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USE IMAGE PROCESSING MODEL TO FRUIT QUALITY DETECTION

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Article Info

Abstract

In recent years, artificial intelligence and image processing plays an important role in the agriculture fields such as plant disease detection and plant health issue prediction. The detection of plant quality in the early stages is a difficult task due to the variations in the symptoms, crop species, and climate factors. Several diseases such as late blight and early blight influence the quantity and quality of fruits. Manual detection of fruit quality leaves disease is a quite complex and time-taking process. It requires an expert with high skills to diagnose the fruit quality in the early stage. Therefore, an automated and efficient method is required that can detect the fruit quality. In this research, a novel EfficientB2 convolution neural network model is proposed to extract the deep features from the dataset. The model is evaluated on the Processed Images Fruits dataset. The result shows that the proposed model achieves efficient and improved results as compared to the previous work

Keywords: *Convolution Neural Network, Image processing, EfficientB5, Machine Learning*

Introduction

Evaluation of the quality of fruits is becoming increasingly significant in today's society, and it plays an essential role in the food and agriculture industries. The preferences of the customers are satisfied by the fruits that are available at the market. Consequently, the detection of defects in fruits is essential to maintain quality. For a few years, people used to manually do this operation. The results of manual sorting, on the other hand, are inconsistent and inaccurate. In addition, the human eye is capable of adapting to noticeably subtle shifts in hue, whereas the effect of the surrounding environment on the color that is observed and the perceived intensity of color are the primary sources of inaccuracy. The grading and categorization of fruits are determined by observations and experiences gained through practice. The system classifies and rates the quality of fruits based on their appearance using image processing algorithms. Image analysis techniques that are based on shape and color are used to categorize two-dimensional representations of fruit. However, the values for color and form might be very close or even the same across a variety of fruit representations. Therefore, the identification and differentiation of fruit pictures cannot be accomplished through the use of analysis methods that focus on color or shape aspects. Therefore, to improve the accuracy of the fruit quality identification, we utilized a method that was based on color, shape, and size and combined it with an artificial neural network. This allowed us to get the desired results (ANN). A cascaded forward network is used in the proposed method to grade and classify fruit photos based on the feature values that are acquired. The photograph of the fruit is taken as the first step in the process by the suggested system. After that, the image is sent on to the next phase of processing, which is where the characteristics of the fruit, such as the color, shape, and size of fruit samples, are retrieved. After that, photographs of fruit are put through training and testing process with the assistance of an artificial neural network. In this proposed paper, a neural network is utilized to recognize the form, size, and color of the fruit, and the results obtained are quite promising when these three characteristics are combined. The proposed automated system is intended to solve the issues that are caused by the use of manual methods. The process includes several processes, such as the extraction of features, sorting, and grading. It is intended to combine the three procedures that are depicted in the flowchart that follows. The size of the fruit, its form, and its color are some of the characteristics that are extracted. Height and width dimensions are used to derive size features. The process of determining the size of fruit is known as grading. The most up-to-date method for determining the quality of fruits is being applied in this particular system.

In [28], the authors have shown the method of fruit identification and how to calculate the total number of fruit in the cart. In this paper, the focal factories are peppers and fruit. Different shapes of peppers and different sizes of peppers have been used in this research. The target point, of the proposed application, is, to sum up, green peppers and red pepper as well as locate the positives of these also. For the training algorithm and cross-validation, they used around about 28000 sets of images. These images have been collected from more than 1000 factories. The two-step method has been used, to sum up, peppers fruit as well as locate it. In the first step, one image is used to locate peppers fruit, and in the second step, to increase the accuracy and prediction ratio; multiple views are gathered.

Automation in the food processing industry is used to boost the nation's production, quality, and profitable growth. Fruit grading is a crucial step for producers that has an impact on the assessment of fruit quality and the export market. Although humans are capable of grading and sorting, it is sluggish, labor-intensive, and tiresome. Consequently, a sophisticated method of fruit grading is required. Researchers have recently created a variety of computer vision-based fruit sorting systems. The most popular methods for determining a fruit's disease status, maturity, and class are its color, textural characteristics, and morphological characteristics. Using clustering, color-based segmentation, artificial neural networks, and different classifiers, diseases can be put into different groups. Our job is mostly about getting analyses of different things. Agricultural automation is a rapidly growing field of study because technology could make farming more efficient during and after harvest by lowering labor costs and speeding up processes. Smart farming, agricultural robots, checking the quality of crops after they have been picked, making food, and packaging it are just a few examples of automation in agriculture. The sorting and classifying of fruits by machines is a big part of the field of agricultural automation. Automated fruit classification systems can be used to identify fruits during harvest and tell the difference between different types of fruits that need to be picked. These can also be used to choose fruits, figure out their prices in stores, and test their quality after harvest for the packing industry. The goal is to replace manual tasks with ones that can be done by machines. Image processing is being used in more and more fields, such as industrial image processing, medical imaging, real-time imaging, texture classification, object recognition, and many more. Two areas of agricultural research that are growing very quickly are image processing and computer vision. It is a very important piece of equipment for crop analysis both before and after harvest. It can be used for a lot of different things in farming. Agriculture can be made more productive with the help of several technological advances. The disease is the source of losses in fruits and vegetables. Since diseases can be visible on plant leaves and fruits, disease identification is crucial for agricultural cultivation. Fruit illnesses can be caused by pathogens, fungi, bacteria, microorganisms, viruses, and unfavorable environments. There are numerous methods. Image processing uses computer vision to automatically identify and categorize plant diseases based on color: Shape and texture, Quality can raise the caliber of food, Computer vision inspection.

The term "agricultural automation" encompasses a wide range of practices and technologies, including "smart farming," "agricultural robotics," "post-harvest quality inspection of crops," "food production and packaging," and many others. One of the most important applications in the field of agricultural automation is the categorization and sorting of fruit using automation. During harvest time, automated fruit classification systems can be utilized for the purposes of identifying fruits and differentiating between the many distinct kinds of fruits that need to be picked using robotic platforms. In the post-harvest quality evaluation that takes place in the packaging business, as well as fruit selection and price identification in grocery stores, these can also be used. The goal of these efforts is to increase the quality of the fruit while simultaneously increasing production levels. Aim of this effort is to develop a method that is dependable, efficient, and can be used again and over again for classifying different kinds of fruits based on images of them. Because convolution neural networks require a significant quantity of training data in order to give decent classification results, it was anticipated that a suitable combination of hand-crafted features would produce greater accuracies for a dataset with fewer data for each class. This was due to the fact that convolution neural networks are required to give decent classification results. Comparing the efficacy of a number of well-known approaches to supervised learning is one of the secondary goals of this project, which aims to identify the handcrafted features that result in the best-performing classifier for fruit classification. Extraction of relevant properties and use of an effective classifier are going to be necessary in order to make appreciable progress in the area of automated fruit categorization and sorting.

