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# Enhancing Fruit Quality Detection with Deep Learning Models

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**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.

## 1. 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 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 categories 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, color 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.

### 1.1 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.

**2. Related Work**

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.

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.

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.

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 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%).

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 AlexNet, 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.

## 3. 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 substeps. 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.

**Table 1.** Fruit Name

| Sr. No | Fruit Name |
|---|---|

| | | |
|---|---|---|
| **1** | Apple | Banana |
| **2** | Guava | Lime |
| **3** | Orange | Pomegranate |

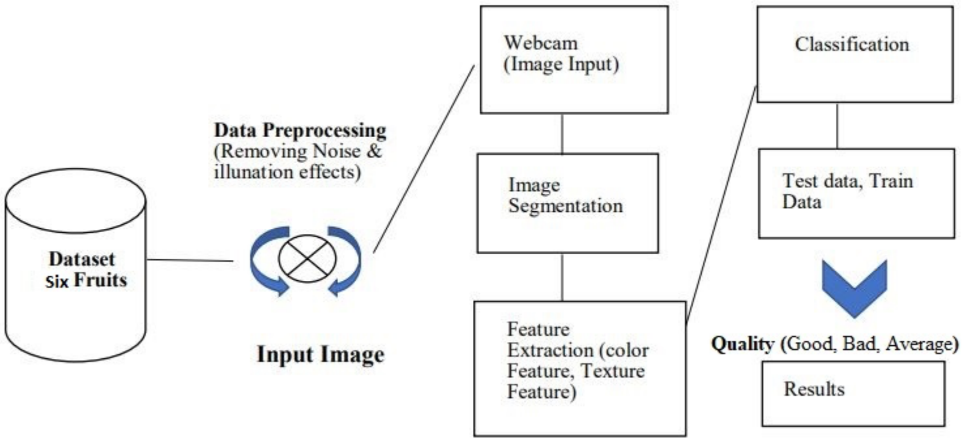


**Figure 1.** Proposed Methodology

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
```

**Figure 2.** Size of Train, Test, and Validate Dataset

3.2 Robustness increases 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 max_size allow. If sample_count size is greater than max_size 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, 256, 250, 133, 113, 113, 102]
```

**Figure 3.** Trim Dataset to make the model more robust

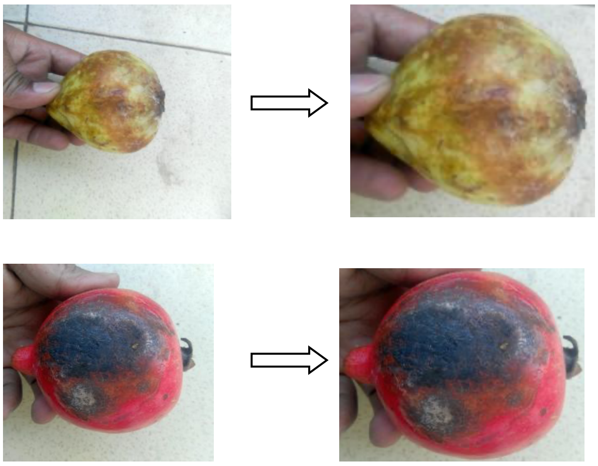

**Figure 4.** Robustness increase by Purifying Training Dataset

3.3 Balance 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 Eimage 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.

