Automated Banana Plant Leaves Disease Classification Using Deep Learning Technique

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Certificate

This is to certify that ***Aradhana Kumari with Roll No.1906033****,* ***Lovely Kumari with Roll No.1906034****,* ***Rishita Singh with Roll No.1906022*** *have carried out the Seminar and Technical writing entitled* ***"Automated Banana Plant Leaves Disease Classification Using Deep Learning Technique"*** *during their 7th semester under the supervision of* ***Dr. Rajib Ghosh****, Assistant Professor Grade-I, CSE Department, in partial fulfillment of the requirements for the award of Bachelor of Technology degree in the Department of Computer Science Engineering, National Institute of Technology Patna.*

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Declaration & Copyright

We, the students of the 7th semester, hereby declare that we have completed the minor project II entitled ***"Automated Banana Plant Leaves Disease Classification Using Deep Learning Technique"*** *has been carried out by us in the Department of Computer Science and Engineering of the National Institute of Technology Patna under the guidance of* ***Dr. Rajib Ghosh****, (Assistant Professor Grade-I) of Computer Science and Engineering, NIT Patna. No part of this project has been submitted for the award of the degree or diploma to any other Institute.*

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Abstract

One of the key agricultural activities in India is the production of bananas. However, this crop has been hampered by a number of diseases,early detection of infections is necessary to prevent financial damage to the farmers. This issue has a direct impact on the nation's economy and will reduce overall banana productivity. Therefore, it is paramount to diagnose and detect these disorders at an early stage. This article proposes a DL model which contains convolution neural network layers (CNN) followed by recurrent neural network (RNN) layers to identify and categorise diseases found in banana plants. The convolution neural network (CNN) generated the feature matrix, and the recurrent neural network predicted the proposals (RNN). The spots on the leaves have been located using pooling layers, which extracts regions of interest. The suggested Automated Banana Plant Disease Classification system's performance was evaluated using dataset from Kaggle which included banana leaves from a variety of both healthy and infected banana plants, and it achieved an f-measure of 99.98%. The suggested system outperforms the current approaches to disease classification, according to experiment results.

Contents

Chapter 1

Introduction

Food is a vital resource for humanity, and agriculture is one of the key elements that determine a nation's economy. For the majority of emerging nations, agriculture is regarded as their primary source of revenue. Agriculture's resources are under a lot of stress as a result of the growing global population. In order to maintain the population and the economy, agricultural yield must be maximised. The primary cause of plant damage that results in financial and production losses in agricultural areas is plant diseases. Plant infections are more frequent now because of the poor climatic and environmental conditions. Plant diseases can have a wide range of symptoms, including spots or smudges that appear on the leaves, seeds, or stems of the plant. The introduction of an automated technique of plant monitoring that can monitor plant conditions and use knowledge-based solutions to detect and categorise numerous diseases is necessary to effectively manage these diseases. The production of bananas, often known as the banana industry, is a significant component of the worldwide agro-business since bananas are a source of many minerals, including calcium, manganese, potassium, magnesium, and iron. People all across the world use this particular crop since it contains so many vitamins and is regarded as an instant energy booster.

According to Wikipedia figures, 15% of the world's banana crop is exported for consumption to western nations. According to statistics on banana production and export, roughly 25.7%. of the world's bananas are produced in India, with the Philippines, Ecuador, Indonesia, and Brazil rounding out the top five producers with a combined contribution of about 20%. About 18% of all banana imports worldwide are made in

the United States, making it the largest importer. The impact of disease and other climate changes infecting banana trees would result in a loss of up to 100% of the global production and export of bananas. Plant diseases are thought to be responsible for annual crop yield losses of up to 100% over the world. Furthermore, the widespread use of crop protection products—which are harmful to the environment and users—is required by the present approaches to managing various diseases. The identification and discovery of various diseases can be accomplished with the help of microscope and DNA sequencing techniques. These infections and pests have a wide range of symptoms. Diseases can be seen in certain crops in the early stages, but in others they won't be seen until later since there won't be a chance to save the crop. Consistent plant monitoring reduces yield loss while also maintaining plant quality and assisting in the early detection of pests and diseases. To prevent these inconveniences and have user-friendly suggestions, automated disease detection can be a viable solution.
However, identifying and detecting diseases in banana plants is a difficult task that includes issues listed below.

