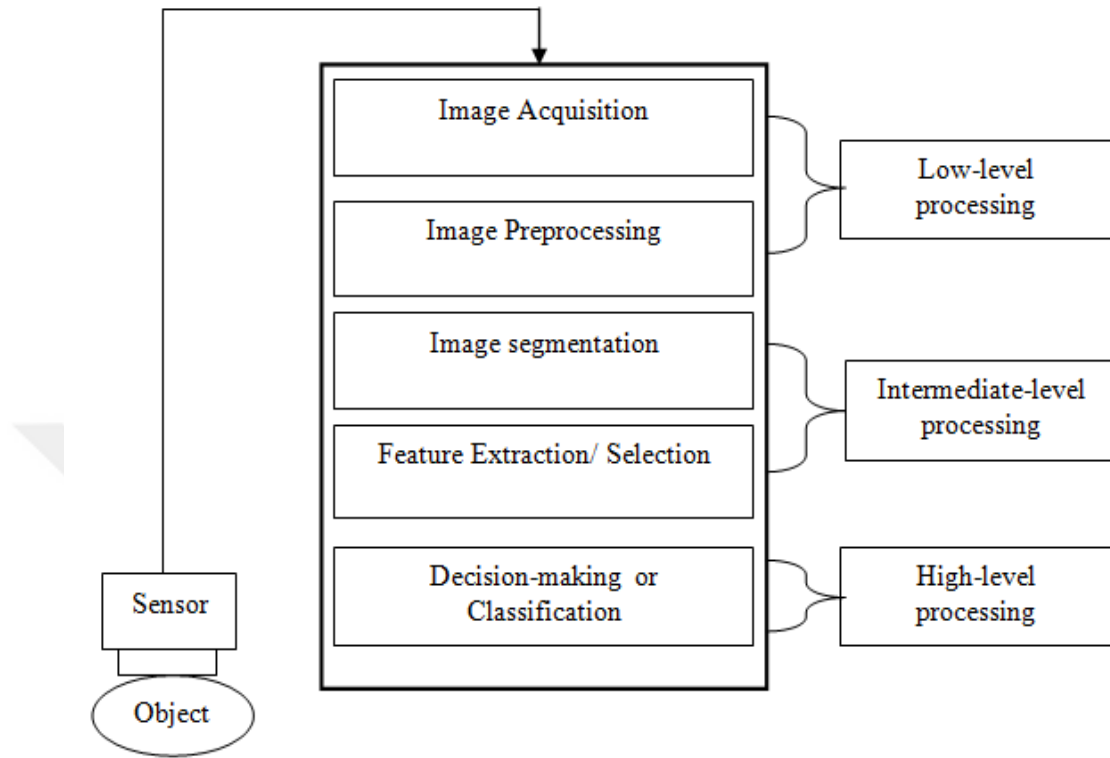


Figure 2.4. A schematic representation for classification process by computer vision system

In the food industry, where machine vision technology has been widely used over the past two decades as a mean to automatically determine and manage food quality such as fruit and vegetables, computer vision technology is becoming increasingly important during last decades (Elmasry et al., 2012). Since most food products have a heterogeneous matrix, visual characteristics such as color, texture, shape, and size can vary significantly even within the typical category of the product. In addition, the appearance of agricultural products negatively or positively influences the acceptability of the consumer and therefore determines the degree of acceptance prior to a purchase. The consumer also identifies a certain internal quality with the product's appearance, which influences future purchasing decisions (Brosnan and Sun, 2004).

Machine vision inspection of agricultural and food products is more versatile than the existing optical and other traditional inspectors. Using machine vision techniques multiple feature processing can be offered. These features can perform

the signals sent by different sensors or obtained through different types of algorithms. The pattern classification algorithms implemented on a machine vision system provide multiple choices for agricultural product classification.

2.6.1. Image Acquisition

Image capturing entails the use of cameras, illumination, lenses, and other vision tools to obtain the best possible images. Acquiring cameras can be monochrome or RGB color cameras, as well as smart cameras. Scene capture can be done using one or more cameras. The vision system's primary goal would be to accurately capture the color, texture, motion, and shape of the object under study. After that, the photos are examined to extract useful information about the situation. The initial challenge in any automated activity is generating a good image of the thing under examination. It is critical to employ a suitable illumination source to get the specified requirements of illumination over the scene to receive all of the useful data about the object. The effectiveness of the light source can also have an impact on the computer vision system's efficiency and accuracy (Novini, 1995). Since the sensor will be receiving reflected light, the energy of the lighting source should be regulated by the sensor's sensitivity.

The image sensor is the most fundamental component of the camera's imaging system for capturing images. Furthermore, the image sensor resolution must be considered, as this impacts the number of pixels in the image. There are various sensors that can be used to create an image, but the most common image sensors are self-scanned solid-state charge coupling devices (CCD) (Brosnan and Sun, 2004). CCD cameras are commonly employed in computer vision systems for industrial monitoring problem that needs a line-scan camera, such as when a product travels along with a transit system. The image is created line by line when the target travels past the camera with these types of cameras. In the agro-food business, color and monochromatic cameras have been widely utilized for quality analysis, product selection, and product classification (Jhawar, 2016; Pearson et al., 1996; Steinmetz et al., 1999).

Digitization is the process of transforming analog photographs to digital format. This is usually done with an image acquisition board or a frame grabber. Normally, the device is mounted in a computer to digitize the analog data transmitted from the sensor by partitioning an image into a two-dimensional grid having picture

elements denoted as pixels (Brosnan and Sun, 2004). Each sensor pixel's analog signal is normally digitized with an 8 bit, giving the signal a scale of 0-255. White pixels are indicated by pixels with a value of 255, whereas black pixels are indicated by pixels with a value of 0 (Narendra and Hareesh, 2010).

2.6.2. Image Segmentation

Image segmentation is a critical component of image processing; It is widely used for image handling and processing purposes, so that the model can recognize them. The image is divided into several portions or objects during the segmentation process (Litjens et al., 2017). The degree to which picture splitting is carried out is determined by the situation that has been addressed. Segmentation should come to an end once the object of an image has been separated. Image segmentation plays a crucial function in image processing. Splitting an image into different pieces makes it easier to process, therefore after the procedure is finished, the image object will be reconstructed. The performance or the accuracy with which an item in an image is recognized is improved by segmentation, and the loss is reduced (Chen et al., 2018). For image segmentation, many image segmentation techniques such as point, line, and edge detection (Abd Warif et al., 2016). Techniques of edge connecting and boundary recognition include: thresholding technique, segmentation process that depends on a particular region, and watershed segmentation methods have been used (Bai and Urtasun, 2017; Yuheng and Hao, 2017). The threshold is a clear, simple, and effective method of dividing an image into real image and background. It is known as a technique for image segmentation that isolates the object by converting grayscale image format into a binary image format (Bormann et al., 2016). It can classify an image's pixel values. Furthermore, pixels in a binary image are either black or white (0 or 1). When converting a grayscale image to binary, a threshold is used. Assume grayscale image values range between zero (0) and 255, which corresponds to black to white. If the image values exceed the value of the threshold, they are transformed to 1 (white), while those just under the threshold are turned to black (0).

2.6.3. Features Extraction and Selection for Classification

Feature extraction is a much more broad method for developing a translation of the input data upon a low-dimensional domain that keeps the majority of the necessary information (Nikolay et al., 2006). Various types of image processing

algorithms are used to complete this task. To establish the object's class, the extracted classification features are fed into several classification algorithms. Because the images are saved as an array of numbers in the computer, processing all of this data takes time and is not suited for high-speed application scenarios (Khalid and Khalil, 2015).

Identifying and isolating needed properties of an image object or pattern for noticing or analyzing applicable information captured from image data is referred to as feature selection (in the measurement space) (Hassaballah and Awad, 2016). The image features that are collected from the image can reflect the characteristics of the entire image or tiny regions of the image (global features) (local features) (Mikolajczyk et al., 2005). Because global features are intended to represent the overall image, only one feature vector is generated for one image, allowing the content of two images to be evaluated by comparing their features. A group of local features derived from various areas of the image is used as the local features (Moreels and Perona, 2006). Color, shape or morphological traits, texture, and flaws are just a few of the image features that can be retrieved and used as categorization features (Li and Allinson, 2008; Liu and Bai, 2012). To acquire quantitative features from a digitized image for classification purposes various methods have been used (Mainali et al., 2013; Zhang et al., 2014).

Depending on the type of application and the problem under study, the image analysis and the features extracted can vary significantly. Object recognition is used in computer vision applications, where the objects detected in the acquired image are compared to previously stored images of the objects in a database. The visual object features that have been discovered can be modeled for 3D recognition and rebuilding. The nature of the data being studied would determine the methodologies and strategies employed to deal with the challenges. Different methodologies can be employed in different application fields including animation, multimedia, and robotics.

2.6.3.1. Color Features

The color features that are extracted from an image are one of the most critical and essential aspects of the image. A subject can be described by its color characteristics concerning a given color range or space or model. Many color features have been used in literature, like RGB, LUV, HSV, and HMMD (Stanchev

et al., 2003). After the color space has been defined, color features or image data can be captured directly from images or patches. The color histogram is one of the most important color properties reported in the literature (Jain and Vailaya, 1996). It represents the color distribution in an image. A color histogram in digital photos reflects the number of pixels with colors from each of a set of color spaces. Another important color features are color moments (CM) (Flickner et al., 1995). They are metrics that represent the color information of an image in the same manner that central moments define a probability distribution precisely. The moment features extracted from color spaces are mostly used in image retrieval characterizations for color indexing and to compare how identical two images are based on color. Color properties such as the coherence vector of the color (CCV) and correlogram of the color are also relevant. Color moments are the simplest and most powerful of all color features. The most prominent moments are mean, standard deviation, and skewness, which can be calculated as follows:

$$\mu_i = \frac{1}{N} \sum_{j=1}^N f_{ij} \quad (2.1)$$

$$\sigma_i = \left[\frac{1}{N} \sum_{j=1}^N (f_{ij} - \mu)^2 \right]^{1/2} \quad (2.2)$$

$$Y_i = \left[\frac{1}{N} \sum_{j=1}^N (f_{ij} - \mu)^3 \right]^{1/3} \quad (2.3)$$

Where f_{ij} represents the i -th color element of the j -th image pixel's color intensity and represents the number of pixels in the object. The values μ_i , σ_i , and Y_i , represent the Mean, Standard Deviation, and Skewness of each picture channel, respectively.

2.6.3.2. Texture Features

As a particularly helpful description for a variety of image types, the texture is a form of feature used to separate images into sub regions and to classify certain parts of an image. In a particular image object, image texture describes the spatial allocation of color combinations or densities. The texture is defined by the spatial distribution or geographic variation of intensity levels in an area. Color is often a pixel attribute, whereas texture can only be assessed from a collection of pixels intensity. Different strategies for extracting texture features from photos have been proposed in the literature. Depending on the domain from which the texture feature is obtained, they are classified into two types: strategies for extracting spatial texture features and methods for extracting spectral texture features. Features are derived in

the former method by computing pixels or detecting features related to pixel intensity in the basic image domain, and in the latter method, the image is transformed into a frequency domain and after that features are calculated from the image (transformed image). Both features related to spatial and spectral domains have upsides and downsides. Among the most prevalent technique for gathering texture features, Gabor filter (Manjunath and Ma, 1996). It is extensively used for capturing texture features from the images. By specifying the central frequency and orientation characteristics, the Gabor filter is designed to collect the frequency domain of a picture. To filter the image, a group of Gabor filters or Gabor wavelets with different spatial frequencies and directions has been used. Each wavelet collects energy at a certain frequency domain and orientation, resulting in a feature vector with a defined frequency.

2.6.3.3. Shape Features

In image analysis for object detection and classification, shape description or representation is a critical issue. The shape is used by humans to recognize and distinguish real-world things, and its goal is to represent simple geometrical structures like parallel lines in various directions. Strategies for extracting shape features can be divided into two categories (Zhang and Lu, 2004). Shape representation generally seeks efficient and perceptually significant shape properties or features depending on shape border data or perimeter with internal content. Many shape features have been generated from the images, including shape signature and signature histogram, shape boundary conditions, moment's features, curvature, context of shape, shape vector, spectral characteristics, and other shape features. The accuracy with which these multiple form attributes permit one to get comparable shapes from a defined dataset is frequently evaluated. In addition, in image processing, a strong correlation is taken into account to form features, which might reveal object placement within an image or relationships between the images of the objects. Spatial location of an image mainly presents in two states: absolute spatial location of regions or areas (Yang et al., 2005) and relative locations of regions (Mezaris et al., 2003).

After extracting the required type of features, a feature selection step can be used to choose a subcategory of characteristics or features with various potential benefits (Guyon and Elisseeff, 2006). As a result of decreasing the number of

characteristics, the classifier has fewer parameters to concern. It also decreases the risk of overtraining and hence increases accuracy, particularly when the number of training data is restricted or limited. It is easier to observe which variables are genuinely relevant to the desired states of mind if only very few characteristics are picked and/or ranked from the standpoint of information extraction. Then, because it should be computationally more efficient, a model with limited parameters and thus fewer parameters can generate faster predictions for a fresh sample. Finally, the amount of data collected and stored will be minimized. Many feature selection techniques, such as filter, wrapper, and embedding approaches, have been found in the literature (Kohavi and John, 1998).

2.6.4. Machine Learning Classifiers

In machine learning, a classifier is an algorithm that intelligently sorts or characterizes data into one or multiple groups. Machine learning is a well-known and extensively researched discipline in artificial intelligence that helps to improve categorization performance in a variety of fields (Abro et al., 2020). It employs a variety of algorithms to solve data problems (Mahesh, 2020). However, supervised machine learning algorithms are the most often used algorithms in machine learning (Singh et al., 2016). It calls supervised learning when the goal of machine learning is to learn a mechanism that converts an input into variables based on example input-output. It derives a function from a group of labeled training data or examples. Also known as the algorithms that demand external assistance where the input dataset is divided into two groups, train and test dataset. Figure 2.5 demonstrates the overall process of supervised machine learning algorithms. In this type of learning, there is an output variable data in the training dataset group that requires be predicting or categorizing. For forecasting or categorizing data, supervised machine learning algorithms categorize patterns from the training data and examples and implement them in the test dataset. Support Vector Machine, Naïve Bayes, classification Algorithm or Logistic Regression, Linear Regression, Decision Trees, and Neural Networks are all types of supervised machine learning methods.

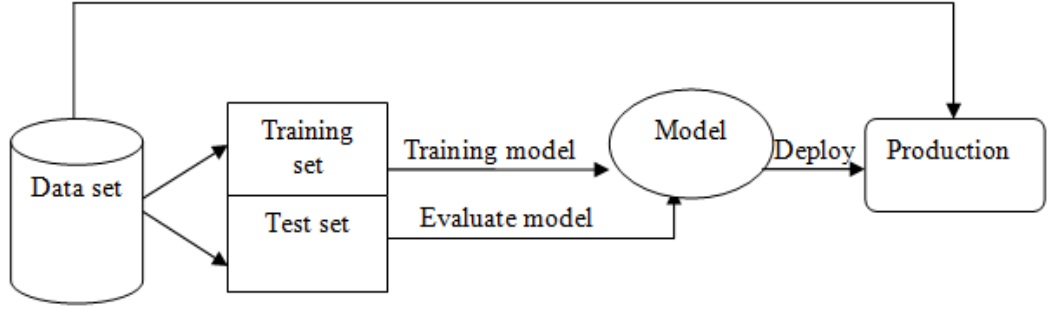


Figure 2.5. The workflow of supervised machine learning algorithm (Awedele et al., 2017)

2.6.4.1. Logistic Regression

A linear classifier is a form of logistic regression. It is used to figure out whether an item belongs in class '1' or class '0'. When the dependent variable is binary, this is the most popular type of logistic regression classifier task. It can also be employed even when there are more than two categories of dependent data. For such circumstances, multinomial logistic regression is employed. The logistic function, which is used to build a probability distribution matching the weighted feature vectors, is the foundation of categorization in logistic regression (Kuha and Mills, 2020). The logistic function is:

$$h_w(X) = 1/1 + e^{-wx} \quad (2.4)$$

The feature map is the independent factor in the preceding equation, with each element representing a weighted independent attribute of the subject and a bias. As a result, the entire input to the logistic function can be stated as:

$$X = W^T X \quad (2.5)$$

'W' is a vector of respect to the weights that includes the bias term, while 'x' is the n-dimensional feature vector.

$$W = (w_n, w_{n-1}, \dots, w_2, w_1, b) \quad (2.6)$$

$$X = (x_n, x_{n-1}, \dots, x_2, x_1, 1) \quad (2.7)$$

The negative log-likelihood function is the goal function of the logistic regression scenario. This is the function that must be optimized to know the classification's maximum margin. The following is the definition of the likelihood Equation:

$$L(W, x) = P r(Y | X; W) \quad (2.8)$$

This is the multiplication of all individual probabilities since the entire input vector elements are supposed to be independent of one another. The minimizing of the above-mentioned function also referred to as the cost function, relates to learning in logistic regression approaches (Hosmer et al., 2013). For easy preparation, the method relies on certain conditions. The data is presumed to be unrelated. This allows using the likelihood function to construct the measured probabilities as a product of individual probabilities. Furthermore, there should be little connection among the independent factors, and the association between the log probability and the independent variables must be linear (Lavalley, 2008). The drawbacks of logistic regression include the fact that it does not presuppose a linear association between the dependent and independent components, that neither the independence nor the dependent variables must be regularly dispersed, and that it can handle non-linear influences. To generate accurate findings, much more training data is required.

2.6.4.2. Naïve Bayes Classifier

The Naïve Bayes algorithm is a basic and efficient classification method that helps to build rapid machine learning models qualified to make quick assumptions or predictions. It is a classification algorithm, which indicates it makes predictions depend on an item's probability. The Naïve Bayes algorithm is a commonly used technique for character recognition, such as the classification of spam and non-spam emails, using frequent patterns as feature vectors. Considering their simple design, they have a lot of real-world uses. The Naïve Bayes model assigns the label ' C_k ' to a feature vector ' x ' with the probability given as:

$$Pr(C_k|x_1, x_2 \dots x_n)$$

This type of model will estimate the conditional probability for each class ' k ' based on the feature vector. This indicates that if the feature vector is really large, this procedure will fail. This classifier, on the other hand, is simple and quick to use and performs well even in multi-class categorization (Arlot and Celisse, 2010). Although the assumption of independence maintains within the data, this methodology works superior to other classification techniques and requires minimal training data.

