



## An Intelligent Computer Vision System for Multi-Crop Plant Disease Detection Using Convolutional Neural Networks

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### ABSTRACT

Plant diseases are influenced by environmental and climatic changes and represent a major natural threat that disrupts plant growth and can lead to plant death from the early stages of seed development through maturity. Many plant disorders are difficult to detect without adequate expertise, and farmers and plantation growers often lack the professional knowledge and resources required for accurate disease identification and management. To address this challenge, this study developed a convolutional neural network (CNN) model for the detection and classification of 24 plant diseases across five major crop species: banana, corn, rice, potato, and tomato. The primary objective was to create an accurate and easy-to-use tool that enables farmers to rapidly identify plant diseases. The CNN model was comprehensively evaluated using multiple performance metrics and achieved an accuracy of 96%. To enhance accessibility and practical usability, the model was integrated into both web-based and mobile applications, allowing farmers to capture or upload images of diseased plants and receive instant disease predictions. This user-centred approach supports timely intervention and improved crop productivity. An image data generator was incorporated to further enhance model performance, increasing classification accuracy to 97% and improving disease recognition reliability. The system can detect plant diseases in less than two seconds, demonstrating strong potential for real-time field deployment. Overall, the proposed integrated solution provides an efficient, accurate, and accessible approach to plant disease detection, with the potential to advance precision agriculture, promote sustainable crop management, and strengthen food security through the application of intelligent technologies.

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### INTRODUCTION

Artificial intelligence application is increasingly becoming wide gaining a foothold in modern science including detection of diseases. The fast advancement of current intelligent technology has given humanity hope for a brighter future Burrows (2021). Plant diseases are kind of natural disasters that affect the normal growth of plants and even cause plant death during the whole growth process of plants from seed development to seedling and to seedling growth (Liu & Wang, 2021). Disease detection in plants is

a known technology that focuses on detecting disease on plants in digital images and videos. Plant disease is one of the main causes that reduces the quantity of the product and its quality.

There are several traits and behaviors of which type of plant disease, many of which are just recognizable. Thus, human expertise is normally needed for disease diagnosis. This allows usage of many image processing, machine learning and computer vision techniques to apply with plant diagnosis problems because disease diagnosis is commonly performed by visual inspection. Using

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such approaches can partially replace plant disease experts. Plant diseases and their prevention techniques are becoming more understood as a result of research and technology improvements. This is accomplished through the creation of disease-resistant crop varieties, advance diagnostic techniques, and environmentally friendly farming practices (Ul Haq & Ijaz, 2020).

The application of technology in the detection and analysis procedures improves their accuracy and dependability (khan et al., 2021). People who employ cutting-edge technology, for example, to evaluate illnesses that emerge unexpectedly have a better chance of managing them than those who do not. In the recent incidence of COVID-19, the global health community relied on cutting-edge technology to establish preventive measures that have helped limit the disease's transmission rate (Khan et al., 2021). Therefore, identifying and detecting diseases in plants at an early stage is an important task for farmers. Roy and Baduri (2021) stated that, early identification and prevention of plant diseases are the important aspects of crop harvesting since they can effectively reduce any growth disorders, and thus minimize pesticide application for pollution-free crop production.

The use of computer vision (CV) and machine learning (ML) application could improve the detection of diseases. Computer vision (CV) is a field of artificial intelligence (AI), that deals with how computers can derived high level of understanding of an object through digital images and videos (Khan et al., 2021). Chohan et al., (2020) proposed a convolutional neural network-based deep learning approach for detecting plant leaf diseases using augmented images from the PlantVillage dataset. The model, trained with multiple convolution and pooling layers and tested on 15% of healthy and diseased samples, achieved a high classification accuracy of 98.3%. Khan et al. (2021) discusses the use of machine learning and deep learning to detect diseases in plants automatically.

Convolutional neural network (CNN) models were trained on segmented image data significantly enhances performance, with the S-

CNN model achieving 98.6% accuracy on previously unseen data more than doubling the accuracy of the F-CNN model trained on whole images. Using tomato plants and target spot diseases as examples, the study shows marked improvements in self-classification confidence for the S-CNN model, thereby enhancing the applicability of automated disease identification systems (Sharma et al., 2020). Also, Shobana et al. (2022) developed a CNN model that fed up with an image of plant diseases to know the results. Plants are identified and the results were proven to be 86% correct. In their research (Reddy et al., 2021) an automated detection model for the three common maize plant diseases has been created, by combining image processing and deep learning methods (Faster R-CNN+ResNet50) to evaluate real-time photos. The suggested system effectively identified three maize diseases with a 91% accuracy rate.

