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A Deep Learning Approach for Papaya Disease Identification

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Abstract: Papaya disease poses a significant threat to farmers worldwide, leading to substantial losses annually. Recognizing the urgency of mitigating these losses, researchers have increasingly focused on developing papaya disease recognition systems. However, farmers often lack awareness of detection techniques, resulting in disease identification only after the papayas are already affected, leading to wasted crops and financial losses. Consequently, many farmers are hesitant to continue papaya cultivation. To address this issue, we conducted research leveraging deep learning technology for papaya disease detection and classification. Specifically, we employed a convolutional neural network (CNN) model using the Keras API. Our model features a fully connected architecture for robust classification, and the entire process is based on deep learning principles. We utilized 200x200 RGB images as input, standardizing the image size for consistency. This research aims to empower farmers with an effective tool for early disease detection, thereby reducing crop losses and revitalizing confidence in papaya cultivation. The proposed system achieves classification accuracy of around 94%.

Keywords: Papaya Diseases, Deep Learning, Keras, Classification.

I. INTODUCTION

Papaya (Carica papaya L.) is a tropical fruit native to Central America and southern Mexico, now cultivated in many tropical regions around the world. It is a rich source of vitamins A, C, and E, as well as papain, a digestive enzyme. Papaya production plays a significant role in the economies of many developing countries, and it is also gaining popularity in developed countries due to its nutritional value and delicious taste. However, papaya cultivation faces numerous challenges, with various diseases significantly impacting yield and fruit quality. Papaya Ringspot Virus (PRSV), Papaya Black Spot (PBS), and fungal diseases like Anthracnose and Phytophthora are some of the most common and destructive diseases affecting papaya crops. These diseases can cause devastating losses, leading to reduced fruit production, poor fruit quality, and even complete crop failure. Early and accurate identification of papaya diseases is crucial for effective disease management strategies. Traditional methods of disease identification rely on visual inspection by farmers. However, this approach has limitations. Firstly, it is subjective and depends on the experience and expertise of the farmer. Inexperienced farmers might struggle to identify diseases in their early stages, leading to delayed intervention and greater yield losses. Secondly, visual inspection is time-consuming, especially for large farms. Finally, some diseases can exhibit subtle symptoms that are difficult to detect with the naked eye. These limitations highlight the need for more objective, automated, and reliable techniques for papaya disease identification. This paper explores the application of deep learning, a subfield of machine learning, for achieving this goal.

II. RELATED WORK

A. Papaya Disease Recognition

Traditional methods of papaya disease identification rely on visual inspection by farmers. This method is subjective and depends on the farmer's experience and knowledge of papaya diseases. An inexperienced farmer might struggle to differentiate between healthy and diseased plants, especially in the early stages of infection when symptoms are mild. Deep learning offers a promising alternative to traditional methods of papaya disease identification. Deep learning algorithms can be trained to automatically identify diseases from images of papaya plants. This approach offers several advantages over visual inspection. Firstly, deep learning models are objective and consistent in their analysis. They can be trained on a large dataset of labeled images, encompassing various papaya diseases and their different stages of progression. This training enables the model to learn the characteristic visual patterns associated with each disease, allowing for accurate identification even in the early stages. Secondly, deep learning models are fast and efficient. They can analyze images rapidly, making them suitable for large-scale disease detection in commercial papaya farms. Finally, deep learning models have the potential to detect subtle visual symptoms that might be missed by the human eye. This can lead to earlier disease detection and more effective disease management strategies.

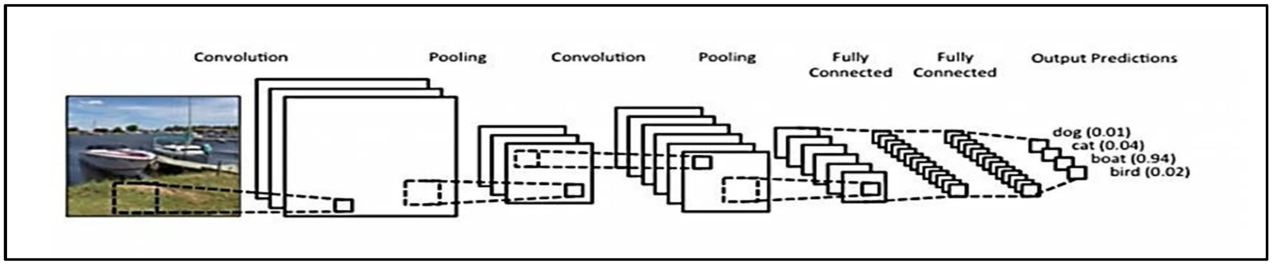


Fig. 1.1 Convolutional Neural Network

B. Machine Learning Techniques

Supervised learning algorithms are fundamental in machine learning, particularly for tasks such as papaya disease prediction. In supervised learning, a labeled dataset is essential, comprising data points (papaya images) each linked to a corresponding label (healthy or diseased). Through analysis of these labeled examples, the machine learning model discerns patterns and connections between features extracted from the images and the presence of specific diseases. There are various types of supervised learning algorithms, but some of the most common and effective choices for image classification tasks include:

1) *Classification Algorithms:* These algorithms are designed to learn a mapping function that maps the input image data (features extracted from the papaya images) to a discrete set of output categories (disease types or healthy). Popular classification algorithms for papaya disease prediction include Support Vector Machines (SVMs), Random Forests, and K-Nearest Neighbors (KNN).
2) *Deep Learning Algorithms:* Deep learning is a subfield of machine learning that utilizes artificial neural networks with multiple hidden layers. These complex architectures allow deep learning models to learn intricate patterns and relationships in data, making them highly effective for image classification tasks. Convolutional Neural Networks (CNNs) are a specific type of deep learning architecture that excel at image recognition. As discussed earlier, CNNs are a powerful choice for papaya disease prediction due to their ability to automatically learn image features directly from the training data.

C. Convolutional Neural Networks

This project focuses on a specific type of machine learning technique called a Convolutional Neural Network (CNN). CNNs are particularly well-suited for image recognition tasks due to their unique architecture. Unlike traditional machine learning algorithms that require manual feature extraction, CNNs can automatically learn these features directly from the image data. This is achieved through convolutional layers that apply filters to the image, extracting low-level features like edges and textures.

D. Data Preprocessing and Feature Extraction

Image preprocessing is an essential step in preparing image data for machine learning models. It involves various techniques to improve the quality and consistency of the image data, ultimately leading to better model performance. Common preprocessing techniques for papaya disease prediction images might include normalization (scaling pixel intensities), reshaping images to a uniform size, and noise reduction to remove irrelevant variations in the images. Feature extraction is another crucial step in machine learning model development.

E. Estimation of Disease Present in RGB Format

This project aims to develop a CNN model capable of analyzing RGB (Red, Green, Blue) images of papaya plants and accurately estimating the presence and type of disease based on visual features. These visual features can include: Color variations: Different diseases can cause distinct color changes in papaya leaves and fruits. For example, Papaya Ringspot Virus (PRSV) often manifests as yellowing or bronzing of leaves, while fungal diseases like Anthracnose may cause dark brown or black spots.

