FRUIT CLASSIFICATION USING IMAGE PROCESSING

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APPROVAL

This Project titled **"Fruit Classification Using Image Processing"**, submitted by Name: Farjana Abedin Boby, ID No:191-15-2470 and Name: Tanzila Rahman Meem, ID No: 191-15-2391 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *05 February 2023*.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Dr. S.M. Aminul Haque, Associate Professor, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Detection of rotten culmination has become big within the agro-industry. In general, the category of sparkling and rotten fruit isn't always powerful for fruit growers and sporting people. People get worn out after doing the equal issue extra than once, however, the machines don’t deliver it up. Thus, the venture proposes a technique of lowering human effort, lowering expenses and time for manufacturing through figuring out fruit defects in agriculture. If we no longer pick out the one’s defects, that faulty culmination can contaminate the coolest culmination. Therefore, we've proposed a version to keep away from decay. From input fruit images, this suggested model identifies good and rotting fruit. For this purpose, we have used good and rotten samples of three types of fruits. Those are apples, bananas, and oranges. In order to extract the features from the input fruit image, the Convolutional Neural Network (CNN) has been used and SoftMax has been used to categorize images of fresh and rotten fruits. Recommended performance data are downloaded from Kaggle to evaluate the model on a dataset and has a precision of 99.36 percent. The findings revealed that the suggested CNN model is at predicting between fresh and rotting fruits. The overall performance of the proposed CNN version transcends today's device getting to know version and business approach.

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CHAPTER 1
INTRRODUCTION

1.1 Introduction

There are a number of essential vitamins and minerals that aren't found in other foods, and fruits and vegetables may contain more of these nutrients than other foods. The nutritional content of plant-based food determines its economic worth. Quality and how it is maintained throughout the production process until it reaches a chain's final customer [1]. The concept of quality encompasses a wide range of factors, including external appearance, dietary components, the presence of health-related compounds, safety, and protection. Even so, companies or superstores that promote end the result may find that quality evaluation of the result is very important. It would be extremely embarrassing for their business if they sold defective or rotten products [2]. Therefore, a high-satisfactory evaluation ought to ensure that their stock is in good condition and that there are no defective or rotten products. These high-satisfactory tests are frequently achieved by keeping or dealer employees visually examining the result and separating the good ones from the bad ones. Human inspection, on the other hand, isn't always reliable due to fatigue, stress, distractions, and a lack of focus. These flaws unavoidably demonstrate the usefulness of automatic photograph classifiers, which have the potential to improve this procedure. Because fruit possesses a variety of characteristics, such as color, odor, texture, hardness, and so on, applying automatic photograph classifiers to the task presents a number of challenging challenges. It's hard to take all of these characteristics into account for an automatic photo classifier system. The growing recognition of neural networks and the significant growth in affordable digital camera hardware, particularly those found in mobile devices, have both contributed to the widespread development and efficiency of system imaginative structures over the past few years [3]. This enables a fee-green photograph-type solution for numerous objects. System a getting to know algorithms to categorize images have become increasingly popular due to the fact that guide inspection using people can be prone to errors and system getting to know structures are becoming increasingly green. In the past, deep learning strategies were more advanced than many established sets of rules for related fields and types of images. Deep Learning treats, data samples with simpler intermediate representations, eliminating the need for additional characteristic extraction pre-processing methods. Convolutional a neural community is one of the successful deep learning strategies for photograph type. Convolutional neural networks, such as Convolutional Neural Networks, multilayer idea, and support vector system for image type, have been shown to be superior to conventional algorithms in terms of predicting lessons in some studies. The application of CNN to classify outcomes as rotten or fresh is our primary objective. Our research is entirely based on VGG net and the version 3 of Inception. We used the CNN classifier a lot in our experiments to see if it could perform better than other methods on our education and testing dataset [4].

1.2 Motivation

Today, a lot of people have become awful culmination and greens by shopping at wonderful stores and department stores without knowing whether they are right or not.
They never look at the end result before making a purchase [5] due to the fact that they spend time eating real meals and trying them out separately. AS a result of this fact, many people eat unhealthy fruit every day, which they should do so at the risk of harming their bodies and fitness. Therefore, our primary goal became to define and connect this issue. If they have a device that allows them to experiment with food in a few seconds, they can always test the product out first before purchasing. so that there is less of a chance of bad outcomes and they can keep their health and money. As a result, the goal of this study is to solve this problem and create a device with photo processing so that customers can quickly experiment and get their results [6].

1.3 Rationale of the study

We read a lot of papers about how much better image classifier technology Convolutional Neural Networks (CNNs) are. CNNs are based on the idea that a local understanding of an image is enough. Numerous image-based projects have been presented, some of which are able to identify fruit-borne diseases or cancerous cells. On the other hand, the Google Tensorflow library is more reliable and efficient. It is still possible to produce precise results with fewer training data. We felt compelled to make use of it. Nowadays, artificial intelligence is used everywhere, and there is a real shortage of fresh food. We tried something new by using artificial intelligence to tell the difference between fresh and rotten fruit. As a result, we are driven to use as many classes as possible to get the best results, and we have finally discovered that Method provides the highest level of accuracy.

1.4 Research Questions

- What are the most effective image processing techniques for fruit classification?
- Are we prepared to observe the percentage of freshness or rottenness?
- How does the algorithm work in this research?
- Who exactly will benefit from this?
- What percentage of accuracy are we likely to achieve?

1.5 Expected Output

We looked at a subset of fruit diseases as part of our project to see if any could be easily identified with artificial language. Using a programming language known as machine, learning, we frequently discover that it is frequently detected extremely quickly. To achieve better outcomes, we will work with additional fruit classification categories in the future and base our fruit classification decisions on those categories.

1.6 Project Management and Finance

To better comprehend the most recent shifts in roles and responsibilities, the survey of project management roles and responsibilities was used to collect data. Project management includes meeting planning and scheduling, general study facilitation, and data entry into databases. The timely recording of study progress was made possible by the timely distribution of meeting agendas and minutes outlining progress and action items. This makes it simple to determine whether the fruit is fresh and significantly lowers the risk of illness. This is because good project management makes it possible to use the right tools, methods, strategies, and predetermined approaches and stick to them. Finance includes budgeting, managing money, managing grants, paying bills, and balancing accounts.

1.7 Report Layout

- The entirety of this challenge can be found in Chapter 1. The challenge's inducement, predicted outcome, and other details are briefly discussed in justification for selecting this one. In a nutshell, bankruptcy is the development of this obstacle.
- Work that has been studied in this area is presented in Chapter 2. Their findings and obstacles are summarized, and the evaluation's scope and challenging circumstances are also noted.
- The subject of evaluation and instrumentation, data survey methods, and implemented mathematical evaluation and implementation requirements may all include mention of the evaluation technique in Chapter 3.
- The discussion, analysis, and experimental values are presented in Chapter 4.
- Provides a brief conclusion in Chapter 5. Moreover, a listing of references.

