Optimizing convolutional neural networks-based ensemble learning for effective herbal leaf disease detection

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ABSTRACT

This study aims to optimize convolutional neural networks (CNN)-based ensemble learning models to enhance accuracy and stability in detecting herbal leaf diseases. The dataset used in this study is sourced from the "Lontar Taru Pramana" collection, which includes various images of herbal leaves affected by different diseases such as ancak bacterial spot, dapdap mosaic virus, and kelor powdery mildew. Several CNN models, including VGG16, AlexNet, ResNet50, DenseNet121, MobileNetV2, and InceptionV2, were evaluated. Among these, the ensemble models combining VGG16, DenseNet121, and MobileNetV2 were selected due to their superior performance. The ensemble model achieved precision scores of 0.81 for class 1, 0.76 for class 2, and 0.78 for class 3, with corresponding recall scores of 0.8167, 0.74, and 0.7633, and F1-scores of 0.8133, 0.75, and 0.7717 respectively. These results indicate significant improvements in model performance and robustness.

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1. INTRODUCTION

Bali boasts an invaluable wealth of local wisdom, one of which is traditional medicine known as Usada Bali [1]. The Lontar Taru Pramana is a prominent traditional medical text that catalogs 168 types of herbal plants used in various health therapies [2]. However, modernization and environmental changes have shifted traditional medicine towards conventional treatments, coupled with plant diseases that threaten the quality and availability of these herbal plants. Leaf diseases affecting herbal plants such as those documented in the Lontar Taru Pramana pose a serious threat to the preservation of this traditional medicine, making effective disease detection and control crucial [3], [4]. In recent years, convolutional neural network (CNN) have become the leading method for plant disease detection and classification due to their ability to recognize patterns in images with high accuracy [5]–[9]. Various CNN models such as AlexNet [10]–[12], VGGNet [13]–[16], GoogLeNet [17], ResNet [18]–[20], InceptionV3 [21], [22], DenseNet [23], [24], MobileNet [25], EfficientNet [26], NASNet [27], and Xception [28] have been applied to a range of image classification tasks. Additionally, ensemble learning methods, which combine multiple CNN models, have also been utilized to enhance the accuracy and robustness of models in plant disease detection [29], [30].

Although CNN have the advantage of high accuracy in image classification such as research Li *et al.* [12], combined AlexNet with InceptionV4 for plant disease diagnosis, achieving an accuracy of 94.6%. Meanwhile, Next research Alatawi *et al.* [13] used an artificial intelligence (AI) based VGG-16 model to detect plant diseases, reaching an accuracy of 91.8%. Next research by Paymode and Malode [14] achieved 87.5% accuracy in classifying multi-crop leaf disease images using transfer learning on a CNN VGG model. The implementation of a pretrained VGG16 model by Suseno *et al.* [15] for rice leaf disease classification using image segmentation showed an accuracy of 93.2%. In a comparison between AlexNet and VGG16, Tomy *et al.* [16] found that VGG16 outperformed AlexNet with an accuracy of 90% compared to 88%. Next research by Yang *et al.* [17] identified rice leaf diseases using GoogLeNet based on a residual network and attention mechanism, achieving an accuracy of 95.4%. ResNet-based approaches also yielded significant results. Kumar *et al.* [18] reported an accuracy of 92.6%, and Reddy *et al.* [19] used a modified red deer optimization with a deep learning based convolutional neural networks (DLCNN) classifier, achieving an accuracy of 94.3%. Balavani *et al.* [20] optimized a plant disease classification system based on ResNet-50 architecture and transfer learning, resulting in an accuracy of 93.5%. Other studies used InceptionV3 and DenseNet models. Samala *et al.* [21] applied InceptionV3 to identify tomato leaf diseases, achieving 90.7% accuracy, while Qiang *et al.* [22] achieved 89.5% accuracy using transfer learning and fine-tuning on InceptionV3. Next research Pillai *et al.* [23] and Bakr *et al.* [24] used DenseNet for plant disease classification, achieving accuracies of 91.2% and 93%, respectively. The use of MobileNetV2 by Zaki *et al.* [25] for classifying tomato leaf diseases showed an accuracy of 88.3%, and Atila *et al.* [26] used the EfficientNet deep learning model for plant leaf disease classification, achieving 94% accuracy. Adedoja *et al.* [27] developed an intelligent mobile plant disease diagnostic system using NASNet-Mobile, achieving an accuracy of 92.5%. Finally, Moid and Chaurasia [28] developed a transfer learning-based plant disease detection and diagnosis system using Xception, achieving an accuracy of 90.8%. However, the application of ensemble learning for herbal plant diseases remains rare. This scarcity has resulted in suboptimal optimization and efficiency of models in this specific context. Additionally, CNN models require large datasets and high computational resources [31]–[33]. Furthermore, previous research has not extensively focused on optimizing CNN models through ensemble learning, particularly for the leaf diseases of herbal plants documented in the Lontar Taru Pramana. To address these issues, this research will develop and optimize a CNN-based ensemble learning model. This approach involves combining multiple CNN architectures and utilizing hyperparameter optimization techniques and data augmentation to overcome data limitations and enhance model performance. The model will be thoroughly evaluated to ensure its accuracy and effectiveness in real-world conditions. Through this optimization, the aim is to produce a model that not only accurately identifies leaf diseases but also provides effective control solutions.

