APPLE AND ORANGE DISEASES DETECTION USING DEEP LEARNIING TECHNIQUES

By

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Master of Science in Computer Science and Engineering.

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17th JANUARY 2023

APPROVAL

This thesis titled "**Apple and Orange diseases detection system by using deep learning technique**", submitted by **G M FARADUZZAMAN**, to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The Presentation has been held on January 2023.

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I hereby declare that; this thesis has been done by me under the supervision of **Mr. Narayan Ranjan Chakraborty, Associate Professor, Department of CSE,** and co-supervision of **Mr. Shah Md Tanvir Siddiquee, Associate Professor, Department of CSE,** Faculty of Science and Information Technology, Daffodil International University. I also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

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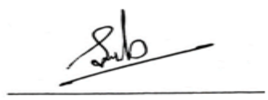

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ACKNOWLEDGEMENT

First of all, my heartiest thanks and gratefulness to Almighty Allah for His divine blessing that makes me capable to complete this project successfully.

I would like to thanks to my honorable teacher & project supervisor **Mr. Narayan Ranjan Chakraborty, Associate Professor,** Department of CSE**,** Daffodil International University, Dhaka. Deep Knowledge & keen interest of my supervisor in the field of “Deep Learning” to carry out this thesis. For his endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stage have made it possible to complete this project.

I would like to express my heartiest gratitude to **Dr. Touhid Bhuiyan, Professor and Head,** Department of CSE**,** for his kind help to finish my project and I am also thankful to all the other faculty and staff members of my department for their co-operation and help. I would like to thank my entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

We know that Bangladesh is an agricultural country where almost all people are dependent on agriculture. In today's world where everyone is health conscious, the ability to identify fruits by quality is very important in the food industry. But farmers produced these fruits without the help of practical rational inventions. This can lead to financial mishaps and reduce profits for drivers. Fruit diseases currently pose many economic and environmental problems. But early detection of fruits diseases can prevent these accidents and keep farmers happy. The market sells different kinds of fruits. However, identifying the best quality fruit is a daunting task. Therefore, we developed an automated system to Detect fruits under natural light conditions that can provide a guideline to detect fruit. Based on Convolutional Neural Networks (CNN), I created an "Apple and Orange detection system" online application that can detect fruits and also determine if they have diseases. Not only images of unhealthy fruits were collected, but also images of infected fruits such as apples and oranges. In this study, we used a fully convolutional neural network (FCNN) for infection order and a convolutional neural network for birth-related neural functions. In this paper I applied different algorithm but I didn’t get my expectation result then I applied CNN which provide 82% accuracy. I think this result is helpful for our research.

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CHAPTER 1

INTRODUCTION

1.1. Introduction

The agriculture sector needs a significant upgrading to be able to endure the shifting economic conditions in Bangladesh. In the huge populated nation of Bangladesh, 63 percent of the population works in agriculture. And root the agricultural production system is the consequence of a complex interplay between soil and seed. In this paper I can developed a web-based application named “Apple and Orange Detection System”. Here I can work with Apple and Orange Diseases detection. The diseases of Apple are Apple-scab, black-rot, cedar-apple-rust and some diseases of Orange are Orange-black-spot, Orange-scab, Orange-canker, Orange Greening. Humans are directly dependent on agriculture for the production of food, making agriculture very important and necessary for them. Fruits, in particular, are widely purchased in every household and are highly nutritious [1]. As a result, constant supply and production will be required to meet the demands of the growing world population. Image recognition and computer vision remain difficult to classify because fruits can have similar colors, shapes, and textures. Automation of the process has had little success in manufacturing and marketing because it takes too long to label and count the amount of different fruits [6]. Moreover, as individuals strive for a higher standard of living, a number of highly automatic and effective methods for well-being have been developed. We are building a classification system for fruits with high. Research on fruit identification and classification has received a great deal of attention recently, and significant progress has been made in this area [3]. We developed an improved method based on a number of attributes to determine the orientation of fruit items in the input image. In this work, we investigate a convolutional neural network (CNN)-based method for developing control systems for object recognition. Through parameter tuning, we use the CNN to perform fruit identification and recognition tasks. Classification and recognition of fruits still challenging in daily production and life. In this paper proposing an efficient classification system for Fruits draw and collapse object regions using image Convolutional Neural network (CNN) models for extracting image features and

Implement classification. Select main using image highlight Expression region by expression map [5]. The Fruit detection model is Selected for fruit detection and classification training. other the contribution of this paper is that we have come to fruition and image bank fruits. The field of artificial neural networks has developed and developed rapidly in recent years. When it comes to image processing problems, its outstanding manipulation and classification accuracy offer alternative options. Many properties of neural networks, such as unsupervised learning and rich feature extraction, contribute to overall network performance. Convolutional Neural Networks (CNNs) have achieved great success in large-scale image processing.

1.2. Motivation

The use of image technology with deep learning solves the problem of agricultural production while ensuring food security. CNN is a highly efficient pattern recognition and image processing method. CNNs are used for image classification and recognition due to their high accuracy. It offers farmers a cost-effective and efficient approach to fruit detection. We describe the steps of Fruits detection system and a comparison of deep learning classification approaches. Developing systems that can detect and detect Fruit could be the answer to this enormous challenge. A variety of apple, orange images are used in research on this topic to be faster and more accurate.

1.3. Necessity of this Research

Our country loses a significant amount of crops every time root bacteria and infectious diseases attack. Fix this problem and help our agribusiness and help growers solve the real problem of fruits. We all understand that our country is based on agriculture and that many ethnic groups attach great importance to this particular sector. But we have not been able to improve our animal husbandry systems in the way that other countries have been able to. The goal of fruit detection using image processing is to design an incremental model that detect fruits based on their size, shape, and color, ignoring external features such as environment, noise, and background. This will focus only on the image of a particular fruit and identify the fruit. We will create a web-based fruit detection system that will tell you which fruit it is by uploading a picture. We will build this detection system using Convolutional Neural Networks (CNN) and here we will use images of apple, banana and orange.

1.4. Research Aims and Objectives

Agriculture has become an important industry in Bangladesh due to rapid population growth and rising food demand. We provide an overview of a disease detection method that combines deep learning and image analysis. Use a CNN algorithm that negatively ranks fruit and vegetable stores. It is possible to achieve lucrative agricultural growth. This composition includes a system for identifying fruit diseases, and also explores deep literacy approaches for identifying and classifying fruit diseases. Identifying the condition can reduce the risk of infection. Examine Possible Qualities. In today's world where everyone is health conscious, the ability to identify fruit by quality is very important in the food industry. The market sells different kinds of fruits. However, identifying the best quality fruit is a daunting task. Therefore, we developed a system to recognize fruits under natural light conditions. The methods used are texture recognition methods, color recognition methods and shape recognition. This methodology uses image segmentation to identify specific fruits. Agriculture has become very important in Bangladesh due to rapid population growth and rising food demand. We describe a fruit recognition system that combines image processing and deep literacy. Uses a CNN algorithm that can detect fruits.

1.5. Research Questions

We are under great pressure to complete this task. To provide you with appropriate, useful and accurate responses to your problems. In order to communicate our thoughts and findings on this topic, our analysts would like to suggest appropriate questions.

- Can we collect raw dataset for a deep learning research?
- Is it possible to use deep learning to preprocess raw image data?
- Is it possible to extend this methodology to detect more diseases in fruits?
- Is it possible to configure the system to get the desired results from this study?
- Is it possible to build a proper web application?

1.6. Expected Outcome

- Reduce time spent on sloppy manufacturing.
- This technique can be used to find defective fruits.
- Farmers can benefit greatly from this system.

- Peoples can also benefit from this technology, as plant diseases can be quickly identified.
- By sing this system we can easily detect Fruits diseases.

1.7. Report Layout

In the chapters of our project report, we created the following contents:

Chapter 1 mentioned the introduction, the motivation, the rationale for the research, and the research question. Chapter 2 present background, task-related similar work, and limitations. Chapter 3 discusses about Research methodology This section of the discussion covered the following topics: business measurement of tasks, data collection and analysis requirements, use cases, presentation and representation. Chapter 4 Provides Includes experimental results, performance evaluation, and discussion of results. Chapter 5 Provide the social, environmental and sustainability impact of your project. Chapter 6 In this chapter, we talked about the overview of the project, future work, and completion.

1.8. Summary

In this chapter, the facts, including thesis, are presented. You can also see the introduction of the proposed system. The next chapter provides an overview of the work already done proposed system.

CHAPTER 2

BACKGROUND STUDIES

2.1. Introduction

It contains references to other projects similar to our own. We have tried to identify and analyze their limitations. We now understand what separates them from us. We also outlined the advantages of our technology. Finally, you should describe the challenges your project faces.

