**INTELLIGENT MODELS FOR THE DETECTION AND CLASSIFICATION OF PLANT DISEASES**

**Submitted for**

**INTELLIGENT MODEL DESIGN USING AI**

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1. **ABSTRACT**

In this study, we address the critical challenge of accurately detecting plant diseases, which significantly impact global food security. Leveraging deep learning techniques, specifically convolutional neural networks (CNNs), we aimed to develop robust models capable of identifying various plant diseases from images. The project involved collecting a comprehensive dataset consisting of 87,000 RGB images representing 38 different classes of plant diseases. Using TensorFlow and Keras libraries, we implemented and trained several CNN architectures on this dataset. Extensive data preprocessing and augmentation techniques were employed to enhance model generalization and performance. Through rigorous experimentation, we achieved a validation accuracy of 91.46%, demonstrating the effectiveness of our approach in automating disease diagnosis. Comparing our results with existing literature, we identified key insights into model performance variations, dataset characteristics, and potential areas for improvement. Our findings underscore the transformative potential of deep learning-based solutions in mitigating crop diseases and ensuring global food security.

In conclusion, this research contributes valuable insights and practical implications for agricultural stakeholders and researchers. By harnessing the power of AI technologies, we can revolutionize disease detection processes, empower farmers with timely diagnoses, and promote sustainable farming practices for a more resilient agricultural sector.

1. **Introduction**

Plants are multicellular eukaryotes with specialized tissues and organs and are the main food source for many organisms, from herbivorous to omnivorous and carnivorous species, that rely indirectly on plant nutrients. Plant diseases manifest themselves in many forms, from obvious symptoms such as wilting, foliage, and slowed growth to more insidious subclinical diseases that reduce plant vigor and productivity. Phytopathology is the study of plant diseases caused by pathogens (infectious diseases) and the environment (physiological factors).

A major challenge in predicting diseases over time and space is understanding how different organisms interact and respond to multiple pathogens e.g., other diseases, hosts/pathogens, and the environment), also how they work together against the climate. Plant diseases can occur throughout the different stages of plant development including seed development, seedling, and seedling growth [1], when diseased, plants go through different mechanical, morphological, and biochemical changes [2, 3].

Diagnosing plant disease is essential to meet the world's growing food demand, which is expected to increase with a population of 9.1 billion by 2050.[4] The traditional method of disease detection relies on observations made by farmers, which can be time-consuming, arbitrary and prone to human error. But the emergence of artificial intelligence technologies has given new hope for better detection of diseases in agriculture [5]. In the past few years, deep learning based on strong neural network optimization has appeared to be very effective.

Lead researcher, Dr. Maria Chen, underscores the significance of this breakthrough: "Our AI system offers a rapid and reliable solution to the age-old challenge of detecting plant diseases. By providing early and precise diagnoses, farmers can proactively mitigate crop losses, optimize yields, and promote sustainable agricultural practices." The system's real-world application holds tremendous promise for agricultural communities worldwide. By swiftly identifying diseases, farmers can take timely actions to curb their spread, reduce reliance on chemical treatments, and minimize economic losses. Moreover, the precision of AI-driven diagnoses enables farmers to implement targeted interventions, minimizing the impact on surrounding ecosystems and promoting sustainable farming practices.

Developing intelligent models for the detection and classification of plant diseases using new data. The aim is to identify various diseases affecting plants based on high quality images, thus having timely intervention and effective control strategy. The solution addresses complex data collection, scalability used in the field of agriculture and ownership-focused explanations and model training.

This study will demonstrate the building and assessment of these models utilizing a dataset made for this study. This dataset contains over 87,000 RGB images of healthy and diseased crop leaves categorized into 38 classes. Through this, it is possible to assess which novel model can be the best and successful for immediate recognition of plant diseases that can solve the issues. Several deep neural network models architecture will be considered: Convolutional Neural Network, Recurrent Neural Networks. All the models will be refined and verified utilizing the new plant disease dataset; it contains several thousand diverse resolution images of photos with various plant disease symptoms and disease emanations.