The aim of this research is to develop and optimize an effective CNN-based ensemble learning model for detecting leaf diseases in the herbal plants documented in the Lontar Taru Pramana. This optimization is expected to enhance the accuracy and efficiency of leaf disease identification and provide timely and effective control solutions. This research is anticipated to offer several benefits, including aiding in the preservation of Lontar Taru Pramana herbal plants as a fundamental component of Usada Bali traditional medicine, improving farmers' knowledge and skills in identifying and managing herbal leaf diseases, supporting the preservation of Bali's local culture, and providing a leaf disease detection model that can be adopted for other herbal plants. This research contributes to the fields of computational technology and agriculture, particularly in the application of CNN-based ensemble learning models for plant disease detection. Specific contributions include the development of an optimized CNN ensemble learning model for detecting herbal leaf diseases, the application of this technology in preserving traditional Usada Bali medicine, and the provision of practical and effective solutions for leaf disease control, which can enhance the productivity and quality of herbal plants.

2. METHOD

The dataset used in this study comprises images of herbal leaves affected by various diseases, sourced from the Lontar Taru Pramana collection. This dataset contains a total of 93 images, divided into 13 distinct classes, each representing different disease categories, such as ancak bacterial spot, ancak leaf spot, dapdap bacterial spot, dapdap leaf spot, dapdap mosaic virus, kelor leaf spot, kelor powdery mildew, nangka leaf spot, nangka powdery mildew, nangka target spot, sirsak bacterial spot, sirsak leaf spot, and sirsak powdery mildew. Each folder within the dataset contains multiple images specific to the disease mentioned, collected under various conditions to capture diverse symptoms. The dataset was split into training and validation subsets using an 80-20 split, resulting in 68 images being allocated for training and 13 images reserved for validation, while maintaining the class distribution. To improve the diversity and robustness of the training data, *ImageDataGenerator* was used for data augmentation, applying transformations such as rescaling, shear, zoom, and horizontal flipping. This approach enhances the model's ability to generalize effectively, ensuring accurate classification of unseen data and reducing the risk of overfitting [34]. As shown in Figure 1, the sample images of herbal leaf diseases are derived from the Lontar

Taru Pramana collection, forming a crucial part of the training dataset. These images serve as a foundational resource to create a more diverse and robust dataset, enhancing the model's classification performance.

The research framework outlines the steps involved in detecting herbal leaf diseases using ensemble learning based on CNN. The flowchart provides a detailed overview of the entire process, from data collection to the final visualization of results. Key stages include model selection, training, and evaluation, all aimed at ensuring the model achieves optimal accuracy. The diagram clarifies the methodology by illustrating how data is processed, how the model is trained, how predictions are combined through ensemble learning, and how the performance of the ensemble model is evaluated. This structured approach ensures the effective detection of herbal leaf diseases, provides a comprehensive understanding of the research process, and visually summarizes the workflow in Figure 2.