Reddy et al. (2021) developed automated detection model for the three common maize plant diseases. Combining image processing and deep learning methods (Faster R-CNN+ResNet50) to evaluate real-time photos. The suggested system effectively identified three maize diseases with a 91% accuracy rate. Harini and Savitha (2021) implemented a Convolutional neural network for disease detection and classification, the authors have considered three crops that are potato, rice, bell pepper and dataset from plantvillage. Hence, in this research, a CNN model was developed to enable early detection of plant diseases using AI technologies to identify and discriminate between visually similar disease types. Computer vision techniques combined with deep learning were applied to classify diseases in potato, rice, maize, banana, and tomato leaves, covering five plant species and 26 diseases, while describing affected regions through extraction of characteristic plant features.

## MATERIALS AND METHODS

This study aims to develop a convolutional neural network (CNN) for classifying plant diseases, categorizing images into 24 classes of healthy plants and diseases. Utilizing TensorFlow and Keras, the model will be

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enhanced through data augmentation methods. The goal is to create a tool for early detection and identification of plant diseases to improve management and treatment efficiency.

### Datasets

To train the CNN model and compute well, 26,432 photos of healthy and diseased plant leaves are used from Plant Village via Kaggle (Singh, 2021). Given how much contextual information is reliant on object detection, many of the photos in the dataset are in their native states.

The dataset was divided into three parts: Training, Testing and Validation:

- 80 % of the dataset was assign for Training,
- the remaining 20% was split into: -
- 10% Testing
- 10% Validation.

Split method was used to utilize memory storage, instead of having a separate folder for Training, Testing and Validation which will require more memory space. The data set structure is described in Figure 1.