2.6.4.3. Artificial Neural Networks (ANNs)

ANN is a non-linear parameterization approach that uses supervised learning methods to provide statistical estimations (Ayoub, 2020). The primary notion underlying artificial neural networks is the biological architecture of neural networks that make up the brain and nervous system. ANN is composed of several layers, each of which comprises several processing units known as neurons. The input layer is the first layer, and it gathers data; the hidden layer (s) is the second layer, and it is the layer that performs the majority of the calculation, and the output layer is the last one, and it estimates the outcomes. Neurons in one layer communicate with neurons in the next layer via links with relative weights to them. To reduce the inaccuracy caused by the discrepancy between the actual and anticipated outputs, inputs (x_j) are multiplied by appropriate weights (w_{ij}), and the total weights are modified by bias. Then this value is transformed using an activation function (f_i), such as ReLU, Unit Step, Sigmoid, Piecewise Linear, or Gaussian (Bishop and Nasrabadi, 2006), as it works as an entrance to assess whether or not the neurons should send fresh info to the following layer. The weights of the neurons are tuned based on the outputs throughout the ANN training procedure. Data is transmitted across the network according to the flow of the data and connected weights, and when it gets to the output layer, the neuron with the highest value demonstrates the final result. The variance between the forecasted or predicted and real results are found here, and the connection weights are changed back to decrease the discrepancy.

The feed-forward neural network is the most popular artificial neural network type. In this network, all connections are forward propagating and exist only between the neurons of layers n and $n+1$, with no backward connections. During the learning process, the error function relating to the existing weights is determined, and the weights are then re-adjusted to reduce the error rate and get closer to the optimum as well as back propagation algorithm is used to implement error correction (Kubat, 2021). For a neural network feed-forward type, the error is the objective function that must be reduced using the gradient descent technique. Equation 2.10 shows the sum-of-squares error function. Where E_n is the error, y_k outputs are linear combinations of the input variables n , and tk is the predicted output.

$$E_n = 1/2 \sum_{k=1}^k (y_k - tk)^2 \quad (2.9)$$

This error function is known as a Lyapunov's function because it meets the condition for Lyapunov's stabilization. The error function given here is simple to modify using a gradient descent approach for normalization. The ANNs are simple and can indeed produce a decent match for whichever function, despite of nonlinearity. They are most effective for difficult problems, such as object categorization or recognition. On the other hand, ANNs are frequently used in situations when straightforward linear regression is feasible. To be appropriately trained, they require a massive volume of information. They're basically a black box that will not enable look at the details. To improve accuracy by a few percent, the network's size must be greatly increased as it performs well even when the input data is noisy (Estaran et al., 2016).

2.6.4.4. Support Vector Machine (SVM)

SVM algorithm is a prominent technique for supervised learning which can be used to solve both regression and classification problems and it is mostly employed in machine learning for categorization difficulties. Furthermore, an SVM classifier is a classic or traditional machine learning technology that can still aid in the classification of large amounts of data. It can particularly assist multi-domain projects in a large data setting (Suthaharan, 2016). The main goal of the SVM algorithm is to find the best line or decision boundary that can divide n-dimensional data into categories so that new data points can be simply placed in the appropriate class or category in the future. The appropriate decision boundary is called a hyper-plane (Kok et al., 2021). The SVM model is trained using a collection of training data points that fall into one of two binary classifier groups. Depending on this, the SVM applies the learned model to the test sample's fresher data points, classifying them into one of two categories. As a result, the SVM is a binary algorithm type that is non-probabilistic.

The concept behind the classification is to use an (n-1)-dimensional hyper plane to divide n-dimensional feature vectors into two distinct classes (Zhu et al., 2021). SVMs have regularization variables that protect the optimization algorithm from over fitting the data. The kernel-trick methodology can also be used to fit data non-linearly. The limitation of SVM is that it only learns the features associated with a specific regularization and kernel option result. Furthermore, if the number of features for each data point is greater than the number of training data samples, the

SVM will underperform (Kumar, 2019). SVM architecture with the decision boundary, support vectors, and maximum margin is considered in the Figure 2.6 below where there are two different classification categories.

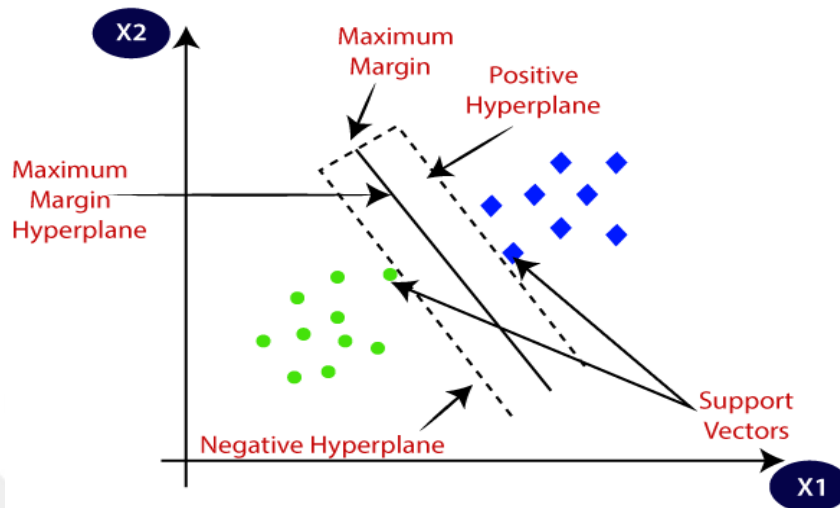


Figure 2.6. SVM classification architecture for two target classes (Suthaharan, 2016)

2.6.5. Deep Learning Classifiers

Deep Learning is involved in machine learning as a subset of it, although Deep Learning has greater power and flexibility than regular machine learning in terms of performance. Traditional machine learning methods extract features manually, but deep learning algorithms attempt to gain knowledge of high-level data incrementally using multiple hidden layers (Figure 2.7). Deep learning is a suggested strategy when we have a huge data set and sufficient computational capabilities. It has performed well when it comes to complicated tasks like image categorization, processing of natural language, and speech recognition.

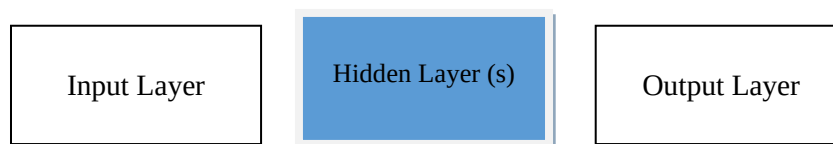


Figure 2.7. Deep learning schematic diagram

Two things are very necessary for Deep Learning algorithms. The first is a large amount of data to train the model with, and the second is powerful computing hardware because deep learning algorithms learn millions of parameters in a model, and the system must be able to rapidly overcome parameter clusters. Deep Convolutional Neural Network (CNN) is a supervised deep learning method that

works with labeled data. Deep recurrent neural networks (RNNs), deep convolutional neural networks (CNNs), and deep neural networks (DNNs) are examples of supervised learning approaches and algorithms for deep learning. Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) techniques are also included in the RNN category. The ability to create a data output from previous information is the most significant benefit of this procedure. Furthermore, due to its capacity to learn with great performance, deep learning is easier than previous techniques. The downside of this strategy is that the decision boundary may be overstrained when the training data lacks samples that have to be in the test data.

Convolutional Neural Network (CNN) is the most widely used form of algorithm in the field of deep learning (Jhong et al., 2020; Zhou, 2020). Moreover, it is the most often utilized network in a wide range of applications and has been widely employed in a variety of sectors, including agricultural application and diseases detection (Etminan et al., 2019), voice recognition (Palaz et al., 2019), face recognition (Li et al., 2020), and computer vision applications (Fang et al., 2020). The required features can be automatically identified using the CNN classifier without the need for human intervention (Gu et al., 2018).

2.6.5.1. Convolutional Neural Network (CNN)

The Convolutional Neural Organization is perhaps the most well-known sort of ANN engineering. With their precise and simple design, CNNs are mostly employed to solve difficult image-driven example recognition (O'Shea and Nash, 2015). CNN has performed well in a variety of computer vision projects such as image classification, location, and segmentation (Donahue et al., 2014; Krizhevsky et al., 2012). The only type of feed-forward neural network is the CNN. CNN is an effective evaluation measure that is commonly used in plan recognition and image processing. It has many features such as simple construction, very few arranging boundaries, and versatility. CNN's design consists of two layers. The element extraction layer associates each neuron's contribution with the previous layer's surrounding response fields and concentrates the neighborhood include. The element map layer is the other; a majority of component maps are used in each layer as well as the weight of the neurons in each element map is equivalent (Liu et al., 2015). Convolution layers, pooling layers (e.g., max-pooling), and fully connected (FC) layers are the construction elements of a CNN (Figure 2.8).

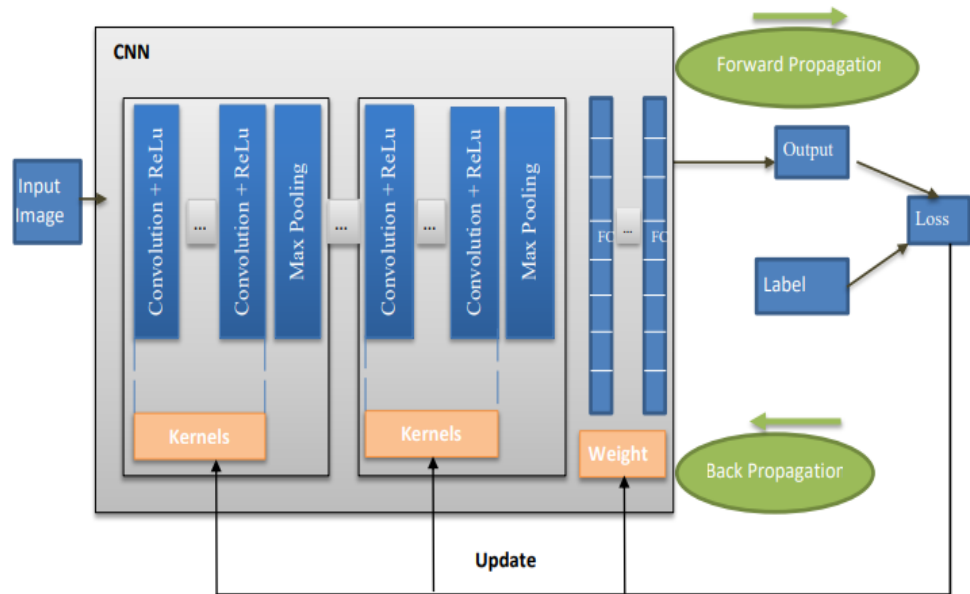


Figure 2.8. CNN Architecture (Daniel, 2021)

Convolution Layer

The convolution layer, which primarily handles feature extraction, is a major element of CNN architecture. In computer vision, images are read as pixels and encoded as a matrix. This is equivalent to height, width, and depth. Depth 3 (three) demonstrates the color image depth that has three channels (RGB). The convolution layer in CNN determines the dot product of the input and weights. The convolutional layer is the most significant part of the CNN architecture. It is constructed of kernels, which are convolutional filters. The output map is calculated by convolving the image with these kernels, which are demonstrated as N-dimensional metrics (Bashir and Sharma, 2012).

Pooling Layer

The next procedure is to decrease the feature maps by down-sampling each feature vector in the sub-sampling layers, which reduces network parameters and speeds up the training process, allowing the over fitting issue to be handled. A pooling mechanism (max or average) is implemented to an adjacent region in all feature mapping processes. In general, the pooling layer decreases a large number of feature maps, resulting in producing smaller feature maps. Throughout each level of the pooling process, it keeps the majority of the dominant data or traits. Tree pooling, gated pooling, average pooling, min pooling, max pooling, global average pooling (GAP), and global max-pooling are some of the pooling approaches that can be used

in numerous pooling layers. The frequently employed pooling strategies are max, min, and GAP pooling (Jansson, 1991).

Fully Connected Layer (FCL)

The FCL receives its input from the last pooling layer. It indicates that every neuron in the preceding layers is associated with every neuron in the following layers, and the input in this layer is in flattened form. To quantify the performance of the model under whole filters and weights with an error function, fully connected layers are used.

Activation Function

The activation function, also known as the non-linearity function, is responsible for transferring input to output by calculating the weighted accumulation of the neuron input along with its bias. The essential function of all kinds of activation functions in all forms of neural network classifiers is the activation function. Sigmoid, Tanh, ReLU, Leaky ReLU, Noisy ReLU, and Parametric Linear Units are the most often utilized activation functions in CNNs and other deep neural networks. The completely linked layer, which is positioned at the conclusion of each CNN model, is then performed. Because each neuron in this layer is connected to all neurons in the previous layer, it is called the fully connected layer. Finally, certain loss functions are introduced to the output layer to determine the projected error caused by the CNN model over the training dataset. The determined error shows the difference between the actual and projected output. In many CNN situations, different types of loss functions are used, such as the Cross-Entropy loss function, which is often used to measure CNN model performance. The probability is the function's output $p \in \{0, 1\}$. It is commonly used to replace the square error loss function in multi-class classification tasks. The mathematical representation of the output class probability for Cross-Entropy loss function is Equation below.

$$p_i = e^{a_i} / \sum_{k=1}^N e^{a_k} \quad (2.10)$$

2.6.5.2. Recurrent Neural Networks (RNN)

RNN is extremely useful when dealing with time arrangement details and has been used in multiple areas, including arrival test scenarios, phenotype recognition, modify abdicate prediction, record estimation, climate prediction, soil humidity evaluation, and event date estimation. The following points highlight the main differences between CNN and RNN:

- CNNs are frequently used to comprehend problems relating to spatial data, such as images. RNNs are far better suited to analyzing global, sequential data, such as subject matter or videos.
- A CNN differs from an RNN in its configuration. CNNs are "feed-forward neural systems" that use networks and pooling layers, whereas RNNs support outcomes back into the system.
- The estimated input and the expected yield are resolved in CNNs. That is, a CNN obtains images of specified measurements and supplies them to the fitting level, together with the forecast's many levels. The input measure and the resulting yield may differ in RNNs.
- Face recognition, therapeutic assessment, and classification are examples of CNN applications. Content interpretations, normal dialect preparation, investigation of estimations, as well as conversation analysis are examples of RNN use cases.

2.6.6. Classification Assessment Methods

2.6.6.1. Accuracy

The most often used parameter for measuring classification performance is accuracy (Acc). It is calculated by subtracting the overall number of correct forecasts by the entire number of predictions, which includes both correct classification and correct non-classification (Tharwat, 2020). Mathematically it can be presented as:

$$Accuracy = TP + TN / TP + TN + FP + FN \quad (2.11)$$

Where, TP/TN = True Positives/Negatives, FP/FN = False Positives/Negatives, and Total Predictions = TP + TN + FP + FN. The Error Rate (ERR) or misclassification rate is a supplement to the accuracy metric. Which is determined as in the equation below and identifies the amount of incorrectly classified data from both positive and negative categories (Bradley, 1997):

$$ERR = 1 - Acc = (FP + FN) / (TP + TN + FP + FN) \quad (2.12)$$

The measurements of accuracy and mistake rate are found to be sensitive to unbalanced data. García et al. (2010) state another issue besides the accuracy is that two types of classifiers can predict the same level of accuracy but perform variously when it comes to the numbers of false and correct decisions they provide. In the case of unbalanced data (the data samples in a class is more than the number of data in the other class), however, accuracy is no longer a reliable measure since it produces an extremely optimistic estimate of the classifier's performance on the majority class (Chicco and Jurman, 2020). When the accuracy data of the balanced and imbalanced data were comparable, accuracy is evaluated as appropriate with imbalanced data (Saito and Rehmsmeier, 2015).

2.6.6.2. Recall

The accurately estimated classifications divided by all the classifications of the members of a given class define recall. The model indicates how many objects that belong to the class in issue are classified outside of that class or are classed incorrectly. The formula below is used to measure recall (Saito and Rehmsmeier, 2015).

$$Recall = TP / (TP + FN) \quad (2.13)$$

2.6.6.3. Precision

Precision is the amount of accurately predicted classes divided by the total amount of predicted classifications. The precision/recall combination in the learning setup gives valuable information about the classifier's performance (Saito and Rehmsmeier, 2015), and can be more useful than the pair specificity/sensitivity, and integrating precision and recall significantly provides other measuring performance metrics. The precision is calculated by dividing the total number of true positives by the total number of true positives and false positives, according to the formula below.

$$Precision = TP / (TP + FP) \quad (2.14)$$

2.6.6.4. Confusion Matrix

The confusion matrix parameter is a table that is frequently utilized to characterize a classification model performance on a set of sample data in which the correct information data are available, and it has been used extensively in deep and

machine learning to quantify the accuracy of the models by comparing predicted and actual values (Zeng, 2020). This matrix is among the most common measures for determining a machine learning algorithm's accuracy and consistency. Furthermore, a confusion matrix is most commonly used in classification issues where the result can comprise various combinations of categories (Sammut and Webb, 2011).

2.6.6.5. F1-Score

F1-score is a performance parameter that considers both precision and recall when calculating an algorithm's performance. The F1-score is now frequently employed in most machine learning applications, not just in binary circumstances, but also in the cases with multiclass categorization where investigators can apply the F1 micro/macro averaging approach (Pillai et al., 2017). The F1-score measure appears to be difficult to grasp at first glance. It essentially incorporates both False Positives and False Negatives to account for decision-making errors. F1- score is also known as the mean of precision and recall formulated as follows.

$$F1\text{-score} = 2 \times (Precision \times Recall / Precision + Recall) \quad (2.15)$$

2.6.6.6. Area under Curve (AUC)

It is also known as Receiver Operating Characteristics (Czimmermann et al., 2020). AUC is a statistical curve or graphical representation of a parameter of a model's classification effectiveness when the discrimination threshold is varied. This curve represents the correlation between true positive rate (sensitivity or recall) and false positive rate (1- specificity). When the area under the curve metric is performed to evaluate the performance of the model, particularly in binary classification tasks it shows how well a model can distinguish between positive and negative class labels. If the relevance of positive and negative classes is similar, this metric can be a valuable performance measure (Lucas et al., 2022).

2.7. Computer Vision and Image Processing for Quality Inspection

The technology of computer vision is becoming progressively essential in the food processing sector, as image processing technology has been successfully adopted as a tool for determining and controlling food quality over the last two decades. Because most food products have a heterogeneous matrix, visual features such as color, texture, size, and shape can vary significantly, even in the same category of the product. Machine vision technology can be used to replace visual

inspection systems in an efficient manner in various applications such as harvesting operation, quality evaluation processes, grading and classification, portioning, and label inspection. It also enables a more real and standardized evaluation of the parameters related to food quality using a large number of samples (Anand and Priya, 2019).

Machine vision systems are an excellent tool for automated inspection systems of fruits and vegetables. In automated inspection, vision systems are typically used to sort, classify, and estimate quality based on external metrics or internal product characteristics. The powerful and broad application of the technology stems from the reality that machine vision systems represent a considerable amount of information about the nature and characteristics of objects present in a scene. Furthermore, machine vision systems have the potential to objectively analyze long-term processes or events that occur outside the visible range, which is beyond the human capabilities (Zude, 2008). Because agricultural products are biological in nature, automated inspection can detect defects that may not be found in other areas. Agricultural products often have similar color, shape, size, and other external characteristics, while fruits and vegetables can have a wide range of attributes.

