Convolutional Neural Network-Based Approach for Plant Disease Identification

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Abstract— The occurrence of plant diseases has become an integral part of influencing agricultural crop yields. Detecting plant diseases helps minimize the losses that occur in the agricultural industry. Detecting plant diseases is a time-consuming activity that requires the involvement of several agricultural experts. It is not feasible to do this in rural areas owing to the scarcity of such experts. This research discusses the application of an efficient approach to identify plant diseases using lightweight convolutional neural networks (CNN). The details of an effective model to diagnose plant diseases along with their remediation are provided here. The architecture of the neural network utilizes inception blocks, residual networks, and depthwise separable convolutions that help reduce the computational burden. These deep learning models can be trained using freely available image data sets of leaves that are either healthy or diseased. The proposed CNN-based model performs better than other deep learning models at reduced computational costs. The design of the application software interface is used to identify and mitigate plant diseases in real-time.

Keywords— Plant Diseases, Deep Learning, Convolutional Neural Network (CNN), Inception Block, Residual Network, Depthwise Separable Convolution, Smart Agriculture

I. Introduction

Agriculture is among the most significant contributors to the economy and food security of an increasing world population. Nevertheless, plant pathogens cause plant diseases, which reduce the quality and quantity of produce. Fungi, bacteria, and viruses are among the pathogens responsible for plant diseases. Diseases caused by plant pathogens lead to enormous financial loss and agricultural production inefficiency. Early and precise detection of plant diseases will contribute to increased agricultural productivity and sustainability.

Conventionally, plant disease detection is done manually through inspection by experts in agriculture. While it is relatively accurate, it is costly, consumes much time, and highly dependent on the experience and knowledge of experts. It is impossible to implement manual detection in large agricultural farms. Rural and developing areas lack expertise in agriculture, making disease detection hard.

The rise in artificial intelligence and deep learning technology has facilitated the development of efficient image classification and pattern recognition techniques. Various deep learning models like AlexNet, VGGNet, ResNet, DenseNet, and Inception have performed efficiently in classifying plant diseases. The models are capable of automating the process of feature extraction from images. Although the current models attain impressive results, they consume significant computational resources and memory capacity.

II. Literature Review

There is quite a number of studies available regarding image processing of plant diseases with Deep Learning (DL). Initially, Machine Learning algorithms were used, but there was a need to construct handcrafted features. Deep Learning models such as Convolutional Neural Networks (CNNs) have proved to be more effective in comparison with other techniques in classification problems.

For example, S. P. Mohanty et al. utilized the AlexNet and GoogLeNet to classify different kinds of plant diseases using the PlantVillage dataset, obtaining extremely accurate results. K. P. Ferentinos reviewed a number of DL models like VGGNet, AlexNet, and GoogLeNet for diagnosis of plant diseases.

G. Geetharamani et al. developed a deep learning-based system based on deep CNN to identify the symptoms of plant diseases. Meanwhile, E. C. Too et al. studied several architectures associated with the DL models including DenseNet, ResNet, and VGGNet. Among all these models, it has been proven recently that DenseNet model works the most efficiently.

Moreover, in their research work, the scientists have paid attention to computational efficiency issues. For example, Hu et al. constructed depth-wise separable convolution that reduced parameters without losing precision in classification.

III. Problem Statement

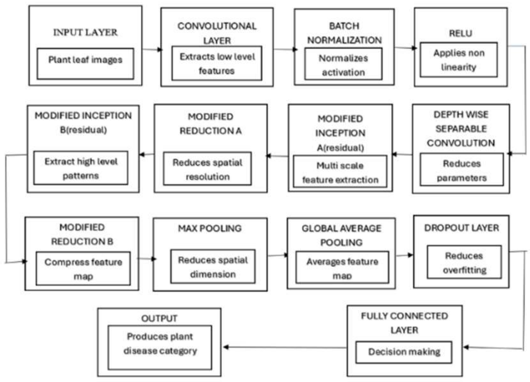
The existing disease recognition systems for plants have the following drawbacks:

- Expert human visual examination of plants
- Complex computation of existing Deep Learning models
- Hard to deploy on low-cost hardware
- Cannot be accessed in real-time by farmers
- Poor performance in complex situations

Considering all these aspects, there is a need to develop an efficient disease recognition system that requires less computational resources but performs effectively.

IV. Proposed System

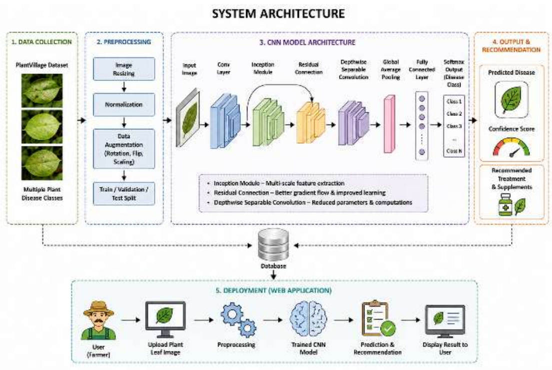
The proposed system introduces a lightweight CNN-based framework for accurate and efficient plant disease detection. The architecture combines Inception modules, residual connections, and depthwise separable convolution for enhanced feature extraction and reduced parameter size.



A. System Architecture

The system comprises the following:

- Front-end: Web-based interface for uploading images and displaying results
- Back-end: Disease prediction engine utilizing CNNs developed in Python
- Database: Repository for storing information related to diseases, treatment plans, and users
- This design ensures efficiency and real-time disease predictions.



B. Image Preprocessing

Plant leaf images are obtained from the PlantVillage database. These images are subjected to preprocessing steps including:

- Image resizing
- Normalizing the images
- Rotating the images
- Flipping the images
- Scaling the images

Preprocessing enhances data quality and minimizes overfitting during model training.