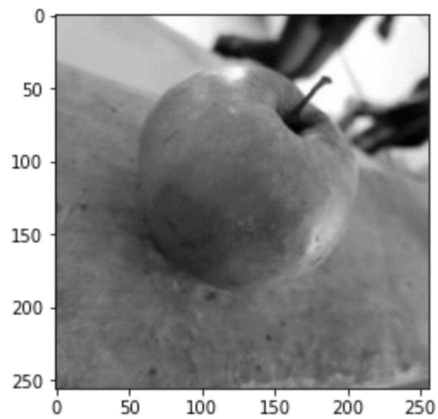


**Figure 5.** RBG to Gray Scale Image

3.5 Image Segmentation

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

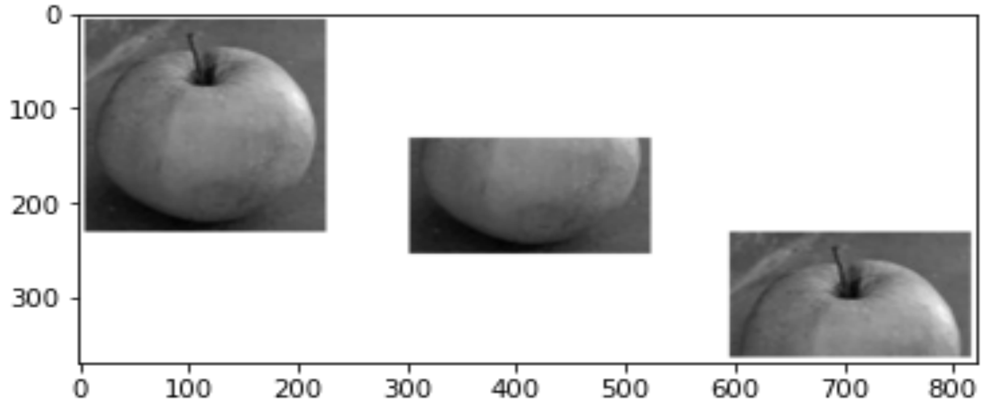


**Figure 6.** Image Segmentation

3.6 Feature Extraction

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

**Figure 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 EfficientNetB5 (CNN)

In this particular model, we will apply EfficientNet to analyses the quality of fruit photographs (Fruits dataset). Google AI announced the release of EfficientNet 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.

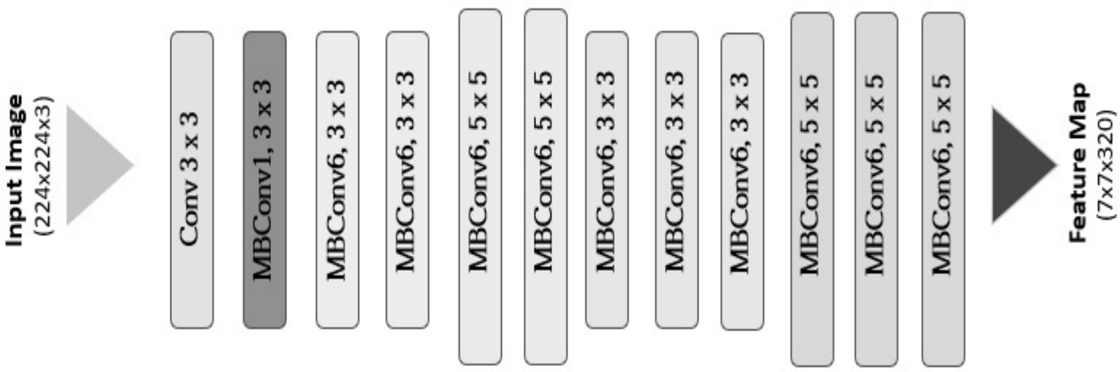


**Figure 8.** Basic Architecture of EfficientNetB5 Diagram

3.8 Classification Model EfficientNetB5 (CNN)

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. The softmax function transforms a vector of K real numbers into a probability distribution with K alternative outcomes. It is often referred to as softargmax or the normalized exponential function. Multinomial logistic regression uses it as an expansion of the logistic function to several dimensions.

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (1)$$

$\sigma$ = softmax

$\vec{z}$ = input vector

$e^{z_i}$ = standard exponential function for input vector

$K$ = number of classes in the multi-class classifier

$e^{z_j}$ = standard exponential function for output vector

$e^{z_j}$ = standard exponential function for output vector

**Table 2.** Hyper parameter for Model

| Identifiers | Values |
|---|---|
| LossFunction | CategoricalCrossentropy |
| ActivationFunction | softmax |
| OptimizerFunction | Adam |
| EpochSize | 10 |
| Verbose | 01 |

3.9 Classification Model EfficientNetB5 (CNN)

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 achieves val_accuracy 95%. Figure 9 is showing that our train model will be able to predict quality of fruit (Apple, Banana, Guava, Lime, Orange, and Pomegranate) with the 96.93% accuracy.

```
229/229 [==============================] - 140s 610ms/step - loss: 14.8612 - accuracy: 0.8693 - val_loss: 10.5566 - val_accurac
y: 0.9498
```

**Figure 9.** Image Segmentation

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

**Figure 10.** Image Segmentation

### 4. 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 performance evaluation while Table 4 presenting model performance based on Accuracy (1), Recall (2), Precision (3), and F1-Score (4). Figure 11 is showing the visualization of result by using confusion matrix.

**Table 3.** Performance Evaluation Matrix [12]

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \times 100 \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \times 100 \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \times 100 \quad (3)$$

$$F1_{Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100 \quad (4)$$

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 55 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 0 | 55 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 0 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 53 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 55 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 56 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 54 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 53 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 1 | 51 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 54 | 3 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | 1 | 0 | 54 | 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 5 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 59 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 294 | 1 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 |

**Figure 11.** 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 |

**Figure 12.** Classification Report of Proposed model

## 5. Discussion

The study conducted a comprehensive and organized examination of the EfficientNetB5 model's prediction algorithm. The model's application goes beyond traditional machine learning tasks and extends to the construction of Production management systems, which could have various applications in the agriculture field. Additionally, the model is evaluated for its effectiveness in predicting fruit quality, which could be significant for industries that rely on consistent and accurate assessments of fruit produce. The introduction highlights the importance of using an advanced algorithm like EfficientNetB5 for the task at hand.

