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Leaf Disease Detection by Convolutional Neural Network (CNN)

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ABSTRACT-

Early identification and preventive action against crop diseases are crucial for enhancing agricultural productivity. This study employs deep convolutional neural network (CNN) models to detect and diagnose plant diseases by analyzing leaf images, leveraging CNN's strong performance in computer vision applications. Typical CNN models demand significant parameters and computational power. To address this, we utilized depth separable convolution in place of standard convolution, which minimizes the parameter load and computational demands. Our models were trained using an open-access dataset comprising 14 plant species, 38 disease categories, and images of healthy plants leaves.

Introduction :

Access to safe and nutritious food is essential for human health, serving as a fundamental energy source and a defense against illness. Food security plays a significant role in social stability and wellbeing; however, the United Nations reported that in 2020, between 720 million and 811 million people globally faced To evaluate the performance of the models, other parameters such as batch size, dropout, and various numbers of epochs were incorporated. The implemented models achieved a disease classification accuracy rate of 98.42%. In comparison with other deep-learning models, the implemented model achieved better performance in terms of accuracy and it required less training time. The accuracy results in the identification of diseases showed that the deep CNN model is promising and can greatly impact the efficient identification of diseases, and may have potential in the detection of diseases in real- time agricultural systems.

food insecurity [1]. Approximately 2.4 billion people, representing over 30% of the global population, were affected by moderate to severe food shortages, regularly facing insufficient food access . The world is showing a dangerous sign to us, what can we do to help solve this problem? One possible solution is the crop disease detection phone app. What the app does is that a peasant could take a picture of their crop, and upload it, and the app could

automatically identify what crop is it and whether it has a disease or not. With this app, farmers can detect crop diseases in the early stage and react correspondingly therefore reducing crop loss due to diseases. However, relevant investigations are still limited, which makes this issue to be of interest to academia[3]. Currently, machine learning is introduced to this field, and achieved numerous achievements[6]. Nevertheless, the accuracy needs improvement, which motivates the author to be involved with this interesting issue.

Literature Review :

Previous studies have leveraged CNN models to classify various plant diseases using data from the Plant Village dataset. For instance, the AlexNet architecture has been used to differentiate plant diseases into 38 distinct categories[6]. The system proposed in these studies provides an effective approach to predict plant diseases, supporting early identification and potentially reducing crop losses. Further research could focus on exploring different learning rates to refine model performance. The methodology involved utilizing images from a specific dataset along with prior datasets to forecast disease patterns in plants through the CNN model[8]. This approach encompasses a wide array of plant leaves, helping farmers recognize unfamiliar species and make informed decisions about crop selection. By employing convolutional neural networks and transfer learning, the system classifies various leaf diseases moreaccurately and quickly than manual inspection[5]. The CNN model has proven effective in correctly predicting plant diseases, with evaluation metrics such as accuracy, precision, recall, and F1 score applied to validate its performance[9]. One example is a system focused on Pomegranate Disease Classification using a Back Propagation Neural Network, which segments the affected area and applies color and texture as key features[2]. This algorithm, enhanced with a plain background for improved focus, demonstrated accuracy in comparison with other machinelearning techniques[10].

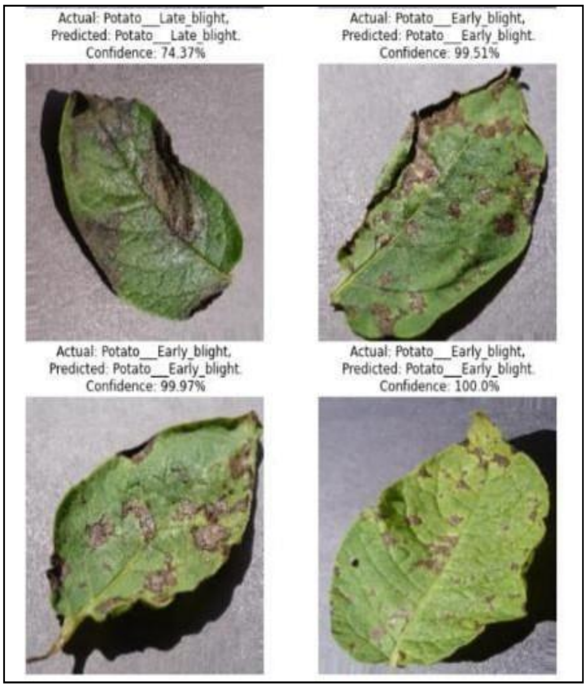

Fig 1: Potato leaf prediction

Methodology :