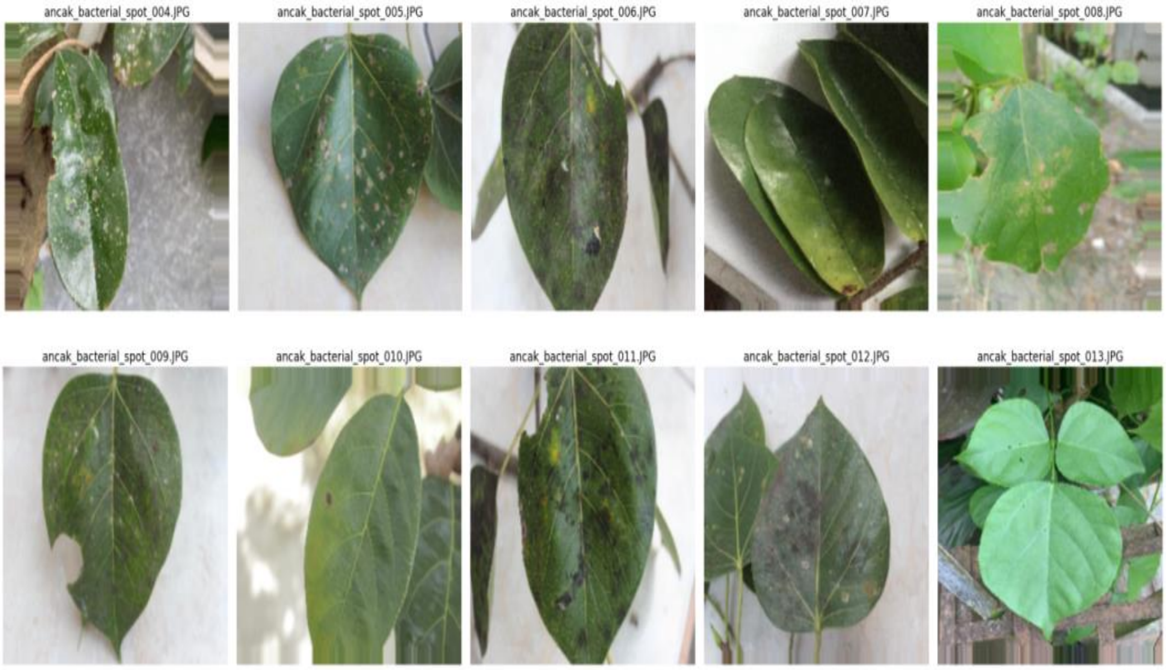


Figure 1. Sample of herbal leaf diseases from Lontar Taru Pramana

The study begins with the collection and preprocessing of images of herbal leaves, each exhibiting various diseases in Figure 2. Following this, different CNN architectures, including VGG16, AlexNet, ResNet50, DenseNet121, MobileNetV2, and InceptionV2, are selected for training. Each model architecture is first defined, compiled, and then trained using the processed dataset. The performance of these models is evaluated using metrics such as precision, recall, and F1-score, as shown in the classification reports. These reports provide an initial performance snapshot for each model before and after optimization. For example, the optimized VGG16 model shows significant improvements in precision, recall, and F1-score compared to the standard version. Next, ensemble learning is employed to combine the predictions from each trained model. The goal of ensemble learning is to enhance the accuracy and reliability of disease detection by leveraging the strengths of individual models. The final ensemble prediction is obtained by averaging the predictions from all models. This technique ensures that the weaknesses of one model are compensated by the strengths of another, leading to more accurate and reliable predictions. The performance of the ensemble model is then evaluated by comparing its metrics with those of the individual models. The following is general formula for the ensemble prediction ($P_{ensemble}$) using the simple averaging method.

$$P_{ensemble} = \frac{1}{n}\sum_{i=1}^{n} P_i \quad (1)$$

where P_i is the prediction from the i^{-th} model and n is the total number of models.