CHAPTER 2
BACKGROUND STUDY

2.1 Preliminaries

The modern human life is extremely busy. Everyone wants to try to complete their tasks quickly, accurately, and cheaply. Therefore, only cutting-edge technology can satisfy this kind of need. Fruit tally takes a long time and requires a large workforce, which costs more. The system's implementation of laptop vision aims to reduce user strain by limiting the number of possible objects. Therefore, it is necessary to have tally algorithmic rules and automatic fruit detection in order to avoid these issues. Different object feature extraction algorithms and machine learning algorithms are utilized to achieve sensible object detection, classification, and recognition. As a result, we typically select the algorithmic rule that achieves the highest classification and prediction accuracy.

2.2 Related Works

In the study [7], a system imagination machine was developed for the purpose of detecting flaws in fruit skin. Color is the most commonly used feature for classification, and a system with an algorithm known as the Support Vector Machine (SVM) was used in this case. On a limited number of datasets, the Support Vector Machine (SVM) produces acceptable results. The functions that are drawn out and those that are chosen for passing on to the system gaining knowledge of algorithm make up the entirety of the system gaining knowledge algorithm's accuracy in type. By deepening our understanding of fashion, we can boost our performance as a whole. These designs make it easier to take pictures inside large datasets. Image processing [8] can help with both disorder-specific and non-disorder-specific culmination. It makes it easier to identify flaws at the mango peak's floor. To begin, the culmination is gathered by hand, and the researchers themselves classify it as either quality or defective. The photographs are then subjected to pre-processing before being sent to a CNN version for the type of project. The accuracy of this version was 99.36 percent [9]. The method, which is entirely based on the CNN principle and laser backscattering imaging evaluation, provides a conceptual and theoretical foundation for online, effective, and non-destructive fruit quality detection. This picture suggests that the method is effective and can routinely and without damaging the disorder, every day, stem, and calyx areas of apples. The overall popularity rate is over 90%. When the disorder areas are similar to the stem and calyx areas in grey traits and shapes, the method can meet the requirements for apple defects detection. The CNN version has a greater impact on disorder popularity than conventional algorithms [10]. Today, CNN's in-depth fashion analysis is frequently used in the form of photographs to illustrate extraordinary issues that arise within the agricultural field [11]. The proposed CNN model provides high accuracy in our research for both the type project of sparkling and rotten culmination. The accuracy of the proposed version is compared to the switch fashion knowledge. From a variety of types, three types of culminations are chosen. The dataset comes from Kaggle and has six training, which means that each fruit is split and looks sparkling and rotten. We looked at the exceptional pre-educated models of VGG16, VGG19, MobileNet, and Xception of switch learning (switch learning styles). While investigating the effect of very important hyperparameters to benefit better results and additionally avoid overfitting [12], this paper introduces a powerful CNN model that has improved accuracy for glowing and rotten end result type tasks over transfer studying models.

2.3 Comparative Analysis and Summary

After reviewing a few research papers and springs, we decided to use the CNN (Convolutional Neural Network) because:

- It excels at detecting natural scenes, unidentified objects, and environmental and forest location categories. In point of fact, it works wonderfully with the fruit that we tend to all like.
- CNN's picture category algorithmic software has the highest accuracy of any other software, ranking 90th or higher with accurate education.
- Numerous resources for parents interested in higher improvement and easy-to-use.
- Utilizing victimization CNN layers effectively and with the appropriate training enables us to achieve precise outcomes and clever consequences.

- Excellent at evaluating images like face and non-face, modern and rotten fruit, and so on.

CNN (convolutional neural network) layers and deep learning algorithms can be used to create artwork because we typically use CNN as our primary category model. In the backend, TensorFlow and Keras were used to force the model. Utilizing Anaconda and internal statistics became our primary objective. Google Collab was our choice due to its widespread use and easy, quick implementation process. To make it easier to build, we typically use Colab and Google's own GPU at runtime. As a result, information consumers are more likely to demand better quality. Our primary objective is to classify good and bad outcomes and evaluate any of them to trigger output. As a result, we typically construct our CNN layer by utilizing the Pooling, Con2D, and Activation layers. We typically begin with oranges, bananas, and apples. We must steer clear of using object classifiers that are hard to spot because they have the potential to deliver incorrect results. Using apples, bananas, and oranges, we will be able to determine the most accurate comparison between their good and rotten predicted values and come up with a range that is satisfactory in terms of accuracy. Is it safe to consume?

2.4 Scope of the Problem

The development of a companion degree machine to evaluate the fruit's freshness and demonstrate that CNN is the best algorithmic software for image classifiers is the primary focus of this evaluation piece. To guarantee health outcomes, we will attempt to use our machines in large factories, fast food restaurants, or restaurants. Our equipment will be made from free materials and made available to everyone. This method will be used by the inspector of an Asian American avenue culmination to identify rotten fruit, just so everyone is aware. It will make painting easier for them. Popular humans are able to make decisions about rotten fruit or send pictures of rotten fruit to executive servers because they are our machine. As a result, the adjudicator knows that the area needs to be watched.

2.5 Challenges

- **Data Collection**

It wasn't hard to get the data for this study because there were a lot of images online. But when we started taking pictures of apples, bananas, and oranges in the area, it was too hard because most sellers didn't like it when we touched their products even though we didn't intend to buy them. More training data are required for greater accuracy. However, I was unable to purchase a significant quantity of fruit. In the end, we decided to collect data by utilizing Kaggle.

- **Model selection**

Any researcher can attest to the difficulty of selecting a model. As a result of the research, fulfillment is determined by the data set and preferred version. While the best opportunity can speed up your progress toward your objectives, the wrong one can also throw off your plans. We frequently test a variety of clothing styles in an effort to identify the most effective one using test data. We also play around with painting in Matlab. We frequently choose the CNN rule after trying everything else because Google already excels at one aspect of it, which is simply shaping our paintings. We can use Google CoLab, but running images would really necessitate an expensive GPU.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

We observe that the evaluation's records are its primary component. A person who studies technology absolutely needs to look for exceptional technology as well as excellent components or versions for his or her evaluation work. He or she should also look over related evaluation papers. Then he or she must be forced to make a lot of choices:

- What kind of data ought to be gathered?
- How can we guarantee the accuracy of the data we collect?
- How are the various pieces of information arranged?
- How do you label each piece of data?