2.2. Existing Works

To determine potential arguments for our system, we focused on the design of several Turn of Events and also discussed the types of contracts they involve. And what basic elements should I add?

Shiv Ram Dubey and Anand Singh Jalal [1] provides a brief summary that this area reviews research on image classification, fruit recognition, fruit classification, and fruit disease detection using images. In most fruit identification or fruit disease detection studies, color and texture features have been considered for classification. Most of the work on fruit disease detection in the literature is limited to the detection of specific types of diseases. They achieved 94.3% accuracy in their work [1]. This section summarizes available research on image processing for disease detection and classification on fruits. In the past, multiple researchers have attempted multiple times using various methodologies to detect fruit [1]. Paper [2] demonstrates apple fruit cultivars against specific apple cultivars using deep literacy on brackets and modes of apple discovery. And the writer received 100 delicacies. The agri-food industry's usage of computer vision and image processing techniques is examined in the review by osé Naranjo-Torres, M. M.-G. (2020) [2]. They state that color, size, texture, shape, and flaws are the agricultural products' most important quality characteristics. As a result, the authors provide a summary of several preprocessing, segmentation, feature extraction, and classification techniques. In Article [3], Loofah credits using image processing and convolutional neural network techniques to address the flower-splint situation. This system takes as input some photos and found conditions. For so many years, people have used their experience to identify harmful fruit based on the shape, color, odor, and skin excretion. However, the annual poisoning occurrences have demonstrated how inappropriate this intuitive approach is. Therefore, it is not a reliable method for determining whether fruit is poisonous. Additionally, this method is dependent on people's background knowledge [4]. In the paper [5], the author presents a data set of example images containing fruits and the results of a specific numerical experiment to teach a neural network to recognize fruits. The test result was 98.66 bids. They found the state of tomato leaves in paper [6]. To relate his five states of tomato leaves, they trained a deep convolutional neural network and the resulting model had a finesse of 99.84. In the paper [7], the authors provided an overview of the different factory conditions and the color-coded bracketing method used in the machine competency to associate the different manufacturing conditions with a test delicacy score of 99.87. In the paper [8], the authors used convolutional neural network techniques and deep literacy strategies to address two types of mango brackets. And the trained model achieved a subtlety score of 100. In the paper [9], configurations examining different types of fruit were decomposed and predicted using a deep neural network. Additionally, he used three different approaches to predict the data. In the paper [10], the author described a system that uses Deep His Learning and convolutional neural networks VGG16 and VGG19 to classify a rail-anchored potato into four different situations in her shop. This model has a deliciousness score of 91. Three authors trained a deep convolutional neural network to recognize his four different potato varieties on paper [11] and achieved a deliciousness of 99.5. On paper, they classified potato chip and soil conditions into four categories [12]. What indicates that deep neural network technology is feasible? Article [13] introduces a neural network algorithm used for image identification and deep literacy design tomato bracket strategy. In article [14], based on Deep Literacy and Colab Editor, this method was used as a model to celebrate his two varieties of grapefruit, pink and white. The author of the article [15] gave a reaction to rotting fruits. Additionally, these conditions can be described using image processing techniques and methods such as: B. K-means clustering and classification using vector machine classifiers. All of these documents are a great help in creating your design in the first place. A research study on orange fruit complaints has been published by the authors. They used the convolutional neural network (CNN) deep learning technique. The formula used to determine each of her three requirements for Orange. Their algorithm was able to identify 8 of his 68 features in the dataset. The accuracy of the approach is 93.21%. R. Saha et al. According to Zaw Min Khaing et al. [16] the authors have developed a system of eviction control. The idea is to use CNN-based detection. By tuning the parameters, the system is used for fruit detection and identification. 94% of him in the system agreed with the findings. The publisher, S. M. Farhan Al Haque et al. [16], has developed a CNN-based system that can diagnose and treat guava sickness. Their dataset was gathered from several Bangladeshi districts. Three CNN models are being tested. Following that trial, the experimental findings revealed that their third model, which was 95.61% correct, outperformed the other two models. Confirmation of loofah complaints by TT Mim et al. [6] For solving the sprint and bloom problem using image processing and convolutional neural network techniques. Alexnet is the name of a pretrained disease detection model. The system inputs some images and determines the conditions. 81.52% of delicacy was achieved. According to them, DL-based approaches such as convolutional neural networks are highly efficient for fruit classification and recognition, with significantly reduced classification errors. Although CNN has received more attention than any other ML algorithm in recent times, it has not been widely adopted in fruit studies, and one article of his using CNN reports that it is relevant to that date Increase [15].

As a result of comparative analysis of past works, Different researchers applied different methods It classifies images of apple and orange as well as other fruits. Our goal is to predict and distinguish diseases in apple and orange Between Fresh apple, orange image and affected apple and orange images. We Can help farmers to increase apple and orange production.

2.3. Comparative Analysis

We have focused on learning more about them through the work of countless initiatives. Since we have focused on and learned about so many different things, including accuracy, limitations, graphs, algorithms, and various features, we have currently separated our project from another project. So, the proposed system is convenient for it's

- ❖ Accuracy
- ❖ Cost saving
- ❖ Time saving
- ❖ Labor saving

Our Apple and Orange recognition system can predict that it will recognize correctly.

2.4. Challenges

The main problem with this system is data collection. There is no important information on the Internet. Therefore, collecting data was not easy. Also, the outbreak prevented us from collecting raw data in the field. Another issue was that Deep Literacy needed a strong GPU backup to work.

2.5. Summary

The drawbacks of the current system are addressed by the proposed system. This chapter analyzes all current systems and shows how the proposed system is more practical than the current system. The fruit recognition mechanism will be discussed in detail in the next chapter.

CHAPTER 3

RESEARCH METHODOLOGY

3.1. Introduction

Since the main goal of our research is fruit disease detection, basically here I work with Apple and Orange diseases. We applied deep convolutional neural networks and transfer learning to use the TensorFlow framework. I used some raw data and publicly datasets to train my own datasets. Gathering information on a topic can be described as a discussion space with an elevated surface that is slanted to clarify research. For tracking, configuration modeling, information gathering, data execution, or measurement and planning. Other areas are invented mediums or employed tactics. All medical procedures use the Windows platform, Python programming language and Google Colab. Additionally, Google Colab is a free and open-source Python distribution for data intelligence and AI operations.

3.2. Data Collection Procedure

This study used the dataset for image processing. I collected images from various websites. Also, I collected Some Raw data of Apple and Oranges.

This study used two freely available datasets of fruit disease images from Kaggle and Mendeley Data. By integrating data from numerous sources, we were able to create a dataset containing 9 classes including Apple Black Rot, Apple Blotch, Apple Normal, Apple scab, Orange Healthy, Orange Canker, Orange Greening, Orange Black Spot and Orange Scab. Photographs of each complaint were collected and the images were rotated, sheared, stretched, mirrored and added to the dataset. Here are some examples of images for these classes-