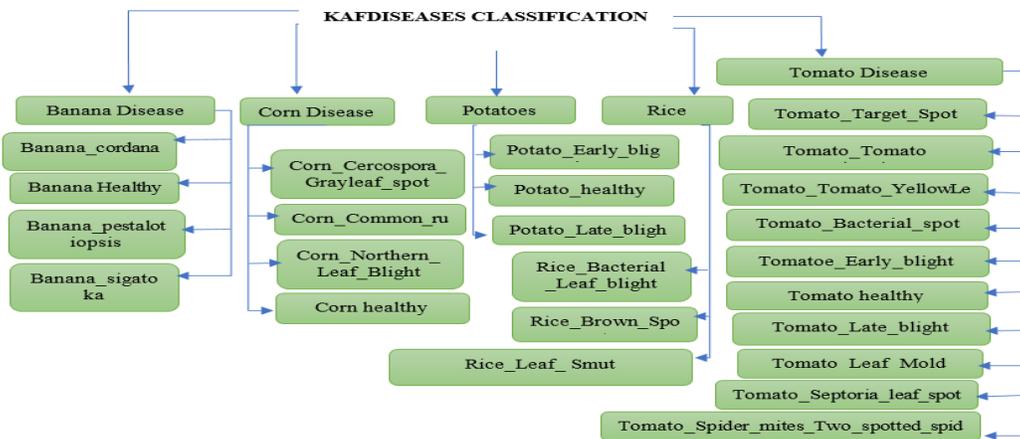


Figure 1: Dataset Structure

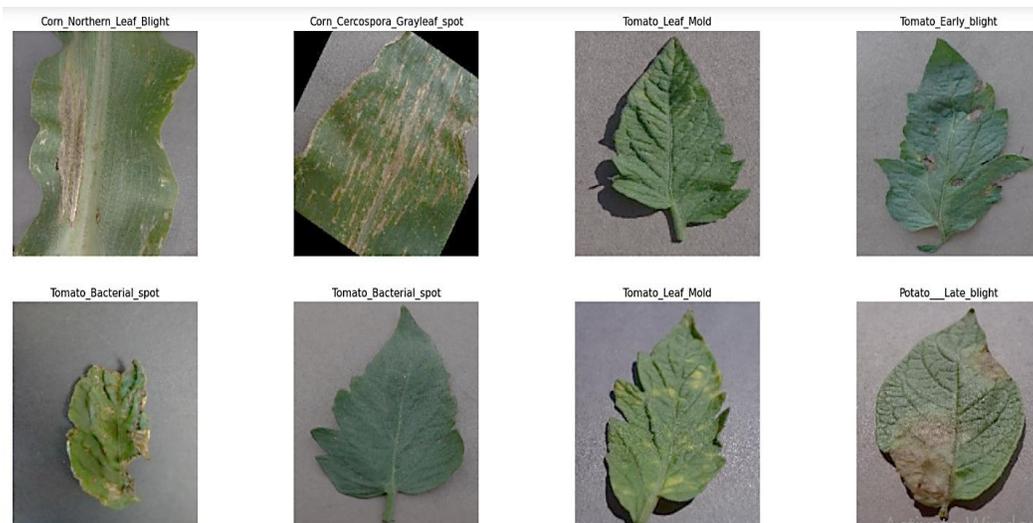


Figure 2: Dataset sample from the train model

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### Convolutional Neural Network Model (CNN)

This study uses Convolutional Neural Networks (CNN) as an underlying deep learning engine for classifying 24 categories of plant

diseases from 5 different crops. A dataset of 26374 images of healthy and infected plant leaves was collected to train, validate, and test the model. The CNN architecture is shown in Figure 3.

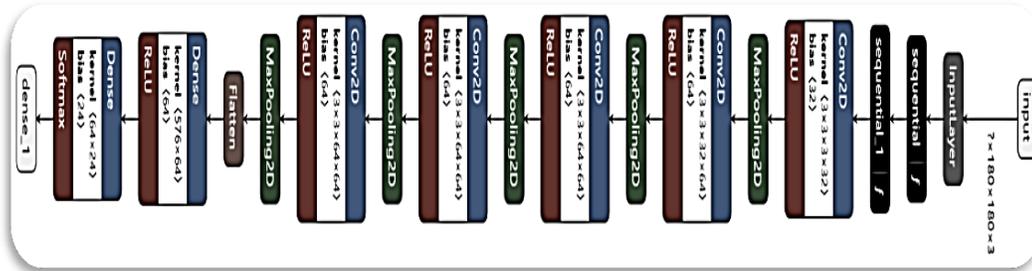


Figure 3:3D model of the CNN Architecture

In order to have better visualization of the CNN model architecture a 3D model architecture was built. The CNN model was trained with 7 layers: 2 sequential layers, 4 convolutional layers, 5 max pooling layers, and 2 dense layers. The sequential layers are used in the model to stack multiple layers of the same types on top of each other. The model was defined using keras sequential API. Hence with the help of multiple layers the model performs sequential operations on the input data to learn features and classify the images. Max-pooling layers are added after the convolutional layers in order to down sample the feature maps and minimize the spatial dimensionality. The output is then flattened and sent through fully connected layers, which pick up characteristics that can be classified using the information collected by the convolutional layers. Finally, the output layer provides class probabilities for the classification task using the SoftMax activation function. The mathematical Equation for the convolutional neural network is as follows:

$$1) \quad y_{i,j,k} = \sum_{l=1}^L \sum_{m=1}^M \sum_{n=1}^N 1 - \sum_{l=1}^L \sum_{m=1}^M \sum_{n=1}^N = 1 - w_{l,m,n,k} x_{(i+1-l, j+m-1, n)} + b_k$$

Where  $y_i, j, k$  is the output at position  $(i, j)$  of the  $k$ th filter. The  $k$ th filter refers to the  $k$ -th feature map that is generated by the convolutional layer. The output of each filter is a feature map that represents the presence of that feature in the input image.

$\sigma$ : The activation function helps the neural network model capture complex relationships between inputs and outputs.

$$2) \quad W_{(l, m, n, k)}$$

The model utilizes the weights to extract features from the input data based on learning patterns.

$$3) \quad x_{(i+1-l, j+m-1, n)}$$

These represent the input values to the network,

$$4) \quad (i+1-l, j+m-1, n)$$

Refers to the position within the input data that the convolutional filter is applied to. This helps capture local relationships and spatial information.

$$5) \quad b_k$$

The bias offers a further learnable parameter that can modify the activation function, giving the model some more adaptability.

The convolutional neural network's output value at a particular location is represented by the equation. Therefore, it combines the bias-adjusted weighted sum of the input values with an activation function that adds nonlinearity. Through this procedure, the network can take features from the input data and use them to generate predictions or categorize data.

