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Potato Disease Detection Using Transfer Learning: An Ensemble Technique Approach

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In agriculture, plant leaf diseases cause significant productivity losses. Manual intervention in plant disease monitoring and control is time-consuming and involves a large human labour force. AI can address these difficulties by enabling the proactive diagnosis of plant diseases. Convolutional neural networks (CNNs) alone have demonstrated potential in automated plant disease diagnosis; but, when employed alone, their accuracy and resilience may be compromised. This study proposes an ensemble learning approach that combines four state-of-the-art CNN architectures: ResNet50, Efficient Net, Mobile net and VGG16. A comprehensive dataset of potato leaf images, categorized into healthy, early blight and late blight leaves, was used. Images were preprocessed and augmented to improve model generalization. Each model was trained separately, and their outputs were integrated using a weighted averaging mechanism to form the ensemble model. The weights for each model were optimized based on validation performance. The ensemble model significantly improved classification accuracy compared to individual models. The proposed method outperforms the other ensemble techniques with 5% improvement for precision and recall,10% reduction in response time,2% improvement in computational efficiency across all data test points.

Keywords: Plant Diseases, Deep Learning, CNN, VGG16, Resnet, Mobile net, Efficient net, Ensemble

1. Introduction

In the majority of developing countries, smallholder farmers account for more than 80% agriculture output, and crop diseases endanger food yield. Several attempts have been launched to prevent agricultural losses due to disease. Potato disease detection systems have various limitations in agriculture. They frequently rely on subjective human visual assessment, resulting in inaccuracies and inconsistencies. Manual inspection is time-consuming and might delay disease discovery, leading to fast infection transmission. Many farmers, especially those in distant locations, cannot afford to train and retain agricultural professionals for disease identification. These approaches often overlook early or asymptomatic illnesses, rely on specific environmental circumstances, lack data documentation, and are not easily scalable. They rely largely on expert knowledge, which limits their applicability. In recent years, integrated pest control (IPM) approaches have surpassed traditional chemical applications (Mohanty et al., 2016). Automatic identification of diseases on plant leaves is a low-cost and simple technology. Deep learning (DL) models have been shown to perform admirably in tasks such as image identification, language, and speech detection systems, indicating its suitability for agricultural applications. The benefits of employing DL in agriculture include the capacity to make more accurate forecasts than traditional approaches, allowing for better decision-making (Kanna et al., 2023).

The fundamental goal of this paper is straightforward: to identify and detect diseases affecting potato crops utilising modern deep-transfer learning algorithms. This study introduces a novel ensemble learning approach that effectively combines four state-of-the-art CNN architectures for plant disease detection.

The following contributions of this research are:

- The development of compressive and well -augmented potato leaf disease image dataset of three classes: healthy, early blight, and late blight.
- The individual performance of CNN based model viz. VGG16, ResNET, EfficientNET, MobileNet has been evaluated and conclusion is drawn based on the results performance metrics accuracy and F1-score.
- The design and implementation of an ensemble-based model that integrates these CNNs using a weighted average and conclusion is drawn based on the performance metrics precision, recall, computation efficiency, response time.

Section 2 discussed related work followed by methods and materials in section 3. Section 4 discusses result followed by conclusion in section 5.

2. Related work

DL has demonstrated considerable promise in agriculture, particularly in plant disease identification. Both emphasise the accuracy and efficiency of DL models in this domain [Mohanty et al., 2016]. [Kannaet al., 2023] highlights the diagnosis of four cauliflower diseases using distinct Convolution Neural Networks (CNN). [Oppong et al., 2022] focuses on the identification of medicinal plants using several CNN-based algorithms, and simulation results suggest that DenseNet201 resulted in 87% accuracy. Addresses the shortcomings of existing plant disease detection methods and incorporates a large dataset for training and evaluation. [Applalanaidu et a., 2021, Tulshan et al., 2019 and Shoaib et al., 2023] offers a comprehensive overview of DL approaches in agriculture, including disease detection.