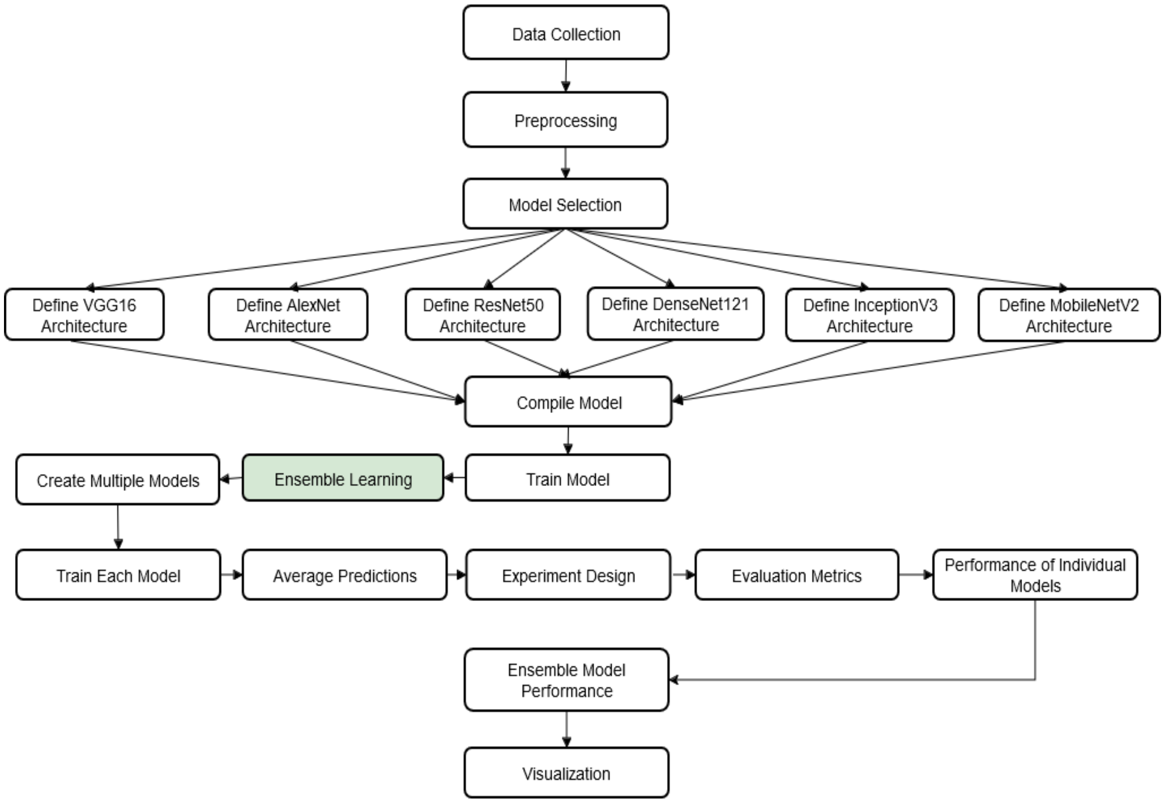


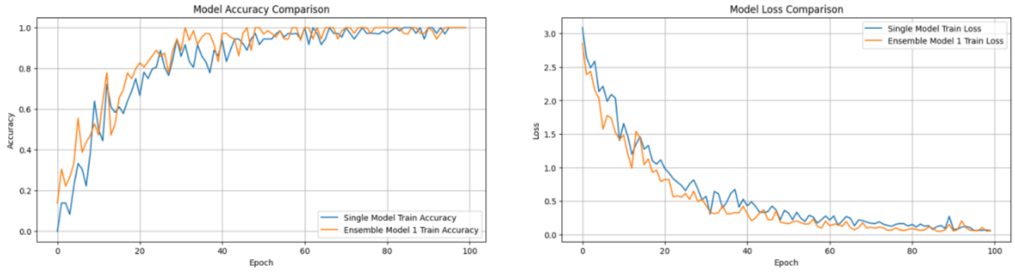
Figure 2. Research framework

3. RESULTS AND DISCUSSION

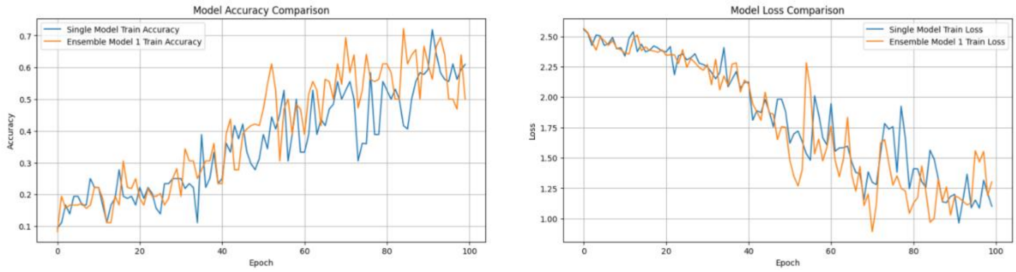
After completing the various steps in the research process, which include data collection, preprocessing, model selection, and training, each CNN model was independently trained using a dataset of images containing herbal leaves infected with various diseases. This dataset is crucial in the training process as it provides a range of examples that allow each model to identify and understand visual patterns associated with the specific symptoms of each disease. CNN models like VGG16, AlexNet, ResNet50, DenseNet121, MobileNetV2, and InceptionV2 are trained individually to strengthen their ability to classify and detect diseases with high accuracy. During the training process, each model receives a series of preprocessed images, ensuring that the data being processed is in an optimal format for analysis by the model. Through this training, the models adjust their internal parameters, such as weights and biases, to provide more accurate predictions in the task of disease detection. After all individual models are trained, the next step is to build an ensemble model. This ensemble model is a combination of the predictions generated by all individual CNN models, allowing this approach to