1. It is frequently quite difficult to appropriately segment the region of interest where the symptoms are present because of elements in the background. One of such document images is presented in Figure 1.1.

FIGURE 1.1: Banana leaf image with noisy background.

2. Capture conditions are difficult to control, which may cause the images to present characteristics that are difficult to predict and make the disease identification more challenging which is presented in Figure 1.2.

FIGURE 1.2: Banana leaf image containing disease symptoms on the area which is difficult to capture.

3. The majority of symptoms gradually dissolve into healthy tissue rather than having sharp borders, making it challenging to distinguish between healthy and diseased regions. One of such situations is illustrated in Figure 1.3.

FIGURE 1.3: Banana leaf image having symptoms with indistinguishable borders.

4. It is possible for symptoms caused by various diseases to appear at the same time, appearing either physically apart or mixed into a "hybrid" symptom that may be challenging to recognise. The approaches must rely on very slight distinctions to distinguish between them because the symptoms caused by various diseases may look similar.One of such situations is illustrated in Figure 1.4.

FIGURE 1.4: Banana leaf image having hybrid symptoms.

Several investigations have been reported[1], regarding disease detection and classification. The primary drawback of the current system is that the majority of works use image processing methods that necessitate time-consuming, complicated picture segmentation stages. Many diseases don't have distinct edges where they manifest themselves and instead may blend in with the healthy leaf tissue, making it difficult to detect them using current methods and requiring the use of a powerful classification system. There are specific ways that are available that are exclusively applicable to certain types of crops. The disease has been detected using many approaches like ANN, KNN and other image processing algorithms is lacking, and they typically take more time to classify the disease.

The contributions of the proposed work are given below.

1. Proposal of pretrained ResNet-101 model, a deep learning method, for classifying the banana images.
2. The Residual network (Resnet-101) backbone architecture has been used to produce four output classes, they are healthy, Cordana, Pestalotiopsis and Sigatoka.
3. Evaluation of state-of-the-art methods in banana plant leaf disease classification using ResNet-101 model is used in the present work.

The remaining portions of the report is organized as follows: the different plant leaf diseases classification using different deep learning models are discussed in Chapter 2. The dataset description is provided in Chapter 3. Chapter 4 infers our proposed work. Evaluation metrics of this work are stated in Chapter 5. Finally, conclusion of this work is stated in Chapter 6.

Chapter 2

Literature Survey

Detection and categorization of the banana leaf disease has been a problem for a very long time, and several types of study have been conducted in this area. Amara el al. [1] proposed an automated system for classifying illnesses in banana leaves based on deep learning. LeNet architecture in particular has been applied to identify image datasets using convolutional neural networks. The initial result shows that the suggested approach is effective even in difficult situations like lighting, complicated backgrounds, and varying resolutions, sizes, poses, and orientations of real scene photos. In 25 rounds, this approach stabilises and, in the final iteration, reaches a good level of accuracy. An artificial intelligence-based method for detecting banana diseases and pests was proposed in [2]. Here, a deep convolutional neural network is used as the disease detection algorithm, and data sets for about 8 different banana diseases have been used. In total, 30,000 images were used as the data set. The proposed system achieves a 90%. accuracy rate. In [3], an image processing-based method for detecting banana plant leaf disease is proposed. Images are first acquired, the RGB colour model is converted into an HSI colour model, and this is followed by preprocessing. Next, the image is segmented using the thresholding method, and the histogram equalisation is discovered for HSI image. The classification is then contrasted with three more classifiers, including back-propagation neural networks, support vector machines, and principal component analysis (PCA).

In another study [4] SVM classifier in a machine learning-based method for early banana plant leaves disease diagnosis. Close-range hyperspectral remote sensing images are those employed in this instance. Overall accuracy is used to assess the performance of the classifiers, and in this case, the average accuracy is the accuracy based on spectral and morphological data, which is approximately 96% in early detection, 90% in mid-detection, and 92% in late detection.The primary goal of this research [5] is to use deep learning methodology to identify obvious banana diseases in banana plants. to accurately categorise the type of disease. It will offer a treatment for the disease that is discovered by building a database of insecticides for the appropriate pests and diseases. Given that CNN and SVM are the best classifiers currently in use, a hybrid model integrating both techniques can result in faster performance.In another study [6], two approaches are used, and the results of their simulations are contrasted to evaluate performance. The images from the PlantVillage data set (for apple, maize, potato, tomato, and rice plants) are enhanced with data in the first section, and convolutional neural networks are used to extract the deep features of the plants' deep features (CNN). A Bayesian optimal support vector machine classifier is used to categorise these features, and the outcomes are measured in terms of precision, sensitivity, accuracy, and f-score.CNN-related rice blast recognition method is proposed in a study [7] .

