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A Deep Learning Based Model for Plant Disease Detection

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ABSTRACT

Plant diseases present increasing threats to agriculture which require precise early disease detection systems and powerful management solutions to preserve crop health and maximize productivity. This research studies the application of CNNs and combines it with ML and DL while investigating their capability to identify plant diseases accurately. Through precise detection capability the system incorporates Artificial Intelligence (AI)-based treatment recommendations which suggest optimal solutions. These innovative technologies enable better agricultural decisions which result in higher crop production with lower losses. Nothing works as effectively toward plant disease management as the early and accurate identification of diseases. Traditional expansive plant disease assessment requires specialized personnel and operates at slow speeds which restricts its practical use on extensive areas. This research develops a computing solution which combines image processing techniques and machine learning for plant disease detection automation. The system performs feature extraction through texture analysis alongside color attribute examination and shape descriptor evaluation applied to images containing healthy and infected plant leaves. A dataset made up of healthy and diseased plant leaf images supports the proposed system that utilizes feature extraction through texture analysis with color properties combined with shape descriptors. A proposed CNN is used on plant leaves to identify healthy versus diseased classes, producing an average accuracy of 94.65% on 14 types of plants having 38 types of diseases.

Keywords: *Detection of Plant Diseases, Convolutional Neural Networks, Machine Learning, Deep Learning*

1. INTRODUCTION

Agriculture serves as a key element of global food security yet faces raising demands for performance improvement combined with resource management requirements. The sector deals with various challenges yet disease detection and plant management emerge as a critical component which directly affects agricultural yield and crop quality performances [1]. Standard methods of detecting plant diseases through manual expert inspection prove both slow and expensive because they follow time-consuming human-based procedures. Advanced plant disease detection approaches became feasible because of modern technological developments [2]. Convolutional Neural Networks (CNNs), Machine Learning (ML) and Deep Learning (DL) create powerful tools for automated disease identification because they surpass traditional approaches by providing both improved precision and swifter processing speeds. Scientists have thoroughly examined these new technologies across numerous investigations which produced favorable results. Our investigation extends previous research through the combination of CNNs for precise disease identification and artificial intelligence-based disease management recommendations [3]. Throughout the generations farmers have employed manual evaluation to detect plant diseases in their fields. The practice of traditional plant disease detection through manual inspection continues from past generations but creates specific problems [4]. The practice of manual inspection requires both substantial physical labor and extended time to undergo assessment while human error frequently occurs throughout extensive crop supervisors.

Plant symptoms in early disease phases remain hard to observe for humans resulting in delayed treatment that leads to higher crop damage.

Modern technological advances have transformed plant disease detection by delivering advanced solutions to address existing detection challenges [5]. The agricultural sector benefits significantly from the recent emergence of artificial intelligence applications and deep learning as its dominant technology element. Convectional Neural Networks serving as AI-based systems revealed outstanding capabilities to detect and classify plant diseases from visual images.

Using 87900 RGB images this approach successfully achieved 94.65% accuracy in recognizing 38 distinct diseases of 14 plants. The proposed method extends beyond traditional detection research by adding custom treatment suggestions, which leads to heightened decisions among farmers. This predictive and recommendation platform represents a fundamental step forward in agricultural technology development.

The proposed work is further organized into seven sections, section 2 covers the problem statement and research contribution which includes problems with plants, objective, scope, and contribution. An overview of the convolutional neural network is given in section 3. Section 4 covers literature review. Complete methodology is given in section 5. Results & discussion and comparative analysis with other state-of-the-art algorithms are shown in sections 6 and 7 respectively. Finally, the paper is concluded in section 8.

2. PROBLEM STATEMENT AND RESEARCH CONTRIBUTION

2.1 Problems with Plants:

- Plant diseases pose a major threat to global food security and agricultural productivity and impose considerable economic losses each year [6].
- Early detection of disease is important to control spread of disease, reduce damage to crops and reduce the need for chemical treatments. However, currently available methods are somehow deficient, often failing to yield timely and accurate results.

2.2 Objective:

- This research aims to develop an automated system to identify plant diseases using learning technique based on machine and image process. With the help of sophisticated algorithms, these leaf images will be classified and diseases diagnosed with great precision and speed [7].
- A real time indicator with visualities like discoloration, spots or lesions will be proposed to be identified as replies to farmers and allied experts.