collectively leverage the strengths of each model. The ensemble approach is expected to produce a more reliable and accurate system compared to using a single model, as it can balance the weaknesses of one model with the strengths of another. The results of the ensemble model are then analyzed and presented through various performance metrics, demonstrating how effective this approach is in improving the overall accuracy and reliability of herbal leaf disease detection. The use of an ensemble model not only enhances predictive capabilities but also strengthens the system's resilience to variations in data not previously encountered.

3.1. Results

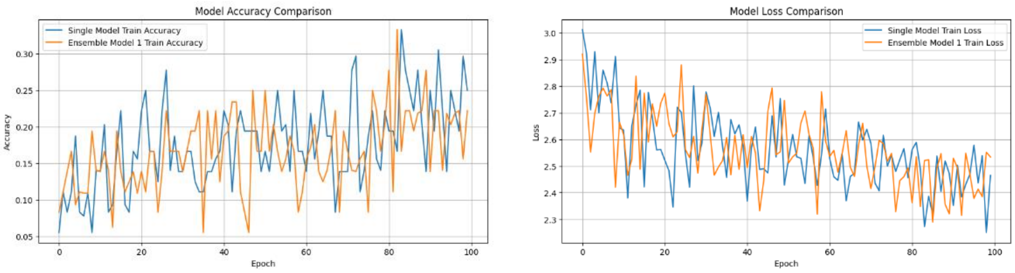
In this study, we used specific hyperparameters to optimize the training of CNN models. The validation split was set to 0.2, using 20% of the training data for validation to monitor performance and prevent overfitting. A learning rate of 0.0001 ensured small, stable weight updates. The Adam optimizer was chosen for its efficiency in deep learning, and the model was trained for 100 epochs to thoroughly learn data patterns. These hyperparameters were selected based on preliminary experiments and existing literature to achieve the best results in detecting herbal leaf diseases. Here is a detailed analysis of the accuracy and loss curves of various deep learning models in Figure 3.