One of the most well-known kinds of fruit plants is the citrus tree, which bears fruit that is high in vitamin C and has a broad variety of uses all across Africa and the Middle East. Citrus trees are also one of the most common forms of fruit trees. In many different agro-industrial processes, citrus plants of all kinds are used as a source of raw materials at some point in the production chain. Citrus plant diseases are a key contributor to the falling output of citrus fruits, which has led to a decrease in the number of businesses that make use of these fruits. This decline is a direct effect of the situation. Researchers and subject matter experts in the field have established that the most common diseases are greening, melanosis, downy, black spot, canker, scab, and anthracnose. These are the diseases that have been found to affect the most people. The manifestation of the symptoms of this disease, which affects citrus plants, can be used as the sole basis for making an accurate diagnosis of the condition using certain computer vision and deep learning approaches. The article (Rauf et al., 2019) displays the data set that consists of 759 pictures of damaged and healthy citrus fruits and leaves. Researchers have the ability to make use of these photos in order to put a variety of computer vision and image processing algorithms through their paces in order to determine the illnesses that citrus plants are susceptible to. A nation that is a part of the European Union came up with the requirements that need to be followed in order to ensure that the items that are sold on the market are of sufficient quality and that agricultural production is carried out in an efficient manner. Today, artificial intelligence (AI) is a field that is actively being researched and has a number of applications in a variety of different businesses. AI also has a lot of applications in the everyday lives of people. The major challenge for artificial intelligence is to solve issues that people can intuitively comprehend, but which are challenging to implement computationally. This presents AI with a unique set of problems to overcome (Naranjo-Torres et al., 2020). As a result, artificial intelligence (AI) systems need to have the ability to learn independently by identifying patterns in raw data. This type of learning is referred to as machine learning. This article (Bhargava & Bansal, 2020) gives a classification scheme that initially classifies numerous distinct kinds of fruits, including apples, avocados, bananas, and oranges specifically. The classification scheme is presented in its entirety below. It establishes the first rank, the second rank, and the options that are not accepted for each kind so that the resulting classification can be as accurate as possible. The algorithm considers the statistical, textural, and geometrical features of the data in order to arrive at a conclusion regarding the differentiation. In order to classify and rank the many different kinds of fruit, (ANN) makes use of the methods of (k-NN), (SVM), (SRC), and artificial neural network (Bhargava & Bansal, 2020).

Hameed et al. examine and contrast a number of different computer vision strategies for recognizing fruits and vegetables in Reference (Hameed et al., 2018). These techniques include of SVM, KNN, decision trees, ANN, CNN, and other additional methodologies for feature extraction. Also, they point out that there are a number of classification algorithms available for quality assessment and autonomous harvesting. However, these methods only work for a small number of classes and small datasets. The study's results shed light on this part of the topic in particular. The findings of their research point to three basic types of classification applications that can be used with fruits and vegetables. These aspects are the evaluation of the product's quality, its automatic harvesting, and its inventory in the store. It identifies only two publications that make use of CNNs in a manner that is comparable to that which was discussed earlier.

Deep learning, which also goes by the acronym DL, is rapidly becoming one of the most well-known approaches to applying machine learning. Both the capacity to automatically learn patterns that are present in images and the high level of abstraction that DL possesses as a characteristic are crucial qualities that it possesses. DL also possesses the ability to automatically learn patterns that are present in text. The major form of deep learning architecture that is utilized for the purpose of image processing is known as the Convolution Neural Network, or CNN (Goodfellow et al., 2016; Lecun et al., 2015). Convolution neural networks, also known as CNNs, are a subcategory of artificial neural networks (ANNs) that are distinguished by the fact that at least one of their layers contains convolution operations. Since Krizhevsky et al. (Gonzalez, 2007) won first place in the ImageNet competition (ILSVRC) in 2012, the use of (CNNs) has seen a meteoric rise in popularity as an effective tool for image categorization across a variety of industries. This is due to the fact that CNNs are able to classify images more accurately than other methods. Methods that are based on CNN have been employed in the world of agriculture, namely in the areas of fruit classification and fruit detection.

It is essential to the practice of sustainable agriculture to conduct regular checks on the physiological health of plants and fruits. The traditional method for identifying fruit illnesses is through the use of visual inspection performed by knowledgeable personnel working in the agriculture industry. This process is not only costly and time-consuming, but there is also a significant possibility that errors will occur along it. In addition to this, there are situations in which it is impossible for specialists to carry out visual inspections since the crops are located in inaccessible regions (Khan et al., 2018). In recent years, there has been a significant growth in the amount of research interest related the automated detection and identification of plant diseases. It is possible to obtain accurate and rapid identification using sophisticated image processing in conjunction with cutting-edge computer vision algorithms. This allows for less time and resources to be spent on the labor of humans while yet achieving the desired results. In this context, a number of different approaches have been proposed for the purpose of identifying and classifying a wide range of fruit diseases, such as apple scab, apple rot, banana sigotka, banana delightful leaf spot, banana diamond leaf spot, and deightoniella leaf and fruit spot, amongst others (Pujari et al., 2015). Products derived from natural sources have a long history of consumption in the form of food, and these resources can also be processed to satisfy the needs of customers. Concerns regarding a healthy diet include aspects of food (both natural goods and processed foods) such as the type of food, its components, the nutrients it contains, and the methods used to prepare it. It is a well-known fact that people of various geographic locations have a variety of dietary preferences.

In order to verify the quality and safety of food for consumers all over the world, it is vital to have a good understanding of the characteristics of food, such as its kind, content, nutrients, and style of processing, among other characteristics (Zhou et al., 2019). As human civilization has progressed in terms of its way of life, more attention has been devoted to the level of quality and diversity of the food that its members consume. Numerous real-world applications have already made use of fruit identification systems, such as at the checkout counter at a store, where it could be employed more effectively than traditional hand scanner tags. In addition to that, it can be put to use as a supportive appliance for persons who are blind. In supermarkets, where the cashier must specify each item type to determine its price, being able to distinguish between the various kinds of fruits is a task that must be performed repeatedly. One of the issues that drives up the cost of doing business in the horticulture industry is the need for trained farm labor. In spite of these obstacles, fruit production must continue to satisfy the rising demands of a global population that is only going to keep expanding, which portends a significant challenge in the near future. The best approach to solving this issue is to implement a fruit recognition system that is also capable of automatically calculating prices and labeling the fruit. Over the course of the previous two decades, numerous applications have been documented for identifying the types of fruits. In the interim, however, there have been no reports of any such advanced techniques for the identification of Indian fruits. As a result, this research is being carried out to categories the most popular fruits in India according to their respective kinds (Behera, 2020).