F. Disease Classification Algorithms

The CNN model will be trained on a dataset of papaya plant images categorized according to different diseases. This allows the model to learn the unique characteristics of each disease, such as color variations, spot and lesion patterns, and overall plant health. During the training process, the model is presented with labeled images, where each image has a corresponding label indicating the specific disease present (e.g., healthy, Papaya Ringspot Virus, Anthracnose, Black Rot, Papaya Leaf Spot).

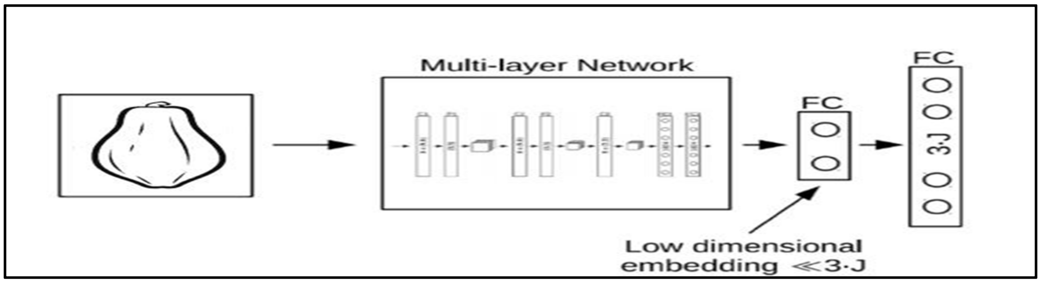


Fig. 1.2 Multi-layer network

G. Deep Learning Advancements and Data Augmentation

Recent advancements in deep learning architectures have opened up new possibilities for papaya disease prediction. Techniques like transfer learning can be employed to leverage pre-trained CNN models on large image datasets. These pre-trained models can be fine-tuned for the specific task of papaya disease classification, even with limited training data available for papaya diseases specifically. Data augmentation is another technique used to artificially expand the training dataset by generating new variations of existing images. This is particularly beneficial when dealing with limited datasets of papaya disease images.

H. Evolving of Deep Learning Structures

It is in record that Artificial Intelligence (AI) is one of the most software engineering's famous exploration subjects, and has series of trial applications. We requested that machines yesterday execute routine work. We are requesting that them today get recordings, discourse and pictures, or even to assist specialists with performing diagnosis. The unavoidable issue in AI is: the means by which to cause a PC to learn all alone.

I. Similarities with Natural Neurons

There's still a great deal of obscure in organic neurons regarding how the mind trains itself. A neuron gathers electrical signs from numerous others inside the human mind through fine constructions called dendrites. The core gets the quantity of data sources. In the event that an adequately high sign is gotten it will give a spike in electrical action. The last option is dispatched through the axon. Finally, structures known as neurotransmitter move this direct to the accompanying related neurons. The learning happens by means of adjustment of the viability of the neurotransmitters, with the objective that alteration of one neuron influences the other.

III. PROPOSED METHODOLOGY

A. Deep Learning Model Architecture

The core of our methodology revolves around the design and implementation of a deep learning architecture tailored to papaya disease identification. Inspired by state-of-the-art convolutional neural network (CNN) architectures such as ResNet, DenseNet, and Inception, our model comprises multiple layers of convolutional, pooling, and fully connected units. The architecture was optimized to capture intricate spatial features and hierarchical representations present in papaya disease images, thereby facilitating accurate classification and diagnosis.

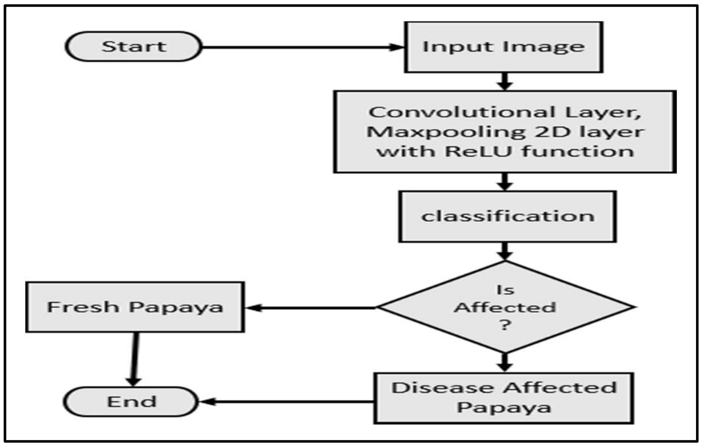


Fig. 3.1 Flowchart for papaya disease classification model

B. Preprocessing for CNN Image Classification

Preprocessing plays a pivotal role in the success of convolutional neural network (CNN) models for image classification tasks. These initial steps are essential for ensuring that the dataset is in a suitable format for training and that the model can effectively learn from the provided data. By meticulously preparing the dataset, researchers and practitioners can enhance the model's ability to generalize well to unseen examples, ultimately leading to more accurate and reliable classification results. The preprocessing pipeline typically involves various operations, including data loading, normalization, and augmentation, each aimed at optimizing the dataset for training. These modules are executed sequentially and generate the required results.

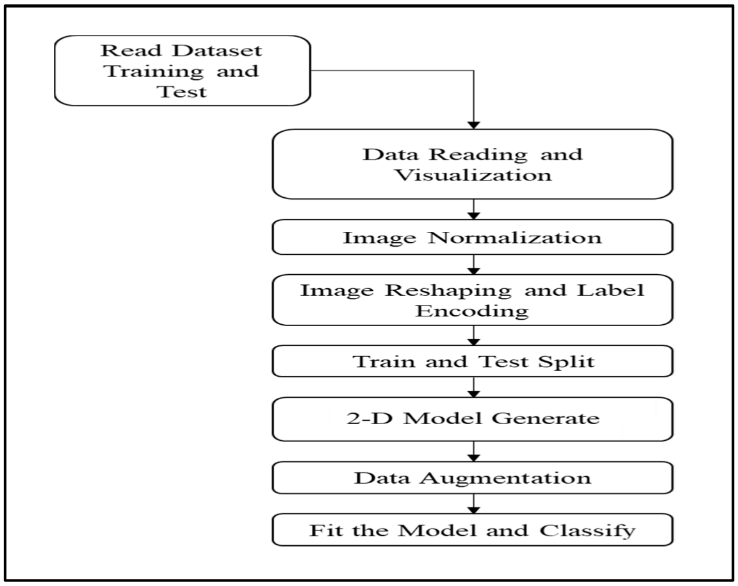


Fig. 3.2 Proposed system architecture for papaya disease recognition

C. Feature Extraction

Feature extraction is a crucial step in the machine learning pipeline, particularly in tasks involving image classification such as papaya disease identification. In essence, feature extraction involves transforming raw input data, such as images, into a format that is more conducive to model training and interpretation. In the context of papaya disease classification, feature extraction entails extracting meaningful patterns or features from images of papaya leaves. These features may include textures, shapes, edges, or other visual attributes that are indicative of different disease types. Feature extraction techniques aim to capture the salient characteristics of the input images in a compact and informative representation, facilitating subsequent classification by the model.