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### System Architecture

This architecture provides a complete pipeline for the development of the plants disease

detection system that makes use of Convolutional Neural Network, Cloud Computing and Mobile app Development as shown in Figure 4.

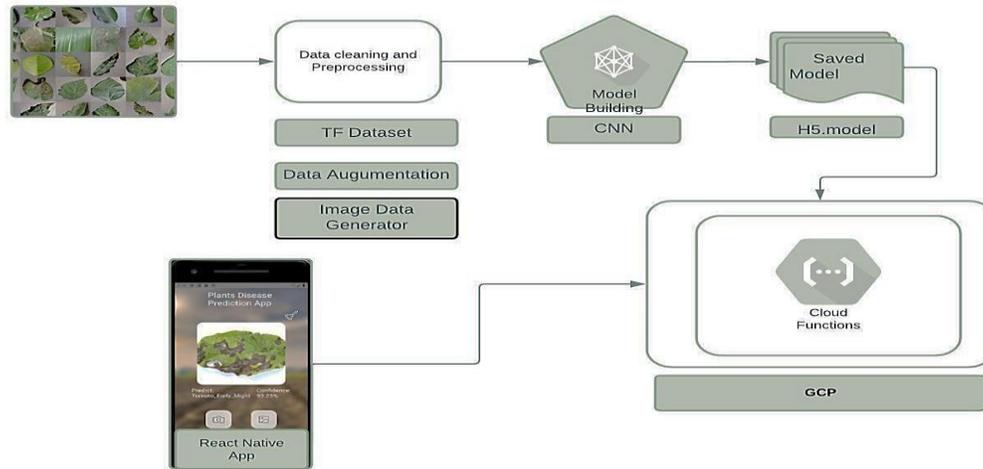


Figure 4: System Architecture (Mobile App)

A cross-platform mobile app developed with React Native enables users to send images

of plant diseases to a Google cloud function, which then provides predictions with confidence about the diseases detected.

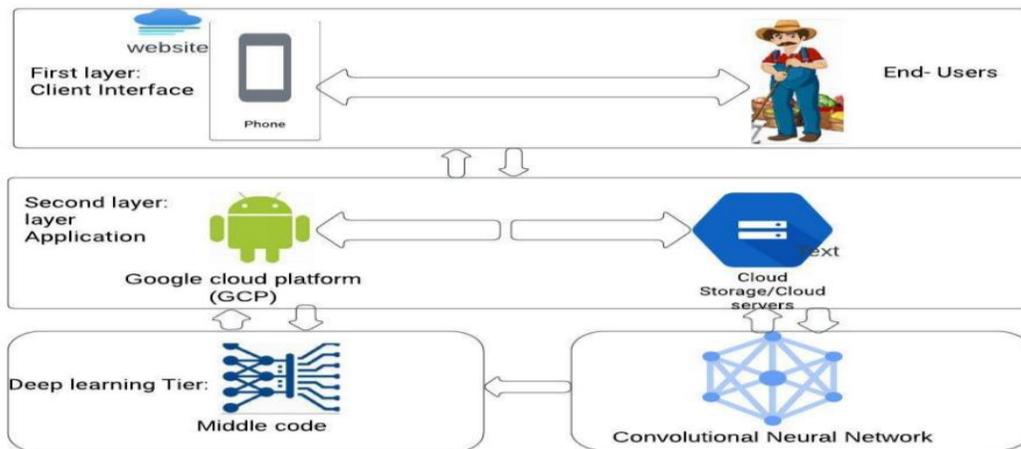


Figure 5: Complete System Architecture (Distributed System)

Figure 5 illustrates the distributed runtime architecture of the plant disease detection system, comprising components for both cloud-based centralized servers and mobile devices. Layer 1 includes the CNN and Intermediate

Representation (IR) model operating on mobile devices. Layer 2 features the user interface developed through an Android application, facilitating user interaction with the system in Layer 3.

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The flowchart of the study is shown in Figure 6.