In the modern age of technology, hyper spectral imaging is one of the most well-known and promising techniques that has shown good results in research, control, and industry. The hyper spectral imaging approach can be used to make spatial maps, find targets, save pure materials, predict chemical and physical components, and check the safety and quality of food. The main reason for the development of hyper spectral imaging was to combine spectroscopy with imaging techniques to make it easier to see the different parts and where they are located in the object being looked at (Jaiswal, 2021). The disease that is present in the fruits has led to a decline in both the quality and quantity of the fruits and vegetables that are being produced. Because of this, agriculture and other economic sectors and industries suffer significant losses. Taking the example of soybean rust, which is a fungal disease that affects soybean plants, it has been claimed that eradicating the disease from plants by only 20% resulted in a profit of 11 million dollars. Rust is a type of soybean plant disease (Singh & Singh, n.d.). The method that is provided in these publications can be utilized in the process of constructing an automated system for the identification of apples that are both healthy and flawed. In the agricultural industries, there is a wide variety of potential applications for image processing. These include color scanners and cameras, both of which are used to take images as an input, which are subsequently processed in order to produce the required outcome. In the course of this (Singh & Singh, n.d.) Work, they have endeavored to develop more sophisticated methods for processing images and analyzing them using machine learning. Both the creation of the necessary infrastructure and the implementation of the requisite computational procedures are required in order to successfully detect and prevent the aforementioned diseases. The utilization of machine learning as an approach for the early stage diagnosis of plant diseases has become an increasingly frequent method in recent years. The great majority of traditional classifiers are only helpful for analyzing the data from relatively small datasets, and they base their categorization conclusions on human identified visual qualities. This limitation limits their use. On the other hand, applications of convolution neural networks directly on images taken from larger datasets have been shown to be helpful in removing challenges that are associated with human-crafted features. When it comes to the forecasting of plant diseases, the utilization of visualization techniques for the comprehension of disease symptoms and the localization of those symptoms has been shown to be even more effective and precise than previous methods.

This is particularly the case when it comes to the prediction of plant pathogens (Reddy et al., 2020). In practice, deep learning is a subset of machine learning; yet, deep learning and machine learning both refer to the same notion theoretically. Deep learning and machine learning perform the same kinds of tasks, but deep learning is capable of more. Both of these areas are extremely important in the modern world of technology. Because of the closeness of their relationship to one another, the two constantly switch the names that they call one another for different reasons. When it comes to functions, an algorithm that uses machine learning needs an exterior supervision from humans if it generates wrong predictions. On the other hand, when it comes to models that use deep learning, the algorithm is able to learn on its own through the neural networks, independent of any interaction from a human, whenever the final judgment is inaccurate or imprecise. In contrast to this, machine learning algorithms need to be supervised by humans whenever they produce false predictions. This is because machine learning algorithms are still learning. Both of these subfields have a wide variety of applications, some of which include computer vision, marketing, medical diagnostics, the agriculture business, natural language processing, information retrieval, internet advertising, and a number of other domains. Deep learning strategies are currently being developed, and some examples of these strategies include machine translation, automatic identification, segmentations, and tracking (Dhiman & Kumar, 2021).

Fruits are an essential component of a healthy diet and offer a number of advantages to one's physical well-being. While there are fruits that are available throughout the entire year, there are also fruits that are only available during specific times of the year. Agriculture is and will continue to be a significant economic source for India. Agriculture occupies around 70 percent of India's land area. The production of fruit is one of India's primary economic activities. As a result of this, the utilization of deep learning algorithms to sort fruits is beneficial not only for retailers but also for end users. Computer science and information technology are currently seeing an increase in their application within the agricultural sector of the economy. Artificial intelligence and other technologies based on soft computing are utilized for the purpose of fruit classification in order to make it possible for customers to purchase fruits of a high grade. It is important to have software that can recognize and categories fruits since it contribute to improving the overall quality of the fruits. At the market, it can be difficult to determine what kind of fruit one is purchasing. Hand classification and pricing of items is a difficult process. It's a tough job to count ripe fruits by hand and judge how nice they are, but someone's got to do it. A number of problems, including rising labour costs, a shortage of trained employees, and falling storage costs, are among the most fundamental obstacles that must be overcome in order to successfully cultivate, sell, and store fruit. You can get essential information about the variety and quality of fruits with the use of the Soft computer vision system. This lowers expenses, ensures quality requirements are satisfied, and gives you critical information.

In the process of designing computer-assisted recognition systems, some of the most prevalent types of soft computing, such as artificial neural networks (ANN), fuzzy logic, and evolutionary computation models, are applied. ANN tends to learn from examples and to categorize patterns that it hasn't encountered before (Gill et al., 2022). One of the most recent developments in computer vision is identifying the type of fruit that an object is using computer vision. The quantity of features, the types of features, the method by which the features are chosen from the extracted data, and the type of classifier utilized all play a role in determining how well a fruit identification system performs. Images of fruit captured during periods of poor weather tend to be less clear and reveal less detail. Therefore, there is a need for methods that can improve the appearance of fruit photographs so that they contain a greater number of features. Arranging fruit into categories and being able to differentiate between them the categorization of fruits is one of the subfields within computer science that is experiencing rapid expansion. The accuracy of the system that classifies fruits is determined by the quality of the fruit images that are collected, the number of features that are extracted, the types of features, the selection of the best classification features from the features retrieved, and the kind of classifier that is utilized. Because the images were captured during a storm, it is difficult to make out the individual fruits and essential characteristics are obscured (Gill et al., 2022). Putting fruit photographs into groups and determining the different types of fruits that each picture depicts can be accomplished through the use of classification and recognition. On the other hand, colour picture categorization methods are difficult to understand, particularly in conditions when there is not a lot of light. Using image enhancement techniques can help make an image look better, which in turn makes it more helpful for potential future applications involving vision (Gill et al., 2022).

This study employs three unique forms of CNN models in order to determine which kind of accuracy is ideal for fruit categorization as well as fruit defect classification. The purpose of this research is to discover which kind of accuracy is optimal for these tasks (Mirra, 2022). The developments in artificial intelligence (AI) and computer vision that are helping to improve the manufacturing industry's quality as well as its efficiency are having a positive impact on a variety of different industries. Farmers and manufacturers can improve their productivity and overcome the typical challenges they face when working in an unfavorable environment with the assistance of artificial intelligence in the fields of agriculture and the food industry. This enables farmers and manufacturers to take advantage of the opportunities presented by artificial intelligence. The implementation of artificial intelligence in companies whose primary focus is agriculture has made a significant contribution to the general advancement of the technology.

The food processing facilities that have implemented techniques of automation have demonstrated promising results due to good production and clever packaging as a result of the implementation of these techniques. As a result of the implementation of these techniques, the facilities have demonstrated promising results. In the twenty first century, businesses that deal in fruit and those that process food are both experiencing phases in which there is an exceptionally high level of rivalry. Both the flow of international trade and the market for fruits and vegetables have an effect on the geographical proximity of exporters and importers to one another. When exporting or importing, there is a lengthy and time-consuming process of transportation, which presents a barrier in terms of assessing the quality of decaying or nearly rotten fruits that may be present among a large amount of fruits. This is the case regardless of whether the fruits are being brought in or shipped out. As a direct consequence of this, it is projected that worldwide fruit production and trade will undergo a greater degree of shrinkage when compared to levels that were observed in previous years. The unpredictability of the weather conditions, shifts in climate, and rises in temperature are also primary causes of concern behind the drop in commercial activity. These factors contributed significantly to the decline in commercial activity. In addition, in addition to the export and import of fresh fruits, the food processing sectors are also significantly hindered as a result of the scrutiny of rotten fruit and a decrease in the quality of the product. This is in addition to the fact that the food processing sectors are significantly hindered in addition to the export and import of fresh fruits. As a consequence of this, the sorting and grading of fruits of a high grade requires a method that is both skillfully accomplished and very successful in its application.