This method's accuracy was evaluated using a variety of combinations, including CNN alone, CNN with SVM, LBPH with SVM, and Haar-WT with SVM. The results indicate that CNN with SVM provides an accelerating accuracy of roughly 96% AUC curve that reads 0.99.This article [6],offers several approaches for spotting plant diseases using image processing. The suggested system also has a module that recognises the Panama wilt and Blacksigatoka diseases on banana leaves. The ANFIS classifier was used to grade the diseases. The comparison of classifiers has been completed using a confusion matrix.Automatic plant disease identification and classification is to development of automated computer vision or machine vision system with the use of image processing technique.

In this paper [8], convolutional neural network models were created applying deep learning techniques to detect and identify plant diseases using straightforward images of healthy and diseased leaves. The best model architecture out of the ones that were trained identified the corresponding [plant, disease] pair with a success percentage of 99.53% (or healthy plant).

In the Table 2.1, various studies have been analysed and discussed.

TABLE 2.1: Various studies analysis

Study	**Task**	**Features**	**Classifier**
Amara et al[1]	A Deep Learning based approach for banana leaf diseases classification	Convolutional	LeNet architecture
Selvaraj et al[2]	AI-powered banana diseases and pest detection	Convolutional	ResNet50, InceptionV2, MobileNetV1
Narayana et al[4]	Banana plant disease classification using hybrid convolutional neural network	Convolutional	Deep Learning based hybrid CNN
Liang et al[3]	Rice blast disease recognition using a deep convolutional neural network	Convolutional	CNN
Ferentinos et al[8]	Deep learning models for plant disease detection and diagnosis	Convolutional	CNN
Liao et al[7]	Banana Disease detection by fusion of close range hyperspectral image and high-resolution and rgb image	KNN classifier	KNN classifier

Chapter 3

Dataset Description

3.1 Data Description

The dataset used in this project is taken from kaggle [1]

The data has 4 categories of banana plant leaves:

1. Healthy (89 images)
2. Cordana (122 images)
3. Pestalotiopsis (133 images)
4. Sigatoka (433 images)

[1]"https://www.kaggle.com/datasets/kaiesalmahmud/bananaleaf-dataset"