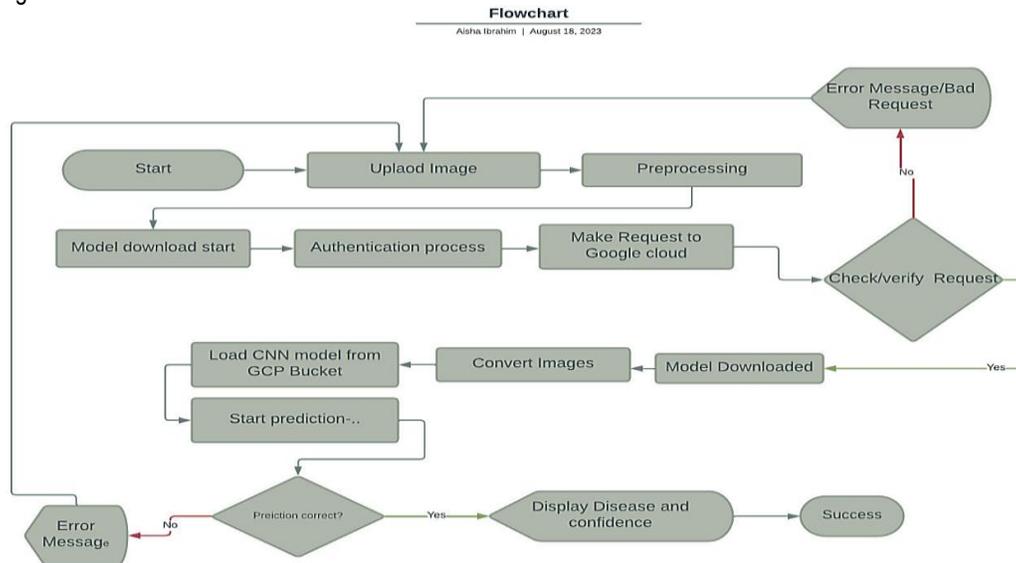


Figure 6: System Flowchart

## RESULTS AND DISCUSSION

The CNN model obtained a 96.16 % accuracy rate, the CNN model was also retrained with Image Data Generator in which the model obtained a 97.83 % accuracy rate, and the solution was developed to incorporate a web and mobile application to boost usability even more. Farmers may rapidly shoot or submit images of diseased or healthy plants, and the algorithm predicts the possibility of a certain ailment. The integrated strategy improves farmers productivity and accessibility while displaying exceptional accuracy in plant disease identification. Before obtaining the results, some operations are carried out to ensure the accuracy of the system.

## CNN IMPLEMENTATION

The Keras development environment was used to implement the CNN model. The TensorFlow back-end engine is used by the open-source neural network framework Keras, which is written in Python. Python-based deep learning models are reasonably simple to design and test for developers thanks to Keras packages that operate on top of TensorFlow.

Keras.preprocessing.image was used as an example. The model would never read the same image twice by using the ImageDataGenerator package to add additional geometric modifications to some of the photos in our dataset. By doing so, over-fitting is reduced and the model's ability to generalize is improved, which in turn improves the accuracy of the model from 96.16% to 97.83%.

The TF dataset serves as the training dataset, utilizing TensorFlow's tf.data API to create a data pipeline that supports batching, shuffling, and parallel processing. This approach enhances computational efficiency by storing the dataset in batches. Images fed into the model must be uniformly sized; in this case, they are formatted to a shape of (32, 180, 180, 3), where 32 indicates the batch size, and the dimensions refer to RGB images with a height and width of 180 pixels.

A computer with a Processor 11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40GHz, 4 Core(s), and 8 Logical Processor(s) with a base clock speed of 2419 MHz was used to do the model training. For the training phase, 50 epochs were run over around 3 days. The author took a record of every 5 epochs in order to monitor the

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progress. The training loss is calculated using a loss function that suits our model which is Categorical Cross Entropy classification (softmax activation function) because the model is a

classification based which classify 24 classes of plant diseases with the following equation:

$$L = -\sum_i^n x_i \cdot \log(y_i)$$

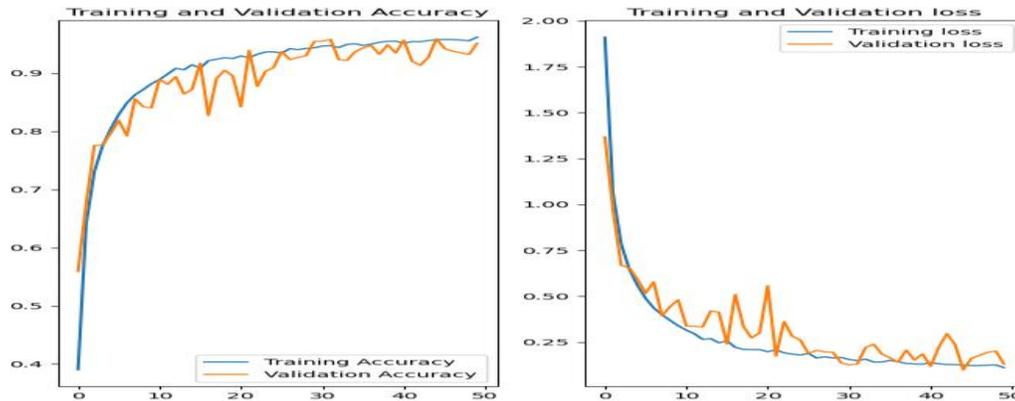


Figure 7: Training and Validation Accuracy, Training and Validation loss of the CNN Model

Figure 7 illustrates the CNN model's training and validation accuracy and loss, where the blue and orange lines represent training and validation performance, respectively. Both accuracy increased and loss decreased with training epochs, indicating progressive model learning and improved prediction capability.

order to prevent overfitting and enhance the model's ability to generalize to new images. The same model architecture is used, and some slight changes were made, like the image size. In the first training, 180×180 image pixels were trained, while with ImageDataGenerator, 256×256 image pixels were used. Training and Validation Accuracy, Training & Validation loss plot for our model using Image Data Generator is shown in Figure 8.

### CNN Implementation Using Image Data Generator

Image data generator with real time data augmentation ware used to retrain the model in

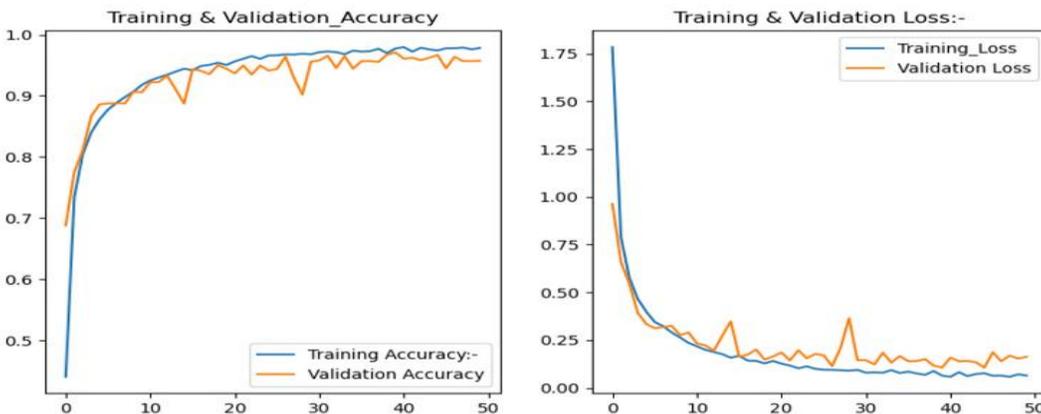


Figure 8: Training and Validation Accuracy, Training & Validation loss

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Figure 8 describes two plots of the trained CNN model: one for "Training & Validation Accuracy" and the other for "Training & Validation Loss. It details how both metrics change over 50 epochs. The accuracy plot shows that training accuracy rises from 0.0 to nearly 1.0, while validation accuracy increases to around 0.8. The training and validation loss are also depicted, indicating effective model training. Overall, the results suggest that the model achieved a high accuracy level during the training phase.