2.3 Scope:

- The leaf images will be collected and preprocessed, features extracted, model trained and evaluated in this study.
- The research will use various machine learning models, such as Convolutional Neural Networks (CNN's) and evaluate their ability to distinguish between 'healthy' and 'diseased' plants.
- The outcomes of the paper will provide support for sustainable crop management practices like providing early disease detection and the promotion of precision agriculture.

2.4 Contribution:

- We introduce this system that predicts more plant diseases than previous work typically focuses on such a small set of diseases.
- In the proposed research a very large collection of 87900 images of healthy and diseased crop leaves from multiple classes have been used. The dataset is split into training set (70,295 images), validation set (17,572 images), allowing 80/20 as split ratio for training and validation respectively.

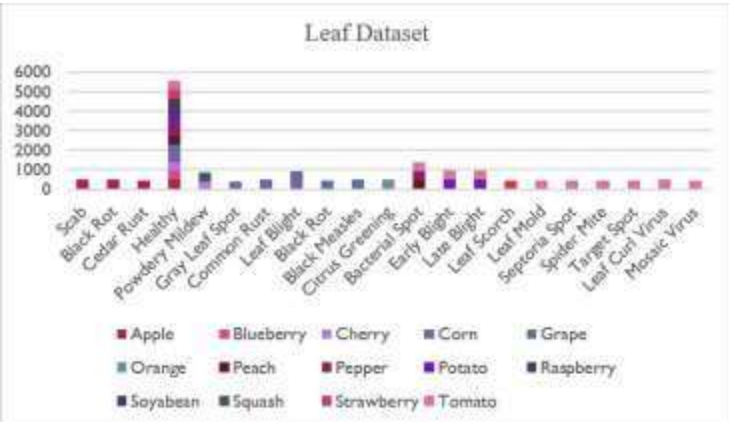

Figure 1. Leaf Dataset

Figure 1 presents a complete dataset that shows data from Apple, Corn, Grapes, Potato and Tomato plants. Plants in this dataset possess multiple diseases including healthy alongside Scab & black rot, cedar apple rust, leaf blight and early blight and Late Blight and Common rust and Bacterial Spot.

3. CNN (CONVOLUTIONAL NEURAL NETWORK)

The deep learning framework known as Convolutional Neural Network (CNN) possesses multiple layers that extract input data features automatically and create output predictions. The system architecture contains multiple processing levels that consist of convolutional and pooling along with flatten and dense layers.

3.1 Convolutional layer

A CNN relies on its convolutional layer functionality to extract vital features across input image areas. Each section of the image receives dedicated filters to extract main components which form the basis of pattern detection.

3.2 Pooling layer

Through the pooling layer the model reduces processing complexity along with parameter numbers. Two main pooling techniques exist to lower feature maps scale: max pooling and global pooling which retain fundamental information.

3.3 Dense Layer

In a CNN the dense layer performs two functions: neuronal connections between prior layers before producing a final output by processing data. As a fully connected final layer it integrates data from multiple sources to assist decision- making by using the learned features.

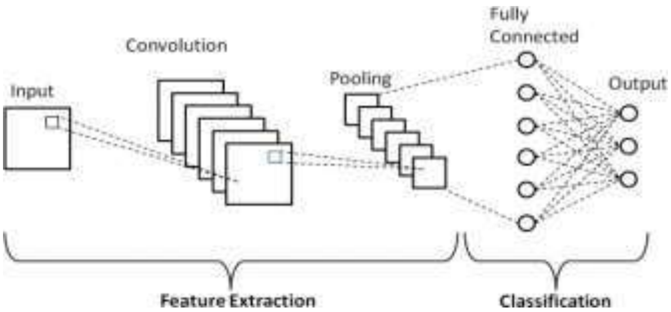

Figure 2. Working of CNN

4. LITERATURE REVIEW

Rangarajan et al. working on both AlexNet and VGG16 models, VGG16 achieving an accuracy of 96.19%, while AlexNet achieved a slightly lower accuracy of 95.81% [8].