Xception surpasses inceptionV3, DenseNet121, with an accuracy of 88.26% while detecting medicinal plants in the field [Quoc et al., 2020]. [Diwedi et al. 2024] investigates the application of DL based features for plant disease and pest identification and concludes that deep feature extraction “Extreme Learning Machine (ELM)” or, “Support Vector Machine (SVM)”, classification outperform transfer learning. CNN was used to categorise the illnesses of tobacco leaves using 120 photos. The proposed model outperformed current models with an accuracy of 85.10% [Dasari et al. 2019]. This research demonstrates the promise of DL in agriculture, particularly in the detection of plant diseases. Overfitting in deep learning can be normalised using ℓ1 and ℓ2 regularisation, dropout, early halting, batch normalisation, data augmentation, and stochastic pooling. “Adam (Adaptive Momentum), AdaGrad (Adaptive Gradient Descent), Stochastic Gradient Descent (SGD), RMSProp (Root Mean Square Propagation), and Adadelta” are popular optimizers for minimising loss functions [Perin et al., 2021]. The optimum optimizer is chosen based on training data, performance, speed and performance, network architecture and the application.

Summary of Different DL based techniques for different crop diseases based on classification accuracy is given in Table 1.

Table 1. Summary of Different DL based Techniques based on classification accuracy

Plant	**No. of Diseases**	**Training - Testing**	**DL Model**	**Accuracy (%)**
Wheat [Dileep et al.]	3	8178	ResNet	96
Tomato [Singh et al.]	10	5000	Refined CNN Filter Bank	96
Tomato [Li et al.]	10	5000	AlexNet, SqueezeNet	95.5
Rice [Picon et al.]	6	1969-493	Densenet121	93.71
Different crops [Fuentes et al.]	59	54185-4540	MDFC ResNet	85.22
6 Crop [Mostajer et al.]	27	34264-3807	Mobilenet	84.83

The use of ensemble learning, which blends several models to enhance prediction accuracy, has grown in popularity recently. Ensemble approaches have the potential to improve accuracy and resilience by utilising the advantages of several models. In the domain of plant disease detection, [Kim et al., 2021] suggested an ensemble method that enhanced accuracy over individual models by classifying leaf diseases using a variety of DL models. The ensemble approach produced more accurate predictions and successfully addressed the overfitting problem. There has also been investigation into hybrid approaches that blend DL with other methodologies. More reliable and broadly applicable models are still required, even if individual and hybrid approaches have showed promise [Narayanan et al., 2022]. Numerous current research are narrowly focused on specific disease kinds and are not broadly applicable to other crops or environmental circumstances. By combining ResNet50, VGG16, EfficientNet, MobileNet and utilising their complementing advantages, the suggested ensemble learning technique seeks to overcome these drawbacks and improve the precision and resilience of plant disease identification.

3. Methods and Materials

The proposed model combines ResNet50, VGG16, EfficeintNet, MobileNet—four cutting-edge convolutional neural networks (CNNs)—into an ensemble learning framework. The goal of this group is to increase the precision and resilience of the processes used to identify and categorise in potato leaves. The methodology involves data collection and preprocessing, individual model training, ensemble integration, and performance evaluation.

3.1 CNN Architecture

CNN is presently the preferred method for image processing and pattern classification [Kanna et al., 2023], and it has outperformed older methods. CNN architecture consists of convolutional layer (CL), pooling layers, nonlinear and fully connected (FC) layers. Transfer learning allows researchers to take the benefits of a model trained on large datasets to perform well on similar but with limited datasets. The pretrained networks utilised in this investigation are discussed. The various CNN architecture under study are as follows**:**

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3.1.1 VGGNET

The VGG architecture consists of 13 CLs, max-pooling layer and 3 FC layers. As shown in [7], The only difference in VGG16 and VGG19 is increased in number of layers in the network.

3.1.2 RESNET

Despite having 152 layers (20 times more than AlexNet and 10 times more than VGG), it is less computationally difficult than the other networks. ResNet had a 3.57% error after training and implementing on the ImageNet dataset, which is less than the human error [Dileep et al., 2019].