3.2 Data Collection Procedure

There are more than 14000 snapshots in our dataset. We get it from Kaggle and divide it into two sections, train and test, each of which contains a different number of snaps. The lack of comparable datasets and the fact that no attempt had been made before to classify the best results solely based on whether they were fresh or rotten were the primary challenges we encountered while compiling the image [13]. There are a few risks associated with downloading images from the internet, and not all outcomes develop in the same way across the globe. Their form also changes depending on the weather, soil, and other factors. Finding pictures of locally grown versions of a particular type of fruit can sometimes be difficult, especially if no one has written anything about it on the internet [14]. The fact that not every fruit vendor is willing to let photographs of their products taken poses an additional challenge when collecting images from nearby fruit shops. It is strictly prohibited to take photographs in specialty and branch stores, and there may rarely be a link to request permission. We were fortunate enough to locate a local fruit vendor who consented to our taking pictures of his products. There is still the problem that not all stores now carry "Temperature/K" in all variations [15]. In Figure 3.1 shows the sample images of Dataset.

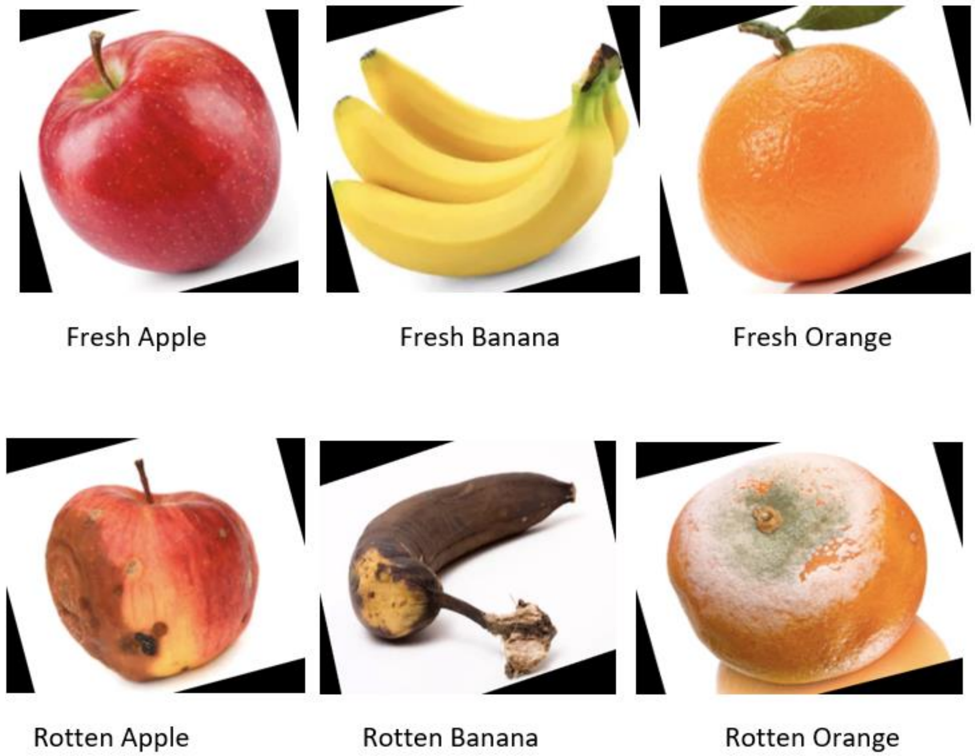

Fig 3.1: Sample images of Dataset

- **Data Pre-processing**

Data preprocessing is the first step in processing datasets. Typically, uncooked data units are unable to carry out operations and produce anticipated outcomes. As a consequence of this, information pre-processing is required. Additionally, it has now emerged as one of this study's most significant components. During this phase, we collect more than 14,000 images from a variety of sources and work to get rid of any that aren't needed or don't make sense.

- **Data Organizing**

We separate the data and save it in folders during this phase: examine and instruct. Additionally, we check the validity of teaching data using the validation folder. The data from the test and training folders were then broken up into additional folders like "fresh apple," "rotten apple," "fresh banana," or "rotten banana," and so on.

• Data Storing

We store all of the statistics in this section in Google Drive because it makes it easier to paint. By following a few easy steps or writing a few codes, we can use the internet statistics that were saved in our assignment. In figure 3.2 shows the flowchart in this study.

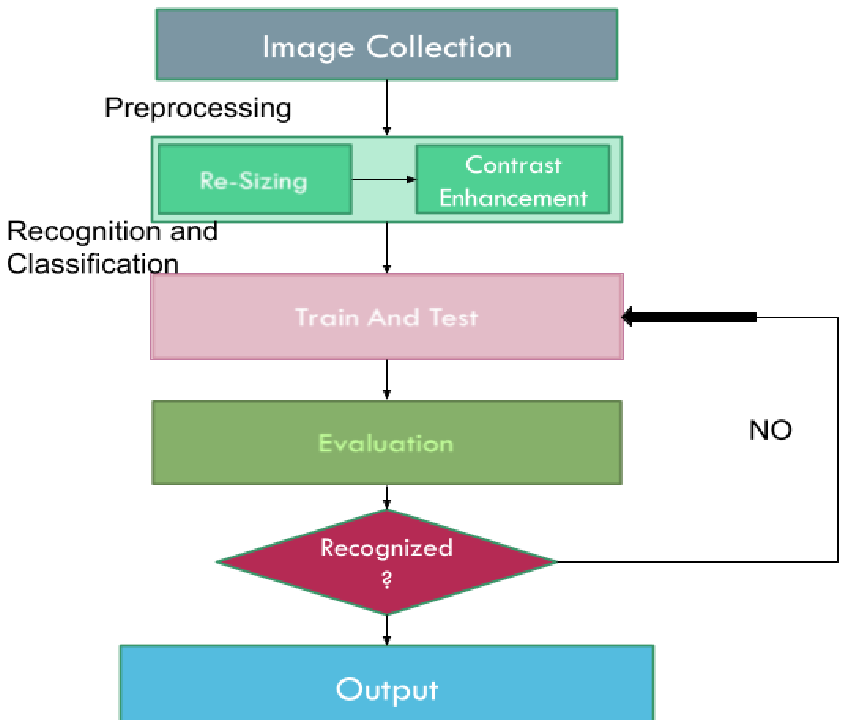

Fig 3.2: Flow Chart of this project

• Train Test Split

We divided the data into two datasets for the purpose of training and evaluating the model: 80% to 20% test and train. For performance evaluation, our model must be tested with unseen data using two dataset splits after training.

3.3 Statistical Analysis

Our total image data collection exceeds 14,000, but after preprocessing, we only have 13,599 data. The train data amount is provided below in table 3.1 and test data amount is provided in table 3.2.

