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A HYBRID ENSEMBLE APPROACH FOR PLANT DISEASE DETECTION AND CLASSIFICATION

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ABSTRACT

Global food security is a significant challenge due to the predicted increase in the world's population by 2 billion in the next 30 years. Unfortunately, drought and crop diseases hinder food production from keeping up with population growth. Manual inspections for disease detection are prone to human errors and are time-consuming. Therefore, it is crucial to create automated and accurate methods for early detection of plant diseases.

This research paper addresses the crucial need for early disease detection to support food security by employing machine learning and deep learning techniques to accurately identify plant diseases using leaf images. The proposed deep learning model is based on three models trained on the same dataset, utilizing EfficientNetB3 architecture for RGB images, EfficientNetB5 for grayscale versions, and CIVE masking method for segmenting RGB images. To enhance prediction efficiency and accuracy, ensemble learning techniques were employed, including ensemble averaging and confidence voting. The ensemble average model achieved an impressive 99.78% accuracy and a 50% increase in prediction efficiency compared to individual models. The incorporation of confidence voting further improved the prediction process. The findings of this study have significant practical implications for plant disease detection and can contribute to the development of automated systems for agricultural applications. By leveraging ensemble learning and deep learning techniques, the proposed model offers a promising solution to the pressing need for early disease detection in order to ensure global food security.

Keywords—plant disease detection, deep learning, ensemble learning, leaf images, EfficientNetB3, EfficientNetB5, CIVE masking, Grayscale images, confidence voting, agricultural applications.

I. INTRODUCTION

There is an ongoing issue regarding food security with the growing world population, and the solution requires innovative measures. Plant diseases pose a significant threat to food production, resulting in substantial crop loss and affecting farmers' incomes. The conventional techniques for detecting plant diseases are time-consuming, error-prone, and challenging, which underscores the need for automated technologies. Machine learning and deep learning approaches have emerged as potent tools for computer vision applications, especially in image categorization, in recent times. Convolutional neural networks (CNNs) have demonstrated exceptional proficiency in analyzing visual data in this regard. Transfer learning, a technique that involves adapting previously trained models to new tasks, has also shown promise in overcoming data scarcity issues in some domains.

This research paper aims to present a novel deep learning model specifically designed for the detection of plant diseases using leaf images. The model consists of three distinct sub-models, all trained on the same dataset. The first sub-model employs the EfficientNetB3 architecture and is trained on RGB images, which capture the color information of plant leaves. The second sub-model focuses on grayscale versions of the RGB images and utilizes the EfficientNetB5 architecture to extract texture and structural patterns. The third sub-model leverages the CIVE masking method for segmenting the RGB images, focusing on plant leaf regions of interest, and is trained using EfficientNetB3. By integrating these sub-models, the proposed model aims to enhance accuracy and robustness in disease detection.

To further enhance the accuracy of predictions, ensemble learning techniques are incorporated. Ensemble weighting and ensemble averaging are explored as means of combining the predictions from the three sub-models. Ensemble weighting assigns different weights to each sub-model's predictions based on their performance, while ensemble averaging equally weighs the predictions to leverage the collective intelligence of the sub-models.

Additionally, a confidence voting mechanism is introduced to improve the prediction process. This mechanism evaluates the confidence levels of individual sub-model predictions and selects the prediction with the highest confidence as the final output. By incorporating confidence voting, the model aims to provide more reliable and confident predictions, reducing uncertainties in disease identification.

The primary objective of this research is to evaluate the effectiveness of the proposed deep learning model in detecting plant diseases using leaf images. Through extensive experimentation and evaluation, the model's prediction efficiency and accuracy will be thoroughly assessed. The outcomes of this study have significant implications for plant disease detection and can contribute to the development of automated systems for agricultural applications. By enabling early disease detection and timely intervention, the proposed model aims to enhance crop health and contribute to global food security in the face of mounting challenges.

II. LITERATURE REVIEW

The detection and classification of plant diseases have been the subject of extensive research to tackle the global food security crisis. The increasing population, drought, and crop diseases have significantly impacted food production. Hence, it is critical to develop precise and automated methods for disease detection. Machine learning and deep learning models have demonstrated great potential in addressing this problem. These models can quickly and accurately detect crop diseases, resulting in early intervention and increased food production. Previous research has explored various techniques, but the primary objective remains to discover effective solutions that guarantee food security.