D. Proposed Classifier

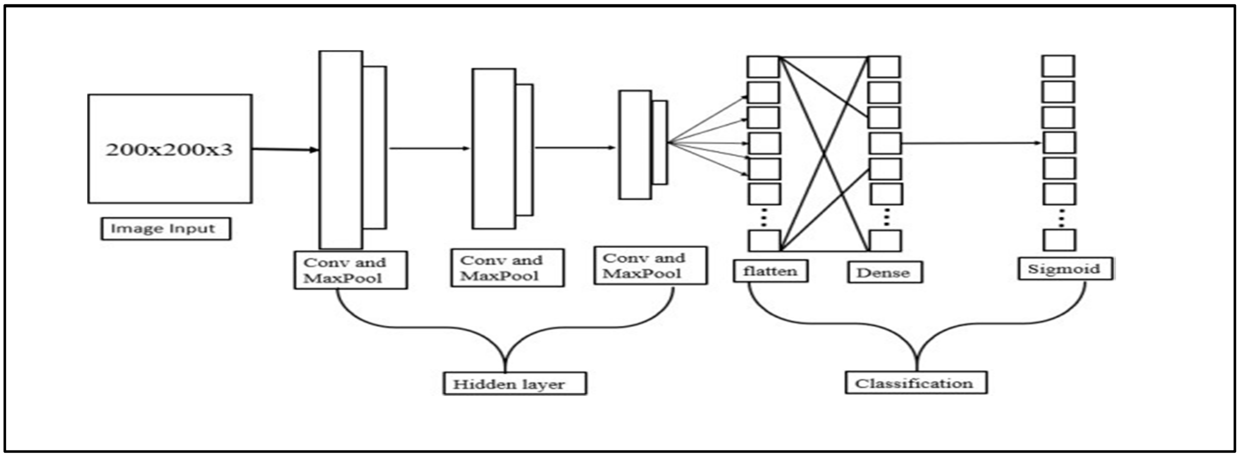


Fig. 3.6 Shows the generic ML layers

ML based classifier is an adaptive interface system incorporates neural network principle to classify the Diseases. This classifier captures the importance of principle gaining maximum efficiency. This method is used for images because of its optimality and efficiency. The way it produces result is far better than the traditional ones. In proposed system, neural network consists of 9 different layers. One is input and output layer and rest are intermediate / hidden layers. The total number of features extracted from the images are suppose N. Hence the input layer contains N different inputs.

The model we have defined consists of several layers. Let's break them down:

1) *Conv2D Layers:* There are three Conv2D layers. Each layer applies a set of convolutional filters to the input image, extracting features from the images. These layers use a ReLU activation function for non-linearity.
2) *MaxPooling2D Layers:* After each Conv2D layer, there's a MaxPooling2D layer. These layers down-sample the input representation, reducing its dimensionality and allowing for assumptions to be made about features contained in the sub-regions binned.
3) *Flatten Layer:* This layer flattens the 2D output of the last convolutional operations into a vector. It allows you to move from a convolutional part of the network to fully connected layers.
4) *Dense Layers:* There are two Dense layers. These are fully connected layers. The first Dense layer has 512 units and applies the ReLU activation function. The second Dense layer has 5 units (for 5 output classes) and uses the softmax activation function to output probability scores for each class.

The output of the ML layer is based on the class-based classification.

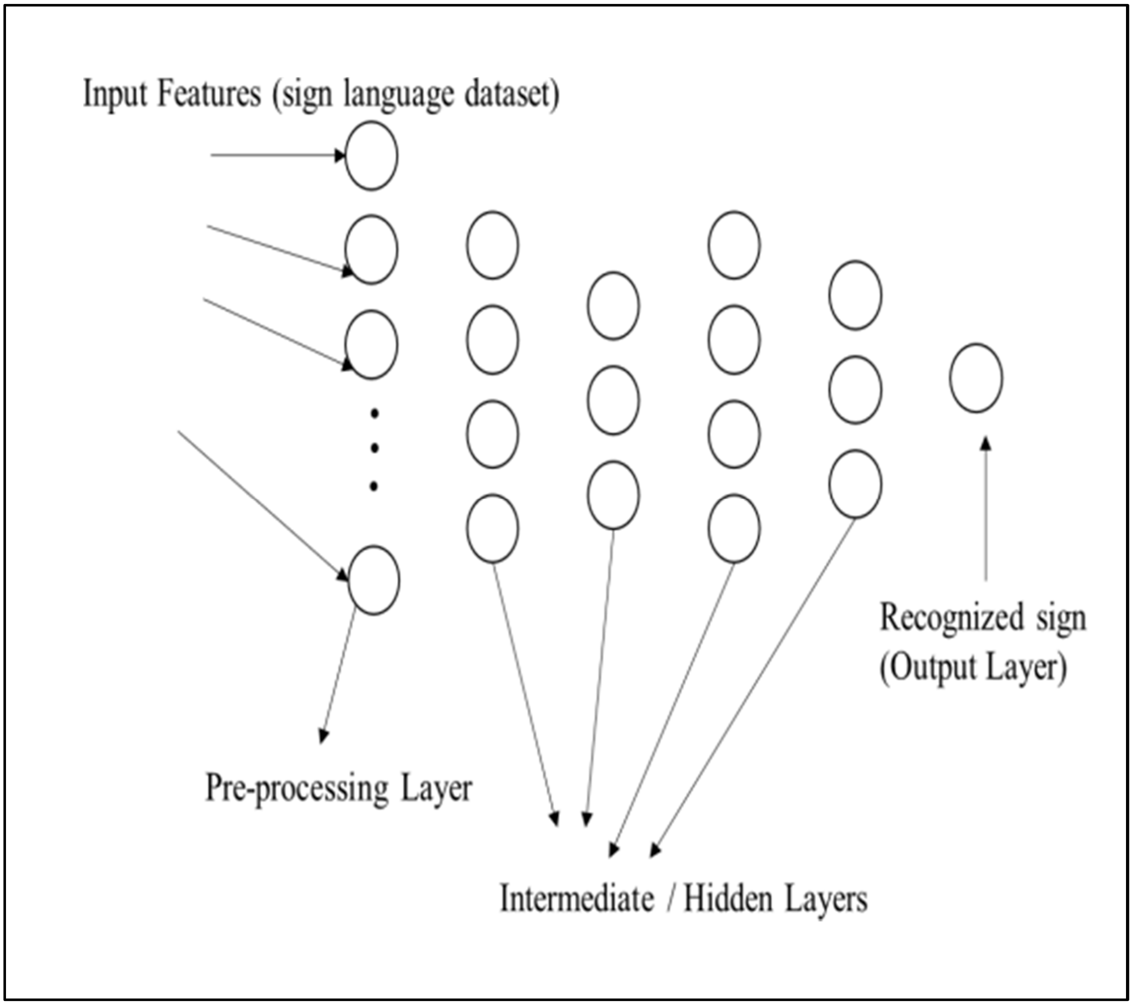


Fig. 3.7 Shows the implemented ML layers

E. Proposed Model

In the pursuit of building an effective papaya disease classification model, the choice of architecture is paramount. Leveraging the Keras deep learning framework, researchers construct the model architecture as a sequential stack of layers, aligning with the principles of simplicity, modularity, and flexibility.