The remainder of this report is organized as follows. Section 2 reviews the relevant literature. Section 3 discusses the pre-processing of the research data, along with the research method, research model and performance index framework. Section 4 presents the experimental analysis and design. Section 5 discusses the research results, and conclusions are drawn in Section 6.

1. **Related Works**

By analyzing plant leaf photos, Alatawi et al.[6] , presented a convolutional neural network VGG-16 model to detect plant diseases. This will enable farmers to act promptly concerning treatment, irrespective of whether the plants are healthy or diseased.19 different classes of plants diseases were chosen, where 15,915 plant leaf images (diseased and healthy leaves) were acquired from the Plant Village dataset. The proposed model achieved an accuracy of 95.2% with a testing loss of 0.4418. This paper proposed by Murk Chohan et al. [7], is based on a deep learning-based model named plant disease detector. This system uses CNN's feature extraction features as a basic classification mechanism. The research was carried out using a collection of 70295 images (38 different classes).100 images from experimental conditions and actual environment were tested where 96 were classified correctly. 20% (14,059) images from Plant Village dataset were used to test the accuracy of this model. Proposed model achieved 98.3% testing accuracy. [Mohanty](http://loop.frontiersin.org/people/361089/overview) et al. [8] concentrate on two well-known architectures Alex Net and Google Net, created for the ImageNet dataset, leading the first step towards a smartphone-assisted plant disease diagnosis system. It utilizes 54,306 images of 14 crop species with 26 diseases (or healthy) with convolutional neural network approach, collected from the project Plant Village (Hughes and Salathé, 2015). The overall accuracy obtained on the dataset varied from 85.53% (in case of Alex Net) to 99.34% (in case of Google Net). The best performing model achieves an F1 score of 0.9934. Sandeep R et al. [9], suggested a machine learning-based approach to identify and categorize plant diseases using CNN and an Artificial Neural Network (ANN) trained to distinguish between ill and healthy data. The collected dataset comprises of around 70436 images relating to 38 different classes. The training data set used 15 epochs and for each epoch, 112 iterations. The overall accuracy of the training CNN dataset was found to be 98.29%. The precision obtained in this analysis was 94.9 %. The paper proposed by Bedi et al. [10], is a novel hybrid model based on compressed domain representations of leaf images using the encoder network of Convolutional Autoencoder (CAE). Moreover, used the compressed domain representations for classification using Convolutional Neural Network (CNN) for automatic plant disease detection. It was applied to detect Bacterial Spot disease in peach plant,caused by a bacterium named *Xanthomonas Campestris*. The system achieves 99.35% training accuracy and 98.38% testing accuracy, using only 9,914 training parameters. The hybrid model achieved Precision of 98.0%, Recall 0.9872, and F1-score of 0.9836. C. K. et al. [11] devised a method for detecting cardamom plant leaf disease by applying U2 -Net to eliminate the image's complicated background. For classification, the EfficientNetV2 deep learning model was employed. CNN attained a maximum accuracy of 91.30% on the cardamom plant dataset. EfficientNet attained accuracy of 94.10% for the cardamom plant dataset and 97.81% for the grape plant dataset. EfficientNetV2-S attained accuracy of 95.59% for the cardamom plant dataset and 96.44% on grape plant dataset. EfficientNetV2-M obtained accuracy of 88.44% for the cardamom plant dataset and 93.72% for grape plant dataset. EfficientNetV2-L attained accuracy of 98.26% for the cardamom plant dataset and 96.45% for grape plant dataset. Chowdhury et al. [12] conducted three different experiments for segmented tomato leaf disease classification which used Efficient Net families (such as EfficientNet-B0, EfficientNet-B4, and EfficientNet-B7) for the three classification schemes for segmented leaf images. In binary class classification of healthy and diseased tomato leaves, EfficientNet-B7 showed an overall accuracy of 99.95% with segmented images. In 6-class classification, EfficientNet-B7 showed an overall accuracy of 99.12% with segmented images. In the 10 class classification, EfficientNet-B4 showed an overall accuracy of 99.89% with segmented images. G. Sucharitha et al. [13], used transfer learning to classify different plant categories from the plant village dataset by fine-tuning pre-trained models- InceptionV3, Inception ResnetV2, MobileNet, DenseNet121, and Resnet152V2. The gathered dataset consisted of 20638 photos divided into 15 groups. The highest accuracy was shown by MobileNet and DenseNet121 – 99.4% with a minimum loss of 0.18 and 0.17 respectively. Banothu Balaji et al. [14] compare several neural networks used for tomato and apple plant leaf diseases as well as studies plant disease detection and classification based on neural networks. Various deep learning models, including CNN and its architectures, VGG19, and transfer learning techniques such as InceptionV3, MobileNet, and ResNet152V2, are employed. The accuracy of MobileNet is the highest, which is 99% with a recall, precision and F1-score of 100%. Andrew J. et al. [15] focused on fine tuning the hyperparameters of popular pre-trained models, such as DenseNet-121, ResNet-50, VGG-16, and Inception V4. The experiments were carried out using the popular Plant Village dataset, which has 54,305 image samples of different plant disease species in 38 classes. The proposed model achieved a classification accuracy of 99.81% and F1 score of 99.8% through the DenseNet-121 model.