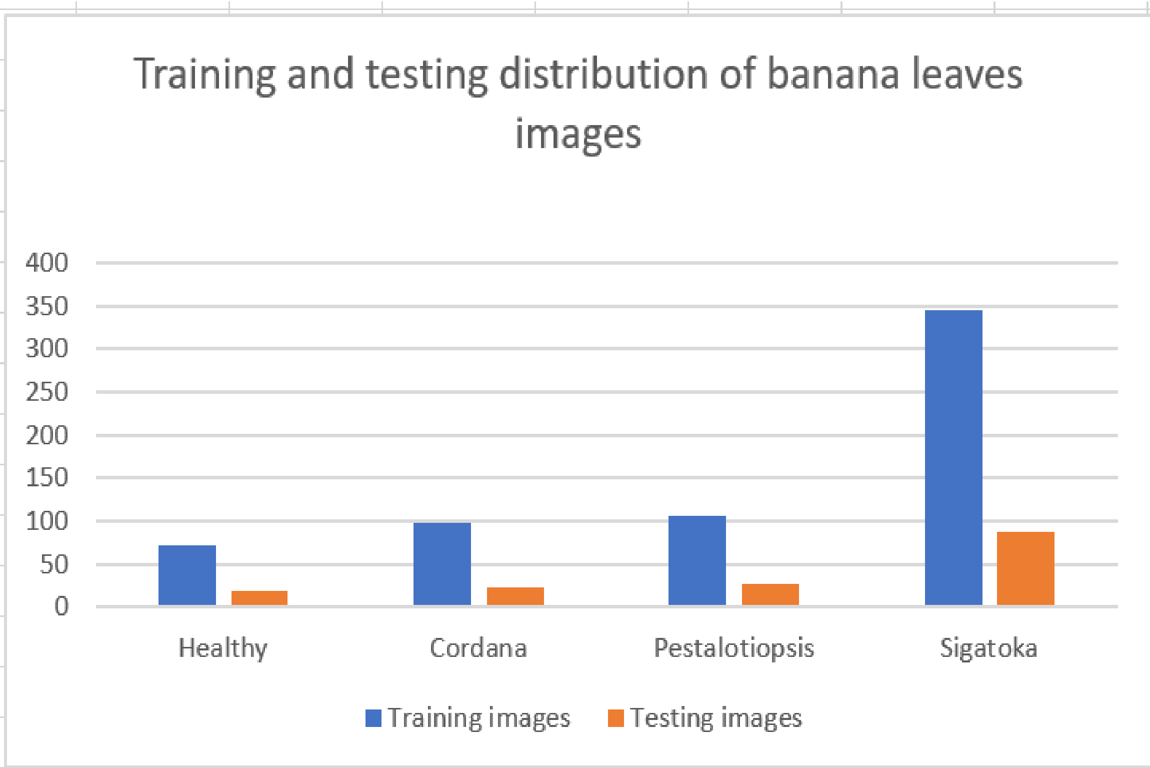
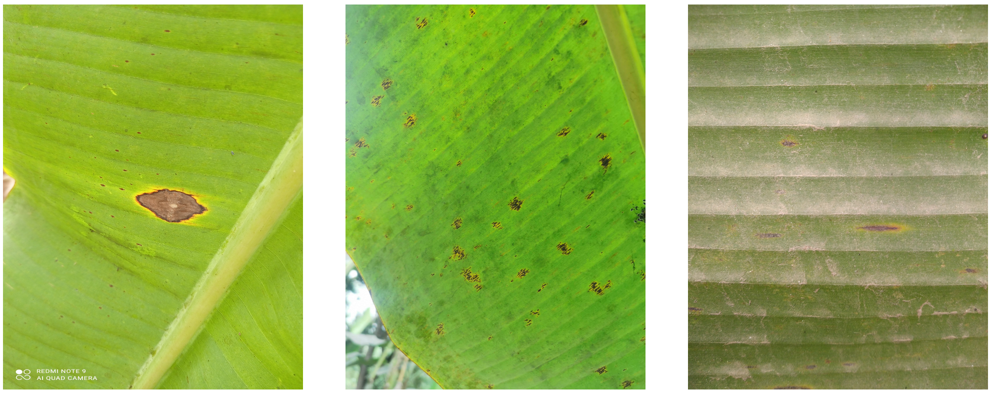


FIGURE 3.1: Dataset

Disease Description

Cordana: Cordana is caused by two Neocordana fungi that are often found as secondary invaders of leaf lesions caused by other fungi. The two Neocordana species that are responsible for cordana leaf spot symptoms are Neocordana musae and Neocordana johnstonii.The symptoms are large, palebrown, ovaltwo, fusiforn necrotic lesions with pale grey concentric ring pattern, with a dark brown border surrounded by a bright yellow halo. The symptoms caused by N. musae are larger and oval to elliptical in shape, while those caused by N. johnstonii are generally smaller and become more fusiform with age.

Pestalotiopsis: Pestalotiopsis is cost due to fungal infection in banana plant. The fungus causes leaf spots, petiole/rachis blights and sometimes bud rot of palms. Unlike other diseases, Pestalotiopsis attacks all parts of the leaf from the base to the tip.



(A) Cordana (B) Pestalotiopsis (C) Sigatoka

Figure 3.2: Banana plant leaves diseases

Sigatoka: Sigatoka is a foliar disease of banana caused by the fungus Pseudocercospora fijiensis. Sigatoka disease in banana leaves appears as small dark brown spots or lines on the underside of third or fourth opened leaf, these spots sunken surrounded by a yellow halo. Overtime, these spots or streaks expand and become brown or black and make a characteristic black patch on the leaves. This is a serious disease of bananas that can result in a severe reduction in fruit yield.