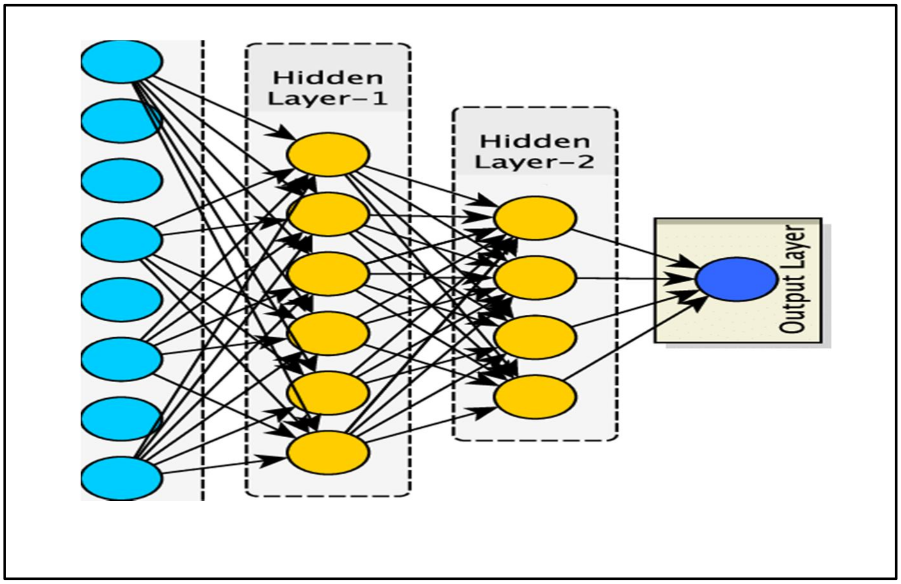


Fig. 3.8 Sequential model layers

F. Proposed Algorithms

At the heart of training a Convolutional Neural Network (CNN) for papaya disease classification lies the iterative optimization algorithm known as back propagation. This fundamental algorithm underpins the learning process of the model, facilitating the adjustment of network weights based on computed error gradients.

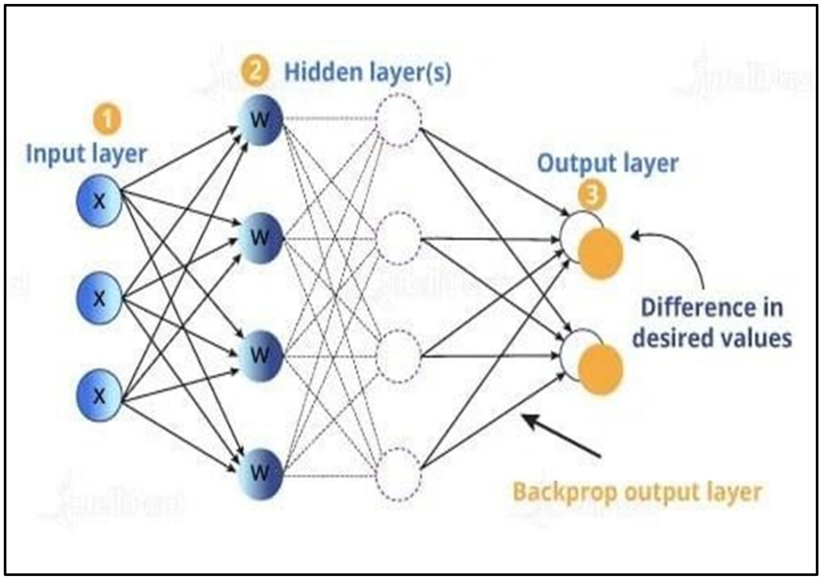


Fig. 3.9 Backpropagation Algorithm layers

By iteratively repeating this process over multiple epochs and batches of training data, backpropagation gradually refines the model parameters, optimizing the network's ability to classify papaya diseases accurately. This iterative refinement enables the model to learn from training data, capturing underlying patterns and relationships within the data to improve prediction accuracy.

G. Proposed Optimizer

In the quest for training the papaya disease classification model, the choice of optimizer holds significant importance. Among the plethora of optimization algorithms available, the RMSProp optimizer emerges as a powerful tool for efficiently navigating the optimization landscape.

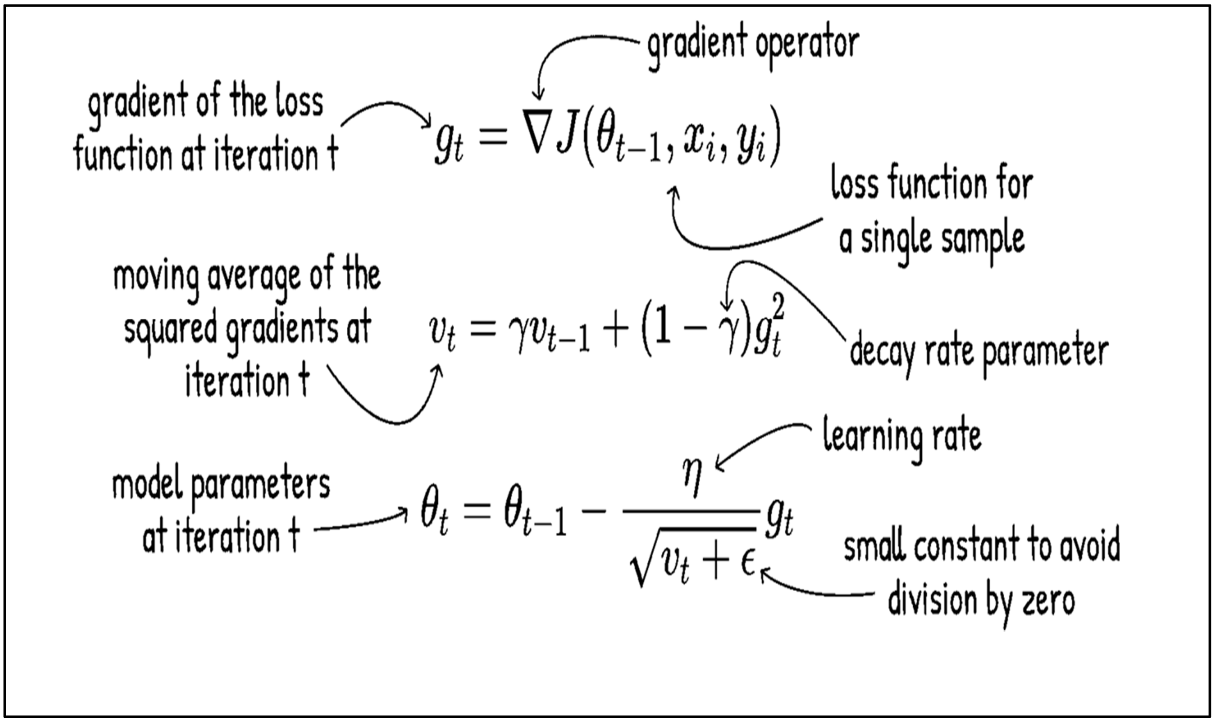


Fig. 3.10 RMSprop Algorithm

IV. EXPERIMENTAL RESULT

In this section various experiments are conducted and its results are presented in the form of graphs and charts. Python is used for performing experiments.