Dataset

A dataset consists of data points utilized to train, validate, and test a machine learning model, directly influencing the model's effectiveness. By learning patterns from a well- structured dataset, machine learning models improve in generalizing to new data. This study used an open-source image dataset published in2016 [4], featuring 70,295 images for training, 17,572 images for validation, and a test set of 33 images.

Preprocessing Images

Preprocessing is a vital part of image classification workflows, involving steps to clean and prepare raw image data for the model. Effective preprocessing enhances model performance. Initially, raw images lacking labels were assigned appropriate tags to serve as ground truth for model training[6]. These images, labels, and class names were organized in a data frame for streamlined processing. The dataset was divided into training, validation, and testing subsets[11]. The train_test_split function separated 80% of the data for training and 20% for validation[6]. Images were resized to 150x150 pixels to reduce memory usage, normalized, and categorized for the trainingphase[5].

Model Construction

Convolutional Neural Networks (CNNs) specialize in interpreting grid-like data, such as images, and have transformed image classification and computer vision tasks[8]. In this study, we used the Keras library to build a CNN model for image categorization. The input layer processed images of size (150, 150, 3), representing the resized image dimensions and RGB color channels. The final dense layer had 39 output units, one for each class, with the 'softmax' activation function providing classprobabilities[9].

Result and Discussion :

Model Result

The CNN model was trained and tested with the prepared data. After running 30 training epochs, the model achieved an accuracy of 92.23%, with a final loss of 0.2683, indicating satisfactory performance[12].

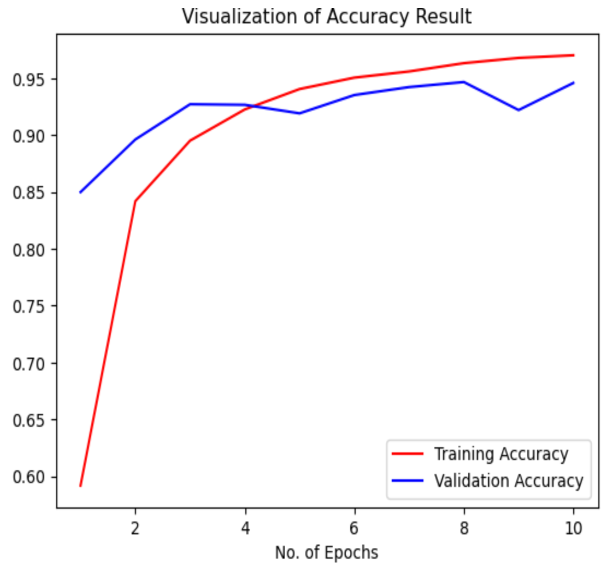

Fig 2: Training and accuracy graph

Discussion and Future Investigation

Implementing machine learning techniques, especially Convolutional Neural Networks (CNNs), for plant disease detection presents significant potential for improving agriculture. This study achieved a disease classification accuracy of 92.23%, underscoring the effectiveness of CNNs in assisting farmers andenhancing crop yields[6]. However, several areas warrant further research.

Data

The dataset used here was enhanced with offline data augmentation based on the original collection, containing around 87,000 images of healthy and diseased leaves across 38classes[5]. The data was divided with an 80/20 ratio for training and validation while keeping the directory structure intact. An additional testset of 33 images was created for predictiveevaluation.

To enhance the model's robustness, future datasets could include a broader range of crop and disease images gathered from diverse regions and climates. Such diversity would improve the model's adaptability, and user- uploaded images could further expand the database for continuous improvement[10].