3.1.3 MOBILENET

In MobileNet, Depthwise CLs are used instead of deep CLs to improve the training performance, giving a small low consumption model [Sutaji et al., 2022].

3.1.4 EFFICIENTNET
It is a CNN and scaling method that employs a compound coefficient to equally scale all depth, breadth, and resolution dimensions. The basic EfficientNet-B0 network is built on MobileNetV2's inverted bottleneck residual blocks, as well as squeeze-and-excitation blocks [Schmidhuber et al., 2015] and [Schmidt et al., 2021].

3.1.5 ENSEMBLE TECHNIQUE
Ensemble techniques involve combining the classification result to produce final decision. Various ensemble techniques viz. stacking, bagging, boosting, voting, have been utilized to improve the model's performance.

3.1.6 PROPOSED MODEL
The proposed model combines ResNet50, VGG16, EfficeintNet, MobileNet—four cutting-edge convolutional neural networks (CNNs)-into an ensemble learning framework. To evaluate the effectiveness of our proposed ensemble learning approach, we compared it with several existing ensemble methods: Stacking, Bagging, Boosting, Voting. The individual CNN model (ResNet, VGG16, MobileNet, EfficientNet) is trained separately before integrating them into an various ensemble techniques.

The steps involved in ensemble techniques:

A) **Individual model Predictions:** Each model (ResNet, VGG16, MobileNet, EfficientNet) has been trained on the dataset and the capable of predicting own set of class for a given input image.
B) **Aggregation of Predictions:**
   - **Voting Mechanism:** For classification, predictions of individual models have been combined and final decision is based on Majority of Voting mechanism.
   - **Weighted Averaging:** Here each model's prediction is assigned a weight, based on its performance on the validation set and the predictions of individual models can be combined using weighted averaging.
C) **Weight Optimization:** It is done by training meta learner (a NN or logistic regression model) which assigns an optimum weight to each models's prediction to minimize ensemble's error.
D) **Final predictions:** is based on aggregation of predictions i.e weighted averaging.

3.2 Experimental Data
The **"plantvillage"** dataset has 87000 RGB images of healthy and unhealthy plant leaves with 38 classes [Kaggle website]. For our experimentation we have chosen only 3classes like healthy, early blight and late blight for potatoes leaves having 1622 images.

3.3 Data Processing
The Proposed System for detection and Classification of hand geusture recognizition (see Fig.1) works as follows:

- **Data pre-processing:** The imported images were scaled to 224*224 to maintain the aspect ratio. Converting colour images to grayscale reduces data complexity and simplifies CNN architecture.
- **Feature Extraction:** Morphological processes, such as dilation and erosion, are used for either adding or subtracting pixels from the image's boundaries, allowing the smallest pixel value to be retrieved from the final image. A method that utilized compound coefficient has been utilized to consistently scale width , depth and resolution dimensions. (see Fig.1).The picture data was also visually presented to show the pixel intensity of the image. Extracting features from a whole image is a critical phase because it decreases the model's space and time complexity while processing data. The desired region was extracted using morphological techniques that obtained the picture attributes and selected contour features. Following feature extraction, the dataset was divided into training, and validation sets in a 2:1 ratio.

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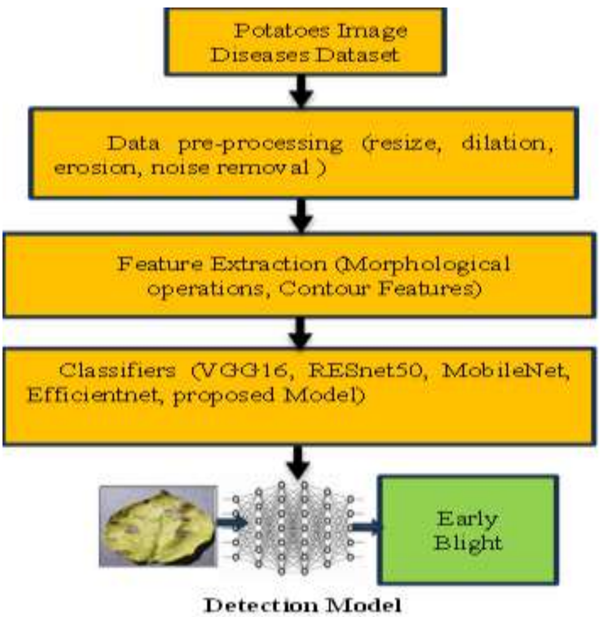