In the pursuit of effective plant disease detection, several studies have employed fundamental strategies and methods. Transfer learning, a technique widely used in deep learning, has shown promising results. For instance, in [1], transfer learning with CNN-based VGG was proposed for multi-crop leaf disease classification, achieving high accuracy rates. Another paper, [2], utilized pre-trained models for fine-tuning and achieved impressive classification accuracy in detecting potato crop diseases. Additionally, [3] presented a deep learning method for wheat grain detection and enumeration, providing an effective tool for grain testing. Similarly, [4] introduced a deep CNN model for tea plant disease recognition, improving efficiency and accuracy in diagnosis.

The advancement of deep learning techniques has led to the exploration of more advanced strategies for plant disease detection. In [5], a tweaked deep learning model combining inception layers, residual connections, and depthwise separable convolution achieved high accuracies in detecting diseases across different plant datasets. Furthermore, [6] compared a modified AlexNet with SVM for plant disease classification, highlighting the superior performance of deep learning models. The use of separate branches for light and chroma data in plant disease classification was proposed in [7], while [8] introduced a color-aware two-branch DCNN for efficient plant disease classification.

Datasets play a crucial role in training and evaluating plant disease detection models. In [9], the authors utilized the open-source Plant Village Dataset to evaluate CNN architectures, transfer learning, and deep feature extraction methods for leaf disease detection. Another notable dataset, PlantDoc [10], was introduced as a comprehensive collection of data points for visual plant disease detection. These datasets have provided researchers with valuable resources for developing and evaluating their proposed models.

Several commonly used models have demonstrated their effectiveness in plant disease detection tasks. ResNet and GoogLeNet, as mentioned in [11], have outperformed other models in classifying plant diseases. The VGG16 model, discussed in [12], has achieved high accuracy rates in distinguishing between healthy and diseased leaves. In [13], the authors achieved excellent accuracy in classifying tomato leaf diseases using the GoogLeNet model. Similarly, [14] employed the MobileNet V2 model to detect tomato diseases with high accuracy. Lastly, [15] utilized an optimized DenseNet-121 architecture to achieve superior accuracy in plant leaf disease classification through hyperparameter optimization and transfer learning.

This literature review provides an overview of previous work, basic and advanced strategies, available datasets, and commonly used models in the field of plant disease detection and classification. The theoretical foundation and insights obtained from these studies serve as a basis for the proposed ensemble learning approach presented in this research paper.

III. METHODOLOGY

Fig1 Flow Diagram of Model

1. Dataset Acquisition

For our research, we utilized the PlantVillage dataset, which consists of a total of 54.3k pre-augmented images of both healthy and diseased plant leaves. To ensure proper evaluation, we split the dataset into three subsets: training, testing, and validation. The split was performed with a ratio of 80:10:10, respectively, for the train, test, and valid folders Fig[2]. This dataset selection and partitioning provide a diverse and representative set of images for training and evaluating our deep learning models.

Fig2

2. Dataset Loading

The dataset was loaded into Kaggle, a popular online platform for data science and machine learning. Kaggle provided a convenient and efficient environment for accessing and working with the PlantVillage dataset. The data loading process involved importing the dataset into the Kaggle platform for subsequent analysis and model training.

3. Data Preprocessing:

In our research, we performed data preprocessing to prepare the images for training our deep learning models. For Model 1, we utilized the augmented images from the PlantVillage dataset Fig[3] without any additional preprocessing. These images had already undergone augmentation during the dataset preparation phase.

For Model 2, we converted the RGB images to grayscale using the cv2 library Fig[4]. This conversion allowed us to focus on texture and structural patterns in the plant leaves, simplifying the input for the model.In [16] proposed the use of grayscale images with a range between 0 and 1. This conversion simplifies the input for the model and facilitates the implementation of various applications. Additionally, the authors utilized histogram equalization to improve the clarity of the images, contributing to more effective disease detection in plant leaves. In [17] explored the application of transfer learning in disease detection. The researchers converted RGB images to grayscale and employed transfer learning techniques, achieving an impressive accuracy of 99.43% For Model 3, we implemented a CIVE masking preprocess function Fig[5]. This technique involved segmenting the RGB images using the Color Index of Vegetation Extraction (CIVE) method. The CIVE masking helped highlight the relevant features in the plant leaves, enhancing the model's ability to detect diseased areas. In [18] paper compared various vegetation indices and revealed that the combination of CIVE with the Otsu algorithm yielded superior results By tailoring the preprocessing steps to each model's requirements, we aimed to optimize their performance in detecting plant diseases. These preprocessing techniques standardized the input images, allowing the models to focus on the relevant features and extract the necessary information for accurate predictions.