Real-world Implementation Challenges

Though CNN-based disease detection shows promise, applying this model in real-world scenarios can pose challenges. Environmental factors such as lighting, weather conditions, and crop growth stages may impact model accuracy[7]. To enable reliable use, models need to be adapted to different environments. Moreover, consistent internet access may be limited in rural areas, potentially affecting the feasibility of mobile applications for disease detection[7].

Continual Model Improvement

Machine learning models perform best with continuous learning and updates. While this model achieved high accuracy, ongoing improvements are necessary. Regularly updating the dataset with images of various disease stages, diverse crops, and different environmental conditions will yield a more comprehensive model capable of adapting to real-world agricultural needs[6].

Comparative Analysis :

In developing a leaf disease detection model, our objective was to build on existing research, specifically improving both the accuracy and versatility of disease detection across multiple crop types. The base research model we compared our results with has an accuracy of 85.6% and focuses solely on detecting diseases in potatoes[2]. While this initial accuracy is promising, its single-crop limitation restricts its utility for large-scale agricultural applications where diverse crop management is essential.

Our model achieved a significantly higher accuracy, reaching 92%, which marks a notable improvement over the base model[6]. This increase in accuracy means that our model can identify crop diseases with a lower error margin, allowing farmers and agricultural professionals to rely more confidently on its predictions. Moreover, our model extends its functionality beyond potatoes, encompassing a wider range of crops, including apples, cherries,corn, grapes, peaches, peppers, strawberries, and tomatoes. This multi-crop capability is particularly beneficial in agricultural settings where farmers often cultivate a variety of crops, each vulnerable to unique pathogens anddiseases[9].

The comprehensive scope of our model provides a unified platform to monitor and identify diseases across multiple crops, improving disease management practices. The ability to analyze different crop types in one model minimizes the need for separate systems, thereby reducing operational costs and simplifying the disease monitoring process. Forinstance, a farmer who cultivates multiple cropscan use our model to detect diseases early across the entire range of their crops, preventingthe spread of diseases and potentially improving yield and crop health[6].

Furthermore, the improvement in accuracy and extended scope enhances the model's practical application in real-world scenarios. With precision at 92%, the model minimizes false positives and negatives, reducing the risk of either overestimating disease presence, leading to unnecessary treatments, or underestimating it, which could allow diseases to progress unchecked[6]. This balance between accuracy and diversity in crop prediction makes our model a more comprehensive solution, effectively advancing the functionality of machine learning in agriculture.

In summary, our model's 92% accuracy and its multi-crop detection capability highlight a significant improvement over the base model. This advancement not only supports more efficient disease management but also empowers agricultural stakeholders to make data-driven decisions that can positively impactcrop productivity and sustainability. Bybroadening the range of crop types it serves, themodel stands as a valuable tool for modern agricultural practices, promoting better diseasecontrol, reduced costs, and improved crop outcomes[6][9].

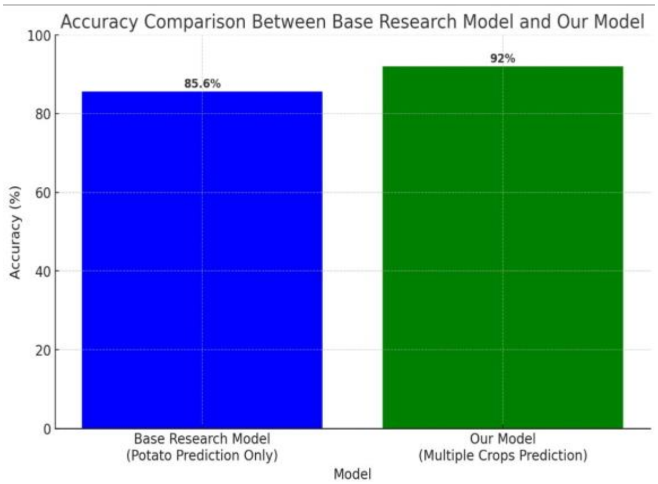

Fig 3: Comparative Analysis Graph

Conclusion :

This research presents a plant disease detection system using CNNs, TensorFlow, and Streamlit, achieving reliable classification results on the Plant Village dataset. The system enables users, including non-experts, to identify plant diseases in real-time, offering valuable assistance to farmers and agricultural specialists. With continued improvements in data collection and model architecture, this approach could transform disease detection in agriculture, promoting more effective crop management and supporting sustainable farming practices.