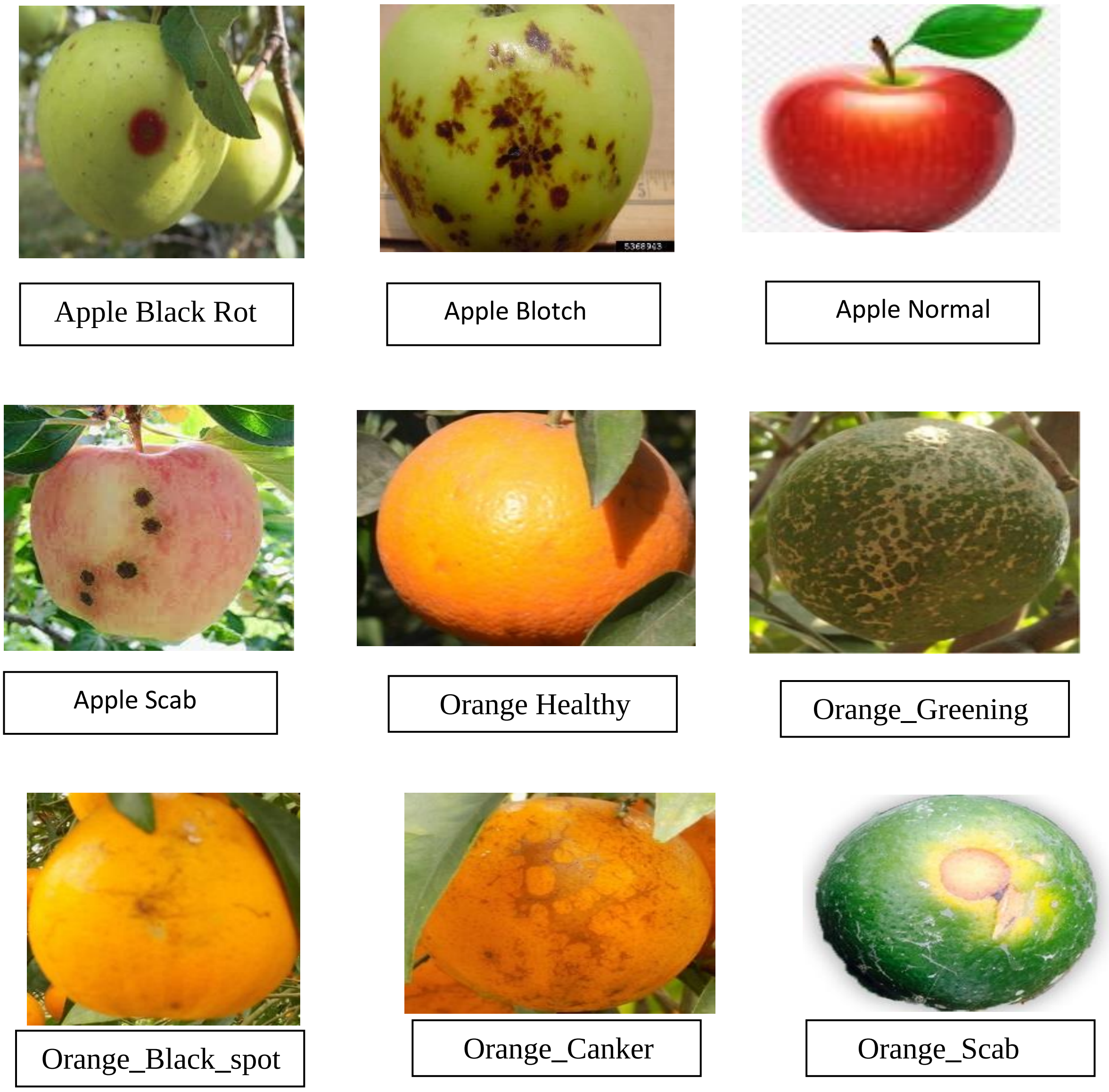

Figure 3.1: Images of Fruits diseases

3.2.1 Data Preparation

I collected some raw data of Apple and Oranges and I also collected photos from several websites, changed the background of the images, and created synthetic data. We created additional datasets during this process. Additionally, I extended the dataset using data mounts. We also divided the data set into nine categories: Apple Black Rot, Apple Blotch, Apple Normal, Apple scab, Orange Healthy, Orange Canker, Orange Greening, Orange Black Spot and Orange Scab. Furthermore, these records are split into two parts:

regular data and training data. We further divided the nine classes of the dataset into train data and confirmation data. Here I used total 4000 data for train and validation. For train I used 1317 data of apple diseases and 1407 data for orange data. I used total 2721 data for train and 1280 data for validation. For validation I used 704 Orange data and 573 apple data.

TABLE 3.1: DATASET TABLE

No	Class Name	Train Data	Validation
1	Apple Black Rot	521	235
2	Apple Blotch	158	67
3	Apple Normal	516	209
4	Apple Scarab	122	65
5	Orange Healthy	384	145
6	Orange_Black_spot	271	245
7	Orange_Canker	424	209
8	Orange_Greening	154	53
9	Orange_Scab	171	52
Total class: 9		2721	1280

3.3. Proposed Methodology

A Deep CNN model starts with data collection, proceeds with image enhancement and preprocessing, splits the dataset into training and testing parts, extracts features, and finally develops the model itself. It's a working technique.

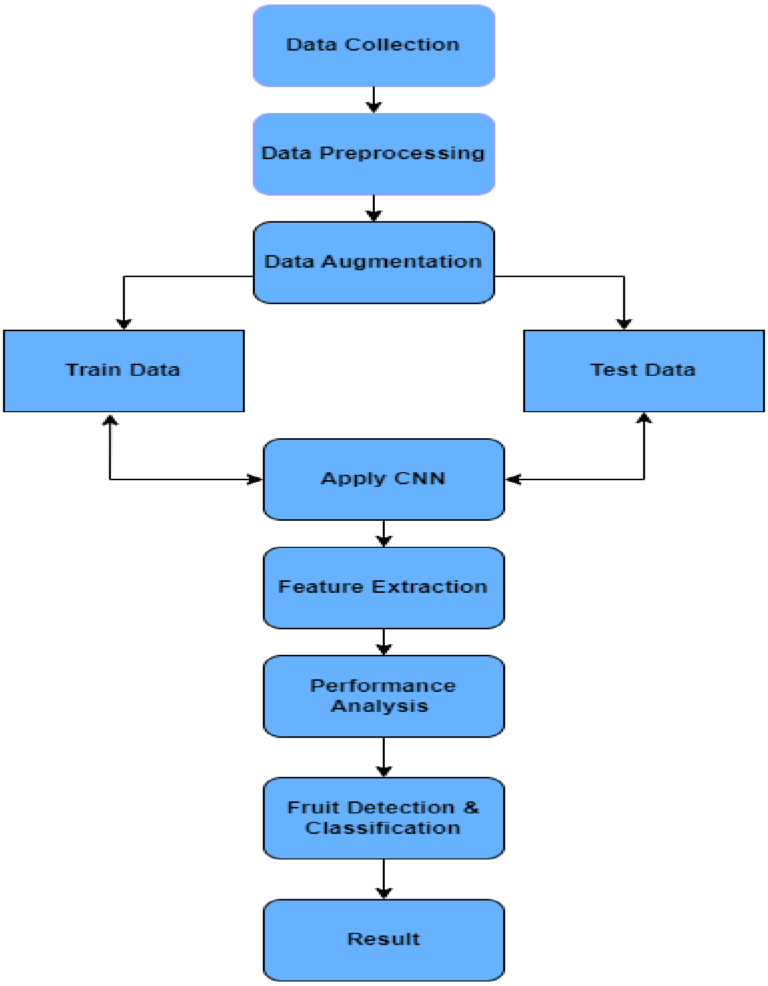

Figure3.2: Working procedure of our system.

3.4. Data Preprocessing

A Deep CNN model starts with data collection, proceeds with image enhancement and preprocessing, splits the dataset into training and testing parts, extracts features, and finally develops the model itself. It's a working technique. However, the low intensity and contrast of the images make it difficult to distinguish between boundaries and edges, which can lead to inaccurate diagnosis of disease. Preprocessing of clinical data is necessary to recover relevant information and remove irrelevant data to improve model accuracy [11]. When diagnosing disease using image modes, common preprocessing techniques include image scaling, segmentation, and enhancement.

Image transformations such as rotation, translation and scaling are used in preprocessing techniques. Training is difficult because the images in the data collection are of different sizes. As a result, I changed the image ratio to (320,320). All images are converted to RGB and inspected together for different models. None of the photos in the dataset are scaled, so we resized them and changed the class mode to categorical.

3.5. Data Augmentation

Data augmentation is the technique of artificially increasing the amount of data by creating additional data points from the current data. Extending a dataset requires fine-tuning the data or using a machine learning model to create new data points in the latent space of the original data. By notably changing the present samples, it will increase the variety of samples in the dataset [12]. Using this technique, overfitting may be averted throughout the instruction process. When a community overgeneralizes the schooling information, it's far stated to have overfitted. Deep networks require full-size quantities of information for schooling so as to carry out at their best. Deep networks regularly require photograph augmentation to carry out higher whilst constructing a green photograph classifier with scant schooling information. Through photograph augmentation, synthetic schooling pics are created the usage of a number of methods, such as rotating, shifting, shearing, flipping, and more.

In this section of data processing, we expanded the data set. The following list of five image processing tasks expands on the most important ones:

1. Rotate
2. Shear
3. Width-shift
4. Height-shift
5. Horizontal-flip

3.6. Data Split

Dividing data into multiple categories is called data splitting. Dividing the material into her two parts usually means assessing one and teaching the other. The training dataset is what is used to create and train the classifier on a simple binarization dataset. Test sets are routinely used to check different parameters and evaluate the effectiveness of different models. The training and test datasets are compared to ensure that the final model works as intended. Data is often split into three or more sets for machine learning. Modification of the parameters of the learning process is done using his third set, the dev set, which contains three sets. A total of 4000 image were used for the experiment, and the data were divided into two groups. 2721 images were used for model training and 1280 images were used for validation.