### Confusion Matrix

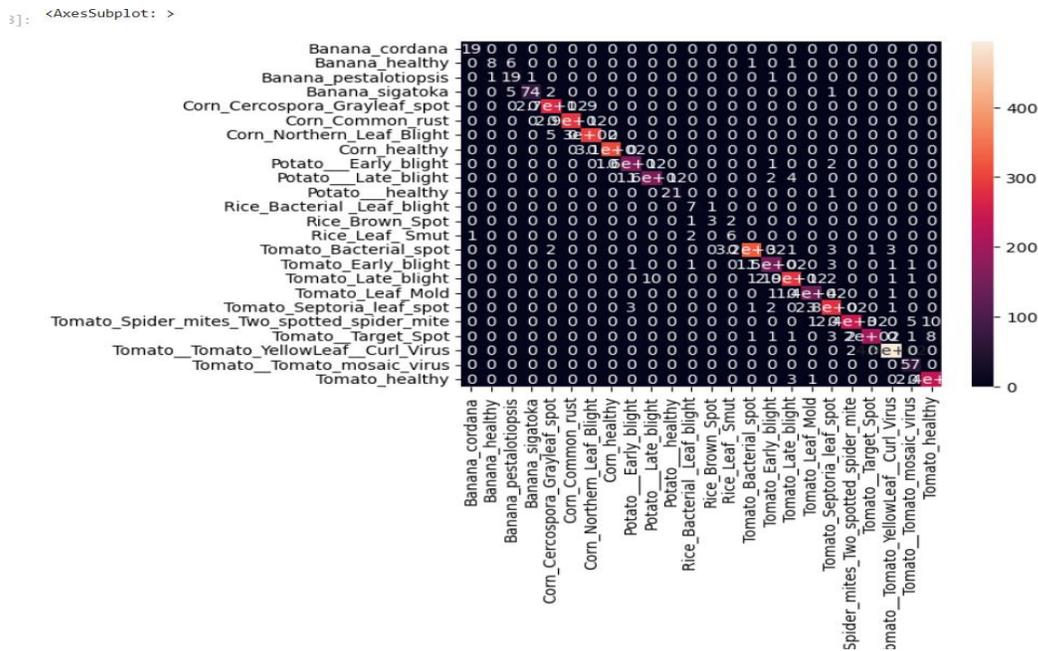


Figure 9: Confusion matrix

The confusion matrix was also used to calculate other performance measures of the CNN model, including accuracy, precision, recall, and F1-score, which assisted us in examining the

The confusion matrix of the CNN model illustrates its performance across various disease classes, with predicted classes in columns and actual classes in rows. Each cell (i, j) indicates the count of samples classified as belonging to actual class i and predicted class j. The off-diagonal cells represent error rates, while diagonal cells show correct prediction percentages. The matrix indicates that the model effectively distinguishes between diseases, achieving accuracies above 96% for common plant diseases like blight, spot, rust, and mold, and 100% accuracy for healthy plants. Shown in Figure 9

model's performance in greater detail. This allows us to deal with data that is out of balance. The accuracy, precision, recall, and F1 score ratios of our CNN model for each class are shown in Table 1.

Table 1: Performance measures

Class	Disease Classes	Precision	recall	F1-score	support
0	Banana cordana	0.95	1	0.97	19
1	Banana healthy	0.89	0.5	0.64	16
2	Banana pestalotiopsis	0.63	0.86	0.73	22

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Class	Disease Classes	Precision	recall	F1-score	support
3	Banana sigatoka	0.99	0.9	0.94	82
4	Corn Cercospora Grayleaf spot	0.97	0.96	0.97	281
5	Corn Common rust	1	1	1	289
6	Corn Northern Leaf Blight	0.97	0.98	0.98	302
7	Corn healthy	1	1	1	310
8	Potato Early blight	0.97	0.98	0.97	163
9	Potato Late blight	0.94	0.95	0.94	168
10	Potato healthy	0.95	0.95	0.95	22
11	Rice Bacterial Leaf blight	0.64	0.88	0.74	8
12	Rice Brown Spot	0.75	0.5	0.6	6
13	Rice Leaf Smut	0.75	0.67	0.71	9
14	Tomato Bacterial spot'	0.98	0.96	0.97	337
15	'Tomato Early blight	0.88	0.95	0.91	159
16	Tomato Late blight	0.97	0.92	0.94	313
17	Tomato Leaf Mold	0.96	0.96	0.96	150
18	Tomato Septoria leaf spot	0.94	0.97	0.95	290
19	Tomato Spider mites Two spotted spider mite	0.98	0.93	0.95	263
20	Tomato Target Spot	0.98	0.92	0.95	218
21	Tomato Tomato Yellow Leaf Curl Virus	0.99	1	0.99	496
22	Tomato Tomato mosaic virus	0.88	1	0.93	57
23	Tomato healthy	0.93	0.98	0.96	240
	accuracy			0.96	4220
	macro avg	0.91	0.90	0.90	4220
	weighted avg	0.96	0.96	0.96	4220