Muhammad E.H Chowdhury et al. emphasize the necessity for automatic recognition systems that cater to the diverse needs of mobile phone users, highlighting the challenge of accurately extracting and identifying leaf region from complex backgrounds. This task becomes more difficult due to varying background patterns. To address this, the system collects 18,161 raw and segmented images of tomato leaves, which are then used in a deep learning architecture based on EfficientNet [9].

S. P. Mohanty et al. proposed a deep Convolutional Neural Network approach, which achieved an accuracy of 96.3%. The advantages of this method include improved classification accuracy. However, one limitation is that fine-tuning and data augmentation are necessary to further enhance the model's performance [10].

S. Ishak et al. conducted research aimed at classifying leaf diseases using artificial neural networks (ANN). The study focused on collecting and analyzing leaf images to identify healthy and diseased leaves from medicinal plants through image processing methods. Feature extraction was performed on the images, followed by the use of ANN for analysis [11].

Emanuel Cortes conducted research that uses a deep neural network in combination with semi-supervised methods to classify crop species and diseases of 57 different classes. The study uses a dataset containing 86,147 images of diseased and healthy plants [12].

S. A. Wallelign et al. uses the Convolutional Neural Networks (CNNs) for detecting diseases in soybean crops. The study uses a dataset of 12,673 images containing leaf images of four classes, including the healthy leaf images. The model achieved an accuracy of 99.21% [13].

G. Latif et al. uses the CNN model for detection of rice plant diseases. The study uses a dataset of 75000 collected images, 15000 of the five different varieties of rice [14].

M. Ahmad et al. uses the CNN for plant disease detection in an imbalanced dataset. It uses datasets of 54,309 images. 39,218 images belong to 5 major classes of diseases whereas 15,085 belong to healthy plant images [15].

S. M. Hassan et al. uses the Novel Convolutional neural Network for plant disease identification. The model has been trained and tested on three different plant diseases datasets. The performance accuracy obtained on plant dataset is 99.39%, on the rice disease dataset is 99.66%, and on the cassava, dataset is 76.59% [16].

5. METHODOLOGY

5.1 Overview of the Proposed Work

The primary objective of the proposed work is to develop automated systems for identifying plant diseases, classifying them into various categories to facilitate easier understanding. This section outlines the operation of the model across different stages. Figure 3 provides a concise summary of the proposed system, along with a detailed explanation of each component involved in the plant disease detection process. This system is broadly organized into four major parts starting from capturing image to image pre- and post-processing followed by leaf disease identification and classification.