Table 3.1: Train image data amount

Fruits Name	**Amount**
Fresh Apple	1,693
Fresh Banana	1,581
Fresh Orange	1,466
Rotten Apple	2,342
Rotten Banana	2,224
Rotten Orange	1,595

Table 3.2: Test image data amount

Fruits Name	**Amount**
Fresh Apple	395
Fresh Banana	381
Fresh Orange	388
Rotten Apple	601
Rotten Banana	530
Rotten Orange	403

Accuracy and F1-Score are statistical parameters used in addition to performance parameters and correlation Precision and Recall. The mean will show the average pixel value.

$$\text{Precision}=\frac{\text{TP}}{\text{TP+FP}} \tag{1}$$

$$\text{Recall}=\frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$\text{F1score}=2\times\frac{\text{precision}\times\text{Recall}}{\text{precision}+\text{Recall}} \tag{3}$$

$$\text{Accuracy}=\frac{TP+TN}{TP+FN+TN+FP} \tag{4}$$

3.4 Proposed Methodology

Model is designed in phases as follows:

- **Input Image:**

A set of high-resolution images was used in the proposed method. 14000 images from the Kaggle dataset are compressed into six distinct classes using the suggested method.

- **Pre-processing:**

The method used to acquire the photos required a number of irregularities. The primary goal of the preprocessing stage is to reduce or eliminate undesirable elements from the image in order to improve quality, clarity, and other aspects. Picture enhancement and grayscale conversion are the most notable methods. Grayscale is used to create all of the images used in this proposed system. Augmentation: New data is generated whenever an image is rotated, flipped horizontally or vertically, shifted horizontally or vertically, or zoomed in. Numerous additional applications for this method do not necessitate additional information. We can avoid over-fitting the data by creating numerous copies of it. Using data augmentation, we can also balance the data for each class in the data set.

- **Convolutional Neural Networks**:

Convolutional neural networks, or CNNs for short, are a popular method for improving image identification precision. CNN (Convolutional Neural Network) is the most effective deep learning system for image processing. A network that employs the mathematical method of convolution is referred to as a "convolutional neural network." An artificial intelligence program known as a convolutional neural network can classify images into relevant groups, provides distinct items in the learnable weights of the images, and accepts images as input. Nearly all similarities exist between CNN and conventional neural networks. It is made up of neurons with biases and weights that can be trained. Neuronal connectivity and the human brain's architecture are comparable. Despite sacrificing essential components necessary for system construction, CNN will compress the images into an easy-to-understand version. Since the pre-processing, this approach to picture classification was chosen. The threshold is extremely low on CNN. The crucial steps that help computers recognize patterns in images are listed below.

- **Convolutional Layer:**

A convolutional neural network's foundation is built on it. A collection of kernels, also known as trainable filters, are created by these layer parameters. These kernels have a small receptive field, but they can take in any input that is available. The bandit can be used for pixel values in the output of other layers in addition to being used for input data. Pooling Max: The Max Pooling layer reduces the size of the image. The next step is taken after each Convolutional Layer has been processed. Through data preparation, this layer's primary objective is to reduce the amount of processing power required to examine the data. The maximum value from the area of an output that the filter covers is returned by residual blocks.

- **Max Pooling:**

The Max Pooling layer reduces the size of the image. The next step is taken after each Convolutional Layer has been processed. Through data preparation, this layer's primary objective is to reduce the amount of processing power required to examine the data. The maximum value from the region of an output that the filter covers is returned by residual blocks. Figure 3.3 shows the project method.