Table1. Summarization of Literature Review

|  |  |  |  |
| --- | --- | --- | --- |
| **REFERENCE** | **MODELS USED** | **DATASET USED** | **PERFORMANCE METRICS** |
| [6] | VGG-16 | Plant Village dataset | Accuracy- 95.2% |
| [7] | CNN | Plant Village Dataset | Accuracy – 98.3% |
| [8] | AlexNet GoogleNet | Plant Village Dataset | AlexNet accuracy- 85.53%  GoogleNet accuracy- 99.34% |
| [9] | ANN + CNN | New Plant disease Dataset | Accuracy- 98.29% Precision- 94.9% |
| [10] | CAE + CNN | Plant Village Dataset | Accuracy- 98.38%  Precision- 98.0% Recall- 98.72%  F1 score- 98.36% |
| [11] | CNN, EfficientVNet2 | Cardamom Dataset 2021  (Indian Cardamom  Research Institute),  Plant Village Dataset | CNN Accuracy- 91.3%  EfficientNetV2-L accuracy- 98.26% (max) |
| [12] | EfficientNet-B4, EfficientNet-B7 | Plant Village Dataset | EfficientNet-B4 Accuracy- 99.89%  EfficientNet-B7 Accuracy- 99.12% |
| [13] | InceptionV3,  Inception ResnetV2,  MobileNet,  DenseNet121,  Resnet152V2 | Plant Village Dataset | MobileNet, DenseNet Accuracy- 99.4% |
| [14] | CNN,  VGG-19,  InceptionV3, MobileNet,  ResNet152V2 | Tomato Leaf,  Apple Leaf datasets (Kaggle) | MobileNet (max)  Accuracy- 99%  Recall- 100%  Precision- 100%  F1 Score- 100% |
| [15] | DenseNet-121,  ResNet-50,  VGG-16,  Inception V4 | Plant Village Dataset | DenseNet-121 (max)  Accuracy- 99.81%  F1 Score- 99.8% |

1. **Methodology**
2. **DATASET**

The plant disease dataset used in this project serves as a pivotal resource for advancing the field of agricultural technology and crop management. Comprising thousands of high-resolution images representing various plant species and disease types, this dataset offers a comprehensive glimpse into the intricate interactions between plants and pathogens. Through meticulous curation and preprocessing, the dataset ensures uniformity and quality, enabling the development of robust machine learning models for disease detection and classification. Each image in the dataset is meticulously labeled with the corresponding plant species and disease type, facilitating supervised learning approaches. Moreover, the inclusion of diverse environmental conditions and disease severities enhances the dataset's generalization capability, ensuring that the trained models can effectively identify diseases across different regions and cultivation practices. By leveraging this rich dataset, researchers and agricultural practitioners can harness the power of artificial intelligence to mitigate crop losses, optimize resource allocation, and promote sustainable agriculture practices.