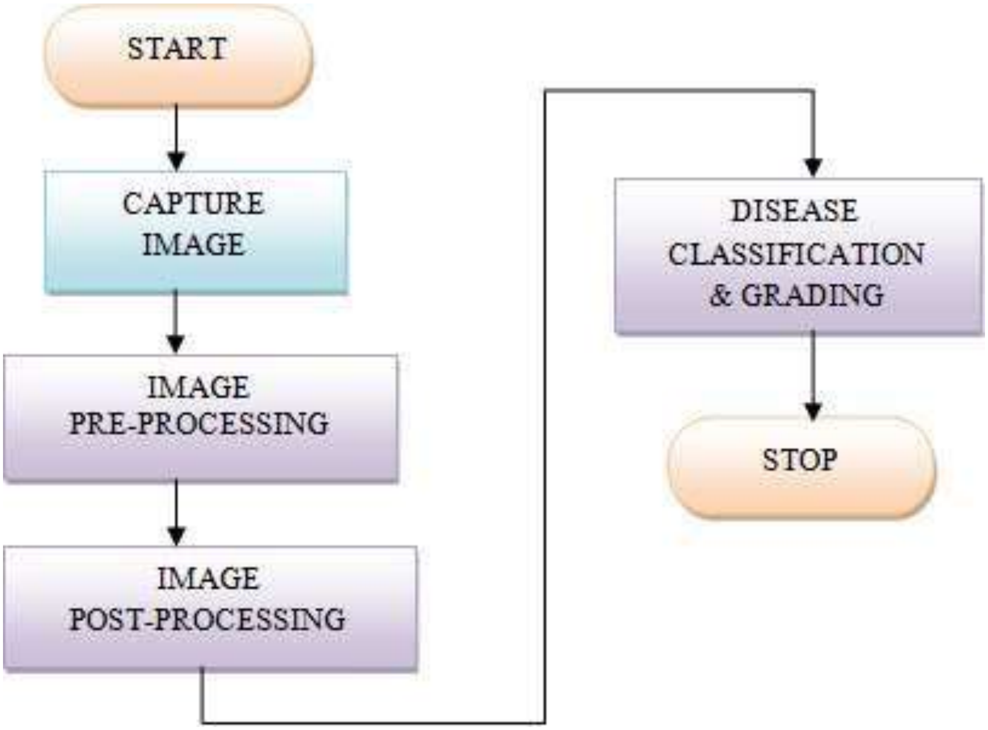

Figure 3. Steps for working model.

5.2 Data Gathering

Building a detailed and diverse dataset which includes healthy and infected leaf images for direct comparison forms the core goal of data collection among different plant species. An extensive collection of healthy and unhealthy leaf images draws primarily from Kaggle in addition to other real-world image libraries [17]. Figure 4 shows a sample of leaf images. In this work there are a total of 87900 RGB images of 14 different plants having 38 different types of diseases have been used.

Figure 4. Sample image of dataset

5.3 Data Pre-Processing

Data pre-processing transforms raw datasets into a training state by removing unwanted noise then strengthening data integrity before CNN Convolutional Neural Network (CNN) consumption.

5.4 Image Resizing

The altered leaf image collection requires uniform size adjustments to create standardized dimensions. Processing the data delivers equalized results while adapting it to CNN operation. Image normalization creates standard data values which normalize mean values to zero units and contribute to rapid network convergence while boosting CNN performance.

5.5 Balanced Data

Dataset consists of imbalanced distribution of classes so one type of image occurs often compared to others this can result in model bias which prioritizes the class with more occurrences. This problem has been solved by applying under sampling the majority class and oversampling the minority class. Rearranging the data frequency maintains a model that lends itself toward improved performance during training.

5.6 Data Splitting

The next step requires splitting the available data into independent training and validation and testing data sections.

- **Training Data**: A significant part of the available data serves as training material for the CNN model because the training process demands the majority allocation. For training purposes 70295 images are used.
- **Validation Data**: During training the model performs assessments using this data to determine its overall effectiveness. Validation uses 17572 images.
- **Test Data**: The model assessment occurs on this segment following its training operation concludes. The testing is done on 33 images.

5.7 Model Training

Convolutional Neural Networks (CNNs) are utilized to identify diseased leaves. During training, CNN learns to recognize patterns and features in leaf images, which it uses to classify new images as either healthy or diseased. The network is trained on an extensive dataset containing both healthy and diseased leaves, allowing it to differentiate between the two categories. The architecture generally consists of several convolutional and pooling layers, culminating in a fully connected layer that outputs the final classification.

5.8 Algorithm for Plant Disease Detection System

Step 1: Import Required Libraries

IMPORT streamlit as st

IMPORT tensorflow as tf

IMPORT numpy as np

Step 2: Define Function for Model Prediction

```
DEFINE FUNCTION model_prediction(test_image):
    LOAD trained model ("trained_plant_disease_model.keras")
    LOAD test_image and RESIZE to (128,128)
    CONVERT image to array
    EXPAND dimensions to create batch
    PREDICT using model
    RETURN index of highest probability prediction
```

Step 3: Create Streamlit Sidebar

```
st.sidebar.title("Dashboard")
app_mode ← SELECT from ["Home", "About", "Disease Recognition"]
```

Step 4: Define Home Page

```
IF app_mode == "Home":
    DISPLAY HEADER: "PLANT DISEASE RECOGNITION SYSTEM"
    DISPLAY Home Page Image
    DISPLAY Description about the project:
        - Upload an image
        - System detects plant disease
        - Provides results & recommendations
```

Step 5: Define About Page

```
ELSE IF app_mode == "About":
    DISPLAY HEADER: "About"
    DISPLAY Dataset Information:
        - 87900 images in 38 classes
        - Training: 70295, Validation: 17572, Test: 33
```