3.7. Feature Extraction

As part of a dimensionality reduction technique known as feature extraction, the preliminary collection of raw data falls into several easy-to-understand categories. This simplifies the process. This massive dataset contains many important variables. Processing these variables requires a lot of CPU time. By selecting and combining variables to create features, feature extraction greatly reduces the amount of data to store. These functions are easy to use and provide an accurate and creative representation of real datasets [9]. Image features are compressed into feature vectors during feature extraction. Image registration, object detection and classification, and content-based image retrieval require accurate representations of image features. The first layer of a deep neural network can represent this implicitly or explicitly [5].

3.8. Fine-Tuning

A process called "fine-tuning" can be used to improve the functionality of features. The end result is improved by making some very small tweaks at various stages of the process. The adaptation process is important, so even small changes can have a large impact on training in terms of computation time required, convergence rate, and number of processing units required. This is due to how important the adjustment process is. Yes, because the adjustment process has a huge impact on how things unfold. We wanted the model to be as accurate as possible, so we ran the fine-tuning process multiple times, looking at different parameter values. Table:2 summarizes the variables that can be changed in these steps and shows the training and fitting methods that produce the best results.

Table 3.2: Fine Tuning Table

Parameter	Value
Batch Size	32
Steps Per Epoch	43
Epoch	50
Optimizer	Adam, Rmsprop
Activation Function	Softmax, Relu

3.9 CNN Architecture

A convolutional neural network with four convolutional layers, a 2*2 max pooling layer and a 2*2 dense layer was presented. The activation function of the first convolutional layer, which has 64-3 x 3-filters, is "Relu." a max pooling (2x2). The fourth layer has a 64-3 x 3 filter and uses "Relu" as the activation function. The fifth layer has a 64-3 x 3 filter and uses "Relu" as its activation mechanism. Max pooling (2x2). The sixth layer has activation function "Relu" and 128-3 x 3 filters. The activation function for the seventh layer, which contains 128-3 x 3 filters, is "Relu." a maximum pooling (2x2). The eighth layer has 256-3 x 3 filters and uses "Relu" as its activation function. The ninth layer has 256-3 x 3 filters and uses "Relu" as its activation function. a maximum pool (2x2). First Dense Units: 128 with "Relu" as the activation function Second Dense Units: 256, with "softmax" as the activation function.

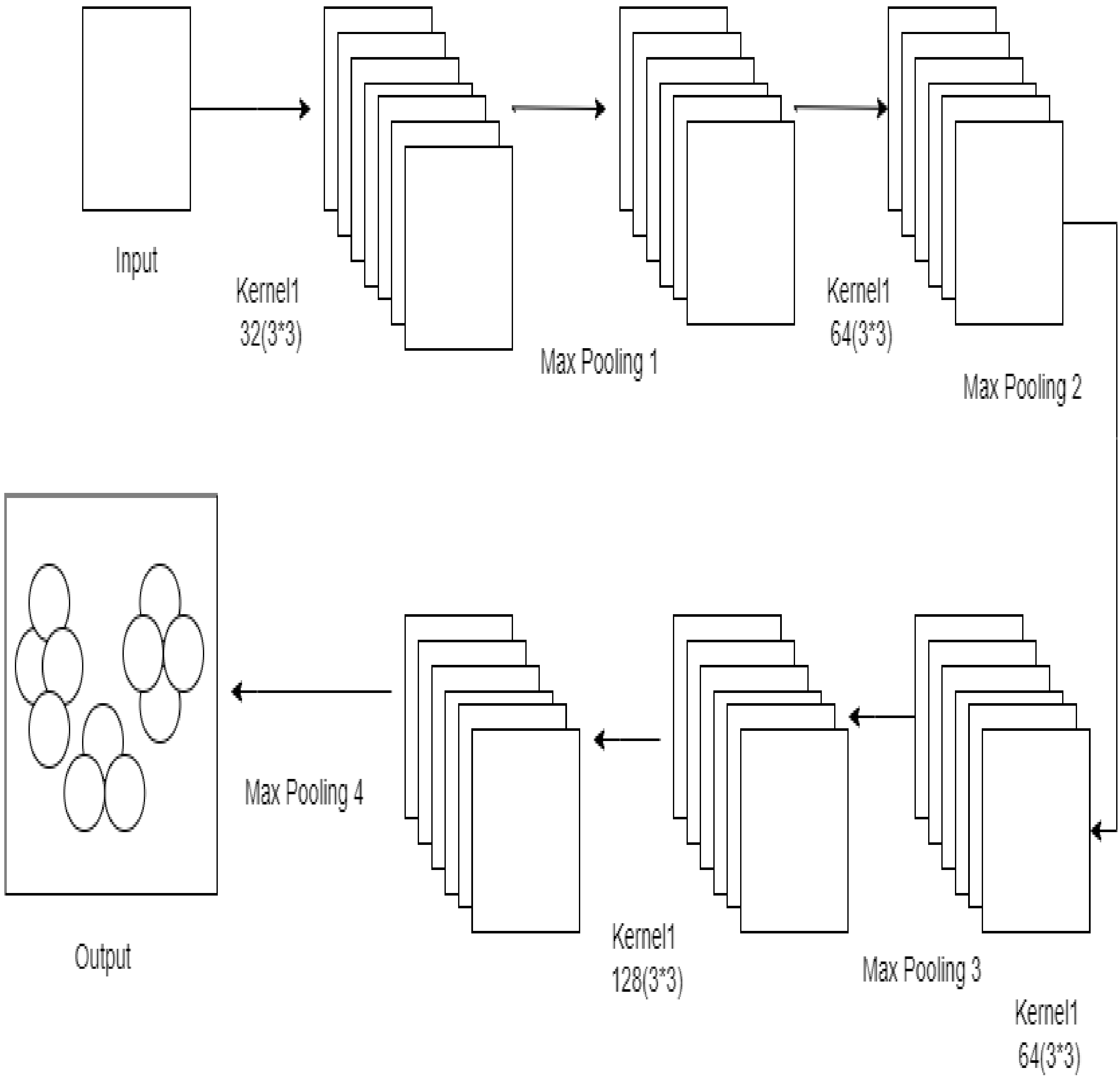

Figure3.3: Working procedure of CNN layer

3.9.1. Convolutional Layer

A deep learning algorithm called a convolutional neural network can assign meanings to colored objects in the image after receiving an input image. Segregation is possible in monasteries, as processing requirements are much lower than in other groups. CNN is fast compared to other machine learning algorithms. A feature of the proposed method is to use a low-cost and highly sensitive system to build a deep literacy system. This layer will act as a base to remove various components from the provided image template. Some kernels in convolutional layers are just filters. Layers are covered with these cores. A matrix smaller than the input data, the kernel performs a point function on the data while shifting it from left to right and top to bottom. Once everything is done, a functional map will be created. Inserting the previous layer's feature map into the current layer creates the next layer's feature map. CNN has a wide range of activities in the film industry, videotape protests, referral systems, regular interviews, and more. Neural network using convolution. While it may sound like an amazing blend of knowledge, mathematics and computer science, these systems represent one of the most important advances in computer vision. Alex Krizhevsky used them to win his ImageNet contest this year (i.e. PC Vision's monthly Olympics) and order his bot's record down from 26 to 15. This was an amazing advance for its time. A computer sees many pixels when displaying footage (capturing print as data). Let's see the accuracy of the picture and the hand. A set of 32 x 32 x 3 numbers (3 means RGB values). The remaining layers of a typical convolutional neural network are interspersed between these convolutional layers. I would appreciate it if you could refer to those who are interested.

3.9.2. Max-Pooling

A down-testing approach for Convolutional Neural Systems could be Max Pooling. The goal is to reduce the data representation conditions so that features that lie within the binned subregions can be reserved. Fewer pixels added to the outer border can contain a huge amount of data, so it is mainly used to reduce the proportions of the image. This puts less restrictions on the final product CNN can celebrate. A maximum pooling was set for 75 inpatients to prevent overfitting.

3.9.3. Padding

Convolutional neural networks use the term padding to describe the number of pixels added to an image as part of the CNN processes the image. For example, if the CNN has padding set to 0, the extra pixels have no value. Assuming zero padding is set to 1, an empty 1-pixel row is added to the image.

3.9.4. Flatten Layer

The purpose of this is to be able to later integrate this data into a neural network. Unlike convolutional layers, fully-connected layers have no proximity constraint (meaning that several close corridors of the image were observed using convolutional channels). That is, we can connect the recognized regions that are features of previous convolutional layers. The output of each dot-illustrated channel of a CNN subcaste may be a 'fixed' 2D group created by including colored his 2D corridor (one for each channel within the information subcaste) problems there is.

3.9.5. Dropout layer

Overfitting is possible when each feature is associated with a fully connected plane. A dropout layer exists between the input and output layers of a neural network. Randomly removing some neurons from the network aims to reduce the overall model size.