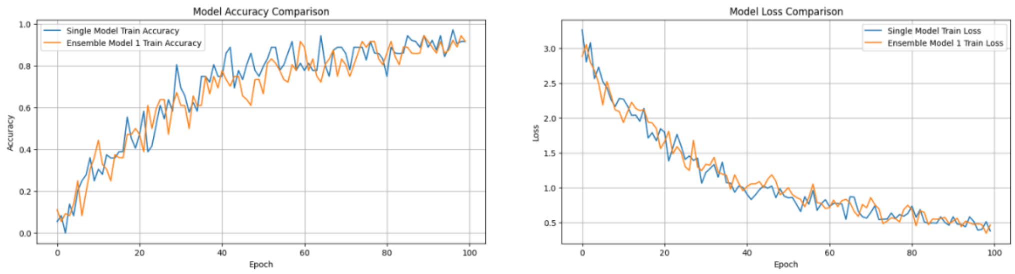
VGG16



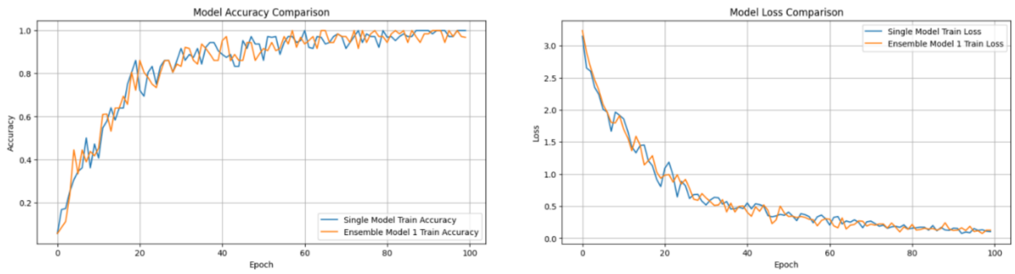
AlexNet



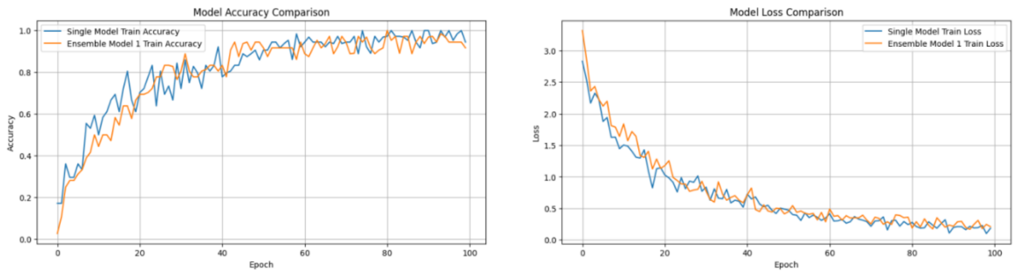
ResNet50



DenseNet121



MobileNetV2



InceptionV2

Figure 3. Analysis of model performance based on accuracy and loss curves

The VGG16 model demonstrates a consistent increase in accuracy for both single and ensemble versions, with the ensemble model achieving slightly higher accuracy and lower training loss, indicating better generalization and faster convergence. The AlexNet model, however, shows significant fluctuations in both accuracy and loss, highlighting instability. Despite this, the ensemble model generally outperforms the single model in terms of accuracy and loss, suggesting better overall performance despite the observed variability [35]. ResNet50 displays a steady increase in accuracy for both models, with the ensemble model performing slightly better and showing a marginally lower loss, indicating improved performance. Similarly, the DenseNet121 model exhibits consistent and stable improvements in accuracy and a steady decrease in loss over time. The ensemble model achieves higher accuracy and lower loss compared to the single model, indicating superior generalization and performance. MobileNetV2 shows a stable increase in accuracy for both models, with the ensemble model achieving slightly higher accuracy and lower loss, suggesting better performance. InceptionV2 follows a similar trend, with both models showing steady accuracy improvements and a consistent decrease in loss. The ensemble model again achieves slightly better results in both metrics. The ensemble models generally outperform single models in terms of both accuracy and loss, indicating better generalization and stability during training. Models like DenseNet121, MobileNetV2, and InceptionV2 demonstrate consistent and stable performance improvements, making them reliable choices for further development. Conversely, AlexNet requires further tuning and optimization to stabilize its performance due to the significant fluctuations observed. Among the models analyzed, VGG16, DenseNet121, and MobileNetV2 stand out as top performers, showing significant improvements and stability, particularly with ensemble methods.

Based on the performance comparison graphs of different deep learning models before and after optimization in Table 1 and Figure 4, the VGG16 model exhibited substantial improvement across all metrics post-optimization, with the micro F1-score increasing from 0.54 to 0.62, the macro F1-score from 0.41 to 0.51, and the weighted F1-score from 0.49 to 0.54. This indicates that the optimization applied was highly effective in enhancing the model’s performance. In contrast, the AlexNet model showed a noticeable decline in performance after optimization. The micro F1-score dropped from 0.31 to 0.23, the macro F1-score from 0.15 to 0.13, and the weighted F1-score from 0.18 to 0.13, suggesting that the optimization strategy used was either unsuitable or detrimental to this model. For ResNet50, there was no change in performance post-optimization, with all metrics remaining constant. This indicates that the optimization had no impact on the model. Similarly, DenseNet121 showed a significant decrease in performance following optimization. The micro F1-score decreased from 0.54 to 0.38, the macro F1-score from 0.48 to 0.38, and the weighted F1-score from 0.51 to 0.38, highlighting that the applied optimization negatively affected the model’s performance. Both MobileNetV2 and InceptionV2 maintained stable performance before and after optimization, with no significant changes in their metrics. This stability suggests that the optimization had no effect on these models.