Step 6: Define Disease Recognition Page

```
ELSE IF app_mode == "Disease Recognition":
    DISPLAY HEADER: "Disease Recognition"
    test_image ← UPLOAD Image
        IF "Show Image" button is clicked:
         DISPLAY Uploaded Image
      IF "Predict" button is clicked:
        DISPLAY Snow Animation
        DISPLAY "Our Prediction"
        result_index ← CALL model_prediction(test_image)

        DEFINE class_names = [List of 38 disease classes]

        DISPLAY Predicted Disease using class_names[result_index]
```

6. RESULTS AND DISCUSSION

Model : Sequential_18		
layer (type)	output Shape	param#
conv2d_124 (conv2D)	(None, 128,128,32)	869
conv2d_125 (conv2D)	(None, 126,126,32)	9284
max_pooling2d_62 (Max Pooling2D)	(None, 63,63,32)	0
conv2d_126 (conv2D)	(None, 63,63,64)	18496
conv2d_127 (conv2D)	(None, 61,61,64)	36928
max_pooling_63 (MaxPooling2D)	(None, 30,30,64)	0
conv2d_128 (conv2D)	(None, 30,30,128)	72856
conv2d_129 (conv2D)	(None, 28,28,128)	147584
max_pooling_64 (Maxpooling2D)	(None, 14,14,128)	0
conv2d_130 (conv2D)	(None, 14,14,256)	295168
conv2d_131 (conv2D)	(None, 12,12,256)	590080
max_pooling_65 (MaxPooling2D)	(None, 6,6,256)	0
conv2d_132 (conv2D)	(None, 6,6,512)	1180160
conv2d_133 (conv2D)	(None, 4,4,512)	2359808
max_poolin_65 (MaxPooling2D)	(None, 2,2,512)	0
dropout_45 (Dropout)	(None, 2,2,512)	0
flatten_26 (Flatten)	(None, 2048)	0
dense_34 (Dense)	(None, 1500)	3073500
dropout_46 (Dropout)	(None, 1500)	0
dense_35 (Dense)	(None, 38)	57038
total params : 782762 (29.92 MB)		
trainable params : 782762 (29.92 MB)		
Non-trainable : 0 (0.00 Bytes)		

Figure 5. Model Summary

Figure 5 provides a summary of the model details and all relevant parameters. The number of parameters is 7,842,762, with all of these parameters being trainable, as there are no non-trainable parameters in the model.

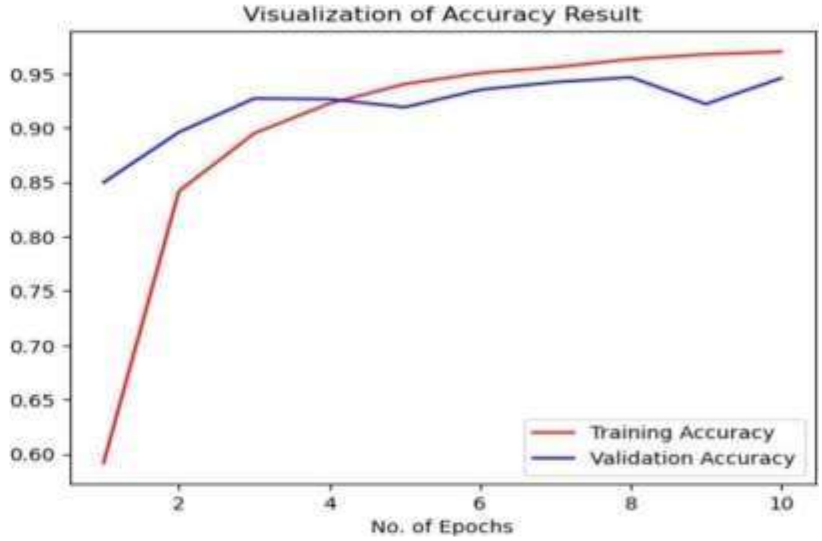

Figure 6. Graphs for accuracy

Figure 6 gives information about how visualization of result accuracy through evaluated the images internally up to 10 epochs.