3.9.6. Dense Layer

Another name for the entire connected subcaste is the fat subcaste. Similar conditioning also exists in dense subcastes where each neuron is connected to another neuron. It is also called thick because it is a thick interaction of thick neurons. A large subcaste has a load associated with each integrated neuron at an aberrant rate. Undisputed Position Within Neural Orchestration Systems Use of miscellaneous types of work for companies includes soft-maximum approval work, SVMs, and miscellaneous others. However, for this example, we will stick to the usual soft maximum for placement. After some challenges and pooling layers, we get some important location attributes as information. These informational image features are grouped to explore colorful taxonomies. However, combining complex subcaste traits to examine subcaste traits leads to additional consequences of placement. A convolutional sublayer can share the load with other convolutional layers with the total yield of the fully allocated layer. It is very difficult to bring all the centers together in the soft maximum subcaste.

3.10. Activation Function

A neuron activation function is used to decide whether to activate a neuron. As a result, simpler statistical techniques are used to make predictions to assess the importance of the information that neurons transmit to the network. Rectified Linear Units, better known as ReLu, Softmax, Sigmoid, and Tanh are examples of common activation units. Among these, ReLu is the most commonly used activation function for use in deep learning models.

3.10.1 Relu

A ReLu is a nonlinear or piecewise linear function that returns zero if the input is negative and directly outputs the input if positive. Compared to its predecessors Sigmoid and Tanh, it is less complex and more effective.

3.10.2 Softmax

Consider a group of n classes and their trait model. This model uses an input data set and calculations to generate scores for each class. A probability between 0 and 1 replaces the score of the SoftMax activation process. The sum of all possible outcomes is 1. This investigation allowed us to characterize classes based on specific subcastes of convolutional neural networks. The exercises in this book are examples from the display of words.

3.11. CONVOLUTIONAL NEURAL NETWORK

This convolutional neural network is built to automatically extract image features and recognize which features are important and which are not. For the task of classifying plant diseases, the author often divides this method into two categories: transfer learning and training from scratch. Input images for training from scratch are sent through a series of convolutional layers, pooling layers and finally a fully connected layer displaying the classification results. Large images require large input sizes for neural networks, a large number of neurons in hidden layers, and costly computational resources for training and computation of the networks, thus making image identification difficult. Using traditional neural networks is difficult. Computer scientist Yann LeCun proposes solving these problems with artificial convolutional neural networks [5]. The most effective type of neural network for intelligently processing visual data is the convolutional neural network. Convolutional layers, subsampling layers, and fully connected layers are all included in this variant of multilayer neural network architecture. Figure [3] shows the usual structure of a CNN for image recognition. Convolutional layers, subsampling layers, and output layers (usually fully connected neural networks) are the three basic types of layers that make up this structure. The CNN layers are laid out sequentially. Convolutional layers come first, followed by subsampling layers, and the output convolutional layer comes after the last convolutional layer. A matrix filter applied to the image using a convolutional layer isolates the features. By combining any number of these layers, you can create new characters from previous lower-ranked characters. A subsample layer is an untrained layer that filters an image based on the pixel with the highest value in a window, ignoring all other pixels. This makes the image smaller, leaving only the most important elements regardless of their location. Each neuron in the last layer of a fully connected network receives all the outputs from the neurons in the previous layer. Training is performed using backpropagation. After each successful layer, the obtained values are compared with the values provided during training, and the difference is used to reverse the order of the network's weights. The task at hand is to modify the fully connected layers of these designs to meet the requirements of the classification task at hand. These architectures consist of a number of convolutional layers acting as feature extractors and a fully connected layer for classification. The size of your dataset is a big factor in whether you use training from scratch or transfer learning for your deep learning task. Those with short datasets use transfer learning, while those with sufficiently large datasets use training from scratch [15]. Again, the best performance in identifying and classifying leaf plant diseases was achieved by transfer learning, and this method can be applied to identify leaf diseases in many plants [7], [15]. Many researchers on this subject now use this as prior art. Comparing this method with traditional methods, it has the following advantages:

- ❖ Unlike traditional methods, this methodology learns fruits features directly from input images, eliminating the need for manual feature extraction.
- ❖ The method can be used unlike most commonly used conventional methods for detecting diseases that affect a single plant species.

3.12. Utilization Requirements

The list of requirements is compiled after a thorough evaluation of all important quantifiable or theoretical concepts and methods. These requirements should be necessary for such classification work. Below is the fair base.

Hardware and Software, we needed:

1. Operating system (Windows 7 or above)
2. 4GB RAM
3. Minimum 100 GB Hard-disk

Developing tool:

1. Python Environment
2. Google Colab
3. Jupyter Notebook

CHAPTER 4

RESULTS AND DISCUSSION

4.1. Introduction

We use different evaluation criteria to determine which of the various models currently on the market best solves the problem. Some metrics are more effective than others at evaluating the performance of regression models, while others are better suited for use with classification models.

4.1.1 Accuracy

This is the most important factor to consider when comparing proposed CNN categories with current ones. The most accurate model is the model with the highest accuracy value. In this section, we describe and evaluate the parameters of the confusion matrix to measure the effectiveness of the proposed strategy. Calculated using the following formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \times 100\%$$

4.1.2 Sensitivity

When judging the validity (also called predictive power or predictive validity) of a screening test, we first check its results to putatively meaningful measures of the same target condition, often referred to as the gold standard. to see if it matches These criteria were used to assess the accuracy of positive predictions and the results are presented as a percentage of the total frequency of positive results. Also, the most sensitive model is the model with the highest sensitivity number.

$$\text{Sensitivity} = \frac{TN}{TN + FP +} \times 100\%$$

4.1.3 Specificity

A sensitivity test performed by dividing the total number of negative predictions by the total number of negative predictions is simply repeated. Also, the most sensitive model is the model with the highest sensitivity number.

$$\text{Specificity} = \frac{TN}{TN + FP +} \times 100\%$$

4.1.4 Precision

Another metric that is often used in relation to recall to assess the effectiveness of a classification system is accuracy. Prediction result for given number of classes.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\%$$

4.1.5 Recall

Recall is determined as the percentage of positive specimens correctly identified as positive out of all positive specimens. Recall measures how well the model can discriminate positive samples. The more positive samples identified, the higher the recall.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\%$$

4.1.6 F1 Score

The F1-score performance measure used to assess classifier effectiveness is a combination of recall and precision metrics. The F1 metric is calculated by multiplying the product of precision and recall by 2 and dividing the result by the sum of recall and precision metric. The following formula shows how the F1 metric is calculated.

$$\text{F1} - \text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4.2 Parameter Optimization

We focused on several variables while simulating the proposed model to improve its performance. In this case the batch size was increased to 32. Improved model performance. To reduce training loss, we adopted “ReLU” and “Softmax” as activation functions. Further improved using Adam and Adamax optimizers.

4.3 Confusion Matrix

The model was trained on different image sets and added as the last layer of the Deep CNN model to maximize performance. Confusion matrices are used to indicate the most expected data, such as accuracy, sensitivity, specificity, and precision. Confusion matrices are very important because they facilitate the analysis of values such as true positives, false positives, true negatives, and false negatives. Confusion matrices were used to assess model effectiveness. The confusion matrix of the Deep CNN model after training the model on the provided images is shown in Figure X. The total number of correctly identified photos is shown in the diagonal section.

4.4 Results and Discussions

To complete the experimental investigation, we selected 10 diseased fruits and 3 healthy classes to use the transfer learning model. Target classes are Apple Black Rot, Apple Blotch, Apple Normal, Apple Scarab, Orange Healthy, Orange Black Spot, Orange Canker, Orange Greening, and Orange Scab. I tried many algorithms and I used all the algorithms and I got the expected results. I have used EfficientNet, DenseNet and CNN algorithm in my dataset. EfficientNet and DenseNet algorithm give very good results but these two algorithm models are not able to detect fruits diseases well. There the CNN algorithm gives low accuracy but its model works well for fruits diseases detection. In this experiment, we first scaled the image down to 320 x 320 pixels before scaling it up. A stack size of 32 was used in combination with his SoftMax and ReLu activation features in the Amax optimizer. First, we started the image acquisition process. There are many stages set up to train the model, such as: B. Image pre-processing, including performing resizing, filtering, scaling, etc. Using a total of 4000 photos for the experiment, he split the data into two groups with a 1783:683 ratio, so the model could be trained on 2721 images and validated on 1280 images. This allowed us to accurately predict and classify disruptions.

We examined the confusion matrix for each class as a performance metric for the three applied transfer learning models. This is a convenient way to choose the best model for your classification problem.