The utilization of computer vision-based systems that are aided by image processing techniques can lead to the production of results that are exceptionally exact and precise (Roy, 2020). Fruits are a common kind of food that people have been eating since the Stone Age. Because these foods are so good for you, they make up a big part of your diet, which is important for your health and happiness. Fruits that have been burned all the way through need to be checked to make sure they are still good. To reach this goal, a Fruits product location framework can be set up that can tell the difference between different kinds of Fruits based on pictures taken with any digital camera or high-end cell phone in different places. This system will let us check the quality of leafy vegetables and set up an automated system for collecting them from plantations. DL techniques have been added to this framework to make the system stronger. It is very important for a machine to be able to find Fruits products quickly and accurately.

The Fruits product discovery framework is hard to put together because of a number of things, such as: Fruits can be found in scenes with different levels of brightness, can be destroyed by many different things, and can be hard to physically pull away from their bases (Indira et al., 2021). The use of machine learning and computer systems is growing in a wide variety of technological applications. Some examples of these applications include searching the internet, extracting features for image classification tasks, detecting faces in cameras or smart phones, and identifying objects in an image. All of these applications are instances of how computer systems and machine learning are being put to use in the real world. Because it is able to automatically extract information from photographs, the deep learning method has been increasingly popular in application development over the past few years. This is one of the primary reasons why deep learning has become so popular (Lecun et al., 2015). Because of this capabilities as well as its capacity to learn large and complex topics, deep learning has proven to be quite successful when used to vision-based tasks such as recognizing patterns and assigning them to appropriate categories. Learning the most useful extracted feature and automatically classifying a dataset are now two of the most significant processes in the image processing process that can be completed concurrently thanks to the development of deep learning technologies (Nasiri et al., 2019).

Problem definition

Globally Quality detection crisis has been arising; we can say that each algorithm can have advantages or disadvantages over one another. Some have more accuracy but are time taking, similarly some are fast but lacks accuracy. Then there are some that are accurate and fast. . From analysis we can say that for fruit detection extracted features of fruits are important and according to our requirement we can use algorithm, techniques or any other methods. Further the estimation of fruit quality (**Good, Average, Bad**) and the patterns of carrying fruit **quality** threads our sense. So, protection produces took place to control the spread of the **bad** fruit via quality check which holds back inadequate fruit from the human, which is the natural positive control for human health. Due to this, what will be the role of Image processing in our life in the context of global threat, and fruit quality crisis? In this research, we will study the relationship between good, bad and average fruit quality evaluates the comprehensive and self-knowledge reproach related to the **quality detection** outbreak.

1. Related Work

The paper highlight that the performance of different machine learning technology can become problematic rather than overcome problem due to their performance with correct fruit **quality (**Good, Bad, Average**)**. The goal of this work is to find a way to classify different kinds of fruits based on pictures of them that is reliable, works well, and can be used over and over again. Because convolutional neural networks need a lot of training data to give good classification results, it was thought that a good combination of hand-crafted features would give more accurate results for a dataset with less data for each class. This was because convolutional neural networks have to be able to classify things well. This was because convolutional neural networks had to be used in order for classification results to be good enough. One of the other goals of this project is to figure out how well a few well-known ways of teaching supervised learning work. The primary objective of this project is to determine the fruit classifier that achieves the best results by employing features that are painstakingly constructed by hand. To make substantial headway in the realm of automated fruit categorization and sorting, it is going to be important to extract relevant attributes and make use of an effective classifier. This will be the case in order to achieve success.

This (Indira et al., 2021) study begins with a discussion on the recognition of plant fruits and the subsequent feature extraction of those fruits. This is a very significant component of the Agricultural industry. The plan is to construct a foundation that is reliable, efficient, and robust by making use of CNN facts. People could be able to spend less time counting the number of fruits and manually identifying them if they had access to automatic fruit-detecting technology. The second topic that is discussed in this paper is the several ways in which plants can be grouped so that their fruits do not all appear to be the same. The classification of fruits has the potential to assist fruit vendors in distinguishing between several kinds of fruits that have a similar appearance. In the proposed framework, a Convolution Neural Net, or CNN, was utilized in an effort to differentiate between photographs of natural fruits. However, it was just recently discovered that deep learning is a very effective method for identifying photographs, and CNN is a fantastic illustration of how deep learning may be used. Research that was conducted by Kapach and colleagues (Kapach et al., 2012) provided a summary of the visual department of fruit-picking robots and went into great detail regarding the benefits and drawbacks that are associated with the various methods that are currently being used in the industry. Most of the traditional ways to recognize images of fruit are based on the color of the target, while other methods use a combination of features like color, texture, shape, and so on. However, these methods are based on research that was done in specific situations. In other words, the color of the target is usually a part of the traditional methods used to recognize images of fruit. To put it another way, the hue of the target is frequently something that conventional methods of fruit picture identification take into consideration. They have weak endurance, a low recognition efficiency, and are unable to meet the operational needs of picking robots in a variety of surroundings that present a variety of different tough situations. Because of this, using them is difficult. As a result of this, it is vital for us to investigate the possibility of developing a more advanced algorithm for recognizing fruits, one that boasts a greater level of both precision and efficiency than its predecessor.

This research (Risdin et al., 2020) has proposed a fruit detection system that can be used for image data that was obtained by a Smartphone. The system was developed by making use of the most advanced detection framework that is currently accessible, CNN. Grape, apple, leeches, and lemon are just a few of the several kinds of fruit that this technology is able to distinguish between. Overall, the model's ability to recognize fruit photos is quite good. It has an accuracy of about 99.89%, which is what was expected. The CNN method is a very powerful way to use machine learning to correctly identify images of fruits for a given model. This method was used, and this method was chosen because it was used. Also, the CNN algorithm used did a good job of classifying images and finding objects. In the future, more pictures of different kinds of fruits will be added to the database that is already being used. Future research will also look at how to use the proposed system for a wide range of fruits. This will be done to get better performance, which will make it possible to build a system for picking fruit from orchards with robots.

When it comes to agricultural potential, Indonesia is best at making fruit. When it's time to pick the fruit, there is a huge amount of it. But because it takes so long to harvest, the quality is much lower than it could be. Because of this, the price being asked is not very high. Researchers provide a Deep learning method for identifying and classifying many fruits in their (Basri et al., 2019) research paper. This method makes use of a speedier R-CNN. Mangoes and pitayas were included in the production process. The dataset consists of real data that was obtained from a farmer during harvest season. After acquiring the data, we divided it into two classes, with mango and pitaya serving as the classifications for the purpose of object detection training. They utilized the TensorFlow platform in conjunction with the Mobile Net model. During the course of this inquiry, they achieved an accuracy score of almost 99%. This method is exceptionally suitable for developing the process of sorting many fruits in real-time, which is necessary in order to keep the fruit's quality intact.