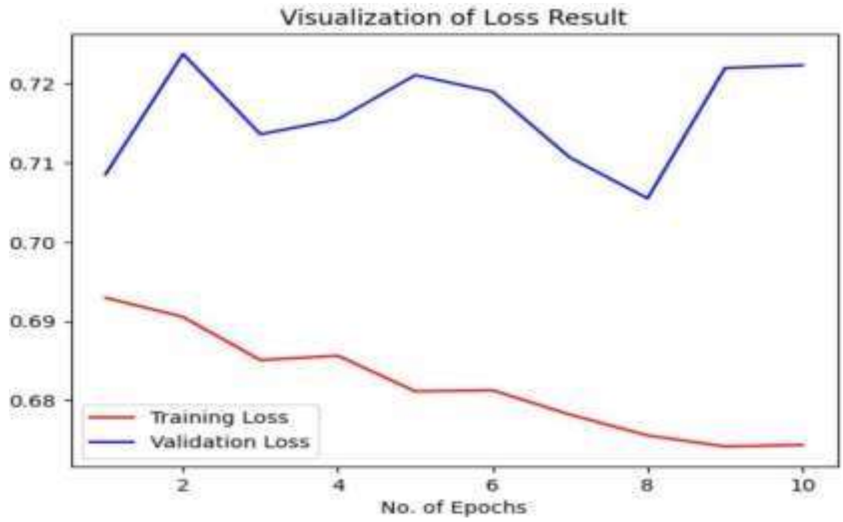

Figure 7. Graphs for Loss

Figure 7 gives information about visualization of result accuracy through evaluating the images internally up to 10 epochs.

Class Name	Precision (%)	Recall (%)	F1-Score (%)
Apple Apple scab	100	84	91
Apple Black rot	96	98	97
Apple Cedar apple rust	95	99	97
Apple___healthy	85	93	89
Blueberry___healthy	85	99	92
Cherry (including sour) Powdery mildew	100	89	94
Cherry (including sour) healthy	95	97	96
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	96	89	92
Corn (maize) *Common rust*	100	98	99
Corn_(maize)___Northern_Leaf_Blight	90	98	94
Corn (maize) healthy	100	99	99
Grape___Black_rot	100	94	97
Grape___Esca_(Black_Measles)	98	99	98
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	96	100	98
Grape___healthy	99	99	99
Orange___Haunglongbing_(Citrus_greening)	93	99	96
Peach Bacterial spot	91	95	93
Peach___healthy	94	99	96
Pepper,_bell___Bacterial_spot	99	89	93
Pepper, bell healthy	99	81	89
Potato___Early_blight	99	94	96
Potato Late blight	90	98	94
Potato___healthy	91	97	94
Raspberry___healthy	89	100	94
Soybean healthy	95	99	97
Squash___Powdery_mildew	100	92	96
Strawberry___Leaf_scorch	96	96	96
Strawberry___healthy	98	98	98
Tomato___Bacterial_spot	97	96	96
Tomato Early blight	85	90	87
Tomato Late blight	86	91	89
Tomato Leaf Mold	98	94	96
Tomato___Septoria_leaf_spot	95	82	88
Tomato___Spider_mites Two-spotted spider mite	89	97	93
Tomato___Target_Spot	92	88	90
Tomato Tomato Yellow Leaf Curl Virus	99	98	99
Tomato___Tomato_mosaic_virus	100	91	95
Tomato___healthy	97	98	98
Overall Accuracy			95
Macro Accuracy	95	95	95
Weighted Accuracy	95	95	95

Figure 8. Evaluation Metrics

Figure 8 outlines the evaluation metrics used for detecting leaf diseases under different conditions like Apple scab, healthy Apple, Grape black rot, Potato early blight, and Peach bacterial spot etc. The metrics include precision, recall, and F1-score, which evaluate the model's performance and accuracy in disease detection. Figure 8 also provides a summary of the model's effectiveness, including overall accuracy, macro and weighted averages, along with the results for leaf disease detection.