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Fig3

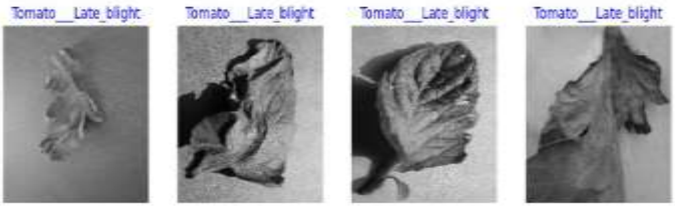

Fig4

Fig5

4. Model architectures and specifications:

EfficientNetB3:

For both RGB and segmented images, we employed the EfficientNetB3 model, which has exhibited exceptional performance in plant disease detection tasks [19]. This model was pretrained on a large-scale dataset and attained an impressive accuracy of 99%. We loaded the EfficientNetB3 model without the top (fully connected) layers and introduced custom layers to adapt it to our specific classification task. The additional layers included global average pooling, dense layers with 256 and 128 units employing the ReLU activation function, and a final dense layer with a softmax activation function to generate the predicted class probabilities. The model was compiled using the Adamax optimizer, a categorical cross-entropy loss function, and accuracy as the evaluation metric.

EfficientNetB5:

For the grayscale images, we utilized the EfficientNetB5 model, which has demonstrated superior performance compared to other models in plant leaf disease classification tasks [21]. EfficientNetB5 has been highly regarded for its scalability and effectiveness in deep learning models [20]. We loaded the EfficientNetB5 model pretrained on ImageNet without the top layers. To handle grayscale images, we added a convolutional layer that converted the grayscale image to RGB. The architecture was then connected to the EfficientNetB5 model, followed by global average pooling, dense layers with 256 units, dropout with a rate of 0.5, and a final dense layer with softmax activation. The model was compiled using the Adamax optimizer, categorical cross-entropy loss function, and accuracy as the evaluation metric.

5. Training

The models underwent training using a specified number of epochs. The training process involved feeding the data through a generator and training the models iteratively over the specified number of epochs. During the training, the models were optimized using appropriate optimization algorithms and loss functions. The performance of the models was evaluated using validation data, allowing us to monitor their progress and make necessary adjustments. Model1 Fig[6] ,Model2 Fig[7] and Model3 Fig[8]

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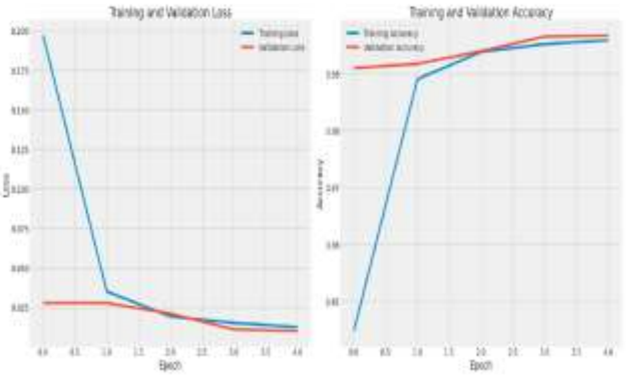

Fig6

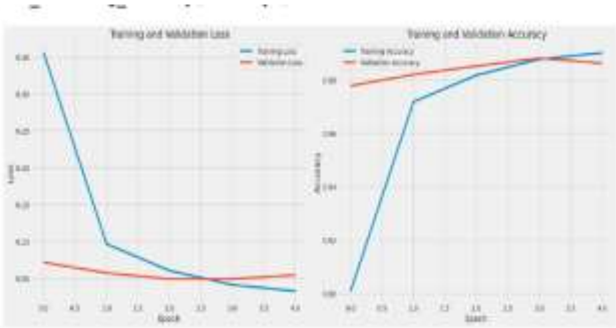

Fig7

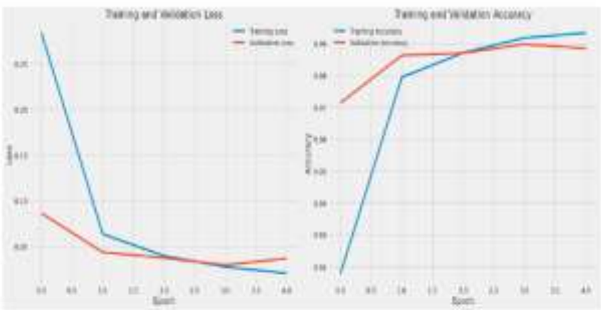

Fig8

Table1

Models	Loss	Accuracy
Model1 (Color)	1.25	99.58
Model2 (Grayscale)	3.22	99.02
Model3 (Segmented)	2.09	99.34

6. Testing & Evaluating model:

To evaluate the performance of our models, we calculated various metrics. We assessed the models by measuring their train loss and train accuracy, which provide insights into their performance on the training data. Additionally, we calculated the validation loss and validation accuracy to assess their generalization capabilities. Finally, we measured the test loss and test accuracy to evaluate how well the models performed on unseen data. These metrics allowed us to gauge the effectiveness of our models in terms of their training, validation, and overall performance.