In the beginning of this article (Zhou et al., 2019), provided a brief introduction to deep learning. After that, they proceeded to explore in further detail the architecture of various well-known types of deep neural networks, as well as the process of training a model. The researchers looked at a lot of articles that used deep learning as a way to analyses data to solve a wide range of problems and concerns in the food industry. Some of the problems and challenges that were found were recognizing food, figuring out how many calories it has, figuring out how good fruits, vegetables, meat, and aquatic items are, and finding problems in the food supply chain and contaminated food. We were able to find answers and solutions to these problems and challenges with the help of deep learning.

It has been believed that the Deep Convolution Neural Network (CNN), which possesses a one-of-a-kind structure that combines the stages of feature extraction and classification, is the most advanced computer vision technology for classification tasks currently available. According to the findings of this research (Nasiri et al., 2019), there is a novel and reliable method to differentiate between high-quality and low-quality date fruits. This technique, which makes use of deep CNN, has the additional capability of estimating when nutritious dates will be ready to consume. The proposed CNN model was constructed with a VGG-16 architecture, and subsequent layers included max-pooling, dropout, batch normalization, and dense layers. This model was trained and evaluated on a set of photos that featured Khalal, Rutab, Tamar, and a disastrous date. The results were satisfactory. This collection of data was gathered by a smart phone under lighting and camera settings such as focus and camera stabilization that were not under the user's control. The CNN model had an accuracy rate of 96.98% when it came to making proper classifications.

For the purpose of this investigation, the hyperspectral imaging (HSI) technology was put to use both outside and within the laboratory to determine the level of maturity of these fruits. Data for the Strawberry HSI were gathered both when the berries were just beginning to mature and when they had reached their full maturity. The data were collected between 370 and 1015 nm. When determining the wavelengths of the spectral features, the sequential feature selection (SFS) algorithm was utilized. Both the field samples (at 530 and 604 nm) and the lab samples (at 604 nm) were analyzed using two different wavelengths (528 and 715 nm).

After that, a support vector machine, also known as an SVM classifier, was utilized in order to evaluate the accuracy of these spectral features. SVM classification models performed well, achieving receiver operating characteristic values for samples obtained in the field as well as in the lab that were greater than 0.95. The spectral feature wavelength as well as the first three principal components were utilized in order to generate the spatial feature images for the laboratory samples. Researchers (Gao et al., 2020) made use of a convolutional neural network (CNN) that had previously undergone training to differentiate between early ripe and fully ripe strawberry samples. This resulted in an accuracy rate of 98.6% for the dataset that was being tested. The results presented above indicated that the real-time HSI system had potential for use in determining the level of ripeness of strawberries both in the field and in the laboratory. Farmers and other producers may be able to use this method to determine the optimal time to harvest their crops.

The identification and classification of various types of fruit is an interesting and potentially fruitful topic of research. This research is beneficial for keeping track of fruits and organizing them into categories based on the type of fruit they are, which allows for the manufacturing chain to move more rapidly. The purpose of this research is for (Behera, 2020) to generate a brand new collection of high-quality photographs of the five most popular oval-shaped fruits and the various varieties of each of those fruits. Recent studies on deep neural networks have led to the development of a wide variety of cutting-edge new tools for precision agriculture, such as the ability to recognize fruits. In this paper, a classification model for forty distinct varieties of Indian fruits is proposed. The model is constructed with the assistance of a (SVM) classifier and deep features collected from the fully connected layer of the (CNN) model. The classification of the fruits would be accomplished with the help of the model. In addition to this, there is a suggestion made for an approach to the subject of Indian Fruits that is predicated on the concept of transfer learning. Experiments are conducted using six of the most capable deep learning architectures, which are Alex Net, Google Net, ResNet-50, ResNet-18, and VGGNet-16 and VGGNet-19 respectively. These architectural configurations are put into practice. Due to the fact that each of the six deep learning architectures is evaluated in two distinct ways, there are a total of 12 categorization models. The efficiency with which each classification model operates can be judged based on a variety of different metrics, such as accuracy, sensitivity, specificity, precision, false positive rate (FPR), F1 score, Mathew correlation (MCC), and Kappa. Other metrics that may be considered include false negative rate (FNR) and false positive rate (FPR). The results of the evaluation indicate that the SVM classifier that makes use of deep learning performs substantially better than its counterparts that rely on transfer learning. This is the conclusion that can be drawn from the findings of the evaluation. When pushed to their limits, the deep learning capabilities of VGG16 and SVM produce a score of 100% for accuracy, sensitivity, specificity, precision, F1 score, and MCC. This is the case regardless of which metric is being measured. The field of hyper spectral imaging has seen substantial development during the past three decades, which has contributed to its spread.

The use of remote sensing was first responsible for the development of the method of hyper spectral imaging. As a result of advancements in technology, the method of hyper spectral imaging has become more developed and has spread into a broad variety of new applications. In addition, data-enhanced data cubes that contain a great deal of spectral and spatial information can be of assistance when it comes to capturing, analyzing, reviewing, and determining the significance of data results. This (Jaiswal, 2021) article focuses on novel applications for hyperspectral imaging, which can be found throughout the review. When selecting new application domains, a key consideration is how much those domains stand to benefit in the long run from the implementation of cutting-edge technologies like deep learning. The application of hyperspectral imaging techniques is concentrated on a select number of domains, including remote sensing, document fraud, the preservation of history and archaeology, surveillance and security, the use of machine vision to evaluate the quality of fruit, and medical imaging. The evaluation is predicated on the datasets and characteristics that are open to the general public and that are utilized in the relevant domains. Experts in deep learning and machine vision, historical geographers, and other scholars can use this review as a jumping-off point since it will show them how hyperspectral imaging is applied in a variety of domains and what the future holds for study in this area.

The purpose of this study (Yu et al., 2018) was to create a deep learning technique for predicting the firmness and soluble solid content (SSC) of postharvest Korla fragrant pear utilizing stacked auto-encoders (SAE), as well as a fully-connected neural network (FNN). After utilizing SAE to extract deep spectral features from the visible and near-infrared (380–1010 nm) hyper spectral reflectance image data of pear, these features were used as input data by FNN to predict firmness and SSC. This action was taken to increase precision. In terms of firmness, the SAE-FNN model achieved a satisfactory level of prediction accuracy with R2 P = 0.888, RMSEP = 1.81 N, and RPDP = 3.05; in terms of SSC, the model achieved R2 P = 0.921%, RMSEP = 0.22%, and RPDP = 3.68. Both of these results are shown in the table that follows. The findings of this study demonstrated that deep learning in conjunction with hyperspectral imaging can be utilized for the rapid and nondestructive identification of firmness and SSC in fragrant Korla pears. This was demonstrated by the fact that the two procedures were complementary. This information may be useful for evaluating the fruit's quality once it has been harvested.