Chapter 4

Proposed Methodology

For early detection of diseases we used a deep learning based approach, pretrained ResNet-101 model is used to classify the banana plant leaves diseases. The general architecture of ResNet-101 model is depicted in Figure 4.2. ResNet-101 model is 101 layers deep. ResNet-101 model may have multiple blocks, each containing a certain number of convolutional layers , and pooling layers between blocks. The number of layers inside each block is computed using some mathematical operations. The schematics of the ResNet-101 architecture includes 33 residual nodes in total. The residual node serves as a building block for the ResNet-101 architecture. Residual block contains stack of convolutional layers set in such a way that the output of a layer is taken and added to another layer deeper in the block, in this wat it allows memory(or information) to flow from initial to last layers.

Deep learning based classification Neural networks contains multiple neurons arranged in layers. The neurons in the adjacent layers are connected to each other. These neurons learn how to convert inputs (preextracted and pre-processed features) into corresponding output (labels). In particular, convolutional neural networks (CNNs) are a family of multilayered neural networks and are considered as the first successful trial for deep learning approachs where many layers of a hierarchy are successfully trained in a robust manner.

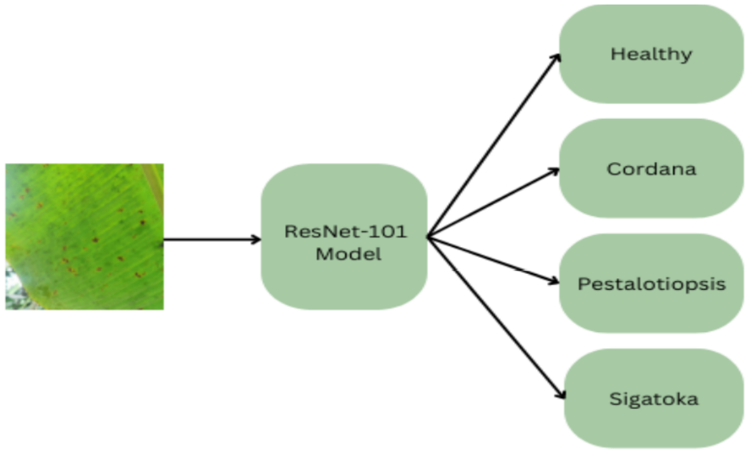


FIGURE 4.1: Banana plant leaf disease classification deep learning model.

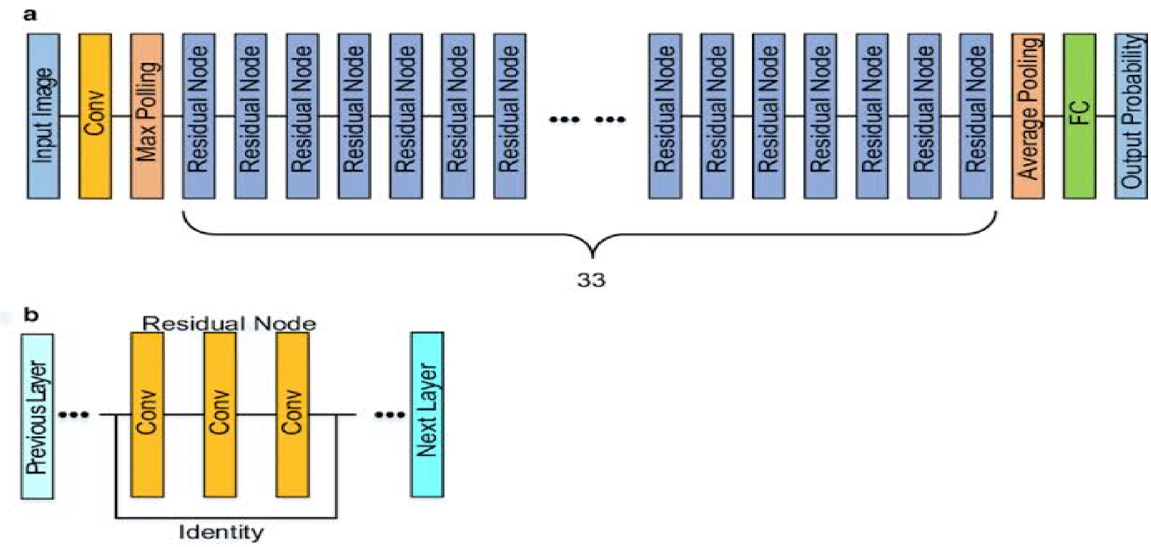


FIGURE 4.2: (a) Resnet-101 architecture (b) Architecture of residual node present in ResNet-101

Chapter 5

Experimental Results and Analysis

This chapter describes the dissertation's implementation and results, in which we examine the dataset used, comment on the implementation and end result, and attempt to compare these results to state-of-the-art results.