The morphological characteristics of fruits and vegetables, such as color and texture, change after harvest and these kinds of features or properties depend on their maturity level and stored method condition such as the surrounding atmosphere, relative humidity and temperature, fungal diseases, as well as the duration of storage. All these limitations confirm that there is a great challenge in the machine vision application in agricultural product quality assessment and evaluation. Fruits and vegetables, external characteristics, appearance and damages are factors that influence consumer choices; therefore, these characteristics play an important role in the quality evaluation of fruits and vegetables (Ma et al., 2016). Because of its non-invasive and non-destructive nature, computer vision has been commonly used to investigate and classify fruits and vegetables. Over the last decade, a number of researches have been carried out and encouraging results have been obtained.

Understanding the application's necessities and determining the correct and appropriate machine vision hardware and software to address the problem under investigation are the first steps in developing a machine vision inspection system.

Generally, a typical inspection vision system constructs a computer-implemented for image processing purposes. This is accomplished through the use of image handling and classification software. Image can be captured by more than one camera to provide a wide range of inspection areas. Mostly, only known objects in a fixed position are inspected by industrial inspection and monitoring systems. The object needs to be appropriately illuminated to simplify the acquisition of the previously known image attributes or features. Elias et al. (2002) displayed a comprehensive study of machine vision applications in the industrial environment, and they categorized industrial vision inspection applications into four types, namely dimensional, structural, surface, and operational quality, based on the investigated characteristics and features of the system. These categories can also be classified according to the flexibility or degree of freedom of the system (DOFs), which is a metric for the ability of the inspection system to inspect independent features. DOF for any system could be increased, however; advanced image classification methods based on well-chosen models and algorithms must be used. This means that, the inspection system can be enhanced to recognize new kinds of defects and problems if supplemental image processing and analysis features are implemented independently from the old ones to acquire more image features.

2.7.1. Computer Vision and Image Processing in Fruit Inspection

Xiao et al. (2010) constructed a real-time detection system to detect apple stains and defects using three implemented cameras. The apple images were captured through the three cameras as three apple images per time. To extract the background of the apple images, multi-threshold methods were applied. In each apple image, the flaws, which include stem-ends and calyxes, are split and considered as regions of interest (ROIs). As a result, it was possible to distinguish between standard and faulty apples properly. The unjustified recognition of damaged apples was lowered from 21.8 % with a single camera to 4.2 % with all cameras. In addition, the apple prediction error decreased from 15% to 11% when false positive and false negative were assessed. However, this strategy has the drawback of being unable to distinguish between different types of defects. Statistical and syntactic classifiers were utilized and trained to categorize the fruits into two or more categories based on these characteristics. The final results illustrated that the feature selection process performed better by using only the most discriminative features, and those syntactic

classifiers were outscored by statistical classification models, achieving good classification performance (93.5% accuracy) in the results (Unay et al., 2011). Another evaluation of bicolored apples was performed for apple analysis purposes (Kang and Sabarez, 2009). A new segmentation technique was used to assess dried apples in this study, and it can also be used to measure various objects.

Furthermore, because purchasers are more likely to look for skin deficiencies when picking fruits, especially oranges, a multivariate image analysis method was coupled with a computer vision approach to determine orange skin deficiencies. A success coefficient of 100% was achieved when evaluating oranges with lesions at the stem end (Blasco et al., 2007b). Blasco et al. (2007a) proposed a region-based segmentation algorithm to detect the most common citrus peel defects. The proposed algorithm was tested on photos of many varieties of oranges and mandarins that highlighted flaws without the requirement for additional training between batches or even types of citrus fruits. For defect detection, the algorithm could achieve a high accuracy rate of 95%.

Since mangoes are highly common in several regions of the world due to their vibrant colors, unique taste, and nutritional content, several studies have been conducted using computer vision and image processing to assess the product's quality such as predicting mangos color degree as very important quality and maturity factor (Zheng and Lu, 2012). Their study created an LS-SVM classification algorithm to identify the degree of browning in mango fruit as a function of the fractal dimension (FD) and Lab values. The best categorization accuracy of the degree of browning was up to 99% according to the findings. Kang et al. (2008) utilized an image processing-based computer vision system to observe the ripening of mangoes and evaluate their quality. The method also allowed for quantitative analysis of the product's color properties. Moreover, computer vision systems were developed to detect enzymatic browning in pear slices (Ronceros et al., 2009), bananas (Quevedo et al., 2009), and avocados (Ronceros et al., 2011).

2.7.2. Computer Vision and Image Processing in Vegetable Inspection

The classification of vegetables before use is a very important process that has a significant impact on quality. Potatoes, for example, are simple to grade due to their various sizes, shapes, and regularities. Various works have been carried out using computer vision technology in conjunction with image analysis to classify

potatoes into various grades. An automated computer vision system has been used by Elmasry et al. (2012) to sort potatoes into multiple grades. In the study, a special algorithm was developed and programmed for the acquisition and processing of images, controlling the entire process, and monitoring the progress of all operations. For each image in the database, eight shape parameters were derived from the size features, as well as the Fourier transform. All of the shape feature parameters were used in a stepwise linear discriminant analysis to obtain the most relevant and discriminative factors that best-described potato regularity. In-line classification of moving potatoes was shown to be 96.2 percent successful in the testing. At the same time, the well-shaped potatoes were identified by size with 100% accuracy, demonstrating that the created machine vision system has a lot of potential for autonomous identification and sorting of deformed products. Additionally, a real-time computer vision system was used for potato defect detection combined with size sorting purposes, a color-based classifier was used and the accuracy of the classification was reached 95% (Razmjooy et al., 2012).

2.7.3. Computer Vision and Image Processing in Nut Products Inspection

Computer vision technology has been widely used to detect defects in nut products and has shown successful results in numerous studies. Pattern recognition technique in machine learning has powerful discrimination ability and has been applied widely with machine learning classifiers for nut classification. A computer vision system based on pattern recognition was used to discriminate wormy chestnuts. Classification accuracy of 100% was achieved for both normal and wormy chestnuts (Wang et al., 2011). Mathanker et al. (2011) used AdaBoost and Support Vector Machine traditional machine learning classifiers, to improve the classification accuracy for pecans. Good and defective pecan samples were taken as X-ray images, segmented, and features extracted. Using AdaBoost and Support Vector Machine, an average classification accuracy of 92.3% and 90.1%, respectively, was achieved. In addition, color, texture, and geometric features were evaluated using computer vision images to study chestnut grading and overall accuracy of 89.6% was achieved (Donis et al., 2013).

Due to the wide range of use of machine vision technology in nut-product inspection as general, Table 2.1 summarizes the technology's application in

evaluating the quality of nut products, taking into account the items evaluated, the type of application, and the technology.

Table 2.1. Application of machine vision system in agro-product quality inspection

Products	Application	Technology used	References
Almond	Defected, roasted, and foreign material classification	RGB Digital camera	(Delila Halac, 2017)
Almond	Pinholes detection	X-Ray imaging	(Kim and Schatzki, 2001)
Pistachio	Sorting different types of defects	X-Ray image histogram features	(Pearson et al., 2001)
chestnuts	insect infestation	NIR spectral tec.	(Moscetti et al., 2014)
Walnut	Separating walnut meat and shell	RGB images	(Jin et al., 2008)

2.7.3.1. Computer Vision and Machine Learning in Hazelnut Quality Inspection

In general, few studies have been conducted on hazelnuts in this area compared to other crops. One of the studies that have been conducted was the identification of hazelnut defects using RGB image analysis and color gram techniques (Giraud et al., 2018). They developed a color-gram-based machine vision system for identifying faulty hazelnuts. The half-cut RGB hazelnut images were taken with a digital camera after being classified by industry experts into three reference categories; healthy, rotten, and infested by pests. The colorgrams were obtained by converting RGB images, and then Partial Least Square Discriminant Analysis (PLS-DA) was developed and used as a classification model. To better distinguish the previously defined classes, the Interval Partial Least Square Discriminant Analysis algorithm (iPLS-DA) by Nørgaard et al. (2000) was applied to use only the most informative and discriminative regions of the color signals.

The whole defective hazelnuts were detected by Kivrak, (2019) using image processing and machine learning techniques. The goal of the work was to distinguish intact hazelnuts from damaged or defective ones. Images of hazelnut samples were captured using a cell phone and processed using image labeling techniques. Satisfactory results were obtained using the supervised learning method. Furthermore, a computer vision system was employed to identify the partly skin removed hazelnut kernel, skin removed and rotten hazelnuts kernels. The processed hazelnut kernels are classified with a classification accuracy rate of 93.57 % (Guvenc

et al., 2015). Solak and Altinisik (2018) classified and detected hazelnut using image processing and clustering techniques. The size and area features were extracted from hazelnut images and hazelnut were divided into three classes. Using of mean-based classification and K-means clustering algorithms yielded 100% detection and classification accuracy. For classifying shelled hazelnuts according to type and commercial definitions, an accuracy rate of 84 % was reached. Image processing and machine learning techniques were also used to determine hazelnut kernel quality using size and shape characteristics. Recently, hazelnut cultivars were classified also by Caner et al. (2020) using Gradient Boosting and Random Forest classifiers. Classification accuracy of 94% and 100% was achieved by Gradient Boosting and Random Forest, respectively.

Recently, Taner et al. (2021) developed a study to identify hazelnut varieties using computer vision and deep learning techniques. In this study, a Convolutional Neural Network classifier was suggested to classify 17 of the commonly planted hazelnut cultivars in Turkey. The results showed that the proposed model can accurately identify the varieties with a 98.63 % overall accuracy. As the quality of hazelnut is very important in term of exportation and consumption, application of computer vision and image processing techniques connecting with artificial intelligent techniques can improve hazelnut quality.

3. MATERIALS AND METHODS

3.1. Materials

3.1.1. Hazelnut Samples

For classification purpose, normal and BMSB-infected hazelnuts were used in this experiment. BMSB-infected hazelnut samples were taken from a commercial hazelnut processing factory, which were previously harvested in the Black Sea Region of Samsun. Before using hazelnut samples in this experiment, specialist assessors from the Plant Protection Department identified the damaged hazelnut samples as BMSB-infested samples. Infected hazelnut samples contained a mixture of hazelnut varieties, however the most commonly observed type was the Tombul variety, which is the most widespread hazelnut variety in the Black Sea Region. Figure 3.1 shows hazelnut samples infested with brown marmorated stink bug at various levels of severity and healthy hazelnut samples.

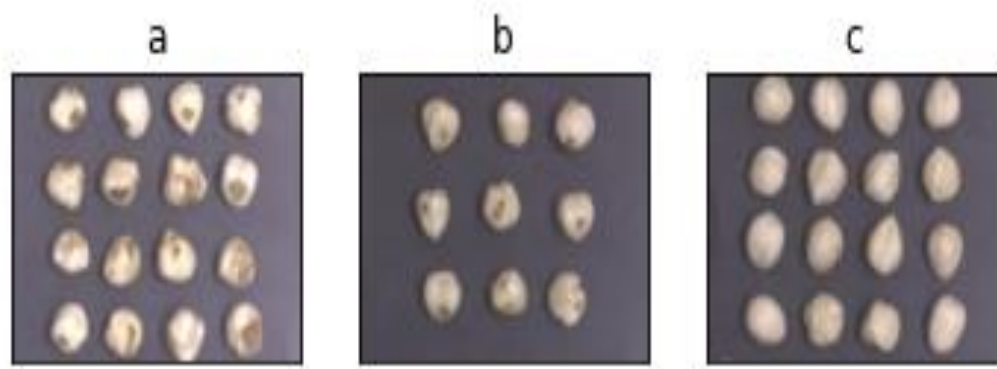


Figure 3.1. Normal and BMSB infected hazelnut samples, a; severely infected samples, b; slightly infected samples, c; normal samples

3.1.2. Computer Vision and Image Acquisition System

The image acquisition and machine vision system in this work was constructed and built in the biological material laboratory of Ondokuz Mayıs University's Agricultural Machinery and Technologies Engineering Department. Figure 3.2 illustrates a schematic diagram of the image acquisition system. The components of the machine vision and image acquisition system were; darkened imaging chamber for adequate and well-distributed light, an image acquisition camera, a halogen lamp, a computer, and software.

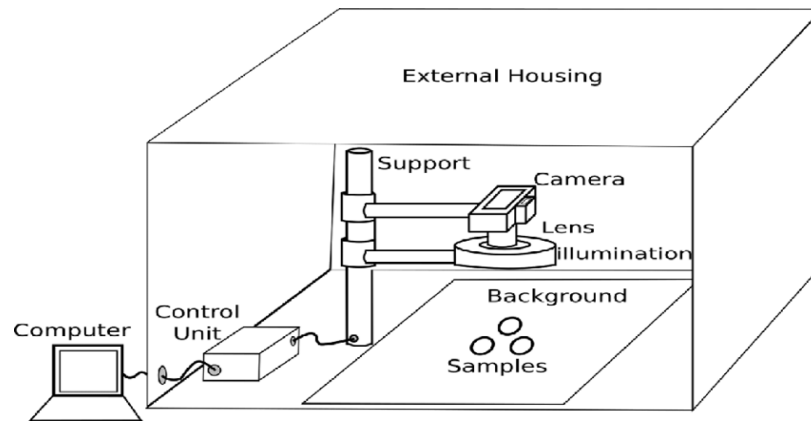


Figure 3.2. Schematic diagram of the computer vision and image acquisition system

3.1.3. Image Acquisition

For image acquisition, an Allied Vision Technology Guppy PRO F-032 economical FireWire camera with a Sony ICX424 CCD type sensor was employed. As demonstrated in Figure 3.3 the sensor used for image acquisition was capable of capturing images in color and monochrome formats at wavelengths extending from 400 to 1000 nm at 82.0 frames per second and 0.3 MP resolutions.

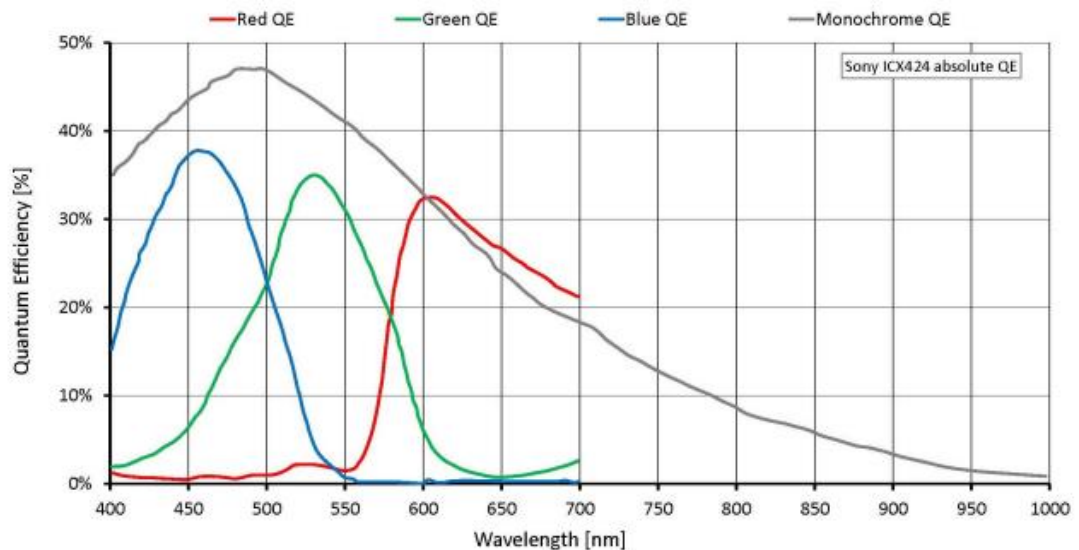


Figure 3.3. Absolute quantum efficiency of the CCD sensor in RGB and Monochrome color spaces

Table 3.1 lists the camera's specifications and performance measures. For image displaying and processing hardware, a Dell desktop computer with Windows 7 and 4 GB RAM was employed. Halogen lamps were utilized for lighting purposes to provide adequate surface reflectivity in color picture generation.

Table 3.1. Specifications and performance measures of the imaging system used in the study

Guppy PRO F 032	
Interface	IEEE 1394b - 800 Mb/s, 1 port
Resolution	656 (H) × 492 (V)
Sensor	Sony ICX424
Sensor type	CCD Progressive
Sensor size	Type 1/3
Pixel size	7.4 μm × 7.4 μm
Lens mount (default)	C-Mount
Max. frame rate at full resolution	82 fps
ADC	12 Bit
Output	
Bit depth	8-12Bit
Monochrome pixel formats	8/12/16
RGB color pixel formats	RGB8
Raw pixel formats	8/12/16

3.1.3.1. Image Acquisition Software

For image acquisition, the AVT Fire Package from Allied Vision Technology (AVT) was utilized, which is a Software Development Kits (SDK) that supports the Visual Studio 6/2003/2005 application development tool as well as other programming languages like C++, Java, and Python. The additionally provided AVT Smart View viewer application allows operating multiple cameras and saving images in BMP format. Figure 3.4 shows the image acquisition with the AVT software.



Figure 3.4. Image acquisition process using AVT software

3.1.3.2. Image Processing and Image Analysis Software

In this study, Spyder (Python 3.8.8) was used as image analysis and image processing software (Figure 3.5), which is initially created and developed by Raybaut, (2009) as an integrated development environment (IDE) for Python-based programming languages. Spyder software incorporates many well-known scientific Python packages. The packages that were used in this research included; NumPy for reading images in form of arrays, SciPy for solving mathematical, scientific, engineering, and technical problems besides manipulating and visualizing data, Matplotlib for plotting images and figures, Pandas for adjusting data in form of data frames, and other open-source software. On the other side, Open CV (Open Source Computer Vision Library) was used mainly as an open-source library for machine and deep learning models, and image processing purposes in this study.

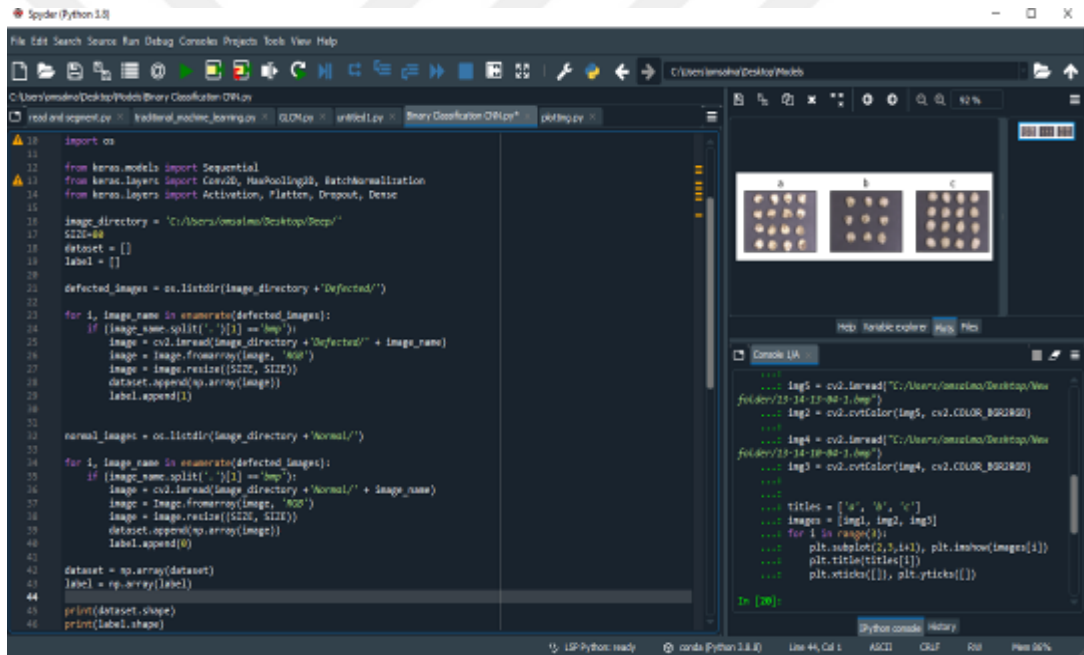


Figure 3.5. Spyder (Python 3.8.8) integrated development environment (IDE) Software

3.2. Methods

3.2.1. Hazelnut Image Acquisition

Using the image acquisition system and the AVT Smart View image capture application with the camera settings presented in Table 3.2, hazelnut samples were manually positioned on the sample holder and placed under the camera one by one as in Figure 3.6. Two separate portions of the hazelnut surface were rotated and randomly captured for each sample.