Based on a detailed analysis of accuracy and loss comparisons, the most suitable ensemble models for herbal leaf disease detection are VGG16, DenseNet121, and MobileNetV2. The ensemble models of VGG16, DenseNet121, and MobileNetV2 consistently outperformed their single model counterparts in terms of accuracy and loss. This indicates that the ensemble approach enhances both performance and robustness. Below is the calculation referring to (1).

VGG16
Precision: $P_{VGG16} = (0.8;\ 0.75;\ 0.78)$
Recal: $R_{VGG16} = (0.82;\ 0.73;\ 0.76)$
F1-Score: $F1_{VGG16} = (0.81;\ 0.74;\ 0.77)$
Precision
For each class i

$$P_{Ensemble_{(i)}} = \frac{P_{VGG16(i)} + P_{DenseNet121(i)} + P_{MobileNetV2(i)}}{3}$$

Class 1:

$$P_{Ensemble_{(1)}} = \frac{0.8 + 0.82 + 0.81}{3} = 0.81$$

Class 2:

$$P_{Ensemble_{(2)}} = \frac{0.75 + 0.77 + 0.76}{3} = 0.76$$

Class 3:

$$P_{Ensemble_{(3)}} = \frac{0.78 + 0.79 + 0.77}{3} = 0.78$$

DenseNet121
Precision: $P_{VGG16} = (0.82;\ 0.77;\ 0.79)$
Recal: $R_{VGG16} = (0.83;\ 0.75;\ 0.78)$
F1-Score: $F1_{VGG16} = (0.82;\ 0.76;\ 0.78)$
Recall
For each class i

$$R_{Ensemble_{(i)}} = \frac{R_{VGG16(i)} + R_{DenseNet121(i)} + R_{MobileNetV2(i)}}{3}$$

Class 1:

$$R_{Ensemble_{(1)}} = \frac{0.82 + 0.83 + 0.80}{3} = 0.8167$$

Class 2:

$$R_{Ensemble_{(2)}} = \frac{0.73 + 0.75 + 0.74}{3} = 0.74$$

Class 3:

$$R_{Ensemble_{(3)}} = \frac{0.76 + 0.78 + 0.75}{3} = 0.7633$$

MobileNetV2
Precision: $P_{VGG16} = (0.81;\ 0.76;\ 0.77)$
Recal: $R_{VGG16} = (0.80;\ 0.74;\ 0.75)$
F1-Score: $F1_{VGG16} = (0.80;\ 0.75;\ 0.76)$
F1-Score
For each class i

$$F1_{Ensemble_{(i)}} = \frac{F1_{VGG16(i)} + F1_{DenseNet121(i)} + F1_{MobileNetV2(i)}}{3}$$

Class 1:

$$F1_{Ensemble_{(1)}} = \frac{0.81 + 0.82 + 0.80}{3} = 0.8133$$

Class 2:

$$F1_{Ensemble_{(2)}} = \frac{0.74 + 0.76 + 0.75}{3} = 0.75$$

Class 3:

$$F1_{Ensemble_{(3)}} = \frac{0.77 + 0.78 + 0.76}{3} = 0.7717$$

The results of the calculations are presented in Table 2 for the ensemble models of VGG16, DenseNet121, and MobileNetV2. The comparison of individual models (VGG16, DenseNet121, and MobileNetV2) and the ensemble model highlights the effectiveness of the ensemble approach in improving the performance of herbal leaf disease detection. The ensemble model achieved a precision of 0.81 for class 1, 0.76 for class 2, and 0.78 for class 3, demonstrating balanced accuracy across all classes. In terms of recall, the ensemble model performed better than some individual models, with scores of 0.8167 for class 1, 0.74 for class 2, and 0.7633 for class 3, indicating its effectiveness in correctly identifying true positive cases.