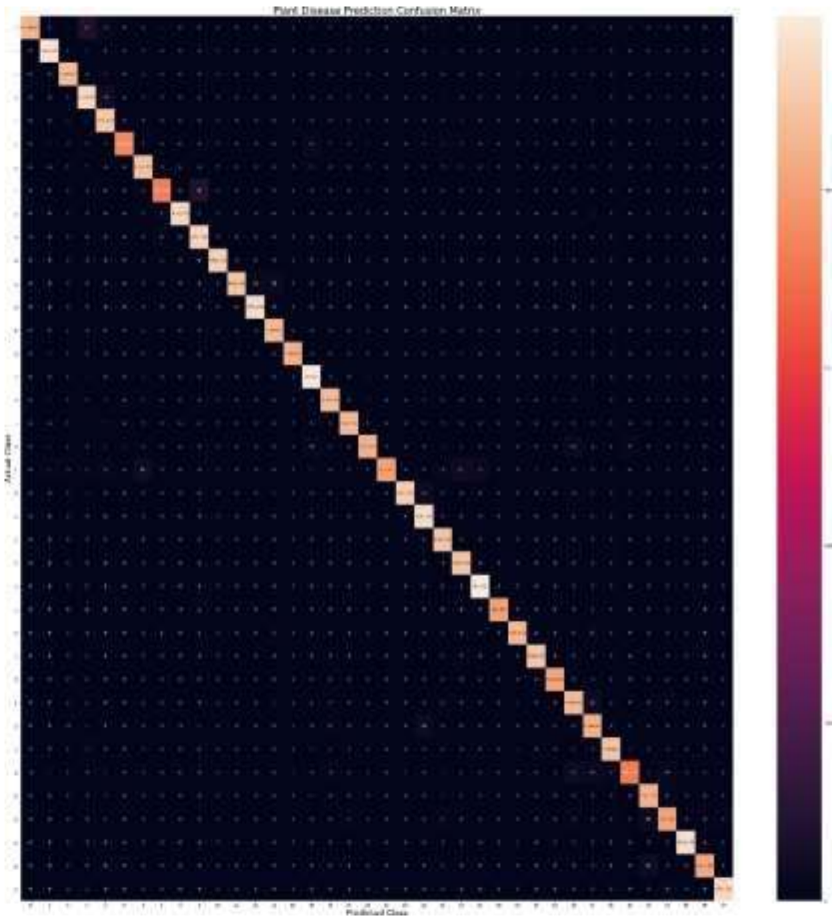

Figure 9. Confusion Matrix

Figure 9 shows the performance of the CNN model for different disease types. The confusion matrix presents actual classes on its rows and predicted classes on its columns. The evaluation matrix presents total data about model performance in dealing with the dataset before evaluating metrics. The matrix shows how predictions match with actual classes for better disease classification assessmen

7. COMPARATIVE ANALYSIS

Table 1: Comparative analysis of different models

Author(s)	Aim	Dataset	Methodology	Accuracy
Rangarajan et al. [8]	To train AlexNet and VGG16n et for plant disease detection, focusing on batch size impact.	Dataset of 54,306 images.	AlexNet and VGG16net trained with varying batch sizes, learning rates for weight, and bias	99.35% accuracy
Chowdhury, M.E. et al. [9]	Automatic recognition and segmentation of leaf regions from complex backgrounds.	Dataset of 18,161 images.	Efficient Net-based deep learning architecture to process segmented and complex leaf images.	99.89% accuracy
Mohanty, S.P. et al. [10]	To classify plant diseases using a deep Convolutional Neural Network.	Dataset of 14 types of plants.	CNN methodology trained with augmentation; fine tuning required for improvements.	96.35% accuracy

Ishak, S. et al. [11]	Classification of healthy or diseased medicinal plant leaves using ANN and image processing.	Data extracted using segmentation, contrast adjustment, and feature extraction algorithms.	Multilayer Feed Forward Neural Networks: Multilayer Perceptron (MLP) and Radial Basis Function (RBF).	90.3% accuracy
Emanuel Cortes [12]	Classification of plant species and diseases using semi supervised learning and DNNs.	Dataset of 86,147 images.	Deep Neural Network, Semi-supervised algorithms rs-net with unlabeled data for experiments	80% accuracy
Wallelign, S. et al. [13]	Soybean disease detection using CNNs in natural environments.	Dataset of 12,673 images.	Soybean disease detection using CNNs in natural environments.	99.21% accuracy on classification
Latif, G. et al. [14]	Rice plant disease detection using DCNN.	Dataset of 75000 images.	Using VGG19 based learning method for detection accurately.	96.08% accuracy
Ahmad, M. et al. [15]	Classification of plant disease symptoms using CNN.	Dataset of 54,309 images.	Using DL approach to classify plant disease.	99.69% accuracy
Hassan, S.M. et al. [16]	Identification of plant disease using novel convolutional neural network.	The model has been trained and tested on only three plant datasets.	Using CNN to classify diseases in plants.	99.66% accuracy
Propose Model	Plant Disease Detection Using CNN	The model has been trained on a large dataset in which 87,900 RGB images have been used, which include 14 different types of plants having 38 different types of plant diseases.	Using CNN to identify the disease in plants.	The proposed model gives 94.65% average accuracy on a huge number of plants and their various types of diseases as compared to other existing models.

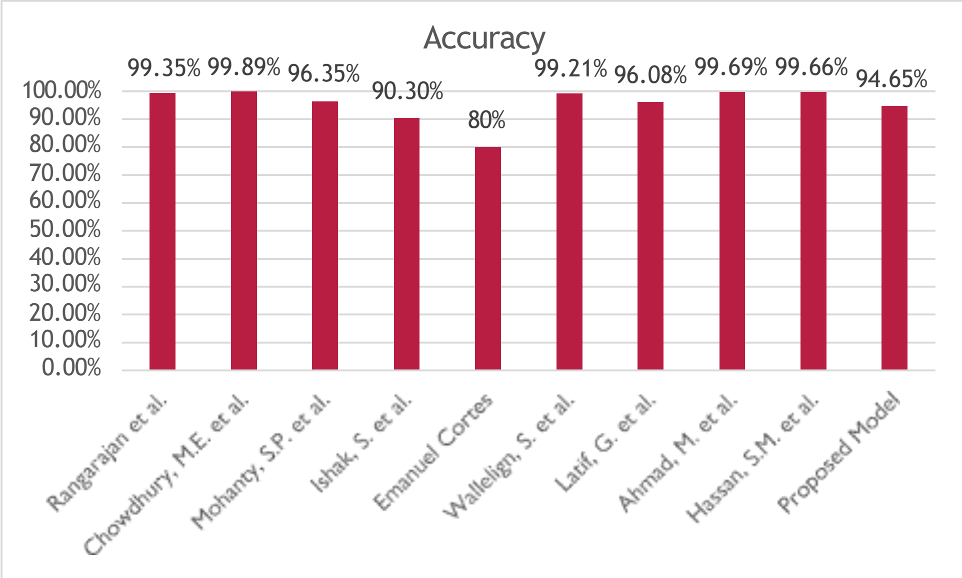

Figure 10. Comparison of the accuracy of different models

Table 1 and Figure 10 shows the accuracy of the models of different authors. The proposed model achieved an average accuracy of 94.65%. This model is capable of to detect the plant disease of 14 different plants. Also, this model is trained to detect 38 types of plant diseases of 14 such plants. Also, this model can easily classify the healthy and diseases plants. The highest accuracy of this model is 99.99% while the lowest accuracy is 84%. When compared with the other existing models it is found that the size of the dataset that is used by other models is very small. Also, the number of plants and types of diseases considered by the other models are very small compared to the proposed model.

8. CONCLUSION

The proposed plant disease detection system achieves an average accuracy of 94.65% on 38 different plant diseases of 14 plants with an F1 score of 94.61%, Recall of 94.66%, and Precision of 94.92% respectively.

- **Efficiency**: The proposed system runs efficiently with straightforward implementation that enables accessibility directly to farmers through any available computer system. The affordable methodology remains essential in agricultural settings since it enables early detection of diseases to affect crop production levels and financial outcomes positively.
- **Automated Monitoring**: Automation of disease detection by the system helps reduce both the requirement for manual labor and trained expert knowledge. Live monitoring of extensive agricultural regions becomes possible through this method which lets interventions start immediately after detecting diseases.
- **Versatility**: Through its ability to detect numerous diseases in various plant types with one unified approach the system showcases its broad application potential. This dataset of 87,000 leaf images supports the system's reliability and robust design.

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