A. Experiment Setup

To evaluate our metrics, we have used Python. Image processing tools are used in our evaluation. Project considered various dataset for recognition of papaya diseases. Table 4.1 shows the specification of our experiment setup.

SNO	Attributes	Value
1	IDE	VS Code
2	Language	Python
3	Version	Python 3.10
4	Tool	Image Processing Tools
5	Method Used	Machine Learning Classifier, Data Augmentation, Normalization Transformation, Transfer Leaning.
6	Dataset	Papaya disease dataset

Fig 4.1: Experiment Setup Configuration Table

B. Dataset Description

The dataset is taken from publicly available dataset Kaggle The web URL for the dataset is https://github.com/imdadulhaque1/papaya. The dataset consists of training, validation and test image datasets around 165 MB or 175 MB of file size. Consisting of 2522 images classified as 5 diseases Named “Anthracnose”, “Black Spot”, “Phytophthora”, “Powdery Mildew” and “Ring Spot” respectively.

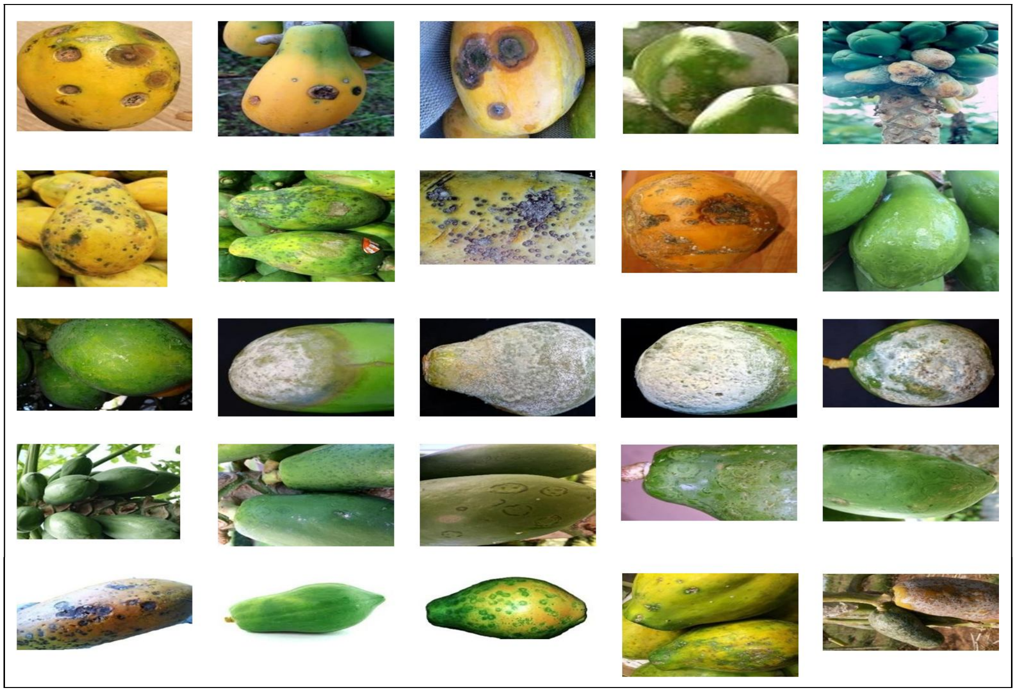


Fig. 4.2 Snapshot of dataset

Anthracnose

Black Spot

Phytophthora

Powdery Mildew

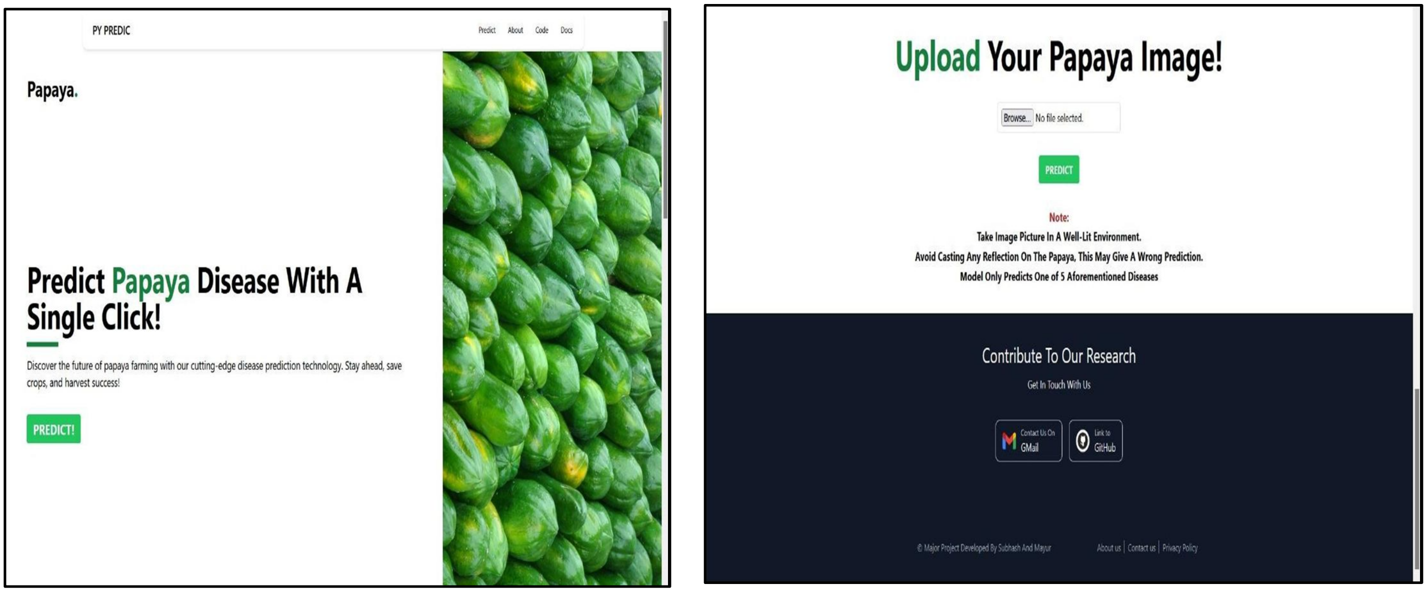
Ring Spot

Fig. 4.3 Snapshots Papaya Diseases Datasets

C. Framework Output

The step-by-step output obtained by the framework is shown in this section.

1) STEP 01: GUI of framework.



Predict Papaya Disease With A Single Click!