The EfficientNetB5 model is put to the test to predict fruit quality using datasets that contain various attributes related to the fruit's appearance and characteristics. To better understand the prediction results, the study employs component analyses of the datasets, breaking down the information into different fruit features and attributes. The study involves extensive data visualizations to present the outcomes effectively. Fruit shape, color, size, and possibly other attributes are carefully analyzed and visualized to determine their impact on fruit quality. By studying these visualizations, the researchers can draw conclusions about how the EfficientNetB5 model performs in assessing and distinguishing good and bad fruits based on the provided features.

After evaluating the results of the EfficientNetB5 model's predictions, the researchers find that it outperforms other machine learning techniques in predicting fruit quality. The use of the EfficientNetB5 algorithm leads to significantly higher accuracy and speed in the fruit quality prediction process compared to alternative methods.

This finding is crucial as it showcases the model's potential for real-world applications, especially in industries where the ability to accurately assess fruit quality is vital for business success.

## 6. Conclusion

Testing Algorithms on a Dataset: The study conducted experiments to assess the performance of various algorithms on a given dataset. The dataset likely contains information about fruits, their quality attributes, and possibly other relevant features. EfficientNetB5 Algorithm Performance; Among the algorithms tested, the EfficientNetB5 algorithm demonstrated good performance. EfficientNet is a family of convolutional neural networks (CNNs) known for their efficiency and accuracy in image classification tasks. The specific variant used here is EfficientNetB5, which is likely one of the larger and more powerful versions within the EfficientNet family. The main goal of the research is to create an autonomous healthcare management algorithm. This algorithm's primary purpose is to predict the quality of fruits automatically, which could have significant implications for public health and agricultural industries. The predictive algorithm aims to evaluate the quality of fruits based on the dataset. Fruit quality can be determined by various factors such as appearance, ripeness, sweetness, nutritional content, and absence of defects or diseases. The proposed autonomous healthcare management algorithm holds potential benefits for various health conditions. The author mentions the possible impact on diseases such as cardiovascular disease, type 2 diabetes, non-alcoholic fatty liver disease, and some cancers. These diseases are associated with unhealthy eating habits, particularly the consumption of excessive junk food.

The study emphasizes the necessity of developing such a predictive algorithm for fruit quality assessment due to the rising prevalence of the mentioned diseases. Unhealthy eating habits and excessive consumption of junk food have contributed to an increase in these health issues. By accurately predicting fruit quality, the proposed model aims to encourage healthier dietary choices, ultimately mitigating the prevalence of these diseases.

The predictive algorithm's potential benefits extend to the agricultural industry and food companies. By accurately identifying the quality of fruits, growers, suppliers, and food manufacturers can ensure that only high-quality produce is supplied to consumers. This, in turn, can enhance customer satisfaction and reduce wastage due to poor-quality fruits reaching the market.

**7. Future Work**

The future research should focus on determining which specific types of "bad" fruits have the most significant impact on human health when compared to other types. The term "bad" fruits likely refer to those fruits that may have negative effects on health due to their nutritional content or potential contaminants. Understanding which fruits are more harmful can help people make informed dietary choices to improve their health. Further need to identify what creates or characterizes these "bad" fruits. This likely involves analyzing their nutritional composition, potential toxins or pesticides, and any other factors that could contribute to negative health effects. By understanding the specific characteristics of these fruits, it can better comprehend why they may be detrimental to human health. The text mentions the "Cluster Heat Map model" as one of the models used in the study. This model is likely used to visualize and analyze the relationships between different variables (such as fruit types and health impacts) in a clustered manner. It also suggests that other types of models have been validated in this context, although further information on the exact nature of these models is not provided.

The importance of validating the applicability of the models used in the research. In other words, study need to ensure that the models accurately represent the relationships between variables and provide reliable predictions or insights. This validation process ensures that the results obtained from the models are trustworthy and can be used to inform future studies or dietary guidelines.

The text suggests that future research should investigate the optimal intensity of fruit consumption, likely referring to the ideal levels of fruit intake that can help prevent the adverse health effects caused by excessive consumption of unhealthy junk food. This research could potentially identify how much of these "good" fruits is required to counteract the negative impact of an unhealthy diet rich in junk food.

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