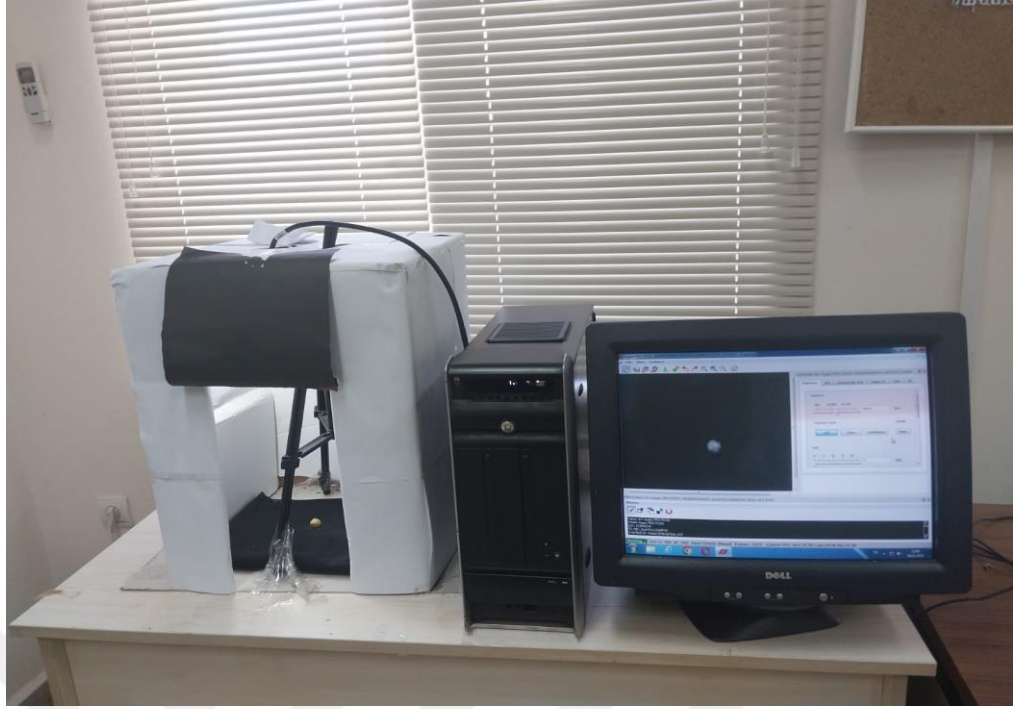


Figure 3.6 . Hazelnut image acquisition one by one

A total of 4540 defective and normal hazelnut samples were captured in RGB (400-700) color space from a distance of 37 cm to be used in deep and machine learning algorithms as training and validation datasets. As the aim of the study was a classification target task, hazelnut images were captured at a resolution of 80x80 pixels.

Table 3.2. Guppy PRO camera settings that used for hazelnut image acquisition

Exposure	Shutter	Gain	Whit balance	
			UB	VR
Manual	70	0	398	452

3.2.2. Image Processing

3.2.2.1. Image Segmentation for Background Removal

In images, the segmentation process is commonly used to identify objects and boundaries (lines, curves, and so on). It is the procedure of attributing a label to each pixel in an image. In this case, a segmentation procedure was used to remove the hazelnut background to reduce the amount of data and make the classification process more efficient. First, hazelnut photos were utilized without any resizing

process, and the binary image of the samples was created from grayscale images using the thresholding approach. Thresholding is a technique of image segmentation in which we adjust the pixels in an image to choose only the areas of interest while neglecting the sections we do not concern about, making the image easier to analyze and interpret when using machine and deep learning models. Various image segmentation techniques are available, but the most applicable methods are; Otsu's thresholding, adaptive thresholding, and simple (global) thresholding techniques. Otsu's technique it's a robust thresholding approach, but Otsu's major flaw is that it assumes binary classes (it divides the grayscale histogram into two groups) and occasionally uses a large T value. Adaptive thresholding is a technique that calculates the threshold value for smaller regions, resulting in varying threshold values for different regions, making this technique unsuitable for our scenario. Global thresholding determines the threshold value based on the histogram of the overall pixel intensity distribution of the image as it performs better under controlled illumination conditions. Since in our case, it was capable to observe the image histogram clearly in the image acquisition software, global thresholding was the suitable method for separating hazelnut samples from the background. An image histogram is a graph that shows the distribution of image intensities in a given color space. In this study, a threshold value from the grayscale image histogram is used to transform hazelnut images from grayscale to binary images (black and white). The binary image was masked with the original image using the Bitwise-and operation to get the segmented RGB hazelnut images. The overall segmentation process is illustrated in Figure 3.7.

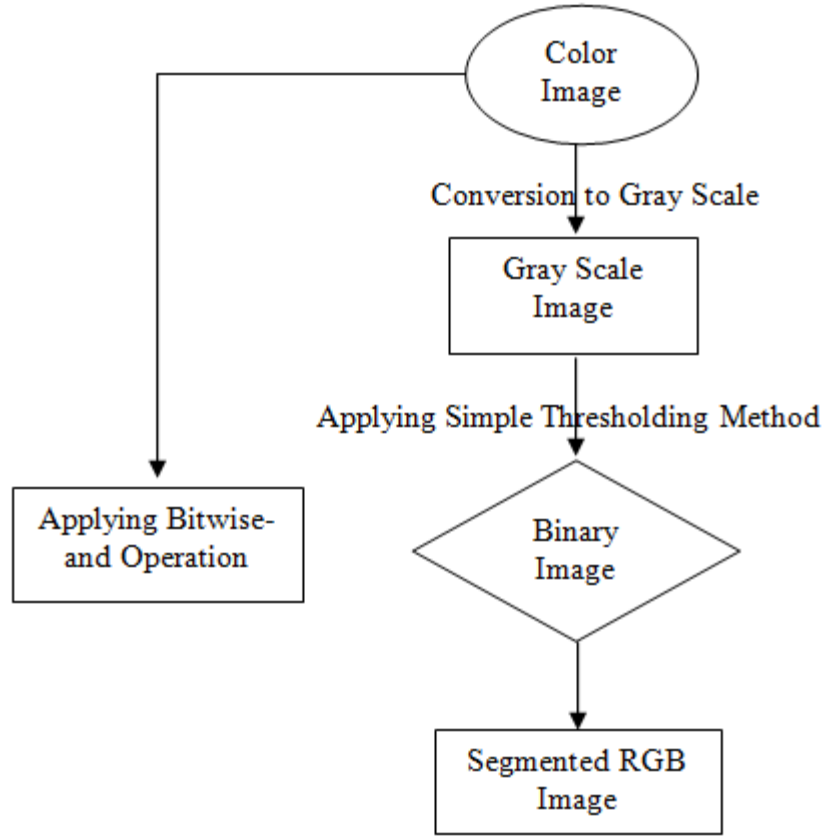


Figure 3.7. The overall process of hazelnut image segmentation algorithm

3.2.2.2. Feature Extraction

Proper feature extraction from the image is a key factor for a proper classification process. An appropriate feature set for a class should form a tight cluster around the centroid of that class. In this study, the insect performs shrivel or corking damage on hazelnut kernels and hazelnut kernel infected with the BMSB varies in their infection symptoms due to the pest's different behaviors. The external symptoms could appear as very clear dark skin injuries and discoloration or very small entry points resulting from the insertion of the mouthpart (Short, 2010). Also, changes in whole kernel color and changes in color where the mouth is inserted were observed (Ali, 2018). To improve the efficiency of hazelnut classification, color features from RGB and CIELAB (a color space specified by the International Commission on Illumination CIE) color spaces were extracted in this work. Therefore, hazelnut images in RGB and CIELAB ($L^*a^*b^*$) color spaces were split into R (red), G (green), B (blue), L (l), A (a), and B (b). Moments features representing mean, variance, range, and skewness were captured from the split color

spaces. The formulas of the moment features are presented below (Teimouri et al., 2016).

$$\text{Mean} = \frac{1}{n} \sum_{i=1}^n x_i \quad (3.1)$$

$$\text{Variance} = \frac{1}{n} \sum_{j=1}^n (x_j - \mu)^2 \quad (3.2)$$

$$\text{Skewness} = \frac{\frac{1}{n} \sum_{j=1}^n (x_j - \mu)^3}{(\sqrt{\text{Var}})^3} \quad (3.3)$$

$$\text{Range} = \max(x_i) - \min(x_i) \quad i = 1:n \quad (3.4)$$

3.2.2.3. Feature selection

A feature selection algorithm was developed to select only the most relevant and discriminative features. Using BorutaPy from Boruta, a feature selector was created using the XGBoost classifier and utilized to fit in the train and test dataset. The contribution of all features was ranked and the features that ranked 1 were kept.

3.2.2.4. Machine and deep learning classifiers

Traditional machine learning classifiers

To determine the capability of RGB and lab color features in classifying BMSB-defected hazelnuts and healthy ones, the extracted features were used to train traditional machine learning classifiers. A total of 400 normal and defected hazelnut samples were used in this study for this purpose. 80% of the samples which count 320 hazelnut samples were applied for training purpose while the remaining 20% (80 samples) was used to test the classifiers. Here, the traditional machine learning classifiers were; Support Vector Machine, Logistic Regression, Naïve Bayes, Decision Tree, and Random Forest classifier with 100 estimators. To evaluate the efficiency of the selected features in hazelnut classification, the classifiers were trained two times, firstly with the bulk features before applying any feature selection algorithm; secondly, the classifiers were trained using only the selected features. The model's performance was measured by calculating classification accuracy, confusion matrix and statistical parameters, and model execution (training) time.

CNN model development

The architecture of a convolutional neural network is split into 2 parts: feature learning and classification. The convolution layer, pooling layer, and fully connected

layer represent these parts. Convolution and pooling layers were used to extract features, and a fully connected layer was used to classify those features (Albawi et al., 2017). In order to classify defected and healthy hazelnuts, we have developed a binary classification CNN model and trained it three times with hazelnut images in RGB and Gray-scale color spaces. The model was trained upon RGB and Gray-scale images with 20 and 30 Epochs using Rmsprop and ADAM Optimizers. Keras Sequential model was selected as the application interface (API) for the model development. For more analysis, Scikit-learn library functions such as confusion matrix and ‘train_test_split’ function were used.

Input layer

It is the most fundamental layer, and it is responsible for reading and writing the image dataset. The images were initially transformed into a matrix. To speed up the training process, hazelnut images were normalized before being fed into the layers. 4540 valid hazelnut images were used and randomly split into training, test, and validation dataset set using the ‘train_test_split’ function in the Scikit-learn library. 70% of the total dataset was used for the training process and the remaining 30% was divided into test set (15%), and validation set (15%) as shown in Table 3.3.

Table 3.3. Samples in the training, validation, and test categories

Categories	Total hazelnut sample
Training	3178
Validation	681
Test	681
Total	4540

Convolutional layer

In designing the CNN model convolutional layer is the major and the most significant layer (Thakur and Kumar, 2021). By applying various types of filters (kernels) to these layers, low-level features can be extracted (Dyrmann et al., 2016). The CNN binary classification model was designed using convolutional layers with 32 filters in this study. The size of all filters used in our convolution neural network was set to be 3×3 because of its good performance in decreasing computational parameters and enhancing model performance (Simonyan and Zisserman, 2014). For an input matrix f (image) and filter k , the two- dimensional discrete convolution operation is given in the Equation below:

$$F(i,j) = (f*k)(i,j) = \sum_m \sum_n k(m,n)f(i-m,j-n) \quad (3.5)$$

Activation function

The activation function of ReLU (The rectified linear activation function) (Ghazi et al., 2017) was employed for all convolutional layers in this study. Because ReLU is the default activation function when creating multilayer perceptron and convolutional neural networks, it eliminates the vanishing gradient problem, allowing models to train quicker and perform better (Brownlee, 2019). Sigmoid, Leaky ReLU, hyperbolic tangent (tanh) function and other non-linear functions can be utilized as activation functions, but we found the ReLU function to be the best fit for our model. The following mathematical procedure is carried out by the ReLU function (Dyrmann et al., 2016).

$$f(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases} \quad (3.6)$$

Pooling layer

Three 2×2 max-pooling layers were applied as sup sampling layers that have the function of decreasing the size of the feature maps that were created (Farooq and Sazonov, 2017) as well as the dimensionality of the feature vector by maintaining the highest values of the feature map (the output of each pooling layer). Because the features obtained in the feature capturing section must be turned into a one-dimensional vector before being fed to the fully connected layer, the flatten layer was used to flatten the output of the last pooling layer.

Fully connected layer

The fully connected layer is the final layer that gathers the data that obtained by previous layers into the final output. Because this is a binary classification task, the output of the last max-pooling layer was sent through a fully connected layer with one neuron corresponding to the probability of class 0 or 1. The sigmoid function was utilized to construct this binary classification CNN model to classify hazelnut into defective and healthy and the mathematical expression for sigmoid is given in the Equation below.

$$\text{Sigmoid}(x) = \frac{1}{1+e^{-x}} \quad (3.7)$$

The CNN model configuration, constructed in this work is presented in Table 3.4. In this table, the shape of the output layers is denoted as (height $\times$ width $\times$ number of channels RGB). And the hyper parameters used to design the optimal convolutional neural network for hazelnut classification are illustrated in Table 3.5.

Table 3.4. The configuration of the developed CNN model

Layer (type)	Output Shape	Parameters
conv2d_1 (Conv2D)	(None, 78, 78, 32)	896
Activation_1 (Activation)	(None, 78, 78, 32)	0
max_pooling2d_1(MaxPooling2	(None, 39, 39, 32)	0
conv2d_2 (Conv2D)	(None, 37, 37, 32)	9248
activation_2 (Activation)	(None, 37, 37, 32)	0
max_pooling2d_2 (MaxPooling2)	(None, 18, 18, 32)	0
conv2d_3 (Conv2D)	(None, 16, 16, 32)	9248
activation_3 (Activation)	(None, 16, 16, 32)	0
max_pooling2d_3 (MaxPooling2)	(None, 8, 8, 32)	0
Flatten_1 (Flatten)	(None, 2048)	0
Dense_1 (Dense)	(None, 64)	131136
activation_4 (Activation)	(None, 64)	0
Dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 1)	64

Dropout layer

The result of the previous max-pooling layer was forwarded to the dropout layer as a normalization method that reduces the risk of over fitting throughout the training process of the CNN model. Here we used one drop-out layer with a 20% dropout rate to eliminate some neurons at random and enable the remaining neurons to participate in the network training process and update their weights. This procedure also aids in learning new features by the neurons (Sladojevic et al., 2016).

Table 3.5. Hyper parameters of the optimal CNN used for hazelnut classification

Parameter	Value/Type
Weight initializer	he uniform
Bias initialize	zeros
Optimizer	Rmsprop, ADAM
Initial learning rate	0.0001
Loss function	cross-entropy
Bach size	64
Epochs	20, 30
Verbose	1

Convolutional block numbers selection

In most cases, increasing the depth of the CNN has an important impact on classification accuracy and performance. Hence, the overall performance increases with increasing CNN depth (Simonyan and Zisserman, 2014). Four convolutional blocks were included in the created CNN (each block contained a convolutional layer, activation layer, and max-pooling layer). To select the suitable convolutional block numbers, the classifier was trained four times. The first time, the classifier was trained with the first convolutional block only and the other three blocks were frozen. In the second step, the first and the second convolutional blocks were used. In the third step, first, second, and third blocks were used. Finally, the classifier was trained with the all convolutional blocks. The convolutional block with the highest performance was selected to be used for hazelnut classification.

Evaluation of CNN model performance

For model performance evaluation confusion matrix related to traditional and convolutional neural network classifiers was extracted. The parameters in the confusion matrix express the actual labels of the hazelnut class and the labels predicted by the classifiers. The instances in the actual class are represented by the columns of the matrix, while the instances in the predicted class are represented by the rows. This can be used to see if the classifier is frequently mislabeling one item as another. A two-class confusion matrix is a two-row, two-column table that enables more detailed analysis than accuracy rate. The confusion matrix and the data entries for two-class classifiers are presented in Table 3.6. We used a confusion matrix in this work because classification accuracy is not a trustable measure for evaluating a classifier's efficiency, and it can generate misleading results when the quantity of samples in different classes varies greatly (Ghosh et al., 2014).

Table 3.6. Confusion matrix for two class classifier

	Predicted class	
	<i>Positive</i>	<i>Negative</i>
<i>Actual class</i>		
<i>Positive</i>	tp	fp
<i>Negative</i>	fn	tn

where ‘tp’ represents the number of positive samples classified as positive, ‘fp’ is the number of negative samples classified as positive, ‘fn’ is the number of positive samples classified as negative, and ‘tn’ is the number of negative samples classified as negative.

Also, the performance of CNN and traditional models were evaluated depending on some confusion matrix metrics such as precision, specificity, and sensitivity. The formulas of these measures are presented in Table 3.7 (Taheri et al., 2015).

Table 3.7. Statistics parameters of confusion matrix and related formulas

Measure	Formula	Evaluation focus
Accuracy	$\frac{nTP + nTN}{nTP + nTN + nFP + nFN}$	Calculate the classifier's general performance.
Recall	$\frac{nTP}{nTP + nFN}$	The class arrangement between the data labels and the classifier's positive labels
Precision	$\frac{nTP}{nTP + nFP}$	An evaluation of a classifier's capacity to identify incidences of a specific class.
Specificity	$\frac{nTN}{nTN + nFP}$	How well a classifier can detect negative labels

4. RESULTS AND DISCUSSION

4.1. Image Acquisition

By using the developed image acquisition system, hazelnut images were captured in RGB format (80×80 pixels) (Figure 4.1) with black background and saved as BMP files. Because the aim of this work was a classification task, no image resizing process had been applied in this study and the images were suitable for developing traditional and deep learning models. According to Saponara and Elhanashi (2022), downscaling images makes it much harder for CNN to become familiar with the characteristics required for classification or detection, because the number of pixels where the critical features are present is significantly reduced. However, image resizing is an important image pre-processing process in computer vision. Deep learning models, in general, train considerably faster on small dataset. A relatively large input image requires the neural network to learn many pixels in a longer period of time, which increases the training time. Enlarging image size in deep and machine learning sometimes results in a pixilated or blurry image. As a result, in machine and deep learning downsizing an image is far safer than enlarging an image (Shin et al., 2016). Here, the created dataset contained normal and defected hazelnut samples with different defection severity levels. Only one hazelnut image was included in each RGB image data.