Discover the future of papaya farming with our cutting-edge disease prediction technology. Stay ahead, save crops, and harvest success!

Upload Your Papaya Image!

Note:
Take Image Picture In A Well-Lit Environment.
Avoid Casting Any Reflection On The Papaya, This May Give A Wrong Prediction.
Model Only Predicts One of 5 Aforementioned Diseases

Contribute To Our Research
Get In Touch With Us

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Fig 4.4: GUI of Framework

2) STEP 02: Display Papaya Diseases.

Anthracnose
Papaya anthracnose is a fungal disease affecting papaya plants, causing fruit rot and economic losses.

Black Spot
Papaya black spot, caused by the fungus Asperisporium caricae, results in leaf lesions and reduced fruit quality.

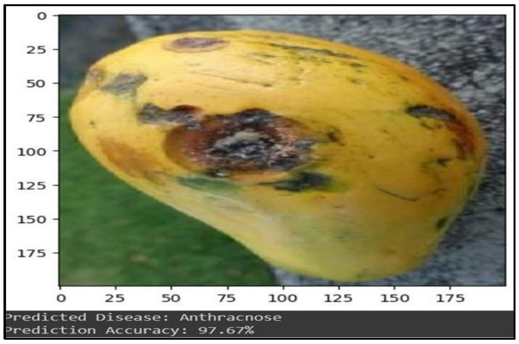
Phytophthora
Papaya phytophthora, a fungal disease caused by Phytophthora palmivora, leads to root rot, wilting, and fruit decay, affecting crop yield.

Powdery Mildew
Papaya powdery mildew, caused by the fungus Oidium caricae, results in white powdery patches on leaves, reducing photosynthesis and fruit quality.

Ring Spot
Papaya ringspot virus stunts plants, yellows leaves, and causes dark rings on fruit.

Fig 4.5: Display Papaya Diseases

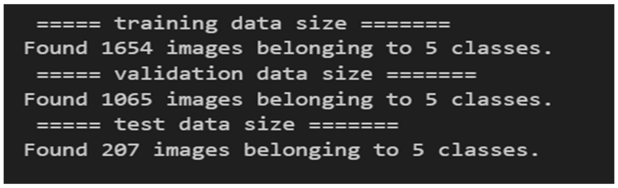
3) STEP 03: Shows the sample Papaya Disease of Anthracnose.



```
Predicted Disease: Anthracnose
Prediction Accuracy: 97.67%
```

Fig 4.6: Sample Papaya disease of Anthracnose

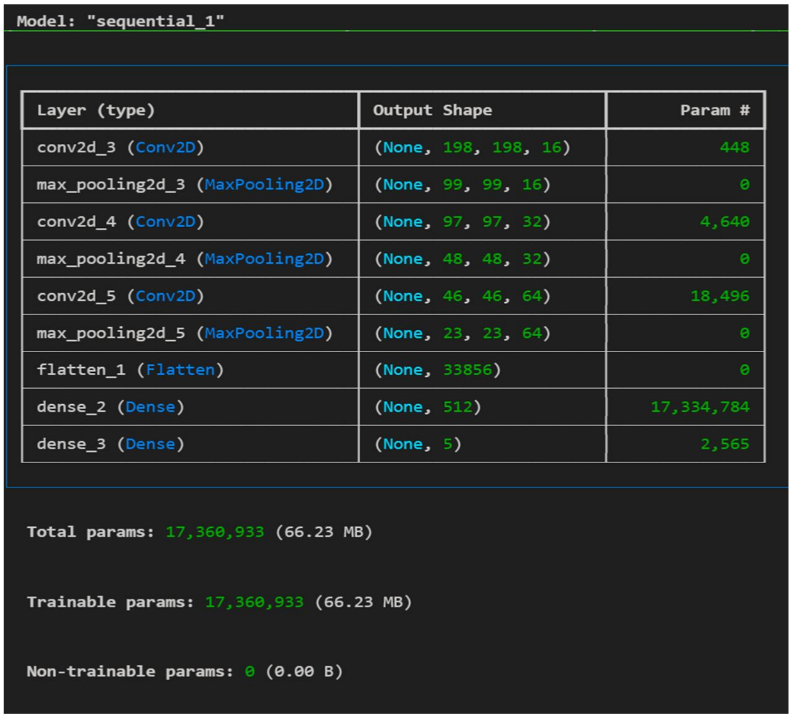
4) *STEP 04: Shows train, validate and test data size.*



```
 ===== training data size =======
Found 1654 images belonging to 5 classes.
 ===== validation data size =======
Found 1065 images belonging to 5 classes.
 ===== test data size =======
Found 207 images belonging to 5 classes.
```

Fig 4.7: Train, Validate & Test Data Size

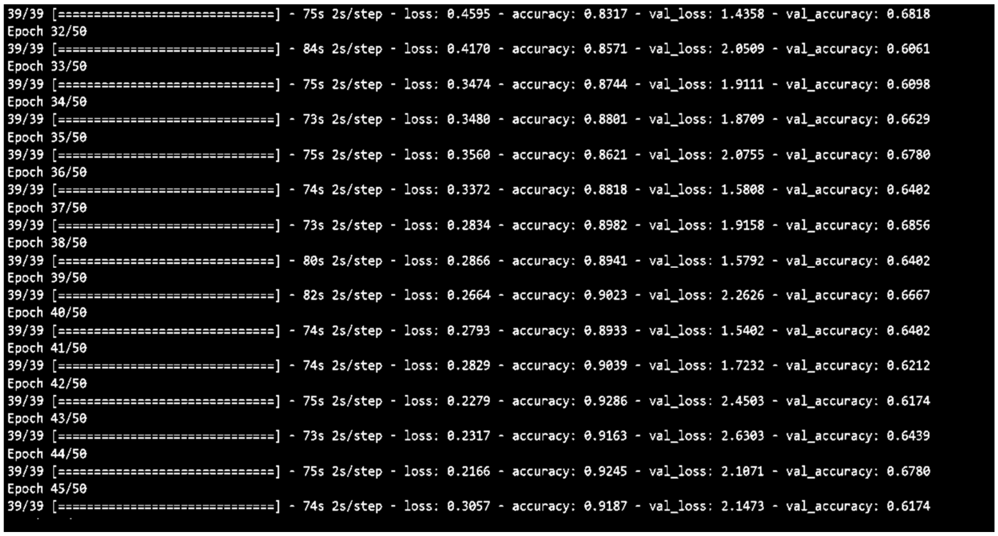
5) *STEP 05: Neural Network Parameters*



```
Model: "sequential_1"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                 ┃            Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━┩
│ conv2d_3 (Conv2D)                    │ (None, 198, 198, 16)         │                448 │
├──────────────────────────────────────┼──────────────────────────────┼────────────────────┤
│ max_pooling2d_3 (MaxPooling2D)       │ (None, 99, 99, 16)           │                  0 │
├──────────────────────────────────────┼──────────────────────────────┼────────────────────┤
│ conv2d_4 (Conv2D)                    │ (None, 97, 97, 32)           │              4,640 │
├──────────────────────────────────────┼──────────────────────────────┼────────────────────┤
│ max_pooling2d_4 (MaxPooling2D)       │ (None, 48, 48, 32)           │                  0 │
├──────────────────────────────────────┼──────────────────────────────┼────────────────────┤
│ conv2d_5 (Conv2D)                    │ (None, 46, 46, 64)           │             18,496 │
├──────────────────────────────────────┼──────────────────────────────┼────────────────────┤
│ max_pooling2d_5 (MaxPooling2D)       │ (None, 23, 23, 64)           │                  0 │
├──────────────────────────────────────┼──────────────────────────────┼────────────────────┤
│ flatten_1 (Flatten)                  │ (None, 33856)                │                  0 │
├──────────────────────────────────────┼──────────────────────────────┼────────────────────┤
│ dense_2 (Dense)                      │ (None, 512)                  │         17,334,784 │
├──────────────────────────────────────┼──────────────────────────────┼────────────────────┤
│ dense_3 (Dense)                      │ (None, 5)                    │              2,565 │
└──────────────────────────────────────┴──────────────────────────────┴────────────────────┘

 Total params: 17,360,933 (66.23 MB)

 Trainable params: 17,360,933 (66.23 MB)

 Non-trainable params: 0 (0.00 B)
```