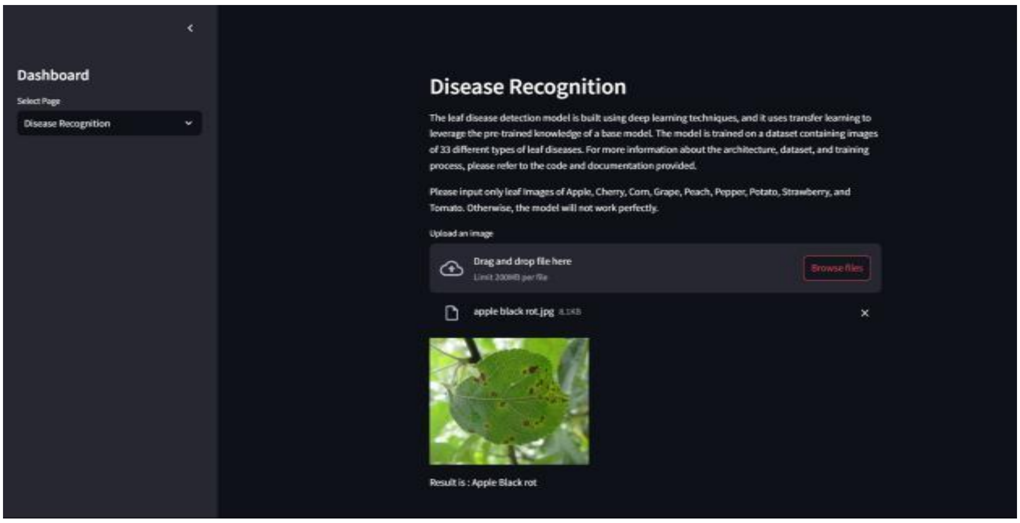

Fig 4: Predicted result of image-1

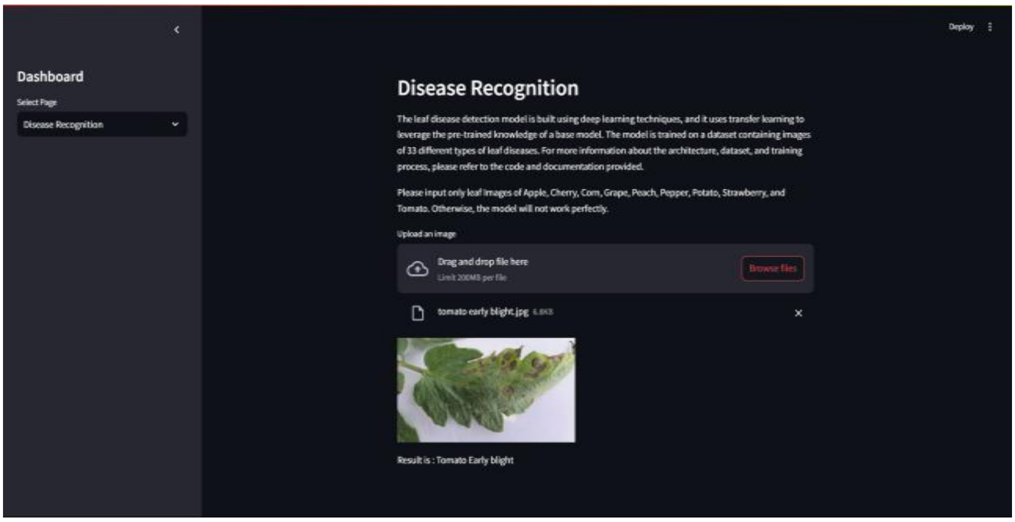

Fig 5: Predicted result of image-2

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