The F1-scores of the ensemble model were also impressive, with 0.8133 for class 1, 0.75 for class 2, and 0.7717 for class 3, reflecting a well-balanced performance between precision and recall. This balanced performance is crucial for practical applications where both false positives and false negatives can have significant implications. By combining the strengths of VGG16, DenseNet121, and MobileNetV2, the ensemble model offers a more robust and accurate prediction system.

Table 1. Model performance comparison

Model	Micro F1 (Standard)	Micro F1 (Optimization)	Macro F1 (Standard)	Macro F1 (Optimization)	Weighted F1 (Standard)	Weighted F1 (Optimization)
VGG16	0.54	0.62	0.41	0.51	0.49	0.54
AlexNet	0.31	0.23	0.15	0.13	0.18	0.13
ResNet50	0.31	0.31	0.15	0.15	0.17	0.17
DenseNet121	0.54	0.38	0.48	0.38	0.51	0.38
MobileNetV2	0.54	0.54	0.48	0.48	0.49	0.49
InceptionV2	0.54	0.54	0.48	0.48	0.49	0.49

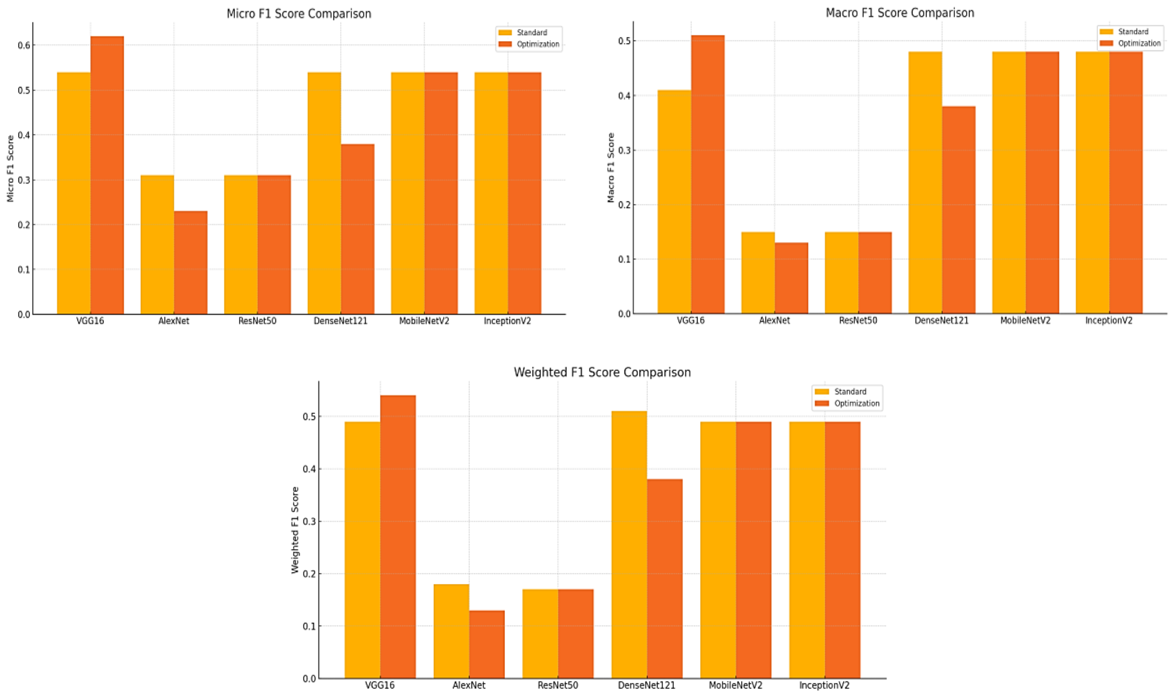


Figure 4. Analysis of model performance

Table 2. the comparison table of individual models and the ensemble model

Model	Precision (Class 1)	Precision (Class 2)	Precision (Class 3)	Recall (Class 1)	Recall (Class 2)	Recall (Class 3