Figure 4.1. Defected and healthy hazelnut samples

4.2. Image Segmentation

Image segmentation process is the primary stage of the image processing task. To segment hazelnut images from the background, simple (global) thresholding approach was applied. A threshold value of 50 was determined from the gray-level histogram (Figure 4.2) and the value was able to separate the background from hazelnut images properly. According to the histogram, hazelnut image pixels with

intensities greater than 50 demonstrate the hazelnut image, while the pixels with intensities less than the threshold value demonstrate the dark background.

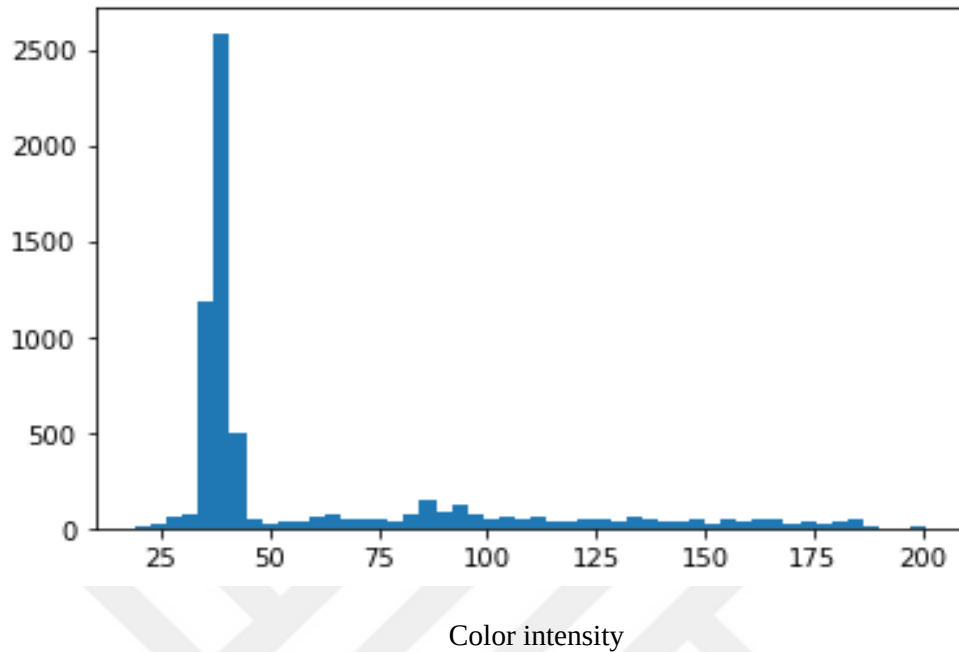


Figure 4.2. Gray-level histogram of hazelnut image

The bitwise operation algorithm was sufficient to get the required RGB hazelnut images as illustrated in Figure 4.3. The technique was efficient in the segmentation process and was applied variously by researchers for background removal purposes (Senthilkumaran and Vaithegi, 2016; Yogamangalam and Karthikeyan, 2013).

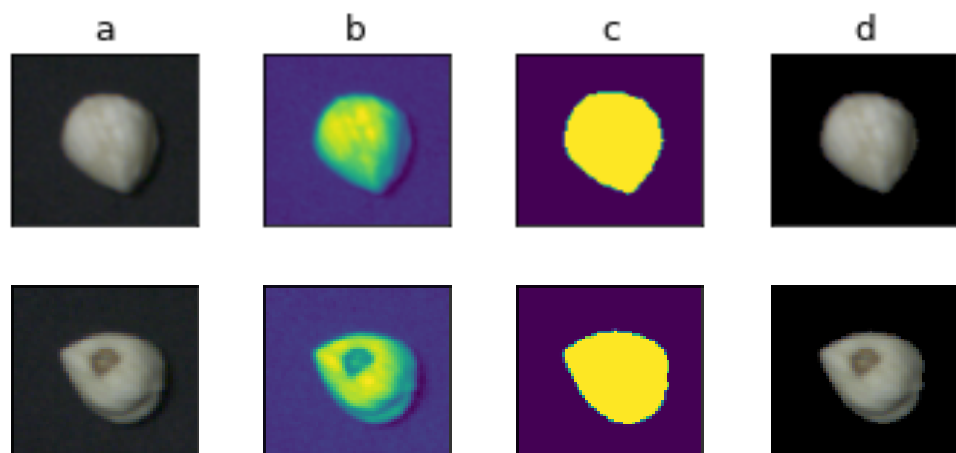


Figure 4.3. Segmentation steps. (a) RGB image, (b) Gray hazelnut image, (c) Thresholded image, (d) Segmented image

4.3. Feature Extraction and Selection

A total of 24 color features were extracted and saved to an excel file. These features were tested by the classifiers to evaluate their performance in predicting hazelnut classes. The applied feature selection algorithm confirmed that out of 24 features only 7 color features were important and discriminative more than the other features. The confirmed and rejected features are present in Table 4.1.

Table 4.1. Confirmed and rejected features by applying BorutaPy

No.	Feature	Status	No.	Feature	Status
1	Red mean	Confirmed	13	l* mean	Rejected
2	Green mean	Confirmed	14	a* mean	Confirmed
3	Blue mean	Rejected	15	b* mean	Rejected
4	Red variance	Rejected	16	l* variance	Confirmed
5	Green variance	Rejected	17	a* variance	Rejected
6	Blue variance	Rejected	18	b* variance	Rejected
7	Red range	Rejected	19	l* range	Rejected
8	Green Range	Rejected	20	a* range	Rejected
9	Blue Range	Rejected	21	b* range	Rejected
10	Red skewness	Rejected	22	l* skewness	Rejected
11	Green skewness	Confirmed	23	a* skewness	Confirmed
12	Blue skewness	Rejected	24	b* skewness	Confirmed

The majority of the accepted features were displayed in the l*a*b* color space, which reflects the reality described by Saruhan (2010) when researching the symptoms of BMSB infestation on hazelnut kernels after harvesting. In the l*, a*, and b* color spaces, the defection caused by the BMSB appears as discoloration and color changes. The characteristics of red mean, green skewness, and green mean were also found to be effective in classifying hazelnut into BMSB-defected and healthy hazelnut. This may support the theory of, BMSB infestations on hazelnut surfaces appear such little yellowish-green spots (Short, 2010).

4.4. Machine and Deep Learning Models

4.4.1. Traditional Machine Learning Classifiers

Using test data, the performance of all trained traditional machine learning classifiers was assessed, as well as the confusion matrix. Table 4.2 shows the classifier's performance resulting from training traditional machine learning classifiers with bulk features before applying the feature selection process.

Table 4.2. Classification accuracy and training time with bulk features

No.	Classifier	Acc. with bulk features	Training time
1	Support Vector Machine	98.75	0:00:00.007994
2	Logistic Regression	96.25	0:00:00.021987
3	Random Forest	95%	0:00:05.538398
4	Decision Tree	93.75	0:00:16.806870
5	Naïve Bayes	90%	0:00:00.001998

Based on all extracted feature vectors, the highest classification accuracy (98.75%) was achieved from the Support Vector Machine model. This model can construct a good hazelnut classification system in real-time applications in food industries. Using the same color features, a Support Vector Machine-based computer vision system was developed and applied in real-time to classify pistachio nut kernels and the same result was obtained (Nouri et al., 2017). Pacheco and López (2019) utilized RGB and $L^*a^*b^*$ color features with the digital image processing techniques for tomato flaws detection purposes. Multiple unsupervised machine learning algorithms were applied to identify the highest classification performance depending on the overall accuracy and confusion matrix metric and performance indices parameters such as precision, sensitivity, and specificity. Classification performances of 98.6, 98.3, 92, and 100% were achieved in the results for accuracy, specificity, precision, and sensitivity, respectively. These results consider very comparable to our results when RGB and $L^*a^*b^*$ color features were used.

Acceptable performance was also achieved by training Random Forest and Logistic Regression models with bulk features, with an overall accuracy of 95 % and 96.25%, respectively. The confusion matrix was extracted to assess the effectiveness of each classifier in predicting individual hazelnut classes using all feature vectors as shown in Figure 4.4.

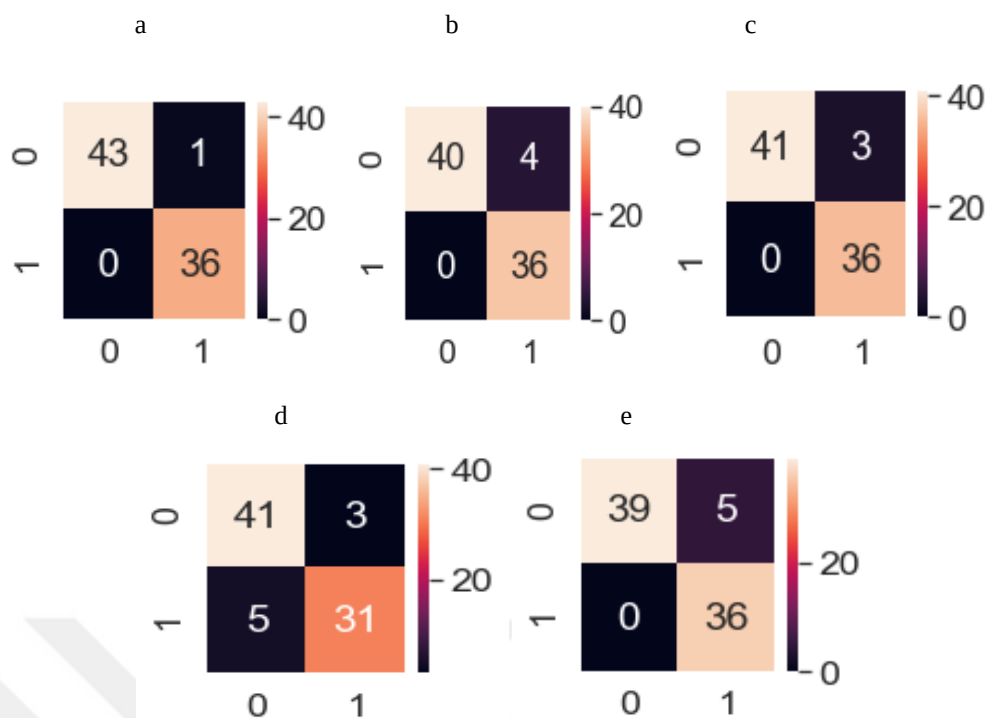


Figure 4.4. Confusion matrix of traditional classifiers; Support Vector Machine (a), Random Forest (b), Logistic Regression (c), Naïve Bayes (d), and Decision tree (e)

The Decision Tree and Naïve Bayes models had the lowest classification accuracy amongst the classifiers, with 90 % and 93.75 %, respectively. A comparable result was achieved from a Decision Tree-based classifier applied to classify areca nuts into healthy and defective nuts (Akshay and Hegde, 2021). Statistical parameters related to the confusion matrix were also calculated and presented in Table 4.3.

Table 4.3. Confusion matrix statistical parameters related to defected and healthy classes with bulk features.

NO.	Measure %	Classifiers				
		SVM	RF	LR	NB	DT
1	Recall	100	100	100	89	100
2	Precision	97.7	90.9	93	93	88.6
3	Specificity	97	90	92	91	87.8

The Support Vector Machine showed the highest accuracy in predicting defective and healthy hazelnut samples when traditional machine learning classifiers were validated. However, the sensitivity of all classifiers (in except of Naïve Bayes classifier) in predicting defected hazelnut samples was very high and reached 100%. When predicting defected hazelnut samples. Individually, the least classification

accuracy of defected hazelnut prediction was achieved from Naïve Bayes classifier. Hence, out of all defected hazelnut samples, 5 samples were falsely predicted as healthy samples which reduced the sensitivity of the model.

The classification accuracy of Random Forest and Naïve Bayes classifiers was improved by using the feature selection technique. That seems to be, the applied feature selection technique reduced the redundant data and minimized the opportunity of making decisions based on noise, resulting in increased accuracy (Balachandran et al., 2018). Furthermore, the Support Vector Machine's classification accuracy with the selected features was reduced to 96.25 %. Table 4.4 shows the performance of traditional machine learning classifiers using the selected features.

Table 4.4. Classification accuracy and training time with selected feature

No.	Classifier	Acc. with bulk features	Training time
1	Random Forest	97.5%	0:00:00.256844
2	Support Vector Machine	96.25%	0:00:00.005997
3	Logistic Regression	96.25%	0:00:00.021984
4	Naïve Bayes	93.75%	0:00:00.001997
5	Decision Tree	93.75%	0:00:00.004996

Since the primary aim of the SVM classifier is to find the best and most appropriate hyper plane in an N-dimensional space that perfectly distinguishes the data point, in our case, using all input data (features) may have helped to create a plane with a maximum margin, which maximized the distance between the data points of the defected and healthy hazelnut classes, resulting in improved classification accuracy. When only selected features were used, all machine learning classifiers performed positively by decreasing model training time. Figure 4.5 represents the confusion matrices of the classifiers with the selected features. Colour features have been identified as powerful features in multiple classification tasks. Hong et al. (2011) used image processing and machine learning approaches to assess the quality of peanut products using the same color features. Based on pattern recognition, the color features R, G, and B of the damaged area were extracted to identify the damaged peanuts. The recognition task was completed with an accuracy of 80.12%. Furthermore, color features were selected from shape and color

combinations to classify white cashew nut kernels using Artificial Neural Networks. From the input cashew kernel images, 24 color features were selected to achieve an accuracy of 88.93% (Narendra and Hareesha, 2016).

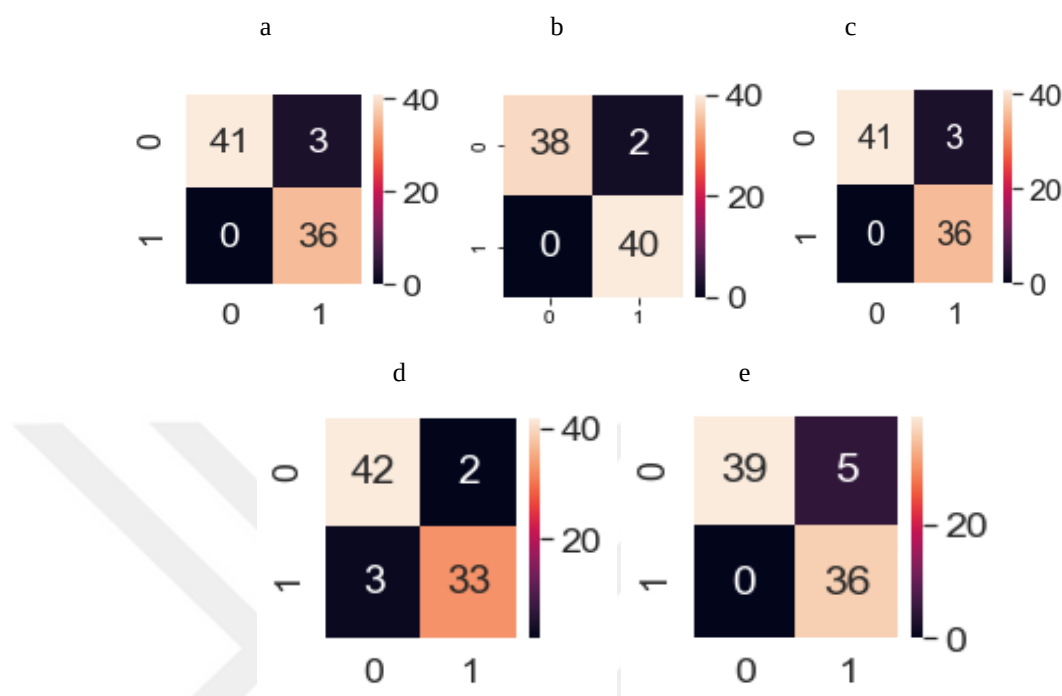


Figure 4.5. Confusion matrix of traditional classifiers; Support Vector Machine (a), Random Forest (b), Logistic Regression (c), Naïve Bayes (d), and Decision tree (e)

While the accuracy Random Forest and Naïve Bayes models was enhanced by considering only the relevant features, precision rate was also enhanced to be 95% for each of them. However, the statistical parameters of the SVM model were generally decreased as the overall classification accuracy was decreased as in Table 4.5.

Table 4.5. Confusion matrix statistical parameters related to defected and healthy classes with selected features.

NO.	Measure %	Classifiers				
		SVM	RF	LR	NB	DT
1	Recall	100	100	100	95	100
2	Precision	93	95	93	95	88.6
3	Specificity	92	95	92	94	87.8

4.4.2. CNN Performance

In order to develop the CNN model as illustrated in section 3, a total of 4540 hazelnut image samples were used. 70% of these samples which count 3178 image samples were utilized to train the model. The remaining 30% dataset was used for validation and test purposes. The developed CNN classifier was trained three times in the training dataset with 20 Epochs. After each training step, one of the convolutional blocks was picked out of the constructed model. Table 4.6 shows the results of each training time performance.

Table 4.6. Comparison of the developed CNN performance in different conditions of convolutional blocks

Active block	Training		Validation	
	Accuracy	Loss	Accuracy	Loss
1	93.99	0.147	91.76	0.145
1, 2	96.21	0.096	94.00	0.151
1, 2, 3	98.58	0.037	98.83	0.041
1, 2, 3, 4	95.36	0.118	92.67	0.248

According to the performance obtained from these training steps, the highest training performance was achieved when three convolutional blocks were used. Thus, this network was approved for hazelnut classification and tested under various conditions.

4.4.2.1. CNN Model Performance in RGB Hazelnut Images

CNN performance with RGB hazelnut images and rmsprop

After training the model with RGB hazelnut images with 20 and 30 Epochs, acceptable results were obtained. The accuracy and loss of training and validation of the network related to the Epochs number are presented in Figure 4.6, and 4.7.