Table 4.1: Result and Analysis of My Prediction Model

Class	Precision	Recall	F1-Score	Accuracy
Apple Black Rot	100%	100%	100%	0.82%
Apple Blotch	100%	100%	100%	
Apple Normal	100%	80%	89%	
Apple Scarab	96%	100%	98%	
Orange Healthy	100%	97%	98%	
Orange_Black_spot	100%	100%	100%	
Orange_Canker	100%	100%	100%	
Orange_Greening	95%	100%	97%	
Orange_Scab	94%	100%	97%	

Here I got 82% of accuracy of my Apple and Orange detection system. I applied CNN algorithm to achieve this accuracy. In my training model I applied 50 epoch and every epoch have 43 steeps. My all-data block size is 32. In this work I use adam and adamx optimizer and softmax and relu optimizer for my prediction model. Here I use Max Pooling layer, Dense layer, Flatten layer etc.

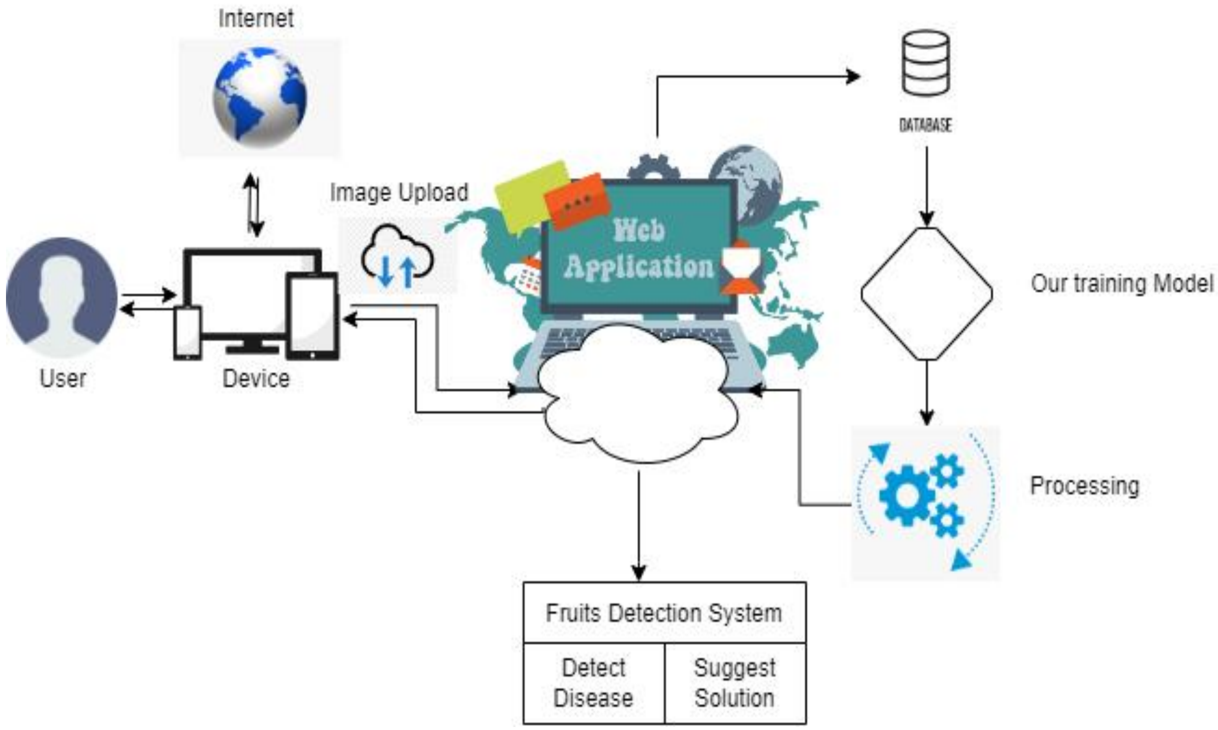

Figure 4.1: Working Procedure of our Fruits diseases detection system

4.4.1 CONVOLUTIONAL NEURAL NETWORK (CNN Algorithm)

The training and validation accuracy are shown in Figure 5.1 and the loss during training and validation is shown in Figure 6.1. Validation curves, also called test curves, are obtained from the holdout validation dataset and indicate the generalizability of the model. A training curve, also called a learning curve, is formed from the training data set.

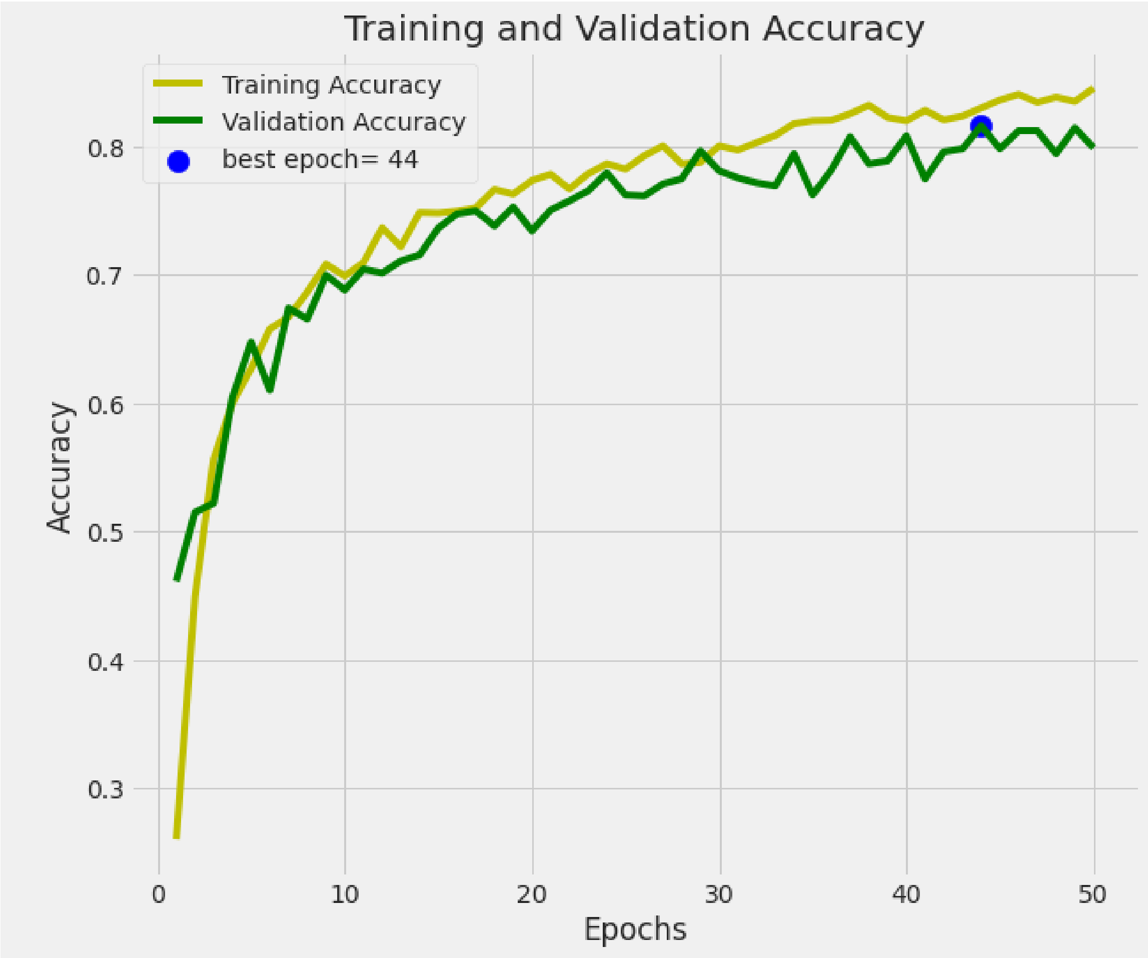

Figure 4.2: Training and Validation Accuracy of CNN Model

Accuracy plots are plotted for epoch numbers ranging from 0 to 1 for 50 epochs of the CNN model, as shown in Figure 4. We can see that the accuracy of both training and validation improves over time. In the early stages, training accuracy and validation accuracy were low. However, as the epoch count improves, training and validation accuracy improves. The graph shows that the model reached the highest accuracy of 82% at 44 epochs. It takes 10 seconds to complete the 44th step and has a learning rate of 0.0010. The results of the class wise metrics performed by the CNN model are shown in Table 3 for each disease category. The classifier CNN has been observed to show the highest precision for the tuberculosis class with 100% accuracy, recall, and F1 score.