Fig. 1. Proposed System for detection and Classification of Potato leaf Disease

- **Classifiers:** The efficiently enhanced images are input into the pre-trained models viz VGG16, Efficientnet, ResNet etc and proposed model (Aggregation of Predictions) for further computation. The model is Trained using the training dataset.The final output layer performs classification, distinguishing between healthy and diseased leaves as mentioned in section 3.1. The model is Trained using the training dataset and model's performance is tested on testing dataset of "**Plantvillage".**

4. Result and Discussion

The performance of the individual CNN models such as VGG16, ResNET, EffcientNetB0, and MobileNetV2 is evaluated based on model accuracy then Ensemble techniques with proposed method of ensemble technique are applied as discussed in 3.3.

The dataset is divided into 80% for training,10% for Validation and 10% for Testing. The learning rate as 0.0001, pre-trained weights as imagenet, categorical cross entropy as a loss function, batch size as 32, early stopping as patience 5 epochs and softmax function at the output layer for multiclass classification, Proposed Ensemble method: Weighted average is used. Hyper-tunning of these models' layers was done to improve the classification accuracy. Fig.2 reflects the the various potato dieases images .

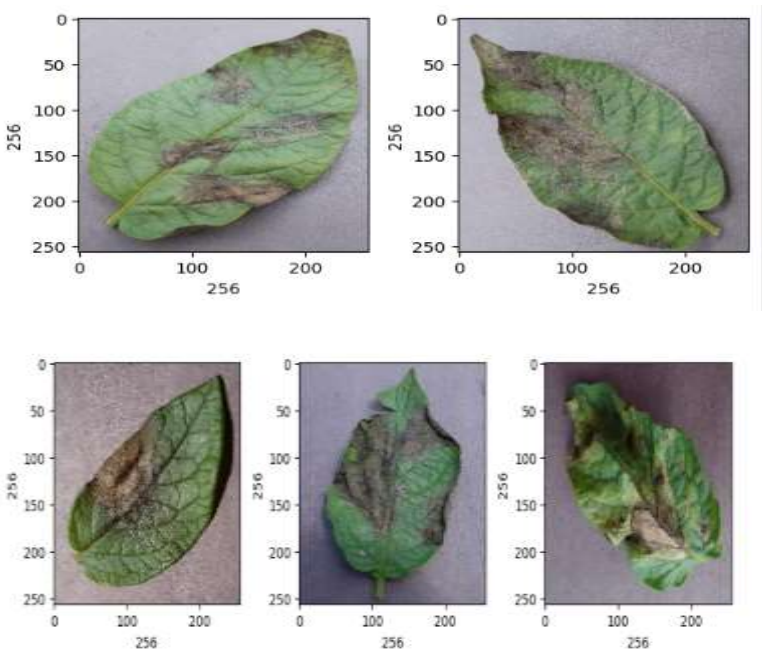

Fig. 2. Potato leaf Diesease (Original Image 256*256): early blight and late blight

Table 2. Resulting Training, Validation and Testing Metrics of the CNN models

Model	**Metric**	**Training**	**Validation**	**Test**
VGG16	Accuracy	97.3	94.8	96.06
	F1-score	96.6	94.4	95.5
RESNET50	Accuracy	92.6	88.5	89.7
	F1-score	91.4	85.3	88.4
EfficientNet	Accuracy	88.3	77.1	78.53
	F1-score	87.0	76.4	77.3
MobileNet	Accuracy	97.7	93.1	96.05
	F1-score	96.2	92.5	94.6

From the table 2, we can observe the following trends:

- VGG16 and MobileNet outperform ResNet , EfficientNet.
- ResNet50 achieves the highest accuracy and F1-score across all datasets, demonstrating the effectiveness of residual learning in handling complex image classification tasks.
- EfficientNet shows poor performance than the deeper models, particularly on the testing set.