5.1 Result Analysis

To evaluate the performance of the this model, a set of quantitative metrics comprising of accuracy, precision, recall and F1-score have been used. They show the highest values of the quantitative metrics obtained until the corresponding epoch number.

Evaluation Metrics: For evaluating the proposed model we used precision, recall, F1-score, support and accuracy. We have used classification report and confus, these metrics are widely used for evaluating supervised machine learning models for classification when the dataset is multi labelled. Suppose a multi-labeled dataset consists of N number of instances, where each instance Ni is given by (xi,yi), where xi represents the set of attributes and yi represents the set of labels. Let us say that yi and yi' represent the labels which are true and labels which are predicted respectively for the ith instance then the metrics can be described for the ith instance which are by the following formulae.

Accuracy: Accuracy is also used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition. That is, the accuracy is the proportion of correct predictions (both true positives and true negatives) among the total number of cases examined.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.1}$$

Precision: It is the ratio of accurately predicted authors as hate speech spreaders or not to the total number of predicted authors. It is computed as given in the equation below.

$$Precision = \frac{TP}{TP + FP} \tag{5.2}$$

Recall: It is the ratio of accurately predicted authors as hate speech spreaders or not to the total number of authors. It is computed as is given in the below equation.

$$Recall = \frac{TP}{TP + FN} \tag{5.3}$$

F1-score: The harmonic mean between Precision and Recall is called F1-Score, which gives the balanced equation between them. It can be represented by the below equation.

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \tag{5.4}$$

To validate the performance of the ResNet-101 which is 101 layers deep, we conducted a set of experiments using a real dataset of banana diseases obtained from kaggle [1]. The dataset contains four categories of banana leaves that is healthy (89 images), cordana (122 images), pestalotiopsis (133 images) and sigatoka (433 images). The dataset is

[1]"https://www.kaggle.com/datasets/kaiesalmahmud/banana-leaf-dataset"