Fig 4.8: Neural Network Parameters

6) *STEP 06: Live Training Accuracy*



```
39/39 [==============================] - 75s 2s/step - loss: 0.4595 - accuracy: 0.8317 - val_loss: 1.4358 - val_accuracy: 0.6818
Epoch 32/50
39/39 [==============================] - 84s 2s/step - loss: 0.4170 - accuracy: 0.8571 - val_loss: 2.0509 - val_accuracy: 0.6061
Epoch 33/50
39/39 [==============================] - 75s 2s/step - loss: 0.3474 - accuracy: 0.8744 - val_loss: 1.9111 - val_accuracy: 0.6098
Epoch 34/50
39/39 [==============================] - 73s 2s/step - loss: 0.3480 - accuracy: 0.8801 - val_loss: 1.8709 - val_accuracy: 0.6629
Epoch 35/50
39/39 [==============================] - 75s 2s/step - loss: 0.3560 - accuracy: 0.8621 - val_loss: 2.0755 - val_accuracy: 0.6780
Epoch 36/50
39/39 [==============================] - 74s 2s/step - loss: 0.3372 - accuracy: 0.8818 - val_loss: 1.5808 - val_accuracy: 0.6402
Epoch 37/50
39/39 [==============================] - 73s 2s/step - loss: 0.2834 - accuracy: 0.8982 - val_loss: 1.9158 - val_accuracy: 0.6856
Epoch 38/50
39/39 [==============================] - 80s 2s/step - loss: 0.2866 - accuracy: 0.8941 - val_loss: 1.5792 - val_accuracy: 0.6402
Epoch 39/50
39/39 [==============================] - 82s 2s/step - loss: 0.2664 - accuracy: 0.9023 - val_loss: 2.2626 - val_accuracy: 0.6667
Epoch 40/50
39/39 [==============================] - 74s 2s/step - loss: 0.2793 - accuracy: 0.8933 - val_loss: 1.5402 - val_accuracy: 0.6402
Epoch 41/50
39/39 [==============================] - 74s 2s/step - loss: 0.2829 - accuracy: 0.9039 - val_loss: 1.7232 - val_accuracy: 0.6212
Epoch 42/50
39/39 [==============================] - 75s 2s/step - loss: 0.2279 - accuracy: 0.9286 - val_loss: 2.4503 - val_accuracy: 0.6174
Epoch 43/50
39/39 [==============================] - 73s 2s/step - loss: 0.2317 - accuracy: 0.9163 - val_loss: 2.6303 - val_accuracy: 0.6439
Epoch 44/50
39/39 [==============================] - 75s 2s/step - loss: 0.2166 - accuracy: 0.9245 - val_loss: 2.1071 - val_accuracy: 0.6780
Epoch 45/50
39/39 [==============================] - 74s 2s/step - loss: 0.3057 - accuracy: 0.9187 - val_loss: 2.1473 - val_accuracy: 0.6174
```

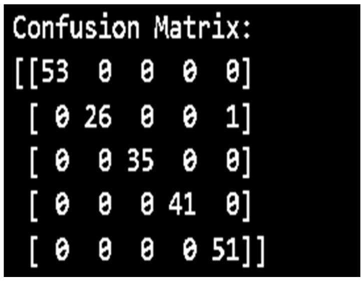
Fig 4.9: Live Training Accuracy

7) *STEP 07: Trained Model Accuracy*

```
Found 207 images belonging to 5 classes.
7/7 [==============================] - 51s 8s/step - loss: 0.0225 - accuracy: 0.9952
7/7 [==============================] - 5s 618ms/step
Test Accuracy: 99.52%
Test Loss: 0.0225
```

Fig 4.10: Trained Model Accuracy

8) *STEP 08: Confusion Matrix.*



```
Confusion Matrix:
[[53  0  0  0  0]
 [ 0 26  0  0  1]
 [ 0  0 35  0  0]
 [ 0  0  0 41  0]
 [ 0  0  0  0 51]]
```

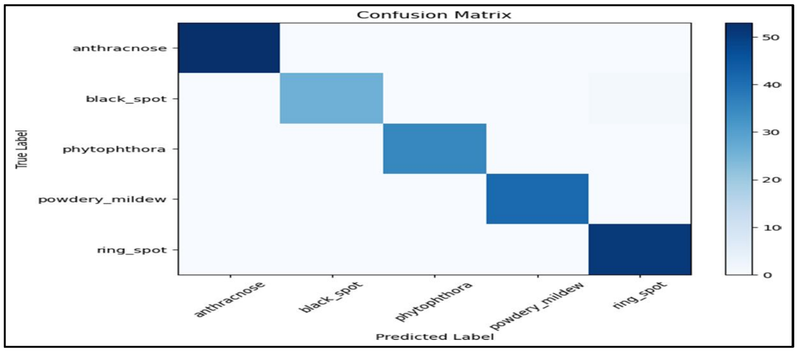
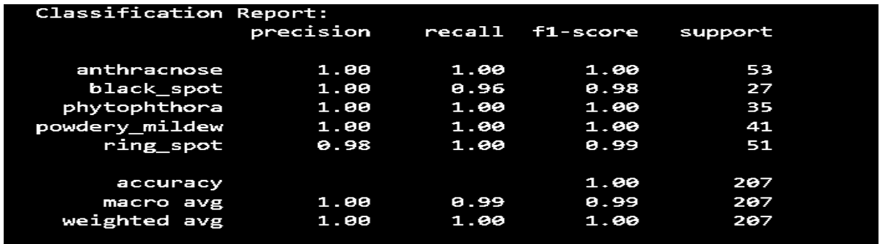


Fig 4.11: Confusion Matrix Graph

9) *STEP 09: Classification Matrix.*



```
Classification Report:
                precision    recall  f1-score   support

   anthracnose       1.00      1.00      1.00        53
    black_spot       1.00      0.96      0.98        27
  phytophthora       1.00      1.00      1.00        35
powdery_mildew       1.00      1.00      1.00        41
     ring_spot       0.98      1.00      0.99        51

      accuracy                           1.00       207
     macro avg       1.00      0.99      0.99       207
  weighted avg       1.00      1.00      1.00       207
```

Fig 4.12: Classification Matrix

D. Result Evaluation

This section deals with the results obtained from the machine learning classifier. There is a significant improve in the system in applying the feature extraction process with the data augmentation method. Both the feature extraction and data augmentation technique enhance the accuracy of the proposed system in a drastic way.