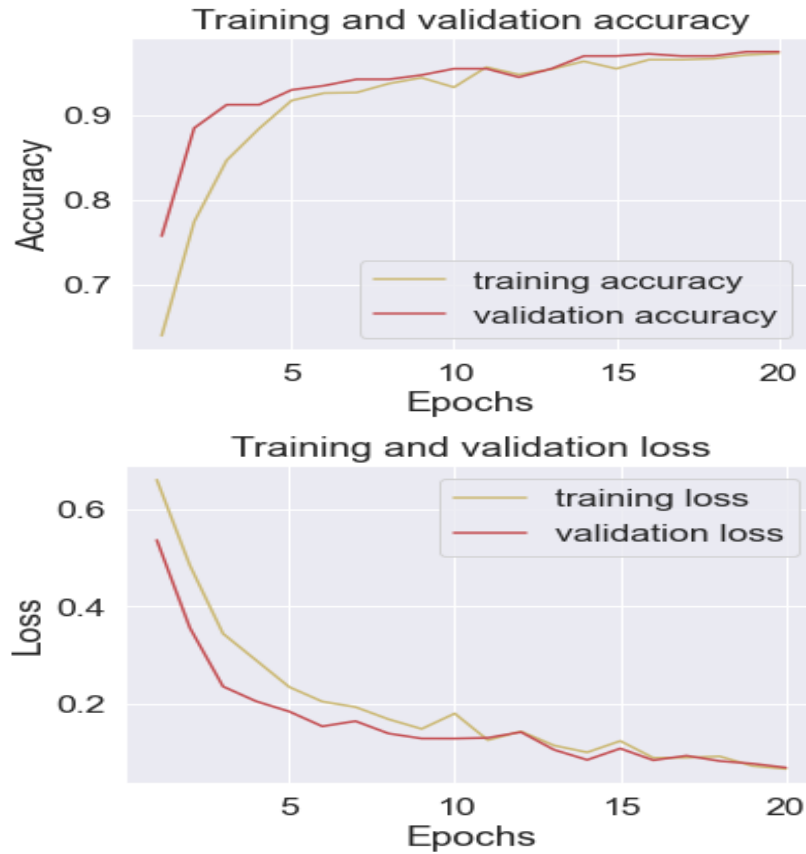


Figure 4.6. Training and validation accuracy and cross entropy loss of RGB hazelnut classification with 20 Epochs

The model had a high error rate at the beginning of the training process (epochs 1–11). However, as the epoch number increased, the error rate significantly reduced and finally reached the minimum at the end of the training process. These results indicated that the number of training repetitions required to achieve acceptable classification accuracy was 20 (epoch) where training and validation data had the least error rate. The error may reduce to the minimum by increasing the epoch's number.

At the beginning of the training process, there was slight over fitting, but it faded as the number of the epochs increased. This means that 20 epochs to train the model was enough to protect the model from the over fitting problem. At the end of the training procedure, the classification accuracy of the training and validation datasets was 0.986 and 0.988 with error values of 0.037 and 0.041, respectively. Overall accuracy and cross-entropy loss values for the test dataset were 98.82% and 0.038, respectively. Another study that used a deep CNN classifier to categorize pistachio nut kernels as defective or normal was conducted and the same result was

achieved (Hosseinpour et al., 2022). Throughout many image classification applications, the deep CNN model has proven to be extremely effective. An improvised algorithm for computer vision-based deep CNN was used for cashew grading purposes. RGB cashew nut images were used to feed the system. Max pooling functions are used to build the CNN network by selecting the largest element from the respective ROI with the ReLU activation function. The system was able to classify cashew nuts perfectly (Sivaranjani, 2018).

By increasing the epoch number, training and validation accuracy were relatively improved to 99.18 and 98.89 %, respectively, and the loss was reduced to 0.029 and 0.39 % (Figure 4.7). When the model's performance was evaluated using test data the same accuracy was obtained. That may demonstrate the fact that increasing the epoch number usually improves model performance by reducing training and validation error, and the training process should be stopped when the validation data error rate is at its lowest. Besides that, increasing the number of epochs consequently may result in an over-fitted model (Hastomo et al., 2021).

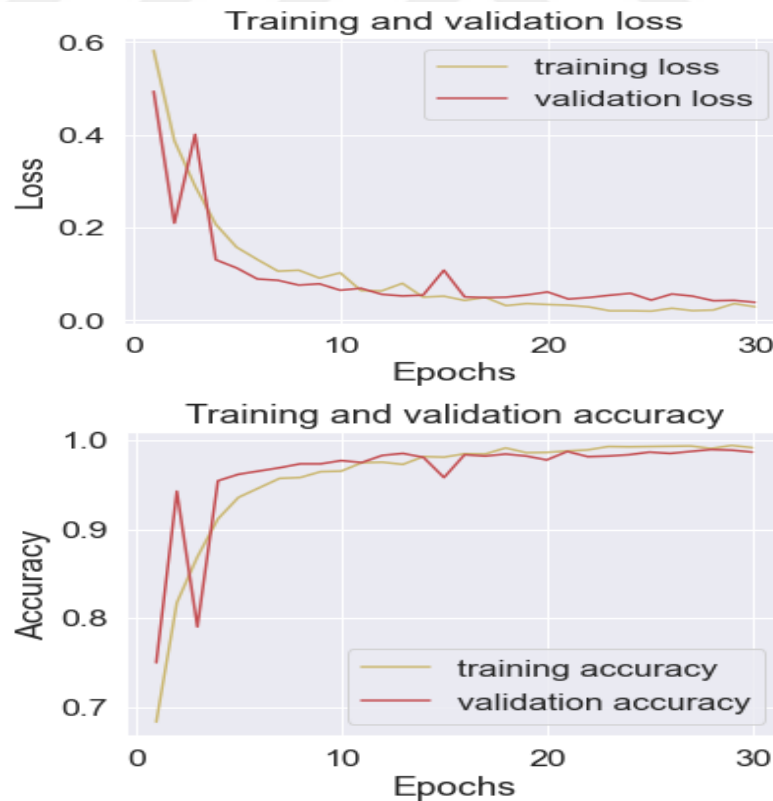


Figure 4.7. Training and validation accuracy and cross entropy loss of RGB hazelnut classification with 30 Epochs

To evaluate the performance of the proposed CNN classifier in hazelnut defect detection and classification, the confusion matrix (Figure 4.8) and the performance of the statistical parameters of the confusion matrix were generated by setting the threshold value as 0.5.

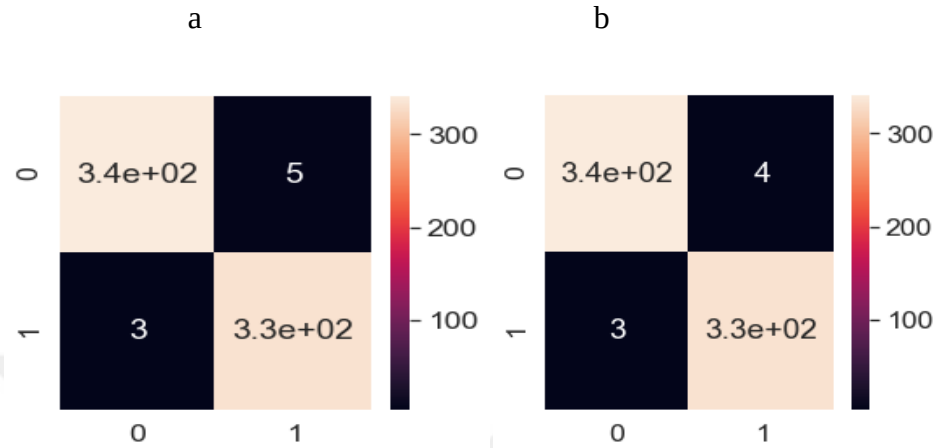


Figure 4.8. Confusion matrix of normal and defected RGB hazelnut mages with 30 Epochs (a), and 20 Epochs (b)

The distribution of hazelnut predictions (with RGB hazelnut images) for each of the two classes is shown in the confusion matrix. Four of the healthy hazelnut samples were misclassified as positive, and three of the defected samples were misclassified as negative, indicating that the defected and healthy samples were accurately classified with 99 and 98.8% recall rates, respectively. Although traditional machine learning algorithms play an important role in classification problems because of their ability to perform feature engineering in small amounts of data and achieve good results, the developed deep CNN model performed better than traditional machine learning algorithms in both training and testing data sets. The result obtained from the Support Vector Machine classifier was comparable to the CNN result, hence deep learning CNN model tries to learn high-level features from data in an incremental manner and overcome generalization and over fitting problems. This eliminates the need for domain expertise and a hardcore feature extraction process. In the last two years, many types of research have been conducted on CNN applications in crop defect detection and classification. Recently, in a study on sour lemon classification, the performance of traditional machine learning models

was compared with deep learning models in defect identification and classification, and comparable results were obtained (Jahanbakhshi et al., 2020).

CNN performance with RGB hazelnut images with and ADAM Optimizer

By changing the model optimizer, the CNN model performance in training and validation data were enhanced when 30 Epochs were applied, however there was no change in the model performance when 20 Epochs were used (Figure 4.9)

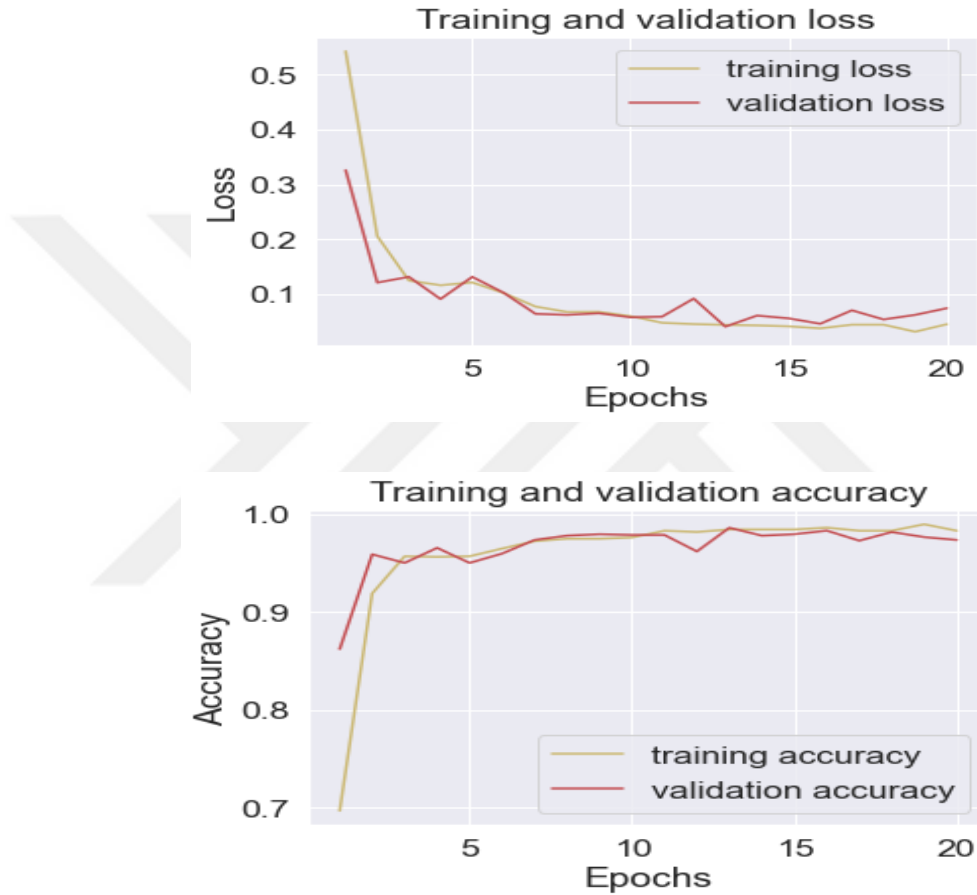


Figure 4.9. Training and validation accuracy and cross entropy loss of RGB hazelnut classification with 20 Epochs

The accuracy of the training and validation process using 30 Epochs was 99.56 and 98.7 %, respectively (Figure 4.10). As a result, in hazelnut classification, the combination of ADAM Optimizer and 30 Epoch number was proved to be more effective. This improvement may have resulted from the implementation of the ADAM optimizer. ADAM is based on the Rmsprop optimizer; however, the gradient is estimated as a momentum parameter to enhance the training speed of the model. Kingma and Ba (2014) carried out an experiment to test CNN model performance

using several types of optimizers, and ADAM outperformed all other methods in various training setups and experiments. ADAM optimizer has been applied in a wide range of image classification and quality estimation systems due to its high performance when compared to other optimizers. A quick and non-destructive method using hyper spectral imaging (HSI) coupled with deep learning classification was applied for canarium nut quality estimation. The best performance was achieved when a combination of 5000 Epochs and ADAM optimizer were used (Han et al., 2021).

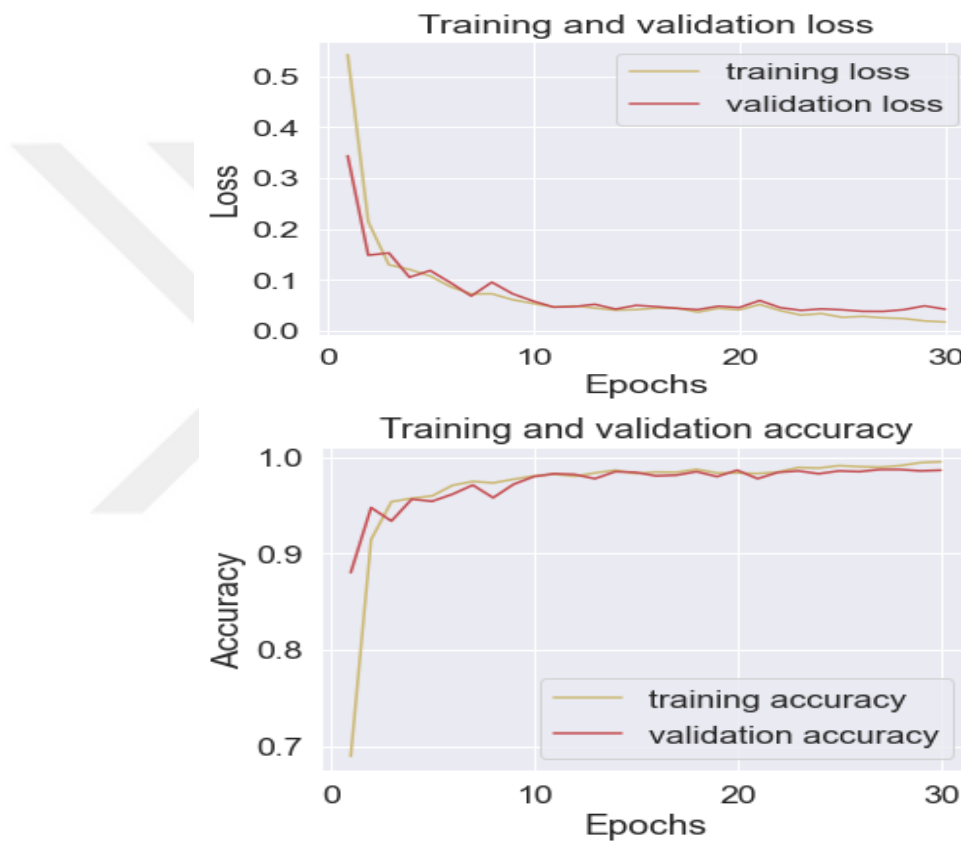


Figure 4.10. Training and validation accuracy and cross entropy loss of RGB hazelnut classification with 30 Epochs

As in the confusion matrix below, the model's performance in predicting healthy and defective hazelnut classes was extremely satisfactory and acceptable (Figure 4.11). The overall classification accuracy was 98.82 %, and the false positive and false negative parameters were both predicted as 4.

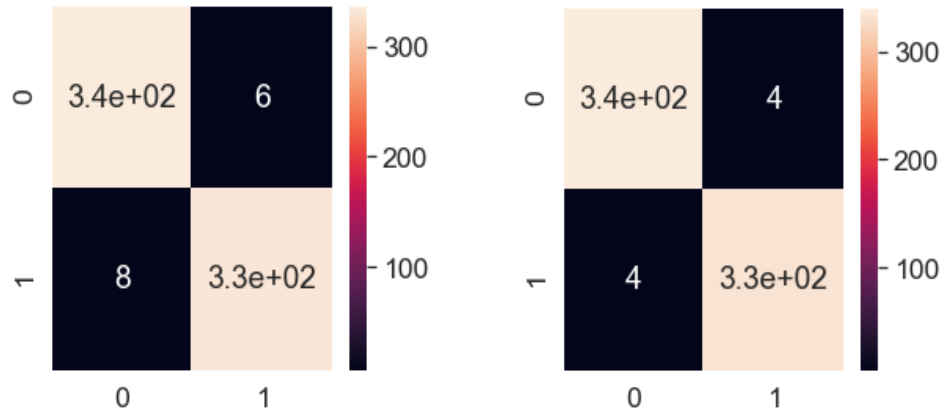


Figure 4.11. Confusion matrix of normal and defected RGB hazelnut mages with 20 Epochs (a), and 30 Epochs (b)

4.4.2.2. CNN Model Performance in Gray-scale Hazelnut Images

Hazelnut images in Gray-scale space are presented in Figure 4.12. When the model was trained with Gray-scale hazelnut images, the performance was decreased compared to the model performance with RGB hazelnut images in general.

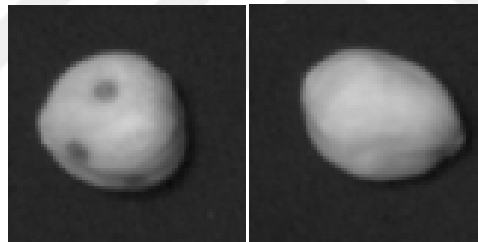


Figure 4.12. Defected and healthy Gray-scale hazelnut image

CNN performance with gray-scale hazelnut images and rmsprop

Using gray-scale hazelnut images with 20 Epochs, training and validation accuracy were reached 98.3 and 97.9%, respectively (Figure 4.13). Using Gray-scale images, machine and deep learning models may present a good performance due to the fewer amounts of channels when compared to RGB images. A deep CNN model was proposed for fruit classification using Gray-scale images. The model was trained using 4793 images (Apple, Citrus, Stone fruit, Tropical, and exotic, Berries, Melons, Tomatoes, and avocado). The model achieved an accuracy of 100% on a held-out test dataset (Mohammed, 2022).

