Automated Detection of Plant Diseases Using CNN

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***Abstract*—Diseased images can severely reduce agricultural productivity and harm a nation's food supply. Typically, farmers and specialists closely monitor the diseases. It can be labor-intensive, costly, and ineffective. Detecting plant diseases can be achieved by affected leaves. The approach for detecting plant diseases by building a classification model that analyzes leaf images. To identify plant diseases, we utilize image processing alongside a (CNN). CNNs are a class of models capable of takes features from images, make an ideal for recognizing disease patterns in plant leaves.**

***Keywords*—CNN, image processing, training set, test set**

I. INTRODUCTION

Agriculture remains fundamental to feeding populations and supporting economic stability, especially in nations with high population densities. In a country like India, where a large segment of the population relies on farming, the agricultural sector significantly influences the economy. Enhancing productivity in this domain can lead to improvements in food availability, rural employment, and overall economic growth.

Although agriculture is essential, it faces several ongoing challenges, with plant diseases being critical. These are not reduce crop yields but also pose serious financial threats to farmers. They can be triggered by a range of factors, including fluctuating weather conditions, degraded soil health, and the rapid spread of pathogens such as viruses, fungi, and bacteria. In the early stages, plant diseases may exhibit mild or indistinct symptoms, which are easily missed, allowing the problem to escalate before any intervention occurs.

Typically involve visual inspection by farmers or agricultural professionals in the field. While visual diagnosis may yield results in certain cases, it is often inefficient, dependent on individual expertise, and lacks consistency. Recent developments in technology have enabled more reliable, quicker, and scalable approaches to detect diseases affecting crops. With the widespread availability of digital technology, even entry-level smartphones can photograph diseased plants, allowing AI-based systems to evaluate and diagnose them efficiently.

The continuous advancement of deep learning techniques has introduced innovative approaches for interpreting and classifying complex visual data. (CNN) stand out in this , The ability to extracting essentials from image datasets, making them well-suited for visual data interpretation.

In the agricultural domain, CNNs can be trained on extensive collections of leaf images to detect and differentiate between multiple plant infections. This project is centered around creating a smart disease identification system that leverages CNN architectures to analyze visual symptoms present in plant leaves. The ultimate aim is to offer a dependable and scalable solution that empowers farmers with early protection, preventing large-scale crop damage and boosting agricultural efficiency.

II. LITERATURES REVIEW

identify plant diseases by analyzing the structural and textural characteristics of leaf images.the early detection of cotton leaf diseases was approached by capturing leaf images, applying segmentation techniques, and extracting color-based features like HSV (Hue, Saturation, Value) components. These attributes were input into an Artificial Neural Network (ANN), which successfully differentiated between healthy and diseased leaves. Likewise, research on medicinal plant leaves utilized image enhancement, segmentation, and feature extraction methods. The classification phase compared radial basis function networks and multilayer perceptrons, with the former delivering superior performance.

The approaches have become increasingly popular for detection.One particular study applied a deep CNN model to classify the diseases, reaching an avg of 96.3%.The model's performance was validated using a carefully curated dataset assessed by domain experts, which strengthened the trustworthiness of the results.

In another investigation, researchers trained a CNN on a vast dataset containing over 87,000 plant leaf images.This model demonstrated remarkable precision with an avg of 99.53% accuracy, underscoring the effectiveness of networks in agricultural diagnostics.Researchers also experimented with the identifying soybean diseases in field conditions with unstructured images.

The model was achieved 98.32% accuracy, it tells for on-the-ground deployment.Efforts have also been made to develop mobile solutions for diagnosing diseases and pests in tomato plants.These mobile systems utilize compact and efficient architectures specifically for handheld devices, allowing quick assessments directly in farming environments.

To enhance accuracy and reduce false detections, some models used frameworks such as Faster R-CNN and SSD.To boost detection capabilities across varied leaf images, these models incorporated sophisticated feature extraction layers built into their deep learning structures, leading to more consistent and accurate results.

its capability to detect diseases by analyzing data beyond the visible spectrum.Despite reaching accuracies as high as 93%, its reliance on expensive equipment limits widespread implementation.Another approach involved training a CNN on high-resolution RGB images for identifying 12 different plant diseases.While it achieved an accuracy of 88.8%, further evaluation revealed challenges with false negatives, attributed to the architectural of the model.

III.METHODOLOGY

A. Dataset Collection
Images showcasing both healthy and diseased from different species were gathered using publicly available agricultural resources such as **PlantVillage**.
These samples were essential for teaching the model how to recognize different disease symptoms by identifying patterns with each condition.

B. CNN Architecture
A customized (CNN) architecture was designed to perform effective classification of plant leaf images.The process begins by applying multiple feature-detecting filters across the input images. These early layers focus on capturing low-level image characteristics that serve as foundational elements for identifying plant conditions.