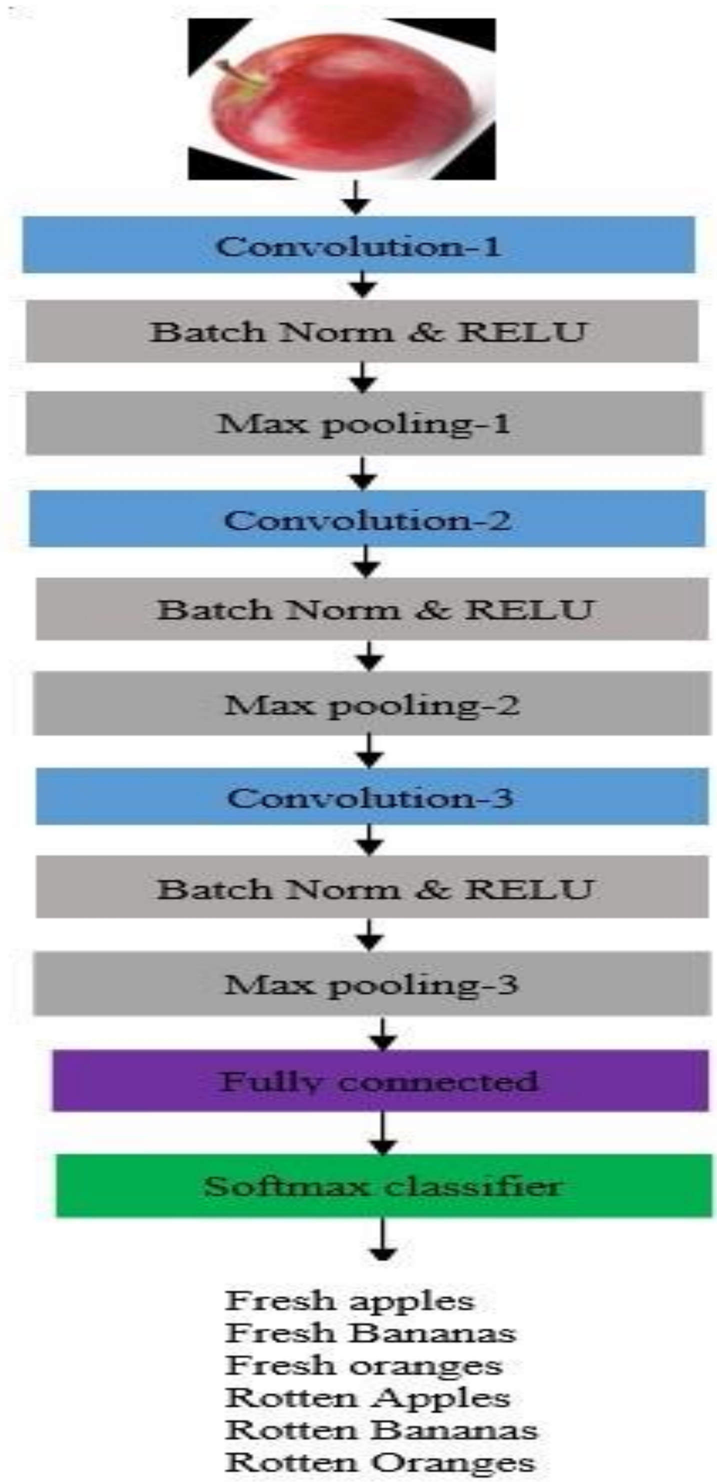

Fig 3.3: Method

• **Fully Connected Layer:**

A fully connected layer is a type of layer in a deep neural network that is used for classification tasks. In a fruit classification using image processing project, a fully connected layer could be used to make the final predictions of the class of a given fruit image. The fully connected layer takes the output from the preceding layer, which is typically a convolutional layer or a pooling layer, and uses this information to make predictions by applying weights and biases to the inputs. The resulting output from the fully connected layer is then compared to the target class labels in the training data to adjust the weights and biases in an effort to improve the accuracy of the predictions. The use of a fully connected layer can provide a more powerful and sophisticated method for fruit classification compared to simpler methods. Figure 3.4 shows CNN Classification.

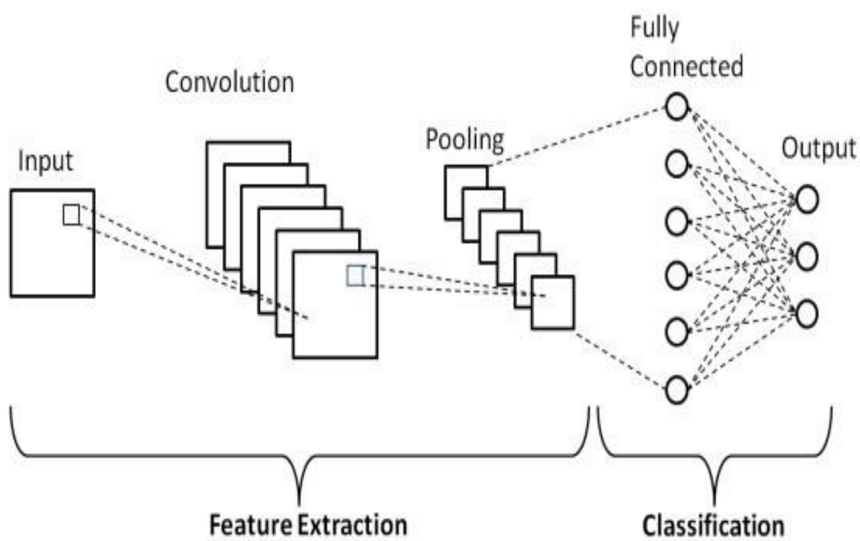

Fig 3.4: CNN Classification

TensorFlow is a useful tool that makes creating, training, and installing device mastering models simple. The images in our dataset are processed with the help of the CNN Model. The fundamentals of CNN can be seen in the image below. A subset of deep neural networks known as convolutional neural networks are frequently utilized in deep learning to investigate visible perception. Multilayer perceptions are fully linked networks in which each neuron in one layer is linked to every neuron in the next layer. The essential CNN mechanism is shown in Figure 3.5.

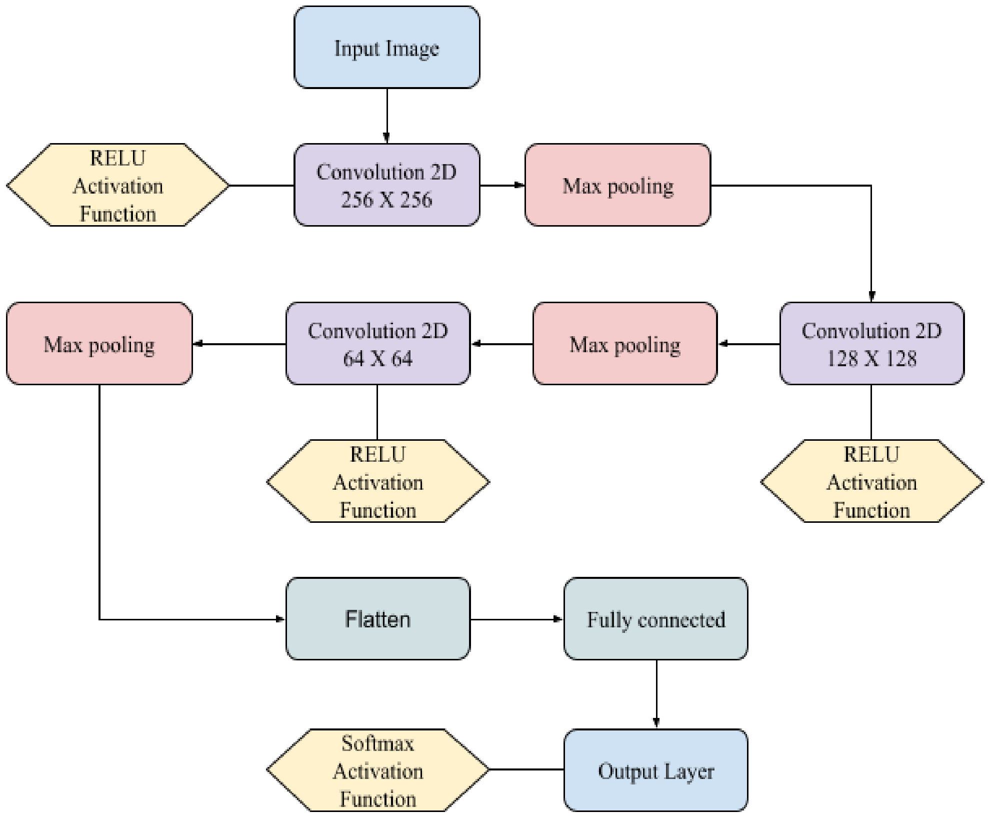

Fig 3.5: Flow chart of CNN mechanism.