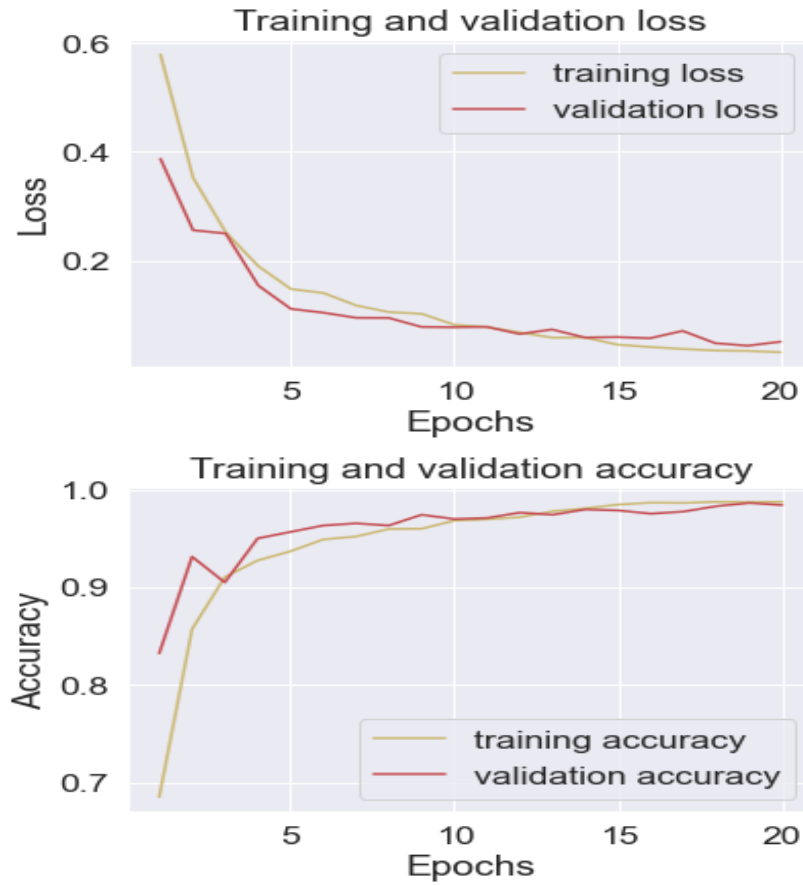


Figure 4.13. Training and validation accuracy and cross entropy loss of gray-scale hazelnut images

This model attained an overall classification accuracy of 97.7 %. On the other hand, the recall, sensitivity, and specificity ratios were reduced to 97.9, 97.7, and 97.6 %, respectively. In general, the CNN model's classification performance on RGB hazelnut images with 20 Epochs was better than the model's performance in this case. The confusion matrix of healthy and defected Gray-scale hazelnut images with 20 Epochs is presented in Figure 4.14.

```

In [10]: _, acc = model.evaluate(x_test, y_test)
...: print("accuracy = ", (acc * 100.0), "%")
22/22 [=====] - 2s 76ms/step - loss:
0.0655 - accuracy: 0.9736
accuracy = 97.35682606697083 %

In [11]: mythreshold=0.4
...:
...: from sklearn.metrics import confusion_matrix
...: Y_pred = (model.predict(x_test)>=
mythreshold).astype(int)
...: cm = confusion_matrix(Y_pred, y_test)
...: print(cm)
[[337  8]
 [ 7 329]]

```

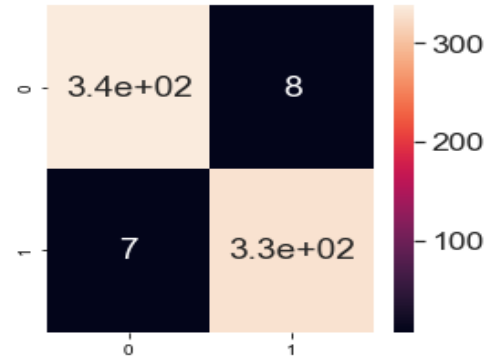


Figure 4.14. Confusion matrix of normal and defected Gray-scale hazelnut images with 20 Epochs

The model was also trained with 30 Epochs. Hence increasing the Epochs number in this model does not affect the model performance compared to the previous performance. As well as less performance (on training, validation, and test data) than the RGB model with the same Epochs number was achieved. The training and validation accuracy of 98.5 and 97.2% were achieved, respectively. Furthermore, as the number of the Epochs increased, more oscillations were recorded, and the model began to over-fit. Figure 4.15 depicts the training and validation accuracy as well as the corresponding error.

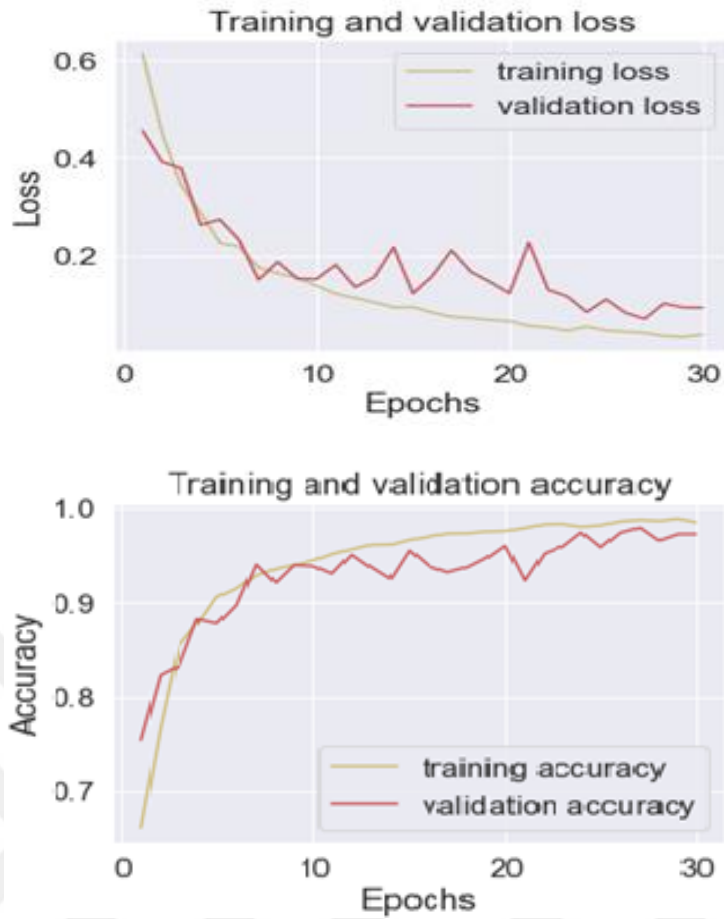


Figure 4.15. Training and validation accuracy and cross entropy loss of gray-scale hazelnut images with 30 Epochs

This model achieved an overall accuracy of 97.35 %, which is less than the classification accuracy of the model with 20 Epochs. The model's confusion matrix is represented in Figure 4.16.

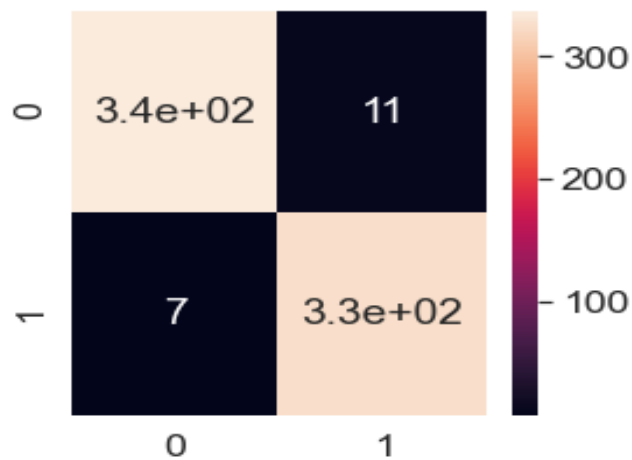


Figure 4.16. Confusion matrix of healthy and defected gray-scale hazelnut image classes with 20 Epochs

CNN performance with gray-scale hazelnut images and ADAM

Figure 4.17 shows the training and validation loss and corresponding accuracies of the CNN model with Gray-scale hazelnut images. The use of 20 Epochs number resulted in stable and non-oscillated training and validation curves. As a result, comparable training and validation accuracies were obtained.



Figure 4.17. Training and validation accuracy and cross entropy loss of gray-scale hazelnut images with 20 Epochs

The CNN model's overall accuracy with gray-scale data was 97.50 %. When 20 Epochs were utilized, there were no significant differences in the model performance between Rmsprop and ADAM optimizers. However, the performance of the model by considering the statistical parameters of the confusion matrix was reduced in this case (Figure 4.18).

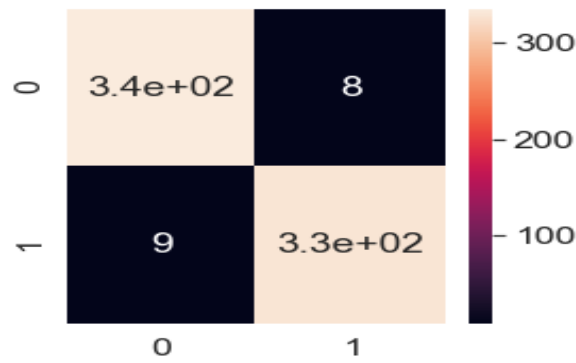


Figure 4.18. Confusion matrix of normal and defected Gray-scale hazelnut image classes with 20 Epochs

The combination of ADAM optimizer with 30 Epochs number on Gray-scale hazelnut images impacted negatively on training and validation performance compared to the same combination on RGB hazelnut images. Also, the model was started to be over fitted at some points. Increasing the number of epochs may have a negative impact on model performance at times. When RGB images were employed in a study by Daniel (2021) for Sunflower leaf disease detection and classification using CNN, training and validation accuracies of 99.19 and 99.99 % were reached by combining 50 Epochs with ADAM optimizer. When the same combination was applied to Gray-scale images, the training and validation accuracies were reduced to 96.97 and 84.27 %, respectively (Figure 4.19).

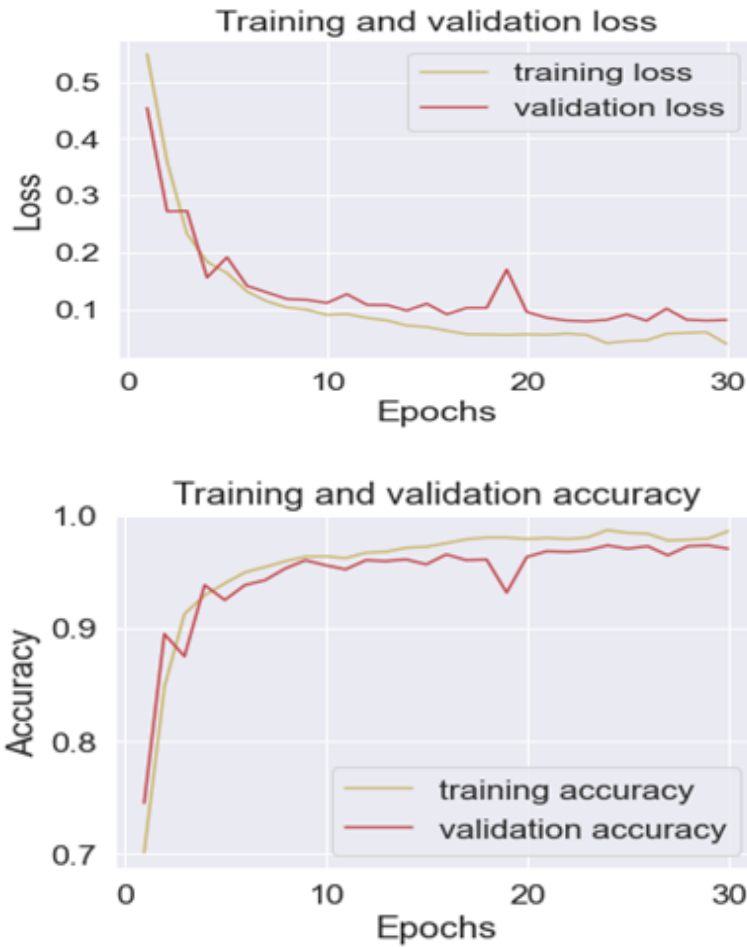


Figure 4.19. Training and validation accuracy and cross entropy loss of Gray-scale hazelnut images with 30 Epochs

Increasing the Epoch number to 30 reduced the error rate of validation data, but there was no improvement in the model performance in terms of accuracy, recall, sensitivity, and specificity. Figure 4.20 presents the confusion matrix of healthy and defected Gray-scale hazelnut classes throughout 30 Epochs.

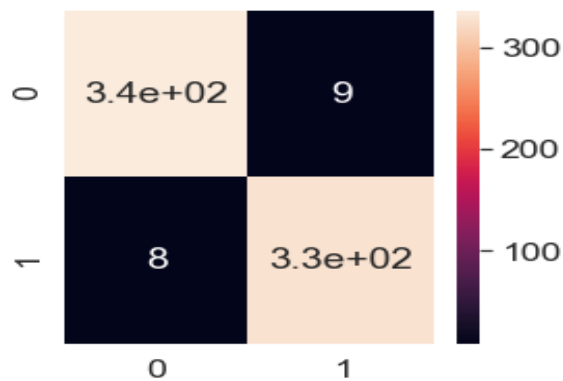


Figure 4.20. Confusion matrix of healthy and defected Gray-scale hazelnut image classes with 30 Epochs

Generally, all CNN models with RGB color spaces outperformed CNN models with Gray-scale images. Jason (2021) demonstrated how decreasing the number of image channels improves model performance. In our case, changing the image mode to a grayscale image mode reduced CNN model performance when compared to RGB images. This could be a result of, the symptoms that appear on hazelnut infected with BMSB concentrate on RGB color space, giving the classifier more opportunities to learn new features. Padmavathi and Thangadurai (2016) analyzed and compared two types of images to detect plant diseases, such as grayscale RGB images. They concluded that the RGB image provided a clearer, noise-free image and it was more suitable for detecting infected leaves than the Grayscale image.

When compared to traditional machine learning models, the proposed CNN deep learning model performed better in this study. This demonstrates the power of deep CNN models in extracting better and more discriminative properties from images. To identify pine nut species, five machine learning methods (Decision Tree (DT), Random Forest (RF), Multilayer Perceptron (MLP), Support Vector Machine (SVM), and Naive Bayes (NB)) were used. A classification model based on five (CNN) models was also used to compare its performance to that of the machine learning model. The experimental results revealed that MLP produced the best classification model, with accuracy close to 99%. This indicates that machine learning models may outperform deep CNN models depending on the problem at hand and the data under investigation (Huang et al., 2022). Wang et al. (2021) also conducted image classification research to compare the performance of traditional SVM and deep CNN models. SVM and CNN achieved accuracies of 88% and 98%, respectively. Another study was conducted specifically to compare the accuracy, recall, precision, specificity, F-score, and image quality assessment metrics of deep CNN and traditional machine learning models. In terms of accuracy, nonlinear function approximation, and the ability to extract and articulate data features, the CNN model outperformed the machine learning algorithm (Günen, 2022). Erbas et al. (2022) established an artificial intelligence-based classification system to detect the hidden defects in hazelnuts. Hazelnut images were captured one by one to classify four hazelnut categories. CNN model was used for model development and the performance of the model was compared with the traditional models. An accuracy rate of 99% was achieved by the model when the model was examined under a moving classification system. In this study, hazelnut images were captured

individually and acceptable performance was obtained using CNN models. This performance can be achieved under a real-time machine vision classification system by controlling the system using the same conditions. Moreover, a machine vision system was performed to classify the processed hazelnut. The partly skin-removed hazelnut kernel, skin-removed, and rotten hazelnut kernels are classified by using the computer vision approach. An accuracy rate of 93.5% was achieved from the system (Ak et al. 2019). In our case, images were acquired by putting the samples directly under the camera using a fixed and stable image acquisition system. Through real-time machine vision systems where the product is transported on a conveyor, the performance of the model may decrease. However, to maintain a stable performance from the system, a multi-camera system can be used. In hazelnut processing factories, the hazelnut classification process is performed manually. Manual classification systems are supported by mechanical classification systems to re-classify the product again. The performance gained from deep machine learning models can be an excellent option for a fully mechanized hazelnut classification system where the machine vision system is artificially lighted and under controlled condition. Moreover, the models can also be applied to improve the existing machine vision systems.

5. CONCLUSION AND RECOMMENDATIONS

As part of post-harvest quality control activities, this study was conducted to address the recently discovered problem of hazelnuts infested with the BMSB, as well as to present a new possibility and improve the effectiveness of hazelnut classification systems in real-world applications in the food industry. As a result, various traditional machine learning algorithms were constructed and evaluated to determine how effective they perform in detecting BMSB-infested hazelnuts. Image segmentation, feature extraction, and feature selection processes were performed in order to construct and recommend the most appropriate model. Furthermore, on RGB and Gray-scale hazelnut images, a deep CNN model with different combinations of deep learning parameters was built and tested, and the performance was compared to determine the most appropriate hazelnut classification models. The obtained results can be summarized as follows:

- After testing different Thresholding background subtraction methods, the applied background subtraction Thresholding method was able to extract the hazelnut image from the background perfectly and overcome the difficulties those results from hazelnut spot color variation.
- The extracted color moment features represented in mean, variance, range, and skewness in the $L^*a^*b^*$ and RGB split color spaces were describable and distinguishable in classifying healthy and hazelnut that defected with the BMSB. When all extracted moment features were applied for hazelnut classification, the SVM classifier performed better than other traditional machine learning algorithms.
- After testing several feature selection approaches, the BorutaPy feature selector was identified as the most suitable one, and able to select the most relevant and discriminative features. Only seven features were selected from a total of 24 $L^*a^*b^*$ and RGB split color feature spaces. Using this strategy, data redundancy was also reduced. The majority of the features selected originated from the $L^*a^*b^*$ color spaces. As a result, the changes in hazelnut generated by brown marmorated stink insect infestation could be recognized to appear mostly in this color space after harvesting.

- By training traditional machine learning classifiers with the selected features only, the performances of most of these classifiers were improved. The performance of Random Forest, Naïve Byes, and Logistic Regression models was increased as well as the training time was reduced. In this case, the features selection objective was achieved by improving the learning process of machine learning models and increasing the predictive power of machine learning algorithms by selecting the most important and the most relevant variables and eliminating redundant and irrelevant features. There was no improvement in Decision Tress classifier performance in terms of accuracy, precision, and recall parameters. However, an improvement in processing time was achieved. The performance of the SVM model by using only the selected features was decreased due to the margin maximization.
- Using RGB hazelnut images with Rmsprop Optimizer, the developed CNN model performance in the training and validation dataset with 20 Epochs reached 98.56 and 98.8%, respectively. The model was also able to classify healthy and defected hazelnut samples with a very high overall accuracy.
- Acceptable performance of 99.5, 98.7, and 98.82 on training, validation, and test data was also achieved by the combination of RGB hazelnut images, 30 Epochs, and ADAM optimizer. Hence, the model was subjected to over fitting in some points as well as the confusion matrix parameters of the previous model were more acceptable.

Although machine learning and deep learning models for computer and machine vision are widely used around the world and applied in various fields, hazelnut research integrating this technology is very limited, leaving a significant gap in the sector. This gab appears in hazelnut processing factories and food industries. In addition, there are still manual and semi-automated hazelnut sorting and classification systems in use in post-harvest activities. These systems are considered very poor, time-consuming, and inefficient systems. To overcome this challenge, we concluded that; more investigations are necessary for hazelnut quality control to facilitate hazelnut processing easier in the food industries. Hazelnut infestation with BMSB is a relatively new problem and is under investigation. In particular, hazelnut infestation by the BMSB poses a serious threat to hazelnut quality on a wide scale and negatively impacts national and international marketability and acceptability. This study is conducted in our laboratory

conditions, in which limited and specific equipments were available. To be suitable for real operating conditions, the classification process of the hazelnut infected with BMSB must perform under moving systems with multiple cameras. Moreover, many precise and sensitive devices, such as hyper spectral and multispectral sensors, can calculate even changes in nutrient material and soluble values caused by BMSB inside hazelnut products are available nowadays. We strongly recommend further research in this field to improve the quality and reduce hazelnut classification error.