Following each convolutional operation, activation functions like ReLU (Rectified Linear Unit) introduced within the data, beyond what a linear model could achieve. and computational complexity, pooling layers—typically max-pooling—are used. These layers retain the features less relevant information, which helps streamline process without losing essential details.To generalizes well and does not memorized strategically added throughout the to reduce overfitting. These layers randomly features In the deeper layers of the network, dense connections compile the learned representations and translate them into outputs aligned with specific classification targets.To determine the final class prediction, a softmax function is used to assign a confidence score to each possible plant disease category. This allows the system to confidently identify the image.

C. Image Preprocessing
images are normalized to fall within the range. which contributed to faster convergence during training and ensured stable numerical operations set and simulate different real-world conditions, a variety of image augmentation techniques were applied.Such modifications made the model more adaptable to real-life variations in image capture, including differences in orientation, lighting, and distance. This approach improved the model's ability to generalize, allowing it to accurately classify plant diseases even in previously unseen scenarios.

D. Model Testing
This approach helped verify how effectively the model could handle new, unseen data.To measure the quality of predictions, various evaluation metrics were employed—such as classification accuracy.To further analyze the classification outcomes, a matrix of true versus predicted classes was developed. This helped in identifying patterns of correct and incorrect classifications across different disease types.Additionally, line graphs showing the changes in training and validation accuracy and loss throughout the training epochs were examined.

E. Model Training
Training was performed over several epochs with a fixed batch size. A validation split was used to monitor model performance and prevent overfitting.

IV.PROPOSED SYSTEM

A streamlined version of model will be incorporated into an Android app to enable real-time detection via the device's camera.To begin, the system utilizes the PLANT-VILLAGE dataset, which features a variety of labeled images depicting both plant leaves.,To enhance the dataset's diversity and robustness, various preprocessing using Keras's ImageDataGenerator API.The system's workflow for classification is outlined.

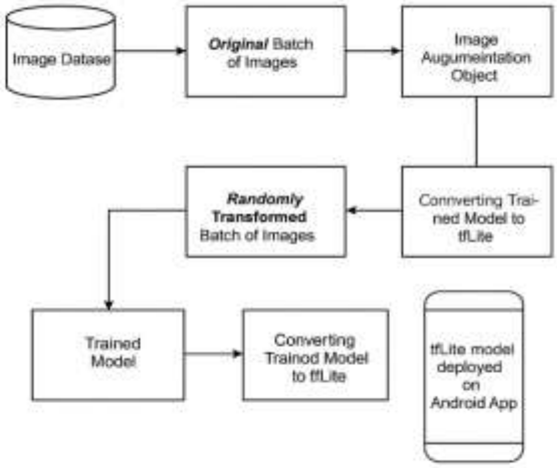


Fig. 1. The Proposed System Diagram

(1) Initial step involves collecting the dataset. We utilize the available PlantVillage , initially provided by the crowdAI platform.

(2) Preprocessing and augmentation are executed with Keras's ImageDataGenerator, which enables dynamic image transformations during the training phase.

(3) The classification model is developed using a CNN based on the VGG-19 architecture to accurately detect various plant leaf diseases.

(4) The trained model will be converted through TensorFlow Lite and incorporated into an Android application for mobile use.

V.Convolutional Neural Network Architecture (VGG-19)

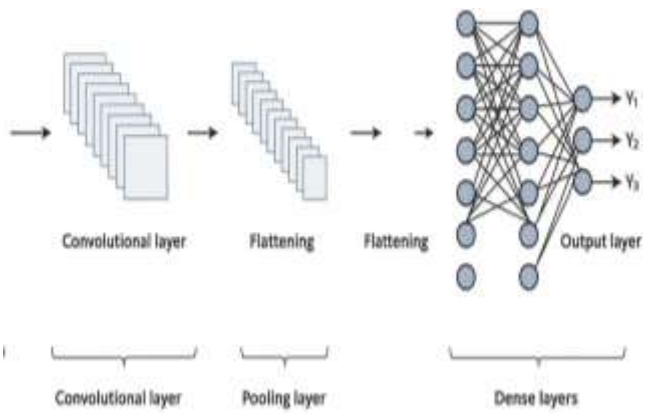


Fig. 2 .CNN Architecture

A CNN has 3 layers: first convolutional layer, Second pooling layer, and Third connected layer. Fig 2 shows all layers together.

CNN layer: produces the map function by scanning the more images using a filter or some techniques.