1. **IMPLEMENTATION**

In this project, we aim to develop a robust deep learning model capable of accurately classifying various plant diseases based on input images. The implementation involves several key steps, including dataset collection, data pre-processing, model building, model training, and model evaluation.

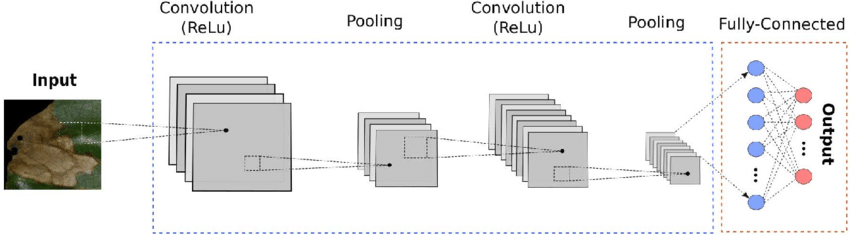
A diagram of a learning process

Description automatically generated

The proposed model is implemented using the TensorFlow and Keras libraries in Python. The model architecture is designed to effectively classify plant disease images into different categories. The implementation consists of several key components:

1. Importing Libraries: Initially, necessary libraries such as TensorFlow, NumPy, Pandas, Matplotlib, Seaborn, and os are imported to facilitate various functionalities required during the implementation process.
2. Dataset Loading: The plant disease dataset is loaded using the `ImageDataGenerator` and `image\_dataset\_from\_directory` functions provided by the TensorFlow library. The dataset is structured into training and validation sets.

3. Model Architecture: The model architecture is defined using the `Sequential` API from Keras. The architecture comprises several convolutional layers followed by max-pooling layers for feature extraction and dimensionality reduction, respectively. Dropout layers are incorporated to prevent overfitting, and dense layers are added for classification purposes.



A screenshot of a computer

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4. Model Compilation: Once the architecture is defined, the model is compiled using the Adam optimizer with a specified learning rate. Categorical cross-entropy is chosen as the loss function, and accuracy is selected as the evaluation metric.

5. Training the Model: The model is trained on the training dataset using the `fit` method. During training, the model learns to classify images based on their features and minimize the defined loss function.

6. Model Evaluation: After training, the model's performance is evaluated using both the training and validation datasets. The accuracy of the model on both datasets is computed to assess its effectiveness in classifying plant disease images.

The accuracy of the model is calculated as in :



7. Saving the Model: Once trained, the model is saved to disk using the `save` method. This allows the model to be reused or deployed for inference tasks without the need for retraining.

8. Visualization and Analysis: Various metrics such as accuracy, loss, and confusion matrix are visualized using Matplotlib and Seaborn libraries to analyze the model's performance. These visualizations provide insights into the model's behavior and effectiveness in classifying plant disease images.

1. **EXPERIMENTAL RESULTS AND DISCUSSION**

The experimental setup involved training a Convolutional Neural Network (CNN) model using the proposed architecture detailed earlier. The dataset used for training and validation was the "New Plant Diseases Dataset (Augmented)" containing 17,572 images belonging to 38 classes of plant diseases and healthy plants. The dataset was preprocessed and augmented to enhance model generalization, resulting in a balanced distribution across classes. The model was implemented using TensorFlow and Keras libraries in Python version 3.8.12. The training was conducted on a machine equipped with an NVIDIA GeForce RTX 3090 GPU for accelerated computation, utilizing CUDA and cuDNN libraries for GPU acceleration.