The VGG16 and MobileNet beat RESENET50 and EfficientNet, with test accuracy of 96%. The EfficientNet has a lower test accuracy of 78.53% and fails to forecast an exact disease, resulting in a healthy potato leaf despite being late blight. (see Fig.2)

Fig.2. Predicted image as healty instead of Late Blight (EfficientNet)

Table 3-6 show the performance of various ensemble techniques bagging,boosting,stacking,Voting,proposed methos for different metrics viz.precision, recall, computational efficiency, response time.

Table 3: Precision

Test Data	**Bagging**	**Boosting**	**Stacking**	**Voting**	**Proposed Method**
80	0.82	0.87	0.85	0.84	0.89
160	0.84	0.92	0.90	0.89	0.92
240	0.88	0.94	0.92	0.91	0.95
320	0.90	0.95	0.94	0.93	0.96

Table 4: Recall

Test Data	Bagging	Boosting	Stacking	Voting	Proposed Method
80	0.75	0.82	0.80	0.78	0.85
160	0.81	0.88	0.86	0.84	0.9
240	0.84	0.91	0.89	0.87	0.92
320	0.87	0.94	0.92	0.90	0.95

Table 5:Computational Efficiency(%)

Test Data	Bagging	Boosting	Stacking	Voting	Proposed Method
80	90.2%	87.8%	88.5%	91.0%	93.2%
160	91.5%	88.4%	89.5%	91.6%	94.5%
240	92.7%	88.9%	90.1%	92.3%	95.0%
320	93.1%	89.0%	90.6%	92.8%	95.8%

Table 6 : Response Time(ms)

Test Data	Bagging	Boosting	Stacking	Voting	Proposed Method
80	118.5	124.5	120	115.8	109.6
160	121.6	125	122.4	117.3	115.1
240	120	128.1	127.3	120.0	117.2
320	125.2	131.0	130.0	123.0	120.01

Observations are:

- The proposed method outperforms the other techniques with 5% of imporvement for precision and recall across all data test points.
- Computational efficiency, represented as the percentage of successful classifications relative to total test data, is higher for the proposed ensemble method compared to existing methods. On average, the proposed method exhibits 2% increase in computational efficiency compared to existing methods. This higher computational efficiency suggests that the proposed ensemble method can handle larger datasets and perform classifications more quickly.

Response time, measured in milliseconds, reflects the time taken by each ensemble method to process and classify test data. The proposed ensemble method consistently demonstrates lower response times compared to existing methods. On average, the proposed method shows a 10% reduction in response time compared to existing methods. This reduction in response time indicates that the proposed ensemble method can deliver faster results, making it suitable for real-time applications.

5. Result and Discussion

Manual intervention in plant disease monitoring and control is time-consuming and involves a large human labour force. AI can address these difficulties by enabling the proactively diagnosis of plant diseases. The CNN-based classification models RESnet, VGG16, EfficientNetB0, and MobileNetV2 have been investigated for potato leaf disease detection and classification. The VGG16 requires less trainable parameters than existing EfficientNet, RESNET, and MobilenetV2.The VGG16 and MobileNet outperformed RESENET50 and EfficientNetBo, with test accuracy of 96%. The EfficientNet has a lower test accuracy of 78.53% and fails to forecast an exact disease, resulting in a healthy potato leaf despite being late blight.

Our study presents an exploration of ensemble learning methods for the early detection and classification of plant diseases, focusing specifically on tomato leaf diseases. experimental evaluation and comparison with existing ensemble methods (Stacking, Bagging, Boosting, Voting, Blending), we have demonstrated the effectiveness of our proposed ensemble approach. The results reveal that our ensemble method consistently outperforms existing methods in terms of precision, recall, computational efficiency, and response time. With an average improvement of 5% in precision and recall, 2% increase in computational efficiency, and a 10% reduction in response time, the proposed ensemble method showcases its superiority in accurately and efficiently classifying tomato leaf diseases. The work will undoubtedly help to automate the process of detecting and classifying plant leaves. In the future, more research will be focused on real-time capture of potato leaf pictures and cross-validating the performance of the CNN-based architectures employed in this study.