In this paper (Singh & Singh, n.d.), talk about what makes a rotten apple different from a healthy apple. To begin the process of classifying apples, you must first extract their textural properties. These features include things like Tamura features, discrete wavelet features, histograms of oriented gradients (HOG), Law's Texture Energy (LTE), and Gray level co-occurrence matrices (GLCM). The apples should then be separated into two groups: those that are poor quality and those that are of higher quality. This can be accomplished with a variety of different classifiers, including SVM, k-NN, logistic regression, and Linear Discriminant, amongst others. The performance of the suggested technique, which makes use of the SVM classifier, was 98.9% better than that of the other classifiers. Plant diseases are caused by microorganisms that infect plants. The fundamental purpose of this current study (Reddy et al., 2020) is to apply a machine learning model to a collection of tomato disease photos in order to proactively take the necessary actions to deal with an agricultural catastrophe. This will be accomplished via the use of machine learning. The information contained in the plant-village dataset was made available to the general public and was incorporated into the information contained in the dataset for this investigation. The hybrid principal component analysis–Whale optimization strategy is used in order to extract the important characteristics included within the dataset. This is done in order to ensure that the most relevant information is obtained. After the data have been collected, they are fed into a complex neural network in order to categories the numerous diseases that can damage tomato plants.

The design of (Dhiman & Kumar, 2021) numerous systems for the categorization and identification of fruits has made use of a wide array of techniques, such as image processing and various kinds of machine learning. In order to speed up the process of sorting fruit, a system that utilizes both machine learning and deep learning strategies has been built. The following nine distinct kinds of fruit—apple, banana, pear, guava, grape, mango, pomegranate, and orange—are all capable of being processed using the technology that has been proposed.

The proposed deep learning classifier (Dhiman & Kumar, 2021) makes use of recurrent neural networks and is taught using both positive and negative extracted data by way of principal component analysis. This process takes place during the training phase. A straightforward method of contrast enhancement was utilized, and this was followed by a conversion to grayscale in order to achieve the goal of balancing the inconsistent light in the input fruit image, which can obscure the object definition. This was done in order to prevent the object definition from becoming obscured. Canny edge detection is utilized during the process of segmentation for the goal of detecting where the boundaries of the fruits are. This is done in order to determine where the individual segments begin and end. It is abundantly clear from the findings of the comparative study with already existing multi-fruit or single-fruit systems that the suggested general-purpose system outperforms them by reaching higher values for accuracy (98.47%), precision (98.93%), and recall (75.44%), and mean square error (1.53%).

The study compared the suggested general-purpose system with already existing multi-fruit or single-fruit systems. The categorization of the numerous fruit types into distinct categories serves as an important framework within the agricultural industry for the purposes of international trade. The classification of fruits involved the utilization of a wide variety of distinct algorithmic approaches.

A Gaussian filter is used to the photos when they are being processed in the pre-processing step in order to remove any unwanted noise from the images in this research (Mirra, 2022). Apples, oranges, and bananas are only few of the fruits that have been segmented off into their own individual groups. Other examples include pears and berries. Their quality is also taken into consideration in order to cut down on the likelihood of any potential health problems that may arise. During this step, the various combinations of fruits are separated into the correct varieties, and after that, the quality of the fruit is examined to identify whether or not it has any flaws. If it does, the fruit is discarded. The initial part of the task (Mirra, 2022) is completed with the assistance of a Convolution Neural Network, an Alex Net, and a MobileNetV2 system. When it was applied to different kinds of fruit, MobileNetV2 was able to obtain a classification accuracy of one hundred percent. In the second part of the process, the classifier is used on the same kinds of fruits as in the first step so that their quality may be assessed. The classifiers that have been mentioned up until this point are also able to be utilized for the categorization of defects. MobileNetV2 achieves an accuracy level of 99.89% when classifying flaws in oranges, whereas it reaches a level of accuracy of 100% while classifying problems in apples. In the fruit processing industries, computer vision has a wide number of applications, which enables those companies to automate the processes that need to be carried out. Classification of the fruit's quality and, as a result, gradation of the same is very important for the industry manufacture unit in order to produce the best quality finished food goods and the finest quality of the raw fruits that are sellable on the market. This is very important for the industry manufacture unit. In the current investigation, it was feasible to ascertain whether an apple had gone bad or was still edible by observing the flaws that were present on the surface of the fruit's peel. This was the case regardless of the apple's overall condition.

Within the scope of this investigation, a semantic segmentation of the rotten region present in the RGB image of the apple has been proposed. The architecture of deep learning (Roy, 2020) is used as the foundation for the segmentation. UNet and an upgraded version of it known as the Enhanced UNet (En-UNet) have been used for the purpose of segmentation, and the results have been encouraging so far. En-UNet is also known as the Enhanced UNet. The proposed (Roy, 2020) En-UNet model provided outputs that were of higher quality than those produced by UNet, with accuracies of 97.46% during training and 97.54% during validation, respectively. In contrast, the accuracy of using UNet as the fundamental architecture was 95.36%. The best mean IoU score that En-UNet was able to get within a threshold of 0.95 is 0.866, whereas the best score that UNet was able to achieve is 0.66. En-UNet was able to earn a higher score than UNet. The results of the trials indicate that the model that was recommended is superior to others in terms of its capability to execute segmentation, detection, and categorization of rotten or fresh apples in real time. This was determined by comparing the model to others.

2. Methodology

Putting an end to **Cardiovascular disease**, **type 2 diabetes**, **non-alcoholic fatty liver disease,** and some cancers **disease** has become a necessity. These diseases rise due to excessive junk food consumption. The quality of data-driven health management for predicting **quality food** can enhance the overall research and safety process, thereby ensuring that many individuals can lead healthy lives. Thus, image processing (IP) enters the picture. We will employ IP algorithms to forecast **fruit quality**, as IP generates accurate and straightforward predictions.

In this research, we have to use image processing techniques e.g., EfficientB2 (CNN), etc. and apply the sentimental analysis to identify the **quality (**Good, Bad, Average**)** in the fruit. After that, we have shown which deep learning algorithm works well. The proposed method consists of six main steps and four sub-steps. **Fruit Quality Detection.** Figure 01 shows the flow chart of our methodology. In this research, we have used the data set named “**Fruits dataset**”. This dataset is private and available in the University of Victoria repository URL. In the dataset, here are a total of 6 fruit in table 1.