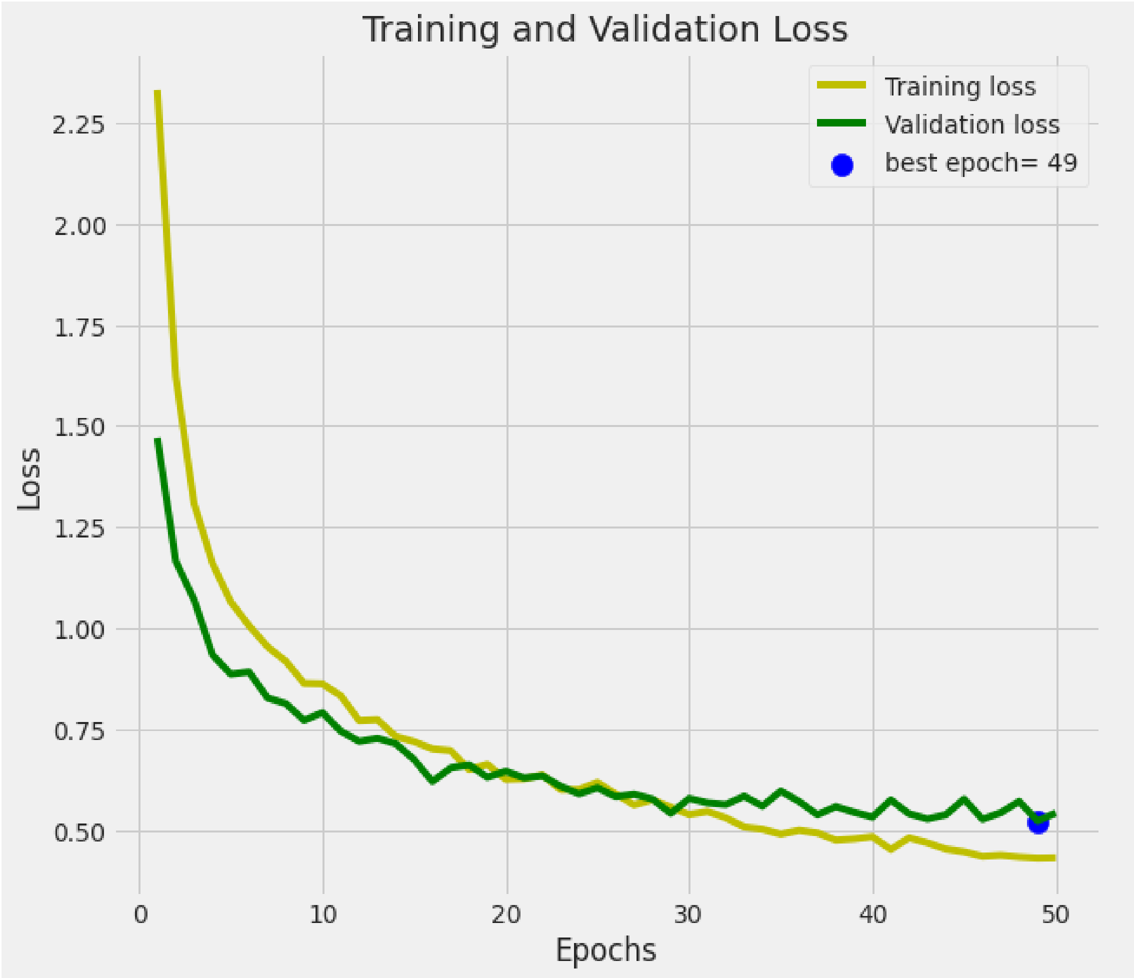

Figure 4.3: Training and Validation Loss of CNN Model

The graph shows that the validation loss at 49 epochs. It takes 10 seconds to complete the 49th step and has a learning rate of 0.0010. The results of the class wise metrics performed by the CNN model are shown in Table 3 for each disease category.

4.4.2 Confusion Matrix

Confusion matrix of our CNN model look like:

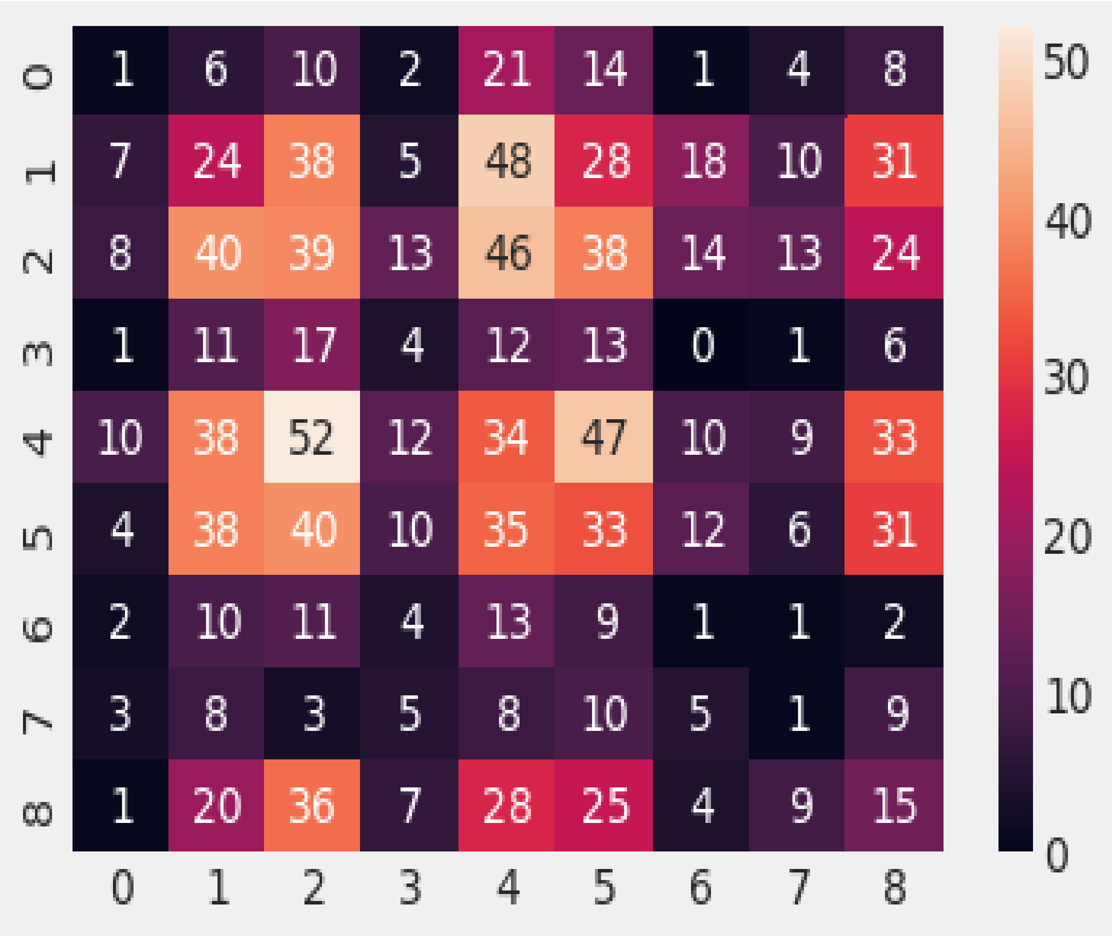

Figure 4.3: Confusion Matrix of our CNN model.

4.5 CONVOLUTIONAL NEURAL NETWORK

Large images require large input sizes for neural networks, a large number of neurons in hidden layers, and costly computational resources for training and computation of the networks, thus making image identification difficult. Using traditional neural networks is difficult. Computer scientist Yann LeCun proposes solving these problems with artificial convolutional neural networks [5]. The most effective type of neural network for intelligently processing visual data is the convolutional neural network. Convolutional layers, subsampling layers, and fully connected layers are all included in this variant of multilayer neural network architecture. Figure [3] shows the usual structure of a CNN for image recognition. Convolutional layers, subsampling layers, and output layers (usually fully connected neural networks) are the three basic types of layers that make up this structure. The CNN layers are laid out sequentially. Convolutional layers come first, followed by subsampling layers, and the output convolutional layer comes after the last convolutional layer. A matrix filter applied to the image using a convolutional layer isolates the features. By combining any number of these layers, you can create new characters from previous lower-ranked characters. A subsample layer is an untrained layer that filters an image based on the pixel with the highest value in a window, ignoring all other pixels. This makes the 1806 image smaller, leaving only the most important elements regardless of their location. Each neuron in the last layer of a fully connected network receives all the outputs from the neurons in the previous layer. Training is performed using backpropagation. After each successful layer, the obtained values are compared with the values provided during training, and the difference is used to reverse the order of the network's weights.