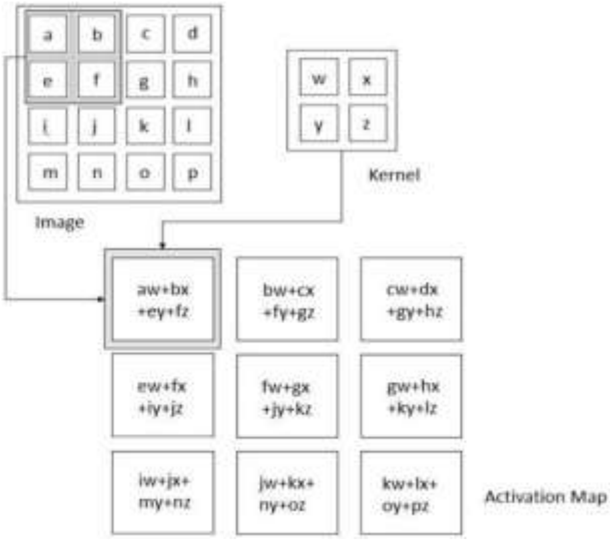
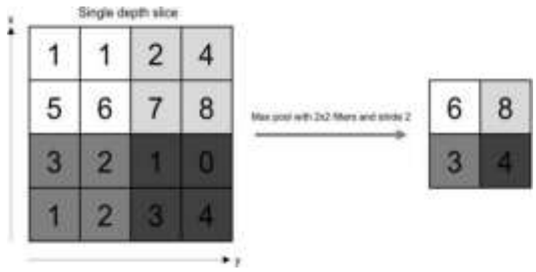


Fig 3 . its shows-the convolution layer.

A. Pooling Layer

The this reduces the size of functions generated by the CNN layer, making more efficient by there memory and processing power. Figure 4 provides a visual representation of how this layer functions.

Fig. 4. Pooling Layer



B. Connected Layer

The input layer – The preceding layers' output is "flattned" and turned into a one single point which is used as an input for the next stage.

The Fully connected output layer generates the final probable scores for each label.

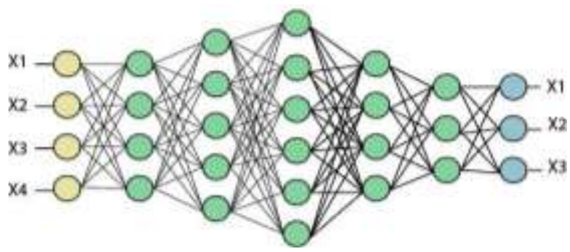


Fig . 5. Connected Layer

VGG19 is a an CNN with already trained layers and a grasp of how an pictures are defined in. Leveraging pre-trained parameters, the CNN model VGG19 analyzes visual data,This enables it to identify structural layouts, color variations, and fundamental shapes within images..

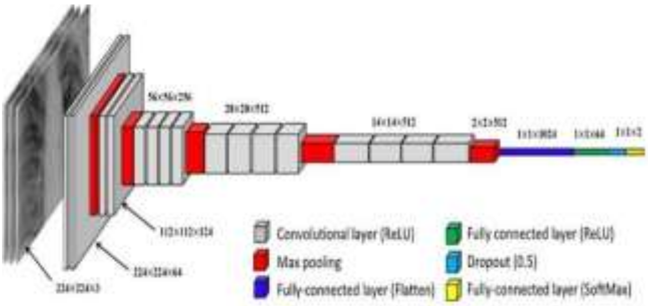


Fig. 6 . vgg

VI . RESULT

A significant accuracy of 95.6% was achieved by training the model across 50 epochs using early stopping. A graphical representation of how training and validation accuracy progressed is provided in Figure 7. Figure 8 demonstrates the successful plant displaying a healthy leaf (left) and an infected one (right). The results are presented,showing a healthy leaf on left and a sick one on the right.

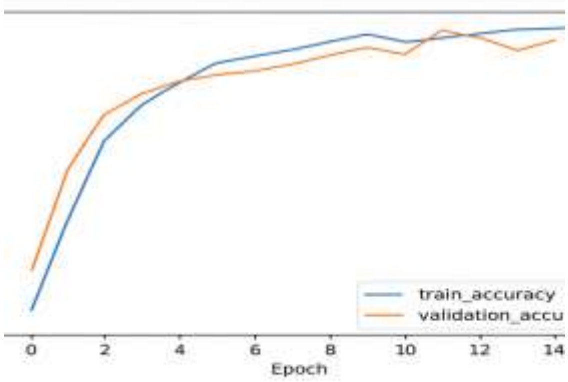


Fig . 7. Trained_accuracy vs Validation _accuracy

VII.CONCLUSION & FUTURE WORK

The proposed system successfully integrates techniques for the real-time identification diseases using a (CNN) model, specifically VGG-19. The implementation of image preprocessing, data augmentation, and model deployment through TensorFlow Lite enables seamless operation within an Android environment. This approach provides a practical solution for farmers to detect diseases early using smartphones. The system is designed to be scalable and adaptable of plant species and diseases, offering a promising tool for improving crop health monitoring and agricultural productivity.

VIII. REFERENCES

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