Table 1 indicates that the model demonstrates excellent performance in identifying classes such as Banana cordana, Banana pestalotiopsis, Corn Cercospora Grayleaf spot, Corn Northern Leaf Blight, Corn healthy, Potato Early blight, Potato late blight, Tomato Bacterial spot, and Tomato healthy, with precision, recall, and F1-scores close to 1.0. Conversely, classes like Banana healthy and the three rice disease classes showed lower scores, indicating increased misclassification. The class 'Tomato Early blight' had particularly low precision, while class Corn healthy achieved near-perfect metrics. The overall model accuracy stood at 96%, with a macro-average precision, recall, and F1-score around 0.90, and a weighted-average of

approximately 0.96, reflecting strong performance despite class imbalances. Most precision and recall values were near 1.0, signifying high accuracy and minimal false negatives for the CNN model.

### Mobile App Deployment

The plant disease detection system is a mobile application developed for Android using React Native, integrating features from the Android SDK and JavaScript for front-end development. A middleware, created in Python 3.11, facilitates the connection between the app and a cloud server hosted on Google Cloud Platform (GCP) in the US. The app enables farmers to take photos of plants and upload

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images from their gallery or camera for analysis. Upon submission, the app sends the images as

JSON to a CNN model on GCP. Successful builds are tested using Android Studio with an Emulator.

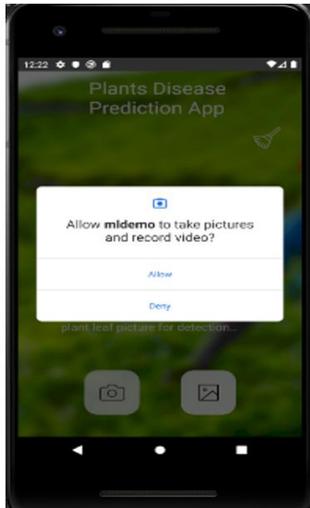


Figure 10: Launching the Mobile App



Figure 11: Selecting Photo from Camera



Figure 12: Predicting Tomatoes disease

Figure 10 illustrates the initial launch of the app, prompting users for permission to access the camera for picture and video capture. Figure 11 displays the image selection interface, using downloaded images rather than trained datasets. Figure 12 presents the CNN model's inference results, showcasing its ability to identify Tomato

Septoria leaf spot disease with a confidence score of 97.26%. The class prediction and result display process takes approximately 0.90 seconds, highlighting the app's capability as a real-time plant disease detector. Additionally, the app features a clean page function accessible via a button in the UI.



Figure 13: Predicting Banana disease



Figure 14: Predicting another Tomato disease



Figure 15: Predicting Rice disease

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### Comparative analysis of CNN Model with and without Image Data Generation

Table 1: Comparative analysis of CNN Model with and without Image Data Generation

Aspect	CNN without augmentation (180*180) Images size	CNN with Image data generation (256 * 256)
Training and Validation Accuracy	Accuracy increases but shows more fluctuations and slightly lower final validation accuracy	Higher and more stable accuracy with closer training-validation curves
Training and Validation Lost Generalization performance	Loss decreases but with noticeable oscillations and higher final validation loss Slight overfitting observed due to gap and instability in curves	Smoother and lower loss values indicating better convergence Better generalization due to augmentation and higher-resolution images

### CONCLUSION

This study presents the design and implementation of a disease detection system using CNN model that enables farmers to detect diseases from the 24 most common plant diseases from five different species. The model was trained with an imagery dataset consisting of 26,432 images of healthy and diseased plant leaves, where the size, color, and background of the photos were taken into consideration. To improve system usability and flexibility, we created a mobile app was developed to enable farmers easily detect plant illnesses at their early stages and minimize the use of inappropriate fertilizers that might harm plant health.

The model was tested and evaluated with Postman by evaluating the performance and classification accuracy, focusing more on the prediction and prediction time. Farmers can take pictures of plant disease in their natural environment with their handy mobile app in less than 2 seconds. This demonstrates that the model is appropriate for real-time inference at the network edge, owing to its high prediction accuracy and response time.

Plant disease detection using CNN has transformed agriculture by providing creative solutions for disease control, resource efficiency, and sustainable crop production. Hence based on the findings of this research, the proposed KAF plantix diseases detector has the potential to alleviate global food security issues while also encouraging ecologically friendly farming techniques.

The system was developed for continues trainings and updates which adds to the literature by addressing the problem of preserving the relevance and efficacy of deep learning models over time in dynamic agricultural situations.

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