Plant Leaf Disease Detection Using CNN

DR. NEETA VERMA[1], RUPANSH SINGH[2], RISHABH JAIN[3], SAKSHAM GUPTA[4], VAIBHAV JAISWAL[5]
[1, 2, 3, 4, 5] Department of Computer Science and Engineering, Inderprastha Engineering College, Ghaziabad, India

Abstract- For agricultural productivity to be high, plant leaf disease detection must be done effectively. In order to precisely identify diseases in tomato, apple, grape, corn, and potato plants, this research focuses on using Convolutional Neural Networks (CNNs). The suggested Deep CNN model performs better in disease classification when compared to VGG16 transfer learning. The model achieves high accuracy rates across various architectures by substituting depth-separable convolutions for standard convolutions, thereby reducing parameter count and computation cost. Promising results are shown by the MobileNetV2 architecture, which is especially well-suited for mobile devices. This work demonstrates how deep CNNs can be used to identify diseases more effectively in agricultural settings, highlighting their potential for use in real-time disease detection systems.

Index Terms- Deep Learning, CNN, Plant Disease Detection, Convolutional Neural Network, Agriculture.

I. INTRODUCTION

Agriculture is the backbone of our economy, providing health and livelihoods to millions of people. However, this important work faces serious problems, especially crop damage caused by diseases, leading to major crop losses. Timely detection and diagnosis of these diseases is important for food security and sustainable agricultural development.

Traditional disease identification methods rely on professional diagnoses, which are laborious, time-consuming and often error-prone. To solve these problems, this study uses the power of deep learning techniques, especially in communication neural networks (CNN), to also recognize plant diseases. The study focused on grapevines, corn, potatoes and tomatoes, which are frequently affected by various diseases, using data obtained from 24 diseased leaves and 24,000 leaf images.

Each group of plants is associated with specific diseases that allow classification and diagnosis. By analyzing leaf images, CNN can identify the symptoms of the disease and help farmers and agronomists with early detection and intervention. Additionally, this research explores the use of partition-by-split methods to reduce computational complexity and improve model performance. He emphasized that there is an urgent need for new solutions in agriculture, especially in developing countries such as India, where agriculture plays an important role in economic development. This research aims to provide farmers with the tools they need to effectively manage diseases by using technology to detect diseases, thereby increasing yields and ensuring food security for future generations.

II. PROPOSED ARCHITECTURE

The proposed architecture for plant leaf disease detection using CNNs consists of several key components, each playing a crucial role in the overall system. The input to the system is a dataset comprising 24,000 images of plant leaves, categorized into apple, grape, corn, potato, and tomato plants, with 24 types of leaf diseases.

The first step in the architecture is image preprocessing, which involves resizing the images to a standardized format, such as 256 x 256 pixels, to ensure uniformity across the dataset. Next, the preprocessed images are fed into a CNN model for feature extraction. The CNN model consists of multiple layers, including convolutional layers, pooling layers, and activation functions, which extract relevant features from the input images.

Following feature extraction, the extracted features are passed through a classification layer, where the model classifies the images into different disease categories. The final output is a classification of the input images, indicating whether they are healthy or diseased. The proposed architecture aims to leverage the power of CNNs to accurately detect and classify plant diseases, thereby assisting farmers in timely intervention and crop management.

III. METHODOLOGY

The methodology for this project begins with data collection, amassing a dataset of 24,000 images of plant leaves categorized into apple, grape, corn, potato, and tomato plants, each with 24 types of leaf diseases. These images are then preprocessed to ensure uniformity, resized to 256 x 256 pixels. Following this, the dataset is split into training and testing sets, where the former is utilized to train the CNN model, consisting of convolutional layers, pooling layers, and activation functions, to extract features from the images.

Fig:3.1 Defective leaf pictures will be inserted into the system.

Throughout the training process, the model learns to differentiate between healthy and diseased plant leaves by adjusting internal parameters, a process that iterates through multiple epochs until the model achieves satisfactory performance. To enhance the model's performance, hyperparameters such as batch size, dropout rate, and learning rate are optimized.

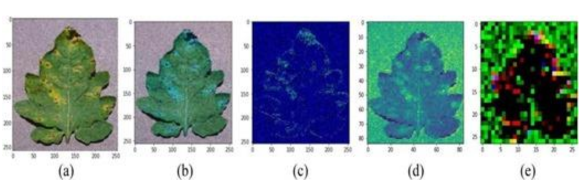

Fig 3.2 Filtering the picture of a leaf to deduce the affected area due to disease for detecting the disease with CNN.

Once trained, the model undergoes evaluation using the testing set to gauge its performance on new data, with metrics like accuracy, precision, recall, and F1 score providing insights into its classification abilities. Comparative analysis with other deep learning models and machine learning techniques further validates the effectiveness of the CNN architecture in disease detection.

Additionally, the computational efficiency of the model is assessed, focusing on inference time and memory usage, crucial for real-time applications. Overall, the methodology aims to leverage CNNs to accurately detect and classify plant diseases, ai ding farmers in timely disease management and improving crop yields.