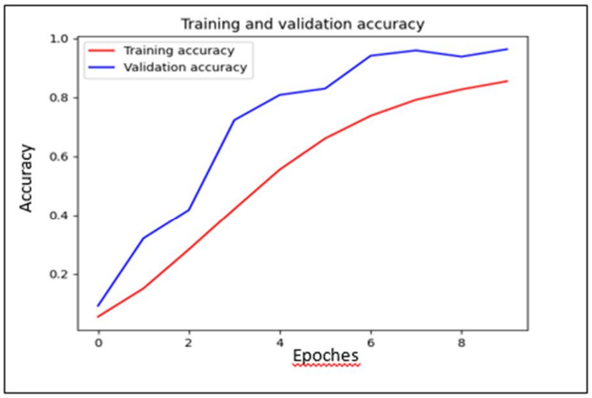


Fig. 5.13 Training and Validation Accuracy Graph

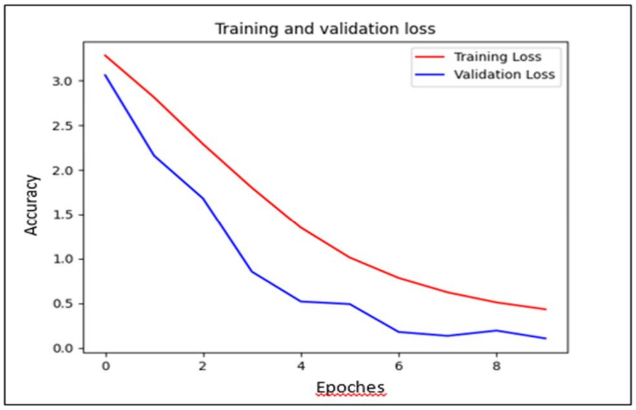


Fig. 5.14 Training and Validation Loss Graph

V. CONCLUTION

This proposed system recognizes Papaya disease Recognition. The strategy utilizes combination of various machine learning approaches. For improvement of older algorithm this thesis utilizes feature extraction with data augmentation technique. The proposed procedure is applied on poor quality papaya images of Kaggle and GitHub dataset, but still we obtained high accuracy in classification of those Diseases. The proposed system achieves ~94% accuracy in recognizing the Papaya diseases.In this project, we implemented many of the concepts. Currently We didn't get the Best and correct dataset, So, in future if we get the correct and best dataset then, In future we would like to carry out the work with the correct and best dataset and increase our models accuracy and under fitting will be minimized.

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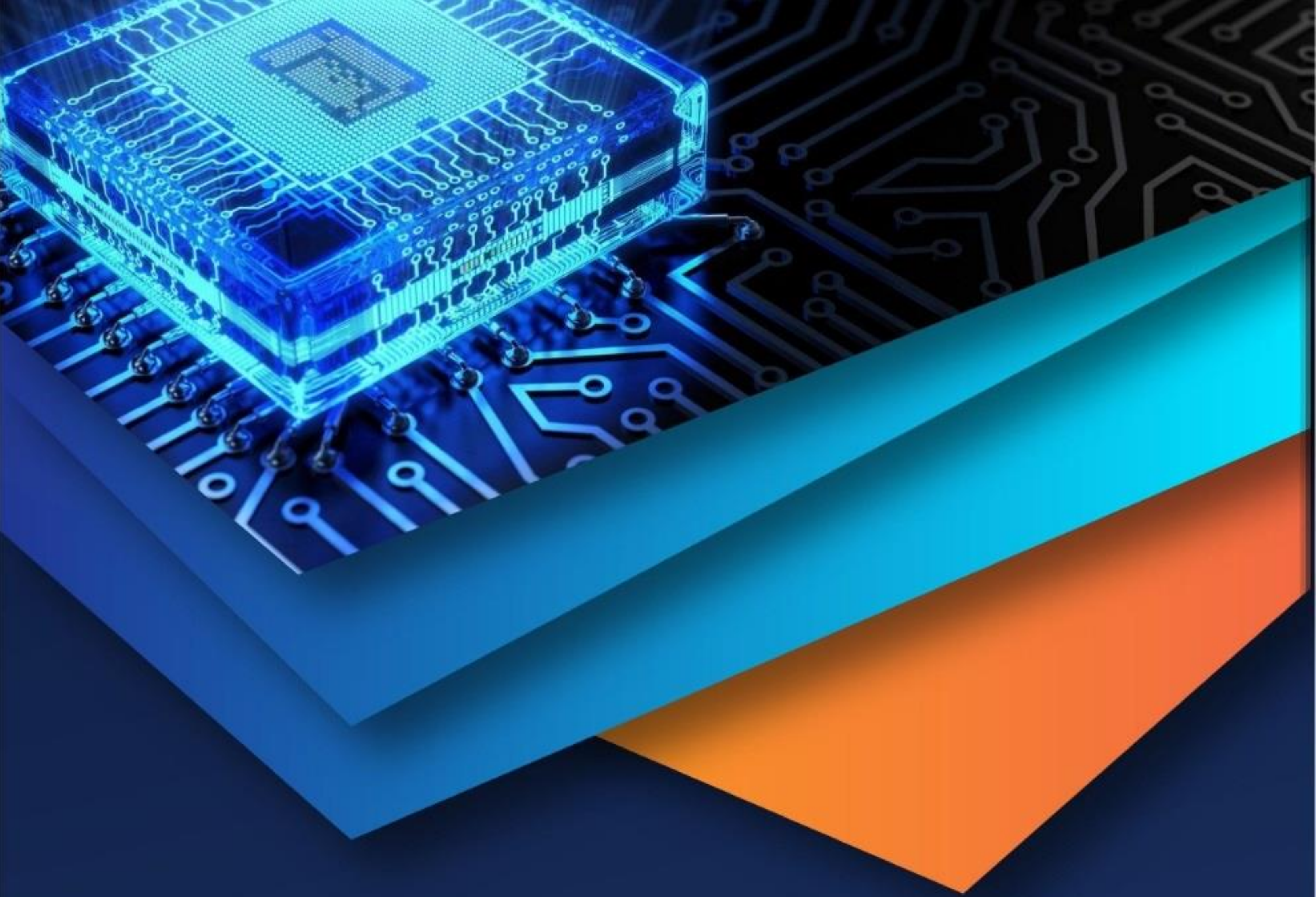

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