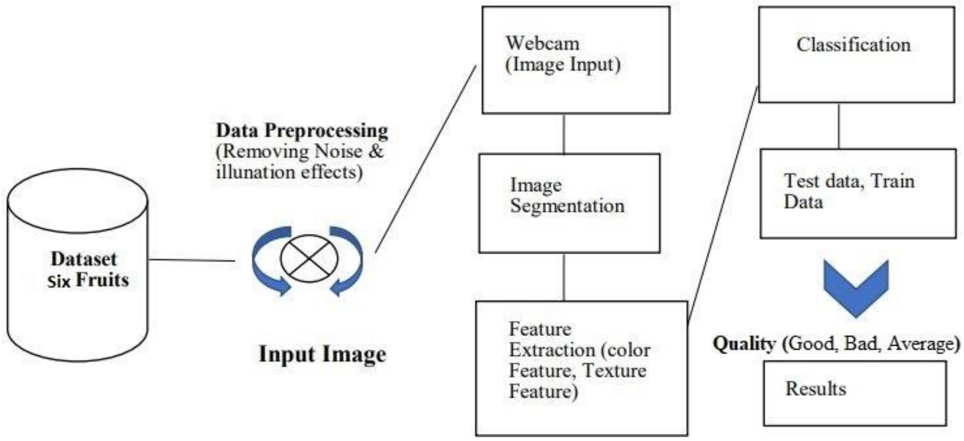

Fig 1 Proposed Methodology

Table 1 Fruit Name

Sr. No	Fruit Name	
1	Apple	Banana
2	Guava	Lime
3	Orange	Pomegranate

In order to overcome issues regarding the classification and recognition of fruits, high-quality photographs of the fruits are necessary. A well-organized and spotless dataset is an essential prerequisite for the development of image processing models. In order to accomplish this goal, we have compiled a dataset consisting of six fruits and giving it the name "**Fruit Clean Dataset**." This dataset consists of around **147,000** high-quality photos of six different categories of fruit that have been processed into a single format.

3.1. Split Dataset Training & Testing

We have utilized the Sci-kit library for the data splitting process, and with the assistance of the train test split header file, we have successfully segmented the Dataset into **80:10:10** proportions. There are a total of **17573** pictures in the dataset used for training, **976** in the dataset used for testing, and **977** in the dataset used for validation. We have also found out the average image height which is **721.152**, and the average width is **702.528**.

```
train_df lenght:  17573   test_df length:  976   valid_df length:  977
            CLASS                IMAGE COUNT
          Lime_Bad                  1085
         Guava_Bad                  1129
      Pomegranate_Good              5940
         Lime_Good                  1094
         Apple_Bad                  1141
        Orange_Bad                  1159
        Guava_Good                  1152
        Apple_Good                  1149
       Orange_Good                  1216
       Banana_mixed                  285
        Banana_Good                 1113
        Banana_Bad                  1087
      Pomegranate_Bad               1187
       Guava_mixed                   148
       Lemon_mixed                   278
     Pomegranate_mixed               125
       Apple_mixed                   113
       Orange_mixed                  125
Average Image Height:  721.152   Average Image Width:  702.528   Aspect ratio:  1.0265099754031157
```

Fig 2 Size of Train, Test, and Validate Dataset

3.2. Robustness increase by Purifying Training Dataset

Figure 4 is showing image after trimming it. The image is trimmed in order to help eliminate the influence of outliers or data points on the tails, which may unjustly affect the traditional mean. This is accomplished by removing these points from the image. In order to accomplish this, we need to develop a function that we will call trim. Using the distinct class label as a divider, we have partitioned the training dataset within this function so that it is distinct from the initial data frame. After we group all data into their corresponding classes and then check the size of the sample with the maximize allow. If sample count size is greater than maximize then trim train dataset size. Else append the sample to train the dataset sample. Figure 5 is showing the final data frame of the training dataset after trimming it.

```
Original Number of classes in dataframe:  18
[300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300
```

Fig 3 Trim Dataset to make the model more robust

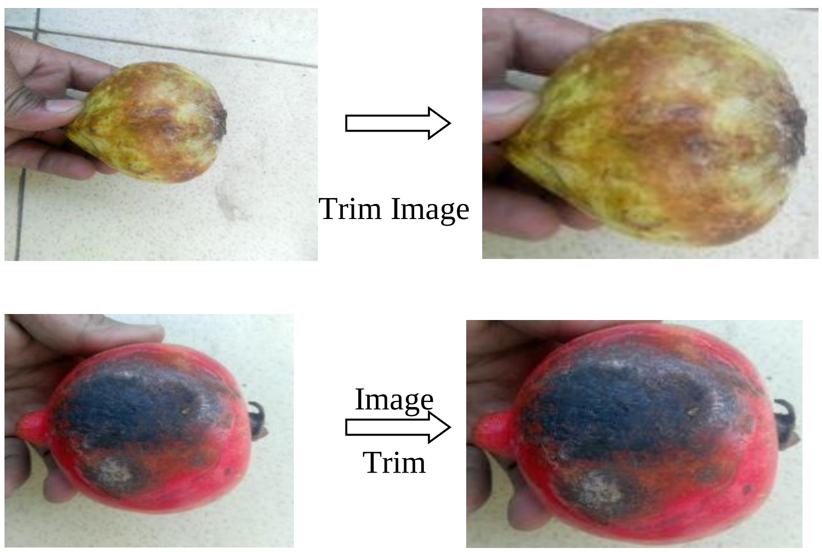

Fig 4 Robustness increase by Purifying Training Dataset

3.3. Balancing Training Dataset

The dataset has a different size image. Some images are captured from high-resolution mobile cameras, and a few images were taken at different backgrounds and in different lighting conditions. So, it needs to balance the dataset. For that, we have made directories to store high-quality images in a separate directory. It will help to increase robustness in the training phase.

3.4. Image Pre-processing

This section gets rid of any noise, makes the image smoother, and resizes any images that need to be changed. In this process, RGB photos are changed to greyscale images, and the contrast of an image is boosted to a certain degree. Photographs of fruit captured using a variety of cameras and cameras of varying quality are included in our collection. These images include images taken with mobile devices, images with noisy backgrounds, and other variations. As a result, it is necessary to employ various methods such as calming, the elimination of noise, and others. It will be useful for the forth coming procedures as show in figure 5.

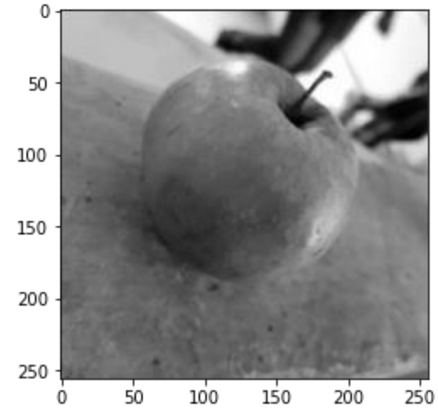

Fig 5 RBG to Gray Scale Image

3.5. Image Segmentation

Segmentation is used for partitioning an image into various Parts. As show in Figure 6.