• **Model Architecture:**

Conv2d, MaxPooling2, and Flatten were the layers in a sequential version that we used. CNN has three levels. In the end, we covered those layers with a denser, flatter layer. Our version becomes more accurate as a result. We found that building a CNN version requires three layers, based on previous research. By including a dense and flattened layer, we can improve the version's output and accuracy. The CNN model used in our project is shown figure 3.6.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 150, 150, 16)      448

 max_pooling2d (MaxPooling2D  (None, 75, 75, 16)       0
 )

 conv2d_1 (Conv2D)           (None, 75, 75, 32)        4640

 max_pooling2d_1 (MaxPooling  (None, 37, 37, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 37, 37, 64)        18496

 max_pooling2d_2 (MaxPooling  (None, 18, 18, 64)       0
 2D)

 flatten (Flatten)           (None, 20736)             0

 dropout (Dropout)           (None, 20736)             0

 dense (Dense)               (None, 512)               10617344

 dense_1 (Dense)             (None, 1)                 513
```

Fig 3.6: The CNN model used in our project

Our investigation made use of a fruit classification dataset. Our dataset split in half, with 80% going to the education dataset and 20% going to the check dataset. Validation and instruction are both ongoing processes. Throughout education, we examined the impact of parameters and modified them to produce an accurate version. The following are the suggested assumptions for the CNN version: After the algorithms were put to the test on a hard and fast of a few clean and a few rotten results, their dependability was evaluated on a check set. Training parameter is given table 3.3.

Table 3.3 Training Parameter

Batch-Size	10
Epoch	50
Training	80%
Testing	20%
Train Samples	10901
Test Samples	2698

3.5 Implementation Requirements

- **Data:** A large and diverse dataset of images of fruits to train and test the algorithms.
- **Algorithms:** Image processing algorithms, such as convolutional neural networks (CNNs), to classify the images of fruits.
- **Hardware:** A computer with sufficient processing power and memory to run the image processing algorithms.
- **Software:** Image processing software, such as TensorFlow develop and run the algorithms.
- **User interface:** A user-friendly interface to input images, display results, and allow users to interact with the technology.
- **Integration with other technologies**: Integration with other technologies, such as machine learning or IoT, if required.
- **Data storage:** A secure and reliable system for storing the collected image data and results.
- **Documentation:** Detailed documentation of the algorithms, processes, and methodologies used in the fruit classification project.
- **Maintenance and support:** Regular maintenance and support to ensure the technology remains up-to-date and continues to perform optimally.
- **Hardware/Software Requirements**
  1. Operating System (Windows 10 or above)
  2. Web Browser (preferably chrome)

3. Hard Disk (minimum 4 GB)
4. Ram (greater than 4 GB

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

In this volume, we examine the consequences of the process's penultimate step using actual data. We were able to achieve rather pinpoint efficiency with our calculations. Our experimental result is shown table 4.1.

Table 4.1 Experimental Result

Serial No	Model	Accuracy
1	sequential	99.36%

4.2 Experimental Results & Analysis

On a set of sparkling and rotting apples, we tested our artwork. First, we divided the dataset into testing (20%) and validation (80%). The validation is completed simultaneously. In order to obtain a more accurate version than the designs that were developed through switch learning, we tuned the parameters during validation and observed how those parameters affected the final result. On Google Colab, the "Keras" Python library is used to implement this deep CNN version.

- **Effect of Batch Size**

The number of enter samples that are sent directly to the network is known as the batch length. The classification accuracy is also influenced by the length of the batch. The accuracy of the version decreases, which also has an effect on the memory requirement [26], and the longer the batch length, the longer it takes to learn the dataset. Therefore, we must exercise extreme caution when selecting the batch length. The upcoming batch sizes complete this version: sixteen, 32, and 64 The version's accuracy increases as the batch length increases—from eight to sixteen, barely decreasing at 32, and decreasing at 64. Figure 6 depicts the findings that the version produced the most accurate results at batch length 16. Figure 4.1 is presented the batch size.