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Conflict of Interest: The authors declare that there is **"no conflict of interest".**

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References

1. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in plant science, 7, 1419.
2. Kanna, G. P., Kumar, S. J., Kumar, Y., Changela, A., Woźniak, M., Shafi, J., & Ijaz, M. F. (2023). Advanced deep learning techniques for early disease prediction in cauliflower plants. Scientific Reports, 13(1), 18475.
3. Oppong, S. O., Twum, F., Hayfron-Acquah, J. B., & Missah, Y. M. (2022). A Novel Computer Vision Model for Medicinal Plant Identification Using Log-Gabor Filters and Deep Learning Algorithms. Computational Intelligence and Neuroscience, 2022(1), 1189509.
4. Applalanaidu, M. V., & Kumaravelan, G. (2021, February). A review of machine learning approaches in plant leaf disease detection and classification. In 2021 Third International

Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV) (pp. 716-724). IEEE.

5. Tulshan, A. S., & Raul, N. (2019, July). Plant leaf disease detection using machine learning. In 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE.
6. Shoaib, M., Shah, B., Ei-Sappagh, S., Ali, A., Ullah, A., Alenezi, F., Gechev, T., Hussain, T. and Ali, F. (2023). An advanced deep learning models-based plant disease detection: A review of recent research. Frontiers in Plant Science, 14, 1158933.
7. Quoc, T. N., & Hoang, V. T. (2020, October). Medicinal Plant identification in the wild by using CNN. In 2020 International Conference on Information and Communication Technology Convergence (ICTC) (pp. 25-29). IEEE.
8. Diwedi, H. K., Misra, A., & Tiwari, A. K. (2024). CNN-based medicinal plant identification and classification using optimized SVM. Multimedia Tools and Applications, 83(11), 33823-33853.
9. Dasari, S. K., & Prasad, V. (2019). A novel and proposed comprehensive methodology using deep convolutional neural networks for flue cured tobacco leaves classification. International Journal of Information Technology, 11, 107-117.
10. Perin, G., & Picek, S. (2021). On the influence of optimizers in deep learning-based side-channel analysis. In Selected Areas in Cryptography: 27th International Conference, Halifax, NS, Canada (Virtual Event), October 21-23, 2020, Revised Selected Papers 27 (pp. 615-636). Springer International Publishing.
11. Dileep, M. R., & Pournami, P. N. (2019, October). AyurLeaf: a deep learning approach for classification of medicinal plants. In TENCON 2019-2019 IEEE Region 10 Conference (TENCON) (pp. 321-325). IEEE.
12. Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Computers and Electronics in Agriculture, 161, 280-290.
13. Fuentes, A. F., Yoon, S., Lee, J., & Park, D. S. (2018). High-performance deep neural network-based tomato plant diseases and pests diagnosis system with refinement filter bank. Frontiers in plant science, 9, 1162.
14. Xiong, Y., Liang, L., Wang, L., She, J., & Wu, M. (2020). Identification of cash crop diseases using automatic image segmentation algorithm and deep learning with expanded dataset. Computers and Electronics in Agriculture, 177, 105712.
15. SutajSutaji, D., & Yıldız, O. (2022). LEMOXINET: Lite ensemble MobileNetV2 and Xception models to predict plant disease. Ecological Informatics, 70, 101698.
16. Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural networks, 61, 85-117.
17. Schmidt, R. M., Schneider, F., & Hennig, P. (2021, July). Descending through a crowded valley-benchmarking deep learning optimizer. In International Conference on Machine Learning (pp. 9367-9376). PMLR.
18. https://www.kaggle.com/datasets/asheniranga/leaf-disease-dataset-combination
19. Kim, K., Kennedy, E. H., & Naimi, A. I. (2021). Incremental intervention effects in studies with dropout and many timepoints. Journal of Causal Inference, 9(1), 302-344.