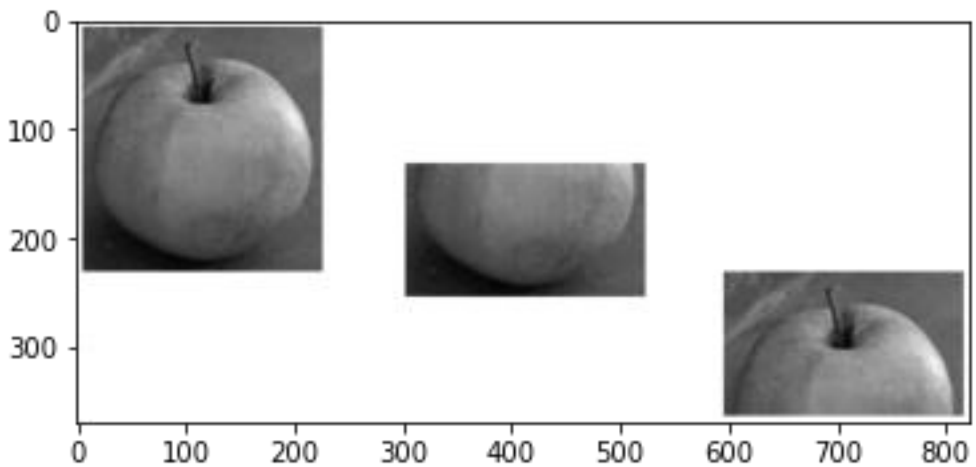

Fig 6 Image Segmentation

3.6. Feature Extraction

In this part, elements like as color, texture, and shape are extracted in order to cut down on the amount of resources needed to explain a huge set of data prior to the classification of the image.

Fig 7 Guava is Oval with green color, and 6-12 centimeters, Lime in Circle shape with green color, and 3-6 centimeters.

3.7. Classification Model EfficientfNetB5 (CNN)

In this particular model, we will apply Efficient Net to analyses the quality of fruit photographs (**Fruits dataset**). Google AI announced the release of Efficient Net in June of this year (2019), and it is now the most advanced method for ImageNet. It presents a methodical approach to scaling CNNs (Convolutional Neural Networks) in a manner that is almost optimal. We will be using version B5 of the kernel for this one. The EfficientNetB5 model delivers a Keras image classification model, which may or may not be loaded with weights that have been pre-trained on ImageNet.

3.8. Model Hyper parameter

We have the **SoftMax** optimizer function of all datasets available to us so that we can determine which of our hyperparameters are the most optimal. During the training of the model, the smooth edge of the dataset was made possible by the SoftMax optimizer function. The value of epochs should be set to **10**. Table 02 presents the information regarding the parameters that have been assigned to our model.

Table 2 Hyper parameter for Model

Identifiers	Values
Loss Function	Categorical Cross entropy
Activation Function	SoftMax
Optimizer Function	Adam
Epoch Size	10
Verbose	01

3.9. Training & Testing Model

To execute the complete experiment for the **Fruit Quality Detection**, we will first train a baseline model. Then, we will conduct more tests to examine the effect that altering the hyper parameters has on the model's overall performance. As shown in figure 8, Our train model achieve Val accuracy **95%.** Figure 9 is showing that our train model will be able to predict quality of fruit (**Apple, Banana, Guava, Lime, Orange ,Pomegranate)** with the **96.93%** accuracy.

```
229/229 [==============================] - 140s 610ms/step - loss: 14.8612 - accura
y: 0.9498
```

Fig 8 Image Segmentation

```
16/16 [==============================] - 23s 1s/step
there were 30 in 976 tests for an accuracy of  96.93
```

Fig 9 Image Segmentation

3. Evaluation

The Confusion matrix played an important role in the process of validating the EfficientNetB5 model. The suggested image processing model has a higher prediction rate of **95.16%** to **98.18%** for the detection of bad fruit, and it has a prediction rate of **94.86%** to **99.66%** for the detection of good quality fruit. Model performance Comparisons between the detection of good fruit and rotten fruit are being investigated here. Figure 13 demonstrates that the suggested image processing model works more effectively for determining the quality of fruit in terms of Precision, Accuracy, Recall, and F1-score. Table 3 presents the proposed model's confusion matrix for your perusal.

Table 3 Confusion Matrix

Classification Report:
----

	precision	recall	f1-score	support
Apple_Bad	0.9821	0.9649	0.9735	57
Apple_Good	0.9649	0.9649	0.9649	57
Apple_mixed	1.0000	1.0000	1.0000	6
Banana_Bad	1.0000	0.9636	0.9815	55
Banana_Good	0.9483	1.0000	0.9735	55
Banana_mixed	0.9333	0.9333	0.9333	15
Guava_Bad	0.9655	1.0000	0.9825	56
Guava_Good	0.9818	0.9474	0.9643	57
Guava_mixed	0.8889	1.0000	0.9412	8
Lemon_mixed	0.7368	1.0000	0.8485	14
Lime_Bad	0.9464	0.9815	0.9636	54
Lime_Good	0.9808	0.9273	0.9533	55
Orange_Bad	0.9818	0.9310	0.9558	58
Orange_Good	0.9474	0.8852	0.9153	61
Orange_mixed	0.8333	0.8333	0.8333	6
Pomegranate_Bad	0.9516	1.0000	0.9752	59
Pomegranate_Good	0.9966	0.9899	0.9932	297
Pomegranate_mixed	0.8571	1.0000	0.9231	6
accuracy			0.9693	976
macro avg	0.9387	0.9624	0.9487	976
weighted avg	0.9710	0.9693	0.9695	976

4. Discussion

Our systematic examination demonstrates the value of EfficientNetB5 model prediction algorithm for the construction of health management systems and the ease and speed of **fruit quality** prediction. **Fruit quality via** component analyses of data sets. Our study summarizes the outcomes of several data visualizations, particularly fruit shape (Good, Bad), fruit color (Good, Bad), fruit size (Good, Bad), and others concerning the fruit quality Result. We have applied EfficientNetB5 algorithm to a dataset and identified the highly accurate algorithm. Based on our findings, we may need to identify statistically significant effects of a particular publication.

Our findings illustrate the correlation between good fruit and bad fruit feature (Size, Color, Shape) for **fruit quality detection.** The efficientNetB5 algorithm has demonstrated superior performance in predicting **fruit quality** compared to other Machine Learning techniques. However, the efficientNetB5method needs further development. This tendency is known as publication bias. It is challenging to exclude bias in research.

5. Conclusion

We tested for the mentioned algorithms on our Dataset. We found that the EfficientNetB5 algorithm performed well. We have developed an autonomous healthcare management algorithm for predicting the **quality** of fruit. Our proposed model will help save **Cardiovascular disease**, **type 2 diabetes**, **non-alcoholic fatty liver disease,** and some cancers **disease** has become a necessity. These diseases rise due to excessive junk food consumption**.** Our predictive algorithm will aid the agricultural industry and food companies in identifying **fruit quality** accurately.

6. Future Work

Future research should investigate which **bad fruit type** will have the most impact on human health relative to the others and what creates this kind. In addition to the Cluster Heat Map model, several types of models have been validated. Regardless, additional model applicability must still be validated. In addition, future research must study the optimal intensity of fruit Test Indication levels to prevent diseases rise due to excessive junk food consumption.

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