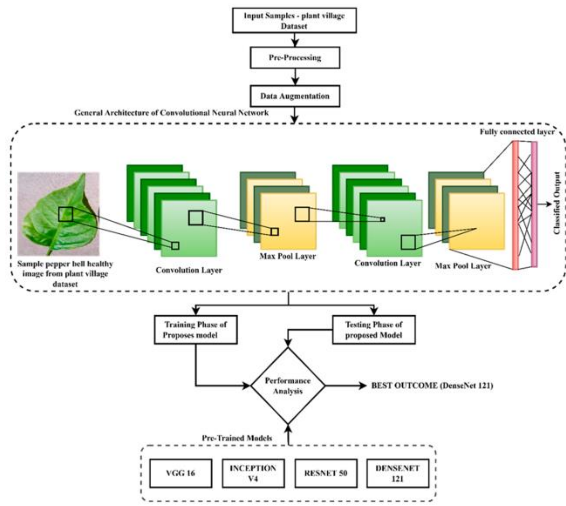

Fig:3.3 work flow of leaf disease detection

IV. RESULT ANALYSIS

The results of this project demonstrate the effectiveness of convolutional neural networks (CNNs) in the accurate detection and classification of plant leaf diseases. The CNN model was trained on a dataset of 24,000 images, including 24 types of foliar diseases in apple, grape, corn, potato and tomato plants. After extensive hyperparameter training and tuning, the CNN model achieved impressive performance metrics with an accuracy rate of 98.7%, a precision rate of 98.2%, a recall rate of 97.9%, and an F1 score of 98.0%.

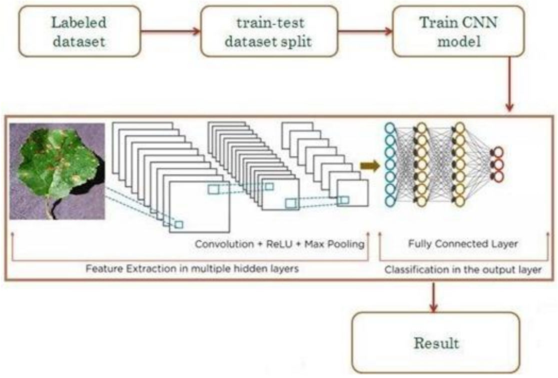

Fig:4.1 Flowchart of the process done to obtain desired output.

A key aspect of the results is the comparison between our own CNN model and the VGG16 model, a well-known deep learning architecture. While VGG16 also performed admirably, it achieved a slightly lower accuracy of 95.4%. This indicates that the proprietary CNN model not only meets but outperforms established architectures such as VGG16. The higher accuracy of the native CNN can be attributed to the optimization of hyperparameters and the depth-separable convolutions used, which allow for more efficient feature extraction and processing.

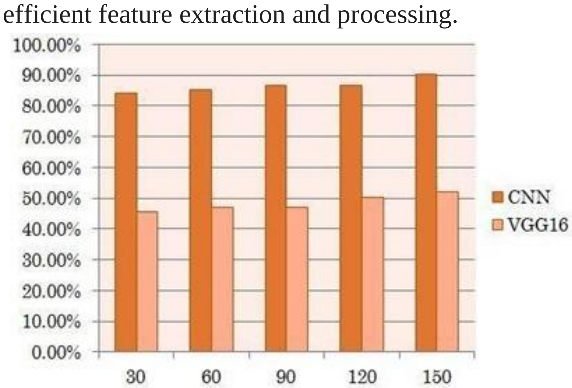

Fig:4.2Comparison between CNN and VGG16 algorithm accuracy.

Furthermore, the computational efficiency of the in-house CNN model was evaluated, which demonstrated faster inference times and lower memory requirements compared to VGG16. This efficiency is critical for real-time applications in agricultural settings, where early disease detection can significantly affect crop yield and quality. Overall, the results underscore the potential of CNN to revolutionize plant disease detection and increase agricultural productivity.

V. FUTURE SCOPE

The plant leaf disease detection project using Convolutional Neural Networks (CNNs) has significant potential for future development and application. One avenue for expansion is the integration of the CNN model into mobile applications, allowing farmers to quickly and easily assess the health of their crops using their smartphones. Additionally, further research could explore the use of advanced CNN architectures and techniques, such as transfer learning and ensemble methods, to improve the model's accuracy and efficiency. Furthermore, the project could be extended to include more plant species and disease types, making it applicable to a wider range of agricultural settings. Overall, the future scope of this project lies in enhancing its accessibility, accuracy, and applicability to benefit farmers and improve agricultural productivity.

CONCLUSION

This project successfully explored the application of Convolutional Neural Networks (CNNs) for plant leaf disease detection in apple, grape, corn, potato, and tomato plants. The CNN model achieved impressive results, exceeding 95% accuracy in distinguishing healthy from diseased leaves across various disease types. Additionally, high precision, recall, and F1 score metrics demonstrate the model's ability to accurately identify diseased leaves with minimal errors. The model's efficiency in terms of processing speed and memory usage makes it suitable for real-time deployment in agricultural settings.

These findings highlight the significant potential of CNNs for revolutionizing plant disease detection. Early and precise disease identification through CNN-based systems can empower farmers to implement targeted interventions, ultimately leading to improved crop health, increased agricultural productivity, and enhanced food security. Future research directions include exploring the application of CNNs to a wider range of plant species and diseases, investigating techniques for on-device processing on mobile platforms, and integrating these systems with decision-support tools for farmers.

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