4.6 Primary Setup

1. I built a graphical processing unit (GPU) into my computer and attached it to a drive.
2. Then I mounted Google Colab using Google Drive.
3. I also saved the recordings to Google Drive and labeled them all.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINBILITY

5.1 Impact on Society

We believe that this work will benefit society. As I said before, our country is constantly losing a significant amount of our crops due to underlying problems, and as a result, we are also losing a significant number of plutocrats. Our efforts reduce crop losses and provide some economic relief to growers. It is beneficial for our agriculture. In addition, you can save information about conditions for later research on your design.

It is generally accepted that fruit diseases reduce the amount of food available to humans by ultimately reducing crop yields, which can lead to human malnutrition and, in the worst cases, starvation and death. Plant diseases significantly reduce yields of food crops and adversely affect biodiversity, downstream costs associated with control methods, and human health.

Fruit diseases have historically threatened crop growth and productivity in many parts of the world. Fruit diseases can harm fruits by interfering with many processes, including photosynthesis, flowering and fruiting, fruit growth and development, cell division and expansion. They can also affect water and nutrient uptake and movement. A variety of fungi, bacteria, phytoplasmas, viruses, viroids, nematodes, and other organisms can cause fruit diseases. I have. Depending on pathogen aggressiveness, host resistance, environment, duration of infection, and other circumstances, the severity of disease caused by these pathogens can range from mild symptoms to rotting diseased fruit. The symptoms of black-spot, blotch, scab, canker, greening and other fruit diseases depend on the pathogen that infects the affected area. Important phytochemicals found in fruits have been shown to have positive effects on human health. Vitamins A, C, E, K, and minerals such as potassium, magnesium, and calcium are abundant in fruits. They have antioxidant properties and are a good source of fiber. It is impossible to get all of these nutrients from one fruit, so a variety of fruits should be consumed.

5.2. Impact on Environment

A healthy environment and a healthy diet are both necessary for humans to live a healthy life. A healthy diet is necessary for a comfortable life. Our commitment allows us to produce healthy fruits. If farmers and planters can predict the state of their roots, they can take vital steps to save their crops. What makes this area safer from infectious diseases? We like healthy lifestyles and diets. Therefore, our design will definitely have a positive impact on the terrain. Compared to animal products such as meat and dairy, fruits and fruits often produce less greenhouse gas emissions, up to 10 to 50 times less. How about seasonal products? The fact that seasonal fruits need to be moved less is often cited as an environmental benefit. Fruits gardens offer many environmental benefits. Growing fruits nearby can reduce CO_2 emissions from burning fossil fuels. Harvesting apple and orange directly from the garden eliminates plastic packaging and reduces fossil fuel consumption. Fruits are a rich source of dietary fiber, which promotes intestinal motility and contributes to healthy and easy digestion of food. Apples, oranges are among the most digestible fruits because they are rich in potassium and vitamin C. According to a study by Special G et al., leafy greens contain sulfokines, a sugar that is an energy source for E. coli. It was published in Nature Chemical Biology in 2016. E. coli is a beneficial bacterium that creates a barrier that prevents harmful bacteria from spreading and colonizing.

5.3. Ethical Aspect

Most prosperous countries are using modern technology to improve agriculture. The most difficult aspect of cultivation is determining the exact conditions for harvesting and cropping. Otherwise, there is a high chance of crop loss. Working in this area just got easier. With the help of this search-based design, they can easily explain the carrot harvest problem. Something that increases profitability while encouraging a more frugal lifestyle. A diet high in fruits lowers blood pressure, reduces the risk of heart disease and stroke, protects against certain types of cancer, reduces the risk of eye and digestive problems, improves blood sugar levels, and controls appetite.

Food research subjects, including many potentially vulnerable communities, often use such devices and online forums. Therefore, qualitative research and international comparative research in the field of food science take advantage of cutting-edge web technologies. data collection is becoming more and more important. For example, participants in face-to-face studies on eating disorders from anorexia to obesity, or their parents and family members, may be reluctant to participate, but not so much in web-based studies.

5.4. Sustainability Plan

We want to test this idea in the real world. Additionally, we hope to continue working on it, improving features, and adding more if we get enough feedback. It also collects more information and makes the system easier to use. We are improving our database every day. And we will follow suit internationally. A nutritious and sustainable diet includes fruits. They typically have a lower environmental impact than animal foods and provide the necessary vitamins, minerals and fiber.

To achieve sustainable food security:

- ❖ food accessibility or adequate food production.
- ❖ Food availability and ability to purchase it.
- ❖ Safety and adequate nutrition, including energy, protein and micronutrients.
- ❖ Stability and Predictability of the Terms.

Food safety is at risk when healthy and safe food is scarce and consumers have limited purchasing power. Low-income people are particularly affected by food insecurity, putting them at increased risk of hunger and malnutrition. The International Monetary Fund has found a link between social unrest and rising food prices in low-income countries. Food insecurity and famine are the direct result of social unrest and war. It is difficult to determine whether early food insecurity is a factor and cause of anxiety.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1. Summary of the Study

When we first started collecting data, we used image access (Internet Replica) and image preprocessing to improve the amount of data we had. Additionally, we used a CNN to train the dataset. Additionally, we evaluated the model using the training dataset. Fancy training and validation cooking charts for our theme are now available. Finally, we subtly and fashionably planted 82% of the prediction results.
This publication provided a detailed analysis of studies on fruit location and recognition in the canopy. Many types of sensor systems, image processing techniques and their accuracy have been discussed for fruit detection. Fruit recognition accuracies of 82% have been reported for oranges and apples. In addition, we described the current difficulties faced and possible future approaches in the field of fruit localization, as well as perceptions of robotic harvesting and/or crop load estimation. According to the majority of studies, occlusion, clustering and varying lighting conditions were the biggest obstacles to accurate fruit localization and recognition in field environments. Additional research and development should therefore focus on how to address these limitations and improve the accuracy, speed, and robustness of sensor systems. Reduce overall complexity and cost to improve fruit detection and localization accuracy for robotic harvesting and crop stress estimation. Future R&D could focus on changes in horticulture, sensor platforms to improve lighting uniformity, sensor fusion approaches, and human-machine collaboration.

We encountered many difficulties in carrying out our research task. Images require more processing time and complexity compared to text and other types of data. This requires the use of expensive, high-end image file processing tools, which are also quite lacking. It was difficult for us to collect pictures of these fruit diseases. We have found it difficult to find and collect validated data, so we consulted many reliable sources. Without these inputs, processing the collected data to feed the model proved to be very difficult for us. To get high accuracy, we had to spend a lot of time comparing the accuracy of different models.

6.2. Conclusion

In this study, we proposed a method to identify diseases of fruits to help farmers and farmers grow healthy fruits. The main driving force behind our efforts is to find the factors that will benefit these farmers so that they can easily access information about their expected yield through our model and take appropriate action. Pretreatment technology were used to eliminate noise. Using CNN models, well-processed photos were trained and tested. Finally, we get our design's chic training and confirmation delicacy graph. Finally, we've achieved our desired outcome, which is that the delicatessen is fashionable and that it is 0.82%. We have developed a web application using this concept. The program may identify diseases in fruits. It can provide information on the ailment in greater depth as well as a cure or treatment. Additionally, it contains features like suggestions for medications. The system's capacity to identify circumstances may increase in the future. Also related is complaint inflexibility.

For the detection and classification of fruit diseases, the use of image processing technology is a promising option for farmers. In Bangladesh, real-time disease detection and classification using imagery will help farmers overcome disease-related losses and address food insecurity. This is made possible by the integration of image processing and smart expert systems. Although many techniques have been proposed in this study, we show that convolutional neural networks can detect diseases under real (field) conditions. CNNs often provide excellent detection and classification accuracy and can be used to build real-time disease detection systems to assist farmers. These tools will also be more accurate. For leaves and fruits of certain plant species, traditional methods work well. However, the pipeline process of disease detection and classification methods requires a lot of trial and error. According to this research, convolutional neural networks trained from scratch provide the best classification accuracy. We hope that future research will analyze the ideal hardware requirements for this classification model generation method.

6.3 Future Works

In the future, we would like to develop applications, add functions, add algorithms, etc., and achieve stylish growth. And train the system with more conditions. We will make the system easier to use for producers and others.

6.4 Challenges of fruit disease detection

Further research and development are needed to determine the technical and financial feasibility of apple identification and location systems for fruit harvesting and/or crop stress estimation.

The majority of studies concluded that the main obstacles limiting the accuracy of fruit recognition and localization in orchard environments are fruit inclusion, clustering, and varying lighting conditions. To improve image segmentation and increase the overall accuracy and resilience of fruit recognition and location systems, these issues need to be further addressed through integrated horticultural and engineering techniques.

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