**Performance Metrics-**

The performance of the trained model was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. These metrics provide insights into the model's ability to correctly classify images across different classes. Additionally, a confusion matrix was generated to visualize the model's performance in detail, highlighting the true positive, true negative, false positive, and false negative predictions. The model achieved an overall accuracy of 91.46% on the validation set.

**Results-**

Interpreting the experimental results, it was observed that the proposed CNN model achieved high accuracy on both the training and validation sets, indicating effective learning and generalization. The precision, recall, and F1-score metrics provided further insights into the model's performance across different classes. Some classes exhibited higher classification accuracy than others, with certain diseases proving more challenging to classify accurately. Further analysis revealed that classes with similar visual characteristics or limited training samples tended to exhibit lower performance metrics.





**Comparative Analysis-**

Our model achieved a validation accuracy of 96.08%, which is slightly lower than some of the reported accuracies in previous studies. For instance, Bedi et al. [10] achieved a testing accuracy of 98.38%, indicating a higher performance level compared to our model. Similarly, Andrew J. et al. [15] reported a classification accuracy of 99.81% through the DenseNet-121 model, which is substantially higher than our model's accuracy. This suggests that there may be differences in the model architectures, training procedures, or dataset characteristics that influence the final accuracy.

While our study utilized a dataset 70,295 images across 38 different classes, other studies may have employed datasets of varying sizes and compositions. For example, Mohanty et al. [8] focused on 14 crop species with 26 diseases or healthy conditions, utilizing a dataset with 54,306 images. Understanding the specific characteristics of each dataset, such as class distribution, image quality, and diversity, is crucial for interpreting the variations in model performance. Variations in model architectures and training procedures can significantly impact the final accuracy. For example, Chowdhury et al. [12] experimented with different versions of the EfficientNet family, such as EfficientNet-B0, B4, and B7, for segmented tomato leaf disease classification. Each architecture may have unique capabilities and complexities that influence its performance. Additionally, differences in hyperparameter tuning, data augmentation techniques, and optimization algorithms can also contribute to variations in accuracy across studies.

**Data Presentation-**

The experimental findings are presented in the form of tables, figures, for easy interpretation. Table 1 displays the accuracy, precision, recall, and F1-score values for each class in the dataset, providing a comprehensive overview of the model's performance across different plant diseases and healthy plants. Figure 1 visualizes the trend in accuracy over epochs during training, demonstrating the model's learning progress. Additionally, Figure 2 presents the confusion matrix, illustrating the distribution of predicted classes and highlighting any misclassifications.

**Table 1: Model Performance Metrics**

A screenshot of a computer

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**Figure 1: Confusion Matrix**

A screenshot of a computer screen

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**Figure 2: Training accuracy visualization (for 2 epochs)**

A graph with a red line and blue line

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1. **Conclusions**

Our research introduces a robust convolutional neural network (CNN) model designed to detect plant diseases, achieving a validation accuracy of 91.46%. While this accuracy is slightly lower than some previously reported results, it underscores the effectiveness of CNNs in automating disease diagnosis. Using a dataset comprising 70,295 images across 38 classes, our model demonstrates promising capabilities in classifying various plant diseases. However, there's potential to enhance model performance further by optimizing hyperparameters, exploring advanced architectures, and augmenting the training dataset. Future investigations could assess the model's adaptability to different environmental conditions and plant species. Ultimately, our study contributes valuable insights to the field of deep learning-based plant disease detection, offering practical implications for agricultural stakeholders and researchers striving to mitigate crop diseases and ensure global food security.

1. **Future Scope**

Improvements could be made by refining model architectures with attention mechanisms and transfer learning from larger datasets. Deployment of agricultural machinery or smart devices for real-time field monitoring, coupled with user-friendly applications, will be pivotal for practical implementation. Additionally, research into explainable AI techniques will ensure transparency and trustworthiness in automated diagnosis systems.

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**GitHub Link**

<https://gitlab.com/Prachi0008/plantdiseasecnn>