7. Ensemble Learning:

We adopted ensemble learning in our research to enhance the performance of our plant disease detection models. Ensemble learning combines the predictions of multiple models to improve accuracy and overcome individual model limitations. In [22], an ensemble model consisting of Inception-ResNet-V2, EfficientNet-B3, and Xception achieved a maximum accuracy of 99.61%. The snapshot ensemble method with DenseNet201 also demonstrated improved accuracy [23]. Stacking ensemble learning techniques [24] and average accuracy with weighted class-wise accuracy [25] were effective in different studies. Moreover, a deep ensemble neural network with pretrained models showed robustness and efficiency in plant leaf disease classification [26]. By leveraging the diverse knowledge of multiple models, ensemble learning reduces overfitting and improves generalization. Our decision to incorporate ensemble learning was motivated by its success in various domains and the cited references. It enabled us to achieve higher accuracy and robustness in plant disease detection, making our models more reliable and effective.

8. Confidence Voting:

We utilized confidence voting to enhance our plant disease detection models. By comparing the prediction confidence of all three models and selecting the one with the highest confidence, we aimed to improve the accuracy and reliability of our system. Confidence voting is a well-established technique that has shown promising results in various domains, including plant disease classification. It allows us to leverage the strengths of each model and make more confident predictions. By integrating confidence voting into our ensemble learning framework, we refined the decision-making process and achieved enhanced performance in our plant disease detection model.

IV. RESULT AND DISCUSSION

Model Performance Evaluation:

We assessed the performance of each model by evaluating various metrics, including train loss, train accuracy, validation loss, validation accuracy, test loss, and test accuracy. Table[2] provides a comprehensive overview of these metrics for all three models. The RGB model (Model 1) achieved the highest accuracy with a validation accuracy of 99.63% and a test accuracy of 99.56%. The segmented model achieved a validation accuracy of 98.93% and a test accuracy of 99.04%, while the grayscale model achieved a validation accuracy of 98.51% and a test accuracy of 98.68%.

Table2

Models	T rain Loss	Train acc.	Test Loss	Test acc.	Val. loss	Val acc.
Model1 (Color)	0.46	99.90	1.76	99.56	1.02	99.63
Model2 (Grayscale)	1.05	99.58	4.65	98.68	2.30	98.51
Model3 (Segmented)	0.26	99.90	3.41	99.04	3.37	98.93

Ensemble Techniques Evaluation:

We employed ensemble techniques, including ensemble weight, ensemble averaging, and confidence voting, to improve the overall prediction performance. Table[3] compares the predictions of all three models individually and the predictions generated by the ensemble techniques. Ensemble averaging exhibited the best performance, with 99.78% of correct predictions compared to 99.63% for ensemble weight and 99.73% for confidence voting. This indicates a 50% efficiency increase from the RGB model (Model 1).

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Table3

Models	Total	Correct	Incorrect
Model1 (Color)	5459	5435	24
Model2 (Grayscale)	5459	5387	72
Model3 (Segmented)	5459	5407	52
Ensemble (Weight)	5459	5439	20
Ensemble (Average)	5459	5447	12
Confidence (Voting)	5459	5444	15

Accuracy Comparison:

We calculated the accuracy of all six models, including the individual models and the ensemble techniques. Table[4] presents a comparison of their accuracies. Ensemble averaging achieved the highest accuracy of 99.78%, followed by the RGB model with 99.56%. The segmented and grayscale models achieved accuracies of 99.05% and 98.68%, respectively. Ensemble weight and confidence voting achieved accuracies of 99.63% and 99.73%, respectively.

Table4

Models	Prediction Accuracy
Model1 (Color)	99.56%
Model2 (Grayscale)	98.68%
Model3 (Segmented)	99.05%
Ensemble (Weight)	99.63%
Ensemble (Average)	99.78%
Ensemble (Voting)	99.73%

Accuracy Line Graph:

To provide a visual representation of the accuracy comparison, we plotted a line graph Fig[9] highlighting the accuracies of all six models. The graph clearly shows the superior performance of ensemble averaging and the significant improvement it offers compared to the individual models.