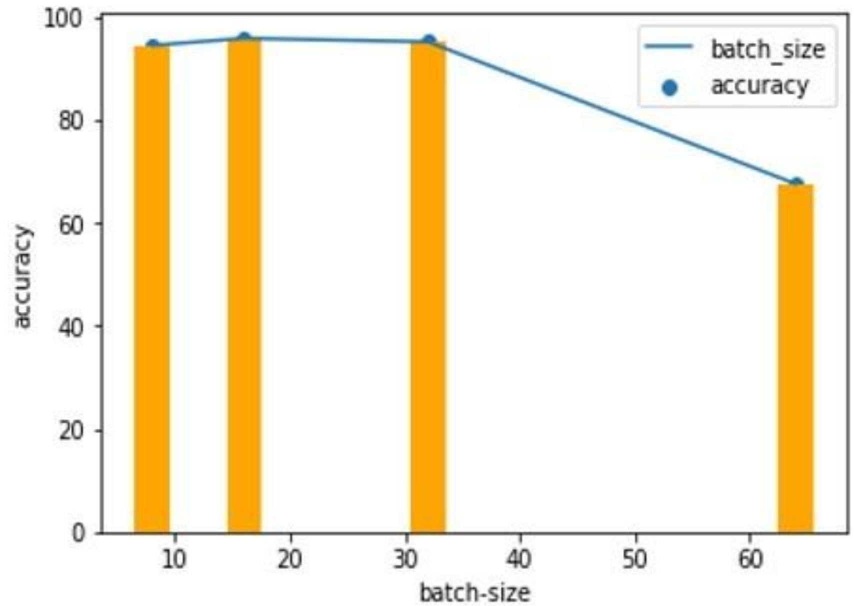

Fig 4.1: Batch Size

• **Effect of Number of epochs**

The number of iterations is all that defines an epoch [27]. The version is now proficient at the following epochs by using the Adam optimizer and maintaining the batch length standard at 16 and the studying price at 0.0001. 15, 25, 50, 75, 150, and 225. According to Figure 5, 225 epochs yielded an accuracy of 99.36 percent. Figure 4.2 is presented the number of epochs.

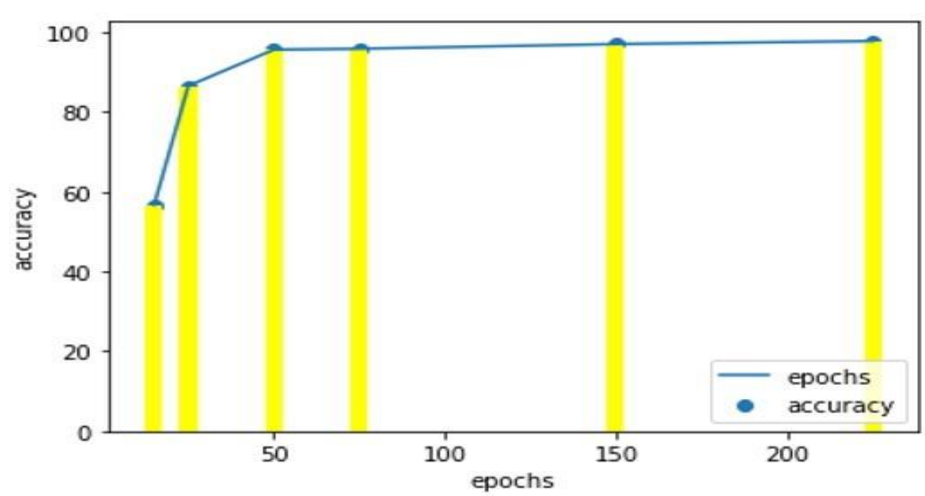

Fig 4.2: Number of epochs

- **Effect of optimizers**

By updating weight parameters, which reduce our loss characteristic, optimizers are used to optimize our version's overall performance. Through enhancing our community's parameters, our objective is to reduce the lack of our neural community [28]. A neural community matches the correct price to the expected price in order to calculate loss for the loss characteristic. In our work, we evaluated four optimizers, comparing their accuracy in Figure 6 to identify the high-quality optimizer. SGD, Adam, RMSprop, and Adagrad are the four optimizers employed [29]. Our version uses the high-quality Adam optimizer, which has an accuracy of 99.36 percent. However, the accuracy of 85.64 percent is also given to RMSprop. Adagrad's accuracy was 54.75%, while sgd's was 34.50%. Optimizer is presented figure 4.3.

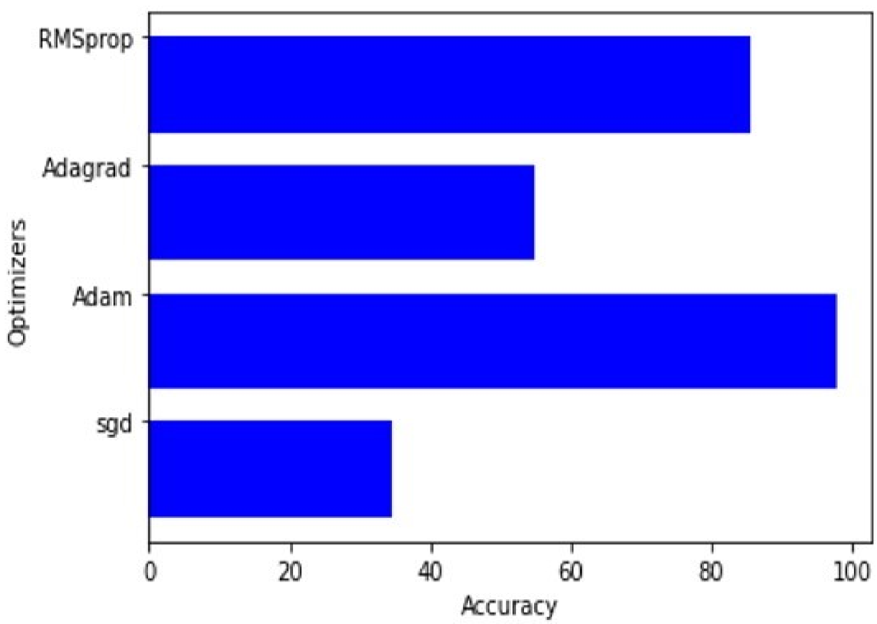

Fig 4.3: Optimizer

- **Effect of learning rates**

During the neural network's education, a few weight quantities are updated. The term "studying costs" refers to these weights. The CNN model uses this important hyper parameter, whose value is between zero and one. One and zero zero. We included four different study costs in our model and determined their effects on accuracy [30]. There are four costs associated with education: zero.1, zero.01, zero.001, and zero.0001. According to Figure 7, the accuracy rises from 17.36 percent to 99.36%when the study costs are reduced from zero.01 to zero.0001. Figure 4.4 is presented the learning rate.

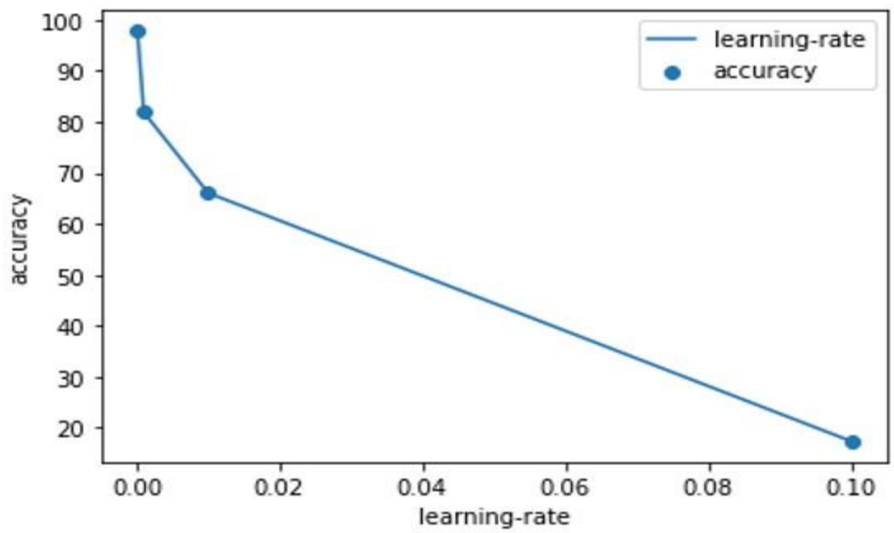

Fig 4.4: Learning Rate

• Accuracy Graph

Figure 4.1 is presented the training accuracy vs validation accuracy and training loss vs validation loss.

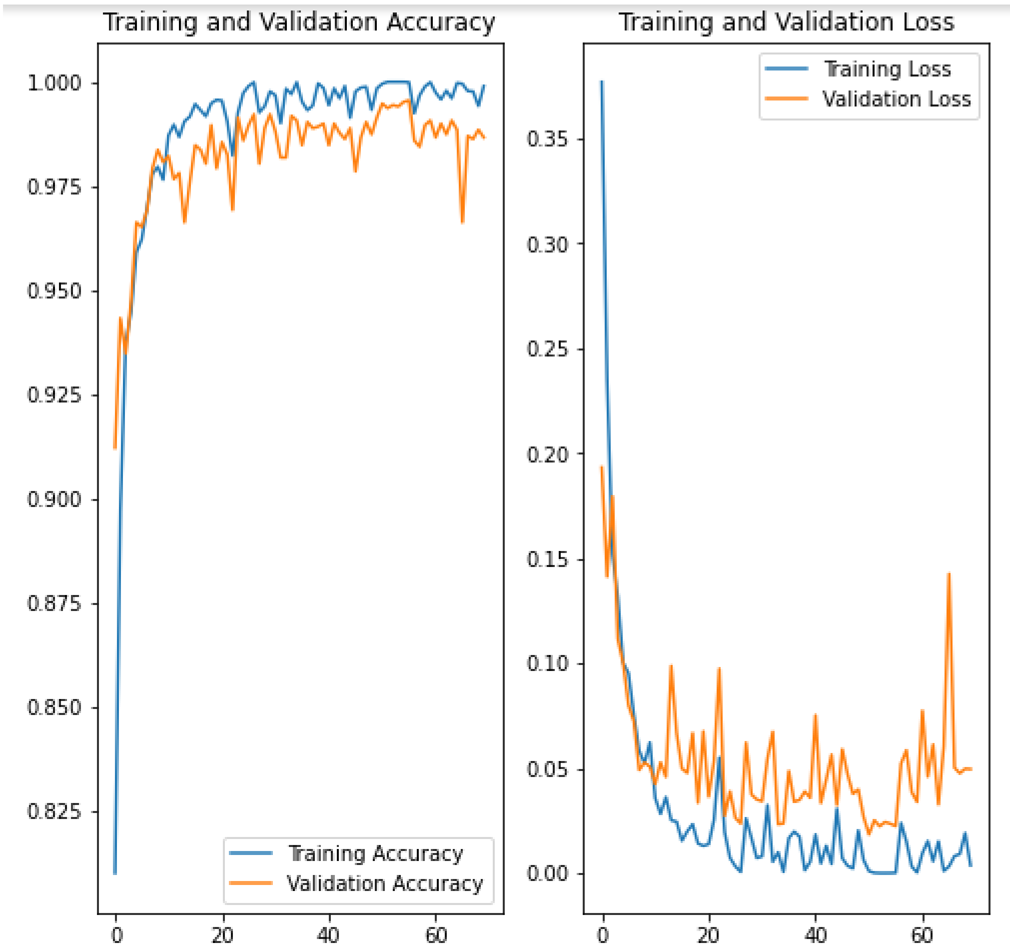

Fig 4.5: Training accuracy vs validation accuracy and training loss vs validation loss

4.3: Discussion

We could also add that the results of this study lend credence to the idea that, after editing our version and dataset, this classifier could be applied to any comparable dataset to evaluate and predict its accuracy. We were able to determine with 99.36 percent accuracy the difference between clean and rotten fruit predictions. It may also be able to tell the difference between fresh and rotting fruits in a lot of percentages. Therefore, we are able to anticipate the variety of rotten and the type of rotten, which ranges from extremely horrifying too relatively rotten.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The impact of using image processing for fruit classification on society can be significant. It can improve efficiency and accuracy in the agriculture and food industries, leading to reduced food waste and increased productivity. It can also have a positive impact on the environment by reducing the use of chemicals in fruit sorting and improving supply chain management. Additionally, it can have health benefits by ensuring that consumers have access to fresh, correctly classified fruit.

5.2 Impact on Environment

The use of image processing for fruit classification can have a positive impact on the environment. It can reduce the use of chemicals in fruit sorting and improve supply chain management, reducing food waste. It can also increase the accuracy of crop yield predictions, leading to more sustainable agriculture practices. Additionally, reducing food waste can help to conserve natural resources and decrease greenhouse gas emissions from decomposing food. The implementation of such technology can contribute to a more environmentally friendly and sustainable fruit industry.

5.3 Ethical Aspects

There are several ethical aspects to consider when using image processing for fruit classification. Privacy concerns may arise if the image data collected is used for purposes other than the classification of fruit. The accuracy of the image processing system must also be considered, as incorrect classification can result in economic losses or even harm to consumers. The use of image processing technology may also raise concerns about job loss in the agriculture and food industries. It is important to address these ethical considerations and ensure that the technology is used in a responsible and transparent manner. Additionally, ensuring fair and transparent data usage policies can help to protect the privacy of individuals and build public trust in the technology.