C. Feature Extraction

The preprocessed images are fed into convolution layers where feature extraction occurs. Multi-scale feature extraction is achieved through inception blocks, whereas residual connections enhance the model's ability to learn and overcome vanishing gradients. Depthwise separable convolution lowers computational cost and reduces the number of parameters.

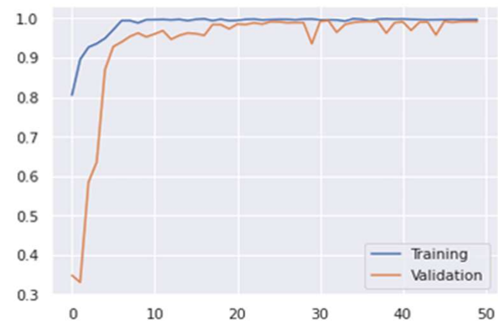
D. Disease Classification

The extracted features are used in classification through fully connected layers and Softmax activation. The model classifies the disease category with corresponding probabilities.

E. Result Generation

The output is presented using a web-based interface the system offers disease treatments supplements and prevention strategies.

Deep learning model	Dataset used	Parameter required	Training acc	Testing acc	Testing loss	Epoch	Training time (sec/epoch)
VGG [7]	PlantVillage	138 million	-	98.87	0.0542	49	4208
AlexNet [5]	PlantVillage	60 million	99.35	93.88	-	30	-
INC-VGGN [6]	PlantVillage	more than 138 million	97.57	91.83	0.2409	30	-
GoogleNet	PlantVillage	7 million	-	97.3	-	20	-
ResNet50+SVM [1]	Rice	23 million	-	98.38	-	-	69.04
Nine layer CNN [17]	PlantVillage	-	97.87	96.46	-	3000	-
Shallow CNN+ RF [30]	PlantVillage	0.26 million	-	94	-	-	-
Deep Residual CNN [25]	Cassava	-	-	58.39	-	80	-
Proposed CNN	PlantVillage	0.42 million	99.73	99.39	0.0549	50	883
Proposed CNN	Rice	0.42 million	99.94	99.66	0.0041	50	227
Proposed CNN	Cassava	0.42 million	98.17	76.59	0.4465	50	221



V. Implementation

This approach has been achieved through the use of Python programming language because it is capable of implementing image processing and machine learning algorithms. Libraries such as TensorFlow and Keras have been utilized in the implementation of the CNN algorithm. The development of the CNN algorithm will be achieved via the use of the Jupyter notebook and Google colab with GPU.

In the current study, PlantVillage dataset will be used in the process of training and evaluating the CNN algorithm. This dataset consists of healthy and unhealthy images of plant leaf. In addition, the dataset contains pictures of various plants. Some images will be used to train the CNN algorithm, while others will be used to evaluate its performance.

The architecture of the CNN algorithm includes layers such as convolution, pooling, inception, residual, and depthwise separable convolution. Moreover, the Adam optimizer and categorical cross-entropy will be implemented as a loss function during training the CNN model.

HTML, CSS, and JavaScript programming languages are utilized in the creation of an easy-to-use interface for users. The uploading of pictures to CNN algorithm and their processing are performed on the back-end side of the website.

VI. RESULTS AND DECLARATION

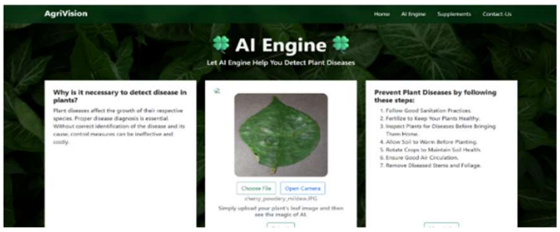
The developed disease detection algorithm exhibits high efficiency and disease identification with high accuracy rates on different crops. The accuracy plots grow gradually, whereas the loss plot drops steadily, which means that the model learned without any signs of overfitting.

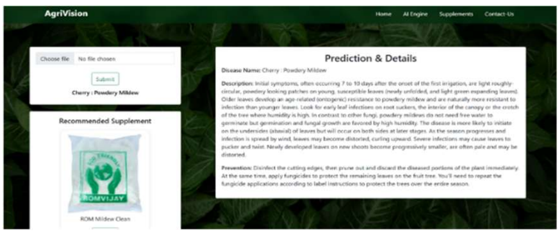
The designed CNN network reaches 99.7% classification accuracy with fewer parameters than networks like VGGNet and ResNet.

The significant benefits of the proposed approach include:

- High Classification Accuracy – Precise classification of diseases on multiple crops
- Efficiency – Fewer parameters and more efficient computations
- Real-Time Accessibility – Web-based system for predicting diseases
- Practical Usefulness – Disease prevention and treatment tips

The obtained results indicate the efficiency and high level of reliability of the proposed system.





VII. CONCLUSION

This research paper suggests a CNN-based system having Inception module, residual connection, and depth-wise separable convolution for detection of diseases in crops. The suggested approach ensures accurate results in classification, which helps reduce computational costs and parameters used.

Web-based approach enables the user to use the system conveniently and helps predict diseases occurring in crops. It has been found out that the suggested system is better than others available in the domain due to efficiency and convenience.

The suggested approach can prove helpful in monitoring agricultural activities and controlling diseases of crops.

VIII. FUTURE WORK

Future developments of the proposed system can include designing mobile applications as well as incorporating IoT approaches to support intelligent agriculture. Future developments could also include monitoring the crop growth using drone imaging technology and actual images of crop fields stored in the database.

Other techniques such as AI approaches that can assist in estimating the level of disease severity and recommending treatment measures can also improve the performance of the system.

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