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APPENDICES

Appendix 1. Part of Extracted Machine Learning Features

Red Skewnes	Blue range	Green range	Red range	Blue variance	Green variance	Red variance	Blue Mean	Green Mean	Red Mean
216351.2111	148	161	163	1757.671913	2445.922715	2580.114365	22.5242188	26.776875	27.5707813
444492.8087	200	205	203	3388.315404	4169.482423	4226.114809	32.3057813	36.11421875	36.4301563
386956.4167	191	199	198	2844.509605	3425.656601	3470.625462	25.9120313	28.65296875	28.8607813
433684.3737	203	212	210	3167.111561	3834.753694	3888.38372	28.56375	31.6325	31.8945313
274125.8593	174	189	189	2159.618744	2828.597386	2919.001181	24.1275	27.79546875	28.2975
225317.6622	157	168	169	1834.010351	2390.090674	2454.991269	21.1878125	24.40671875	24.7882813
289547.0865	174	182	184	2159.669987	2971.085698	3116.773038	25.5396875	30.24765625	31.02
459529.043	202	210	204	3562.621658	4250.477773	4206.039956	31.6421875	34.94515625	34.8364063
474971.0534	209	210	205	3574.654436	4282.669381	4242.707104	31.10125	34.35640625	34.2523438
424547.579	201	208	204	3409.788408	4050.411734	3986.359705	31.3054688	34.511875	34.2828125
366365.1127	200	200	195	3068.924197	3537.69447	3455.409018	27.4582813	29.7578125	29.4810938
460179.8877	208	211	205	3657.160724	4202.643547	4117.43957	30.9267188	33.4346875	33.1757813
257810.7863	152	176	180	1534.281833	2475.432251	2768.054164	20.2640625	25.88234375	27.4278125
443401.9466	217	215	212	3461.164921	4010.300412	3913.883101	29.438125	32.05640625	31.7634375
427305.885	222	220	215	3343.082561	3877.810265	3785.477393	28.89875	31.5259375	31.2364063

B_range	A_range	L_range	B_variance	A_variance	L_variance	B_Mean	A_Mean	L_Mean	Blue Skewnes	Green Skewnes
39	23	168	25.8218301	1.91614353	2774.55844	130.481094	127.559531	28.5984375	125873.6263	201571.9549
56	26	209	21.9117078	2.65210898	4554.26749	130.084844	127.468125	37.9179688	327492.2148	438117.85
51	27	204	16.8390472	1.91585146	3755.2822	129.503906	127.612188	30.1351563	294456.4742	380732.8513
57	26	216	19.2920838	2.21832458	4187.776	129.670781	127.583594	33.21125	326355.4705	426651.2547
55	27	194	23.6953593	2.38242568	3164.02008	130.074688	127.556563	29.5153125	180367.0311	263909.3008
43	25	174	18.6401371	1.93364646	2686.50252	129.839375	127.573594	25.9696875	150622.628	217985.8958
50	26	188	29.6582465	2.18630615	3322.96206	130.698125	127.470313	32.1210938	173413.1735	270954.7641
63	28	213	22.7197478	3.1869	4607.13733	129.754219	127.41	36.5517188	373203.8238	470446.8601
57	29	214	23.0746632	3.1186085	4630.92184	129.716563	127.424063	35.8873438	380952.5451	484833.0593
57	25	211	21.1616142	3.19168711	4401.71267	129.696719	127.369375	36.1520313	350614.472	437194.8017
62	30	205	16.025415	2.55937021	3867.88486	129.210781	127.517813	31.2423438	317332.9369	382779.7625
78	29	214	19.0578582	2.9902947	4547.16189	129.308906	127.504219	34.9351563	397980.5483	478917.3779
44	29	182	47.7484249	2.69003662	2810.38393	131.319688	127.660938	27.6971875	109591.1417	220032.9741
57	30	218	18.2332777	2.73973428	4333.70435	129.373125	127.465313	33.5051563	384792.1709	464324.8549
57	29	223	18.1613767	2.78915771	4194.71425	129.383281	127.457813	32.9832813	372748.5705	447644.1126

label	B_Skewness	A_Skewness	L_Skewness
Defected	262.6998398	8.345946054	241335.234
Defected	243.2162624	14.4019313	493564.12
Defected	194.2999961	9.616512962	431447.421
Defected	233.3023134	12.73906513	480163.304
Defected	275.7121079	13.0790037	307977.366
Defected	192.4862753	9.434402869	256807.998
Defected	320.5032535	9.910174559	316323.695
Defected	316.1457606	17.75971937	523558.34
Defected	335.1236085	18.06435318	538047.239
Defected	273.4425815	16.33210403	488063.422
Defected	212.14415	14.75621837	432454.709
Defected	286.9662904	19.45716866	532193.198
Defected	663.0401343	15.89950094	262435.791
Defected	242.2104257	14.60027503	513182.923
Defected	237.9113661	15.06414344	494455.857

Appendix 2. Image Segmentation Algorithm

```

import cv2
import glob
import os
import matplotlib.pyplot as plt
from skimage.filters import gaussian
import numpy as np
path = "C:/Users/omsalma/Desktop/Train/Normal/*.*"
img_number = 1
for file in glob.glob(path):
    print(file)
    img = cv2.imread(file)
    #rgb_img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    gray_img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    ret,thresh = cv2.threshold(gray_img, 60, 255,cv2.THRESH_BINARY)
    segmented_img = cv2.bitwise_and(img, img,mask = thresh)
    cv2.imwrite("C:/Users/omsalma/Desktop/Train/Normal_seg/segmented_img"+str(im
g_number)+".bmp", segmented_img)
    img_number +=1

```

Appendix 3. Feature Extraction Algorithm

```
import numpy as np
import cv2
import glob
import os
import matplotlib.pyplot as plt
from skimage.filters import gaussian
import matplotlib.image as mpimg
from skimage import img_as_ubyte
import pandas as pd

path = ("C:/Users/omsalma/Desktop/ML2/Train/Normal/*")
R_meandata = [], G_meandata = [], B_meandata = [], R_variancedata = []
G_variancedata = [], B_variancedata = [], R_rangedata = [], G_rangedata = []
B_rangedata = [], R_skewdata = [], G_skewdata = [], B_skewdata = [], l_meandata =
[], a_meandata = [], b_meandata = [], l_variancedata = [], a_variancedata = []
b_variancedata = [], l_rangedata = [], a_rangedata = [], b_rangedata = [], l_skewdata
= [], a_skewdata = [], b_skewdata = [], y = []
for directory_path in glob.glob("C:/Users/omsalma/Desktop/Train/Normal_seg/*"):
    label = directory_path
    y.append(label)
def color_moments(path):
    img_number = 1
    for file in glob.glob(path):
        img = cv2.imread(file)
        RGB_img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        R, G, B = cv2.split(RGB_img)
        R_mean = np.mean(R)
        G_mean = np.mean(G)
        B_mean = np.mean(B)
        R_meandata.extend([R_mean])
        G_meandata.extend([G_mean])
        B_meandata.extend([B_mean])
        R_variance = np.var(R)
        G_variance = np.var(G)
```

```

B_variance = np.var(B)
R_variencedata.extend([R_variance])
G_variencedata.extend([G_variance])
B_variencedata.extend([B_variance])
R_range = np.ptp(R)
G_range = np.ptp(G)
B_range = np.ptp(B)
R_rangedata.extend([R_range])
G_rangedata.extend([G_range])
B_rangedata.extend([B_range])
R_skewness = np.mean(abs(R - R.mean()) ** 3)
G_skewness = np.mean(abs(G - G.mean()) ** 3)
B_skewness = np.mean(abs(B - B.mean()) ** 3)
R_skewdata.extend([R_skewness])
G_skewdata.extend([G_skewness])
B_skewdata.extend([B_skewness])
lab = cv2.cvtColor(img, cv2.COLOR_BGR2LAB)
l, a, b = cv2.split(Orem et al.)
l_mean = np.mean(l)
a_mean = np.mean(a)
b_mean = np.mean(b)
l_meandata.extend([l_mean])
a_meandata.extend([a_mean])
b_meandata.extend([b_mean])
l_variance = np.var(l)
a_variance = np.var(a)
b_variance = np.var(b)
l_variencedata.extend([l_variance])
a_variencedata.extend([a_variance])
b_variencedata.extend([b_variance])
l_range = np.ptp(l)
a_range = np.ptp(a)
b_range = np.ptp(b)
l_rangedata.extend([l_range])

```

```

a_rangedata.extend([a_range])
b_rangedata.extend([b_range])
l_skewness = np.mean(abs(l - l.mean()) ** 3)
a_skewness = np.mean(abs(a - a.mean()) ** 3)
b_skewness = np.mean(abs(b - b.mean()) ** 3)
l_skewdata.extend([l_skewness])
a_skewdata.extend([a_skewness])
b_skewdata.extend([b_skewness])
img_number +=1

df = pd.DataFrame({"Red Mean": R_meandata, "Green Mean": G_meandata, "Blue
Mean": B_meandata, "Red variance": R_variancedata, "Green variance":
G_variancedata, "Blue variance": B_variancedata, "Red range": R_rangedata, "Green
range": G_rangedata, "Blue range": B_rangedata, "Red Skewness": R_skewdata,
"Green Skewness": G_skewdata, "Blue Skewness": B_skewdata, "L_Mean":
l_meandata, "A_Mean": a_meandata, "B_Mean": b_meandata, "L_variance":
l_variancedata, "A_variance": a_variancedata,
"B_variance": b_variancedata, "L_range": l_rangedata, "A_range": a_rangedata,
"B_range": b_rangedata, "L_Skewness": l_skewdata, "A_Skewness": a_skewdata,
"B_Skewness": b_skewdata, "label": y})
color_moments("C:/Users/omsalma/Desktop/Train/Normal_seg/*")
df.to_excel("df4seg.xlsx" , index= False)

```

Appendix 4. Models Training Algorithm

```

df = pd.read_excel('C:/Users/omsalma/Desktop/df3.xlsx')
print(df.describe().T)
df['label'].value_counts()
y = df["label"].values
from sklearn.preprocessing import LabelEncoder
labelencoder = LabelEncoder()
Y = labelencoder.fit_transform(y)
X = df.drop(labels = ["label"], axis=1)
feature_names = np.array(X.columns)
#The data need to be standardized
from sklearn.preprocessing import StandardScaler

```

```

scaler = StandardScaler()
scaler.fit(X)
X = scaler.transform(X)
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.25,
random_state=42)
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree
RF_model = RandomForestClassifier(n_estimators = 100, random_state= 42)
from sklearn import svm
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
svm_model = svm.SVC(decision_function_shape='ovo')
svm_model.fit(x_train, y_train)
RF_model.fit(x_train, y_train)
tree_model = tree.DecisionTreeClassifier()
tree_model.fit(x_train, y_train)
log_model = LogisticRegression()
log_model.fit(x_train, y_train)
nb_model = GaussianNB()
nb_model.fit(x_train, y_train)
test_prediction = nb_model.predict(x_test)
nb_model.score(y_test, test_prediction)
from sklearn import metrics
print("accuracy =", metrics.accuracy_score(y_test, test_prediction))

```

Appendix 5. Feature Selection Algorithm

```

import xgboost as xgb
model = xgb.XGBClassifier()
from boruta import BorutaPy
feature_selector = BorutaPy(model, n_estimators=50, verbose=2, random_state=42)
feature_selector.fit(x_train, y_train)
print(feature_selector.support_)
print(feature_selector.ranking_)

```

```

feature_ranks = list(zip(feature_names, feature_selector.ranking_,
feature_selector.support_))
X_filtered = feature_selector.transform(x_train)
svm_model2 = svm.SVC(decision_function_shape='ovo')
svm_model2.fit(X_filtered, y_train)
RF_model2 = RandomForestClassifier(n_estimators = 100, random_state= 50)
RF_model2.fit(X_filtered, y_train)
tree_model2 = tree.DecisionTreeClassifier()
tree_model2.fit(X_filtered, y_train)
log_model2 = LogisticRegression()
log_model2.fit(X_filtered, y_train)
nb_model2 = GaussianNB()
nb_model2.fit(X_filtered, y_train)
x_test_filtered = feature_selector.transform(x_test)
prediction_nb2 = nb_model2.predict(x_test_filtered)
prediction_RF2 = RF_model2.predict(x_test_filtered)
from sklearn import metrics
print("accuracy =", metrics.accuracy_score(y_test, prediction_nb2))

```

Appendix 6. CNN Model

```

from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, BatchNormalization
from keras.layers import Activation, Flatten, Dropout, Dense
image_directory = 'C:/Users/omsalma/Desktop/Total/'
SIZE=80
dataset = []
label = []
defected_images = os.listdir(image_directory + 'Defected/')
for i, image_name in enumerate(defected_images):
    if (image_name.split('.')[1] == 'bmp'):
        image = cv2.imread(image_directory + 'Defected/' + image_name)
        image = Image.fromarray(image, 'RGB')
        image = image.resize((SIZE, SIZE))
        dataset.append(np.array(image))
        label.append(1)

```

```

normal_images = os.listdir(image_directory + 'Normal/')
for i, image_name in enumerate(normal_images):
    if (image_name.split('.')[1] == 'bmp'):
        image = cv2.imread(image_directory + 'Normal/' + image_name)
        image = Image.fromarray(image, 'RGB')
        image = image.resize((SIZE, SIZE))
        dataset.append(np.array(image))
        label.append(0)
dataset = np.array(dataset)
label = np.array(label)
print(dataset.shape)
print(label.shape)
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(dataset, label, test_size = 0.30,
random_state = 0)
X_train = X_train / 255.
X_test = X_test / 255.
INPUT_SHAPE = (SIZE, SIZE, 3)
model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=INPUT_SHAPE))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(32, (3, 3), kernel_initializer='he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(32, (3, 3), kernel_initializer='he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(0.2))
model.add(Dense(1))
model.add(Activation('sigmoid'))

```

```

model.compile(loss='binary_crossentropy',
              optimizer='rmsprop', metrics=['accuracy'])
print(model.summary())
history = model.fit(X_train, Y_train, batch_size=64, verbose=1,
                  epochs=20, validation_data=(X_test, Y_test), shuffle=False)

```

Appendix 7. CNN Model Performance with, RGB, rmsprop, and 20 Epochs

```

Epoch 18/20
50/50 [=====] - 29s 573ms/step - loss: 0.0449 -
accuracy: 0.9836 - val_loss: 0.0494 - val_accuracy: 0.9853
Epoch 19/20
50/50 [=====] - 29s 586ms/step - loss: 0.0472 -
accuracy: 0.9814 - val_loss: 0.0437 - val_accuracy: 0.9875
Epoch 20/20
50/50 [=====] - 29s 581ms/step - loss: 0.0377 -
accuracy: 0.9858 - val_loss: 0.0419 - val_accuracy: 0.9883

In [496]: _, acc = model.evaluate(x_test, y_test)
...: print("accuracy = ", (acc * 100.0), "%")
22/22 [=====] - 2s 83ms/step - loss: 0.0388 -
accuracy: 0.9883
accuracy = 98.8252580165863 %

```

Appendix 8. CNN Model Performance with, RGB, rmsprop, and 30 Epochs

```

50/50 [=====] - 29s 577ms/step - loss:
0.0210 - accuracy: 0.9937 - val_loss: 0.0522 - val_accuracy:
0.9875
Epoch 28/30
50/50 [=====] - 29s 578ms/step - loss:
0.0224 - accuracy: 0.9909 - val_loss: 0.0423 - val_accuracy:
0.9897
Epoch 29/30
50/50 [=====] - 29s 576ms/step - loss:
0.0362 - accuracy: 0.9943 - val_loss: 0.0431 - val_accuracy:
0.9890
Epoch 30/30
50/50 [=====] - 29s 579ms/step - loss:
0.0294 - accuracy: 0.9918 - val_loss: 0.0390 - val_accuracy:
0.9868

In [72]: _, acc = model.evaluate(x_test, y_test)
...: print("accuracy = ", (acc * 100.0), "%")
22/22 [=====] - 2s 84ms/step - loss:
0.0417 - accuracy: 0.9883
accuracy = 98.8252580165863 %

```

Appendix 9. CNN Model Performance with, RGB, ADAM, and 30 Epochs

```
50/50 [=====] - 31s 629ms/step - loss: 0.0195 - accuracy: 0.9947 - val_loss: 0.0492 - val_accuracy: 0.9860
Epoch 30/30
50/50 [=====] - 31s 630ms/step - loss: 0.0175 - accuracy: 0.9956 - val_loss: 0.0425 - val_accuracy: 0.9868

In [58]: _,acc = model.evaluate(x_test, y_test)
...: print("accuracy = ", (acc * 100.0), "%")
22/22 [=====] - 2s 81ms/step - loss: 0.0376 - accuracy: 0.9883
accuracy = 98.8252580165863 %
```

Appendix 10. CNN Model Performance with, RGB, ADAM, and 20 Epochs

```
50/50 [=====] - 29s 577ms/step - loss: 0.0448 - accuracy: 0.9830 - val_loss: 0.0544 - val_accuracy: 0.9816
Epoch 19/20
50/50 [=====] - 29s 577ms/step - loss: 0.0320 - accuracy: 0.9896 - val_loss: 0.0627 - val_accuracy: 0.9765
Epoch 20/20
50/50 [=====] - 29s 575ms/step - loss: 0.0457 - accuracy: 0.9830 - val_loss: 0.0748 - val_accuracy: 0.9736

In [19]: _,acc = model.evaluate(x_test, y_test)
...: print("accuracy = ", (acc * 100.0), "%")
22/22 [=====] - 2s 78ms/step - loss: 0.0675 - accuracy: 0.9780
accuracy = 97.79735803604126 %
```

CURRICULUM VITEA

Omsalma Alsadig Adam GADALLA holds a bachelor's degree in Agricultural Engineering, Faculty of Agriculture, Kartoum University, in 2013. Topic: "Evaluation of Mechanical Sugar Cane Harvesting in Asalaya Sugar Company", White Nile State, Sudan. Master's degree in Agricultural Engineering, Faculty of Agriculture, Kartoum University, in 2017. Topic: "Comparison Between Fully Mechanized and Semi Mechanized Sorghum Forage", Khartoum, Sudan (2017).

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Publications :

1. Demirel B, Gürdil AKG, and Gadalla OAA (2019). Biomass Energy Potential from Agricultural Production in Sudan. *Erciyes Tarım ve Hayvan Bilimleri Dergisi*, 2(2):35-38.
2. Gadalla OAA and Öztekin, YB (2020). Some Factor Affecting Flax Fiber Yield and Quality. *Journal of agricultural machinery science*, V:16, 3, 26:26-34.
3. Gadalla OAA and Öztekin, YB (2022). Application of computer vision and image processing technology in agro-product quality control. *Journal of agricultural machinery science*.
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Won Awards, Incentives and Scholarships

1. DAAD (Deutscher Akademischer Austauschdienst) in-country scholarship by Germany government, for Master, 2015
2. Turkey scholarships for foreigners, PhD program, 2018