5.4 Sustainability Plan

- **Energy Efficiency**: Implementing energy-efficient technology and reducing energy waste through proper maintenance and usage.
- **Material Recycling:** Encouraging the recycling of materials used in the project to reduce waste and conserve natural resources.
- **Environmental Impact:** Monitoring and reducing the environmental impact of the project through the responsible disposal of waste and the reduction of greenhouse gas emissions.
- **Stakeholder Engagement:** Engaging with stakeholders, including local communities, to understand and address the potential impact of the project on their lives and environment.
- **Continuous Improvement:** Continuously improving the sustainability of the project through regular reviews and updates to ensure that it remains environmentally friendly and economically viable.
- **Ethical Practices:** Adhering to ethical practices in the use and management of data, protecting privacy and ensuring fair treatment of all stakeholders.
- **Long-term Vision:** Creating a long-term vision for the project that balances economic, social and environmental sustainability.

CHAPTER 6
SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION
FOR FUTURE RESEARCH

6.1 Summary of the study

The purpose of the exploration check is to demonstrate that CNN is the great snap classifying system via relating performances amongst glowing fruit and decaying food. Data on snaps becomes required for this disquisition. Data bias are thus gathered from internet sources (Kaggle). After that, all the statistics are stored with pre-processing regulations to steer them to be duly suitable with the structure's terrain. For statistics manage purposes, statistics bias is trained. Then, some of the manufactories have been used for training, at the same time as others have been used for testing.

6.2 Conclusions

We described a moments and complex database of snap shots with check end result. Also, we made some numerical trials thru manner of system of using Tensor Flow library for you to classify the snap shots in line with their content. From our thing of view one of the important solicitations for the future is to embellish the delicacy of the neural network. This consists of farther experimenting with the form of the network. colorful tweaks and adaptations to any layers further to the appearance of new layers can give absolutely one-of-a-type results [34]. Another possibility is to modernize all layers with convolutional layers. This has been examined to offer many developments over the networks which have actually affiliated layers of their form. A check end result of 26 changing all layers with convolutional bones is that there may be a growth with inside the huge fashion of parameters for the network. Another occasion is to modernize the remedied direct bias with exponential direct bias. According to paper this reduces computational complexity and add mainly advanced conception trendy usual overall performance than remedied direct bias on networks with redundant than five layers. We'd love to strive out the bones practices and also to strive to find out new configurations that give thrilling results. In the near future we plan to produce a molecular mileage which takes prints of check end result and labels them consequently [35]. Another end is to amplify the data set to encompass lesser check end result. This is a lesser time eating approach for the purpose that we want to encompass particulars that have been now not applied in utmost others related papers.

6.3 Implication for Further Study

- **Improved accuracy:** continuing to train and refine the algorithms to increase the accuracy and reliability of fruit classification.
- **Expansion to other crops**: exploring classification of other crops and food products beyond fruits.
- **Integration with other technologies:** integrating image processing with other technologies such as machine learning and IoT to create a more comprehensive solution.
- **Real-world application:** testing and implementing the fruit classification technology in real-world scenarios, such as in the agriculture industry, to measure its effectiveness and impact.
- **Human-centered approach:** considering the human factor, such as user experience, in the design and implementation of the fruit classification technology.

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