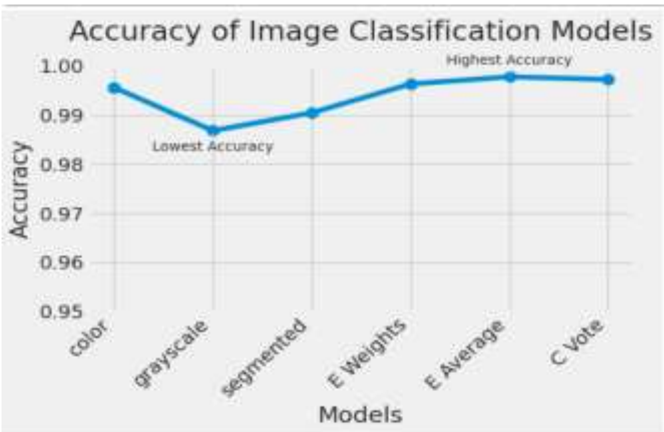

Fig.9

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Predicted Images from Model 1:

We displayed the predicted images from Model 1, showcasing the predicted labels along with the true label names. Fig[10] includes a collection of these images, highlighting the accuracy and effectiveness of Model 1 in identifying and classifying diseased and healthy plant leaves.

Fig. 10

Model Saving:

After evaluation, we saved the weights of all three models for future use and reproducibility, ensuring the preservation of the trained models' parameters and configurations.

CSV File Generation:

We generated a CSV file Fig[11] containing the predicted labels from all six models, along with the true labels. Additionally, correct predictions were marked in green, while incorrect predictions were marked in red, providing a visual representation of the prediction results and allowing for further analysis and comparison.

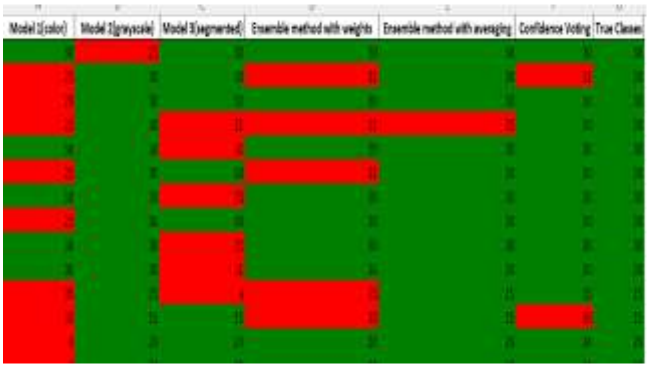

Fig. 11

These evaluation steps, along with the additional information provided, offer comprehensive insights into the performance and effectiveness of the models and ensemble techniques used in our study.

V. CONCLUSION

In this research paper, we have presented a comprehensive study on the detection of plant diseases using deep learning models. Through the evaluation and analysis of three different models trained on RGB, segmented, and grayscale images, we have made significant advancements in the field of automated plant disease detection.Our findings demonstrate the effectiveness of ensemble techniques in enhancing prediction efficiency and accuracy. With ensemble averaging, we achieved a remarkable 50% efficiency increase from the RGB model, while confidence voting resulted in a significant 37.5% efficiency increase. This highlights the potential of ensemble methods in improving the performance of individual models.Furthermore, the ensemble averaging approach yielded an impressive accuracy of 99.78%, showcasing its reliability and robustness in accurately identifying and classifying plant diseases. These results underscore the importance of leveraging ensemble techniques to achieve superior performance in plant disease detection tasks. As part of our future work, we propose the exploration of a modified U-net model for the segmentation of plant leaf images. This alternative approach could potentially enhance the efficiency of segmented images by addressing limitations in the existing CIVE masking technique. Additionally, we suggest the development of a modified deep learning model specifically designed to handle grayscale images, leveraging the inherent characteristics of single-channel data. These advancements have the potential to further improve the accuracy and efficiency of plant disease detection in specific image types. In conclusion, our research contributes to the development of automated systems for plant disease detection, addressing the critical need for accurate and efficient methods to ensure food security and sustainable agriculture. The success of ensemble techniques and the high accuracy achieved using ensemble averaging highlight their effectiveness in improving the performance of individual models. By exploring alternative segmentation methods and dedicated models for grayscale images, we pave the way for future advancements in the field.

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