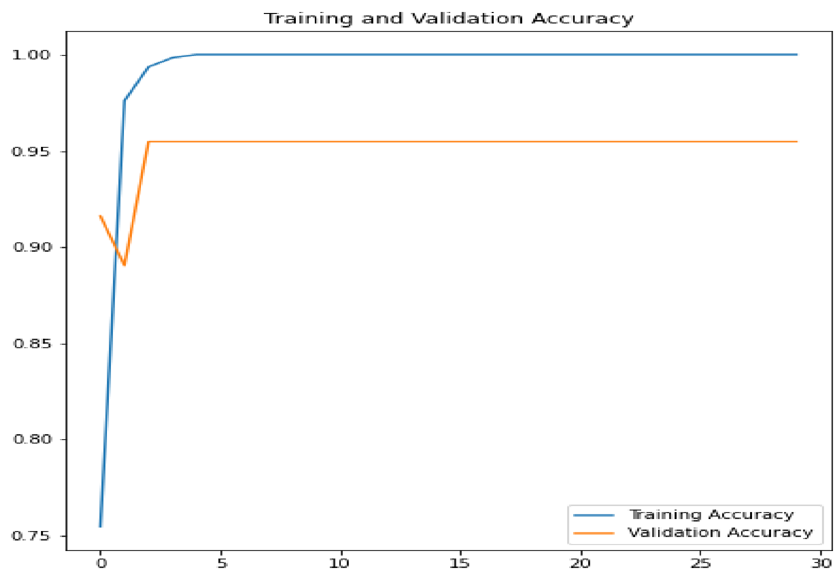


FIGURE 5.1: Comparison of training accuracy and validation accuracy

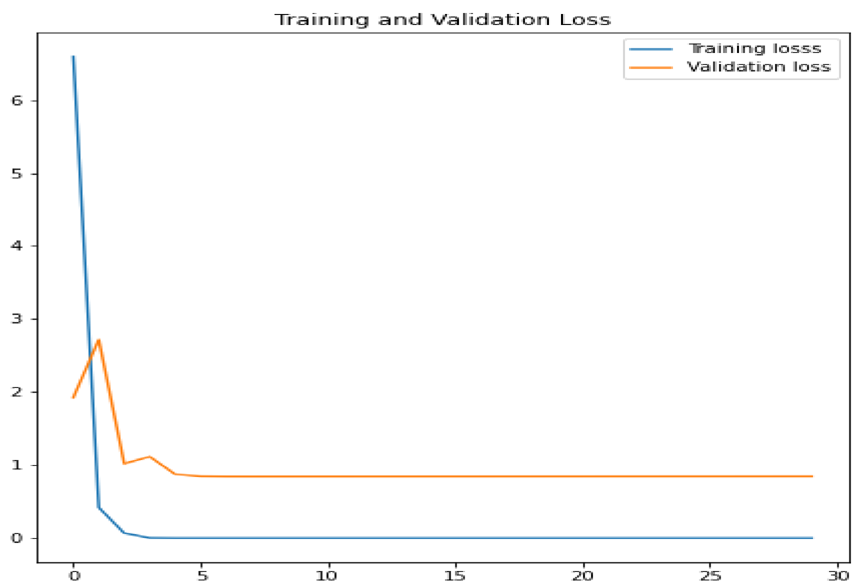


FIGURE 5.2: Comparison of training loss and validation loss

Table 5.1: Comparison with other models

Method	**Result**
VGG16	76%
VGG19	78.75%
Optimised CNN(2 layers)	73.75%
Optimised CNN LSTM(2 Conv2d layers+ 2 LSTM layers)	55%
Optimised CNN GRU(3 Conv2d layers + 2 GRU layers	61.25%
ResNet50	85%
ResNet101	**91.25%**

trained over pretrained model ResNet-101 which will classify the model into four classes. A highest training accuracy of 97% was obtained over 30 epochs of training and overall testing accuracy was obtained to be 91.25%. The plot of train and test accuracy and loss against the epochs provide a means of visualization and indication of the speed of model convergence.

We also trained our model on various models. An accuracy of 76% was obtained over VGG16, 78.75% over VGG19, 85% over ResNet-50, 73.75% over optimised CNN model which got an optimal value of convolution layer as 2 when passed an range of [1, 4], 55% over optimised CNN-LSTM for which we got an optimal value of convolution layer as 2 and for, lstm layers as 2 when passed an range of [1, 3], the pre-trainedimised CNN-GRU model which got an optimal value of convolution laTheer as 3 when passed an range of [1, 4] and for GRU layers as 2 when passed an range of [1,3].

In the Table 5.2, state-of-art of various studies is compared with ResNet-101 model for banana plant leaves diseases accuracy.

Table 5.2: Comparison with state-of-art of various studies

Study	**Disease**	**Features**	**Classifier**	**Accuracy**
Amara et al[1]	Black Sigatoka, Black Speckle	Convolutional	LeNet architecture	92.88%
Selvaraj et al[2]	Xanthomonas wilt of banana (BXW), Fusarium wilt of banana (FWB), black sigatoka (BS), yellow sigatoka (YS) and banana bunchy top disease (BBTV)	Convolutional	ResNet50, InceptionV2, MobileNetV1	70.38% 70.18% 61.99%
Narayana et al[4]	Xanthomonas wilt, Pusarium wilt, Bunchy top virus, Black sigatoka	Convolutional	Deep learning based hybrid CNN	90%
Liang et al[5]	Rice ragged stunt, False smut, Blast (leaf and collar), Sheath blight.	Convolutional	CNN	95%
Ferentinos et al[8]	58 different classes of [plant, disease] combinations	Convolutional	CNN	99.53%
Proposed	**Cordana, Pestalotiopsis, Sigatoka**	**Convolutional**	**ResNet-101**	**91.25%**

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

The field of agriculture suffers from severe problem, plant diseases which affects the production and quality of field. So there is an urgent need to detect the plant diseases at the early stage with viable solutions. In our report, an approach based on deep convolutional neural network is presented to classify banana diseases.

Our main contribution is to apply deep neural networks to detect healthy or three famous banana diseases which are Cordana, Pestalotiopsis and Sigatoka. The ResNet-101 model shows an average performance of an overall accuracy of 91.25% with a decent precision, recall and f1-score which is better than other models discussed in the table, which shows that ResNet-101 model is a better choice.

6.2 Future Scope

This project could be further extended to develop a fully automated mobile app to help millions of banana farmers in developing countries. Encouraged by the obtained results, we intend to test more banana and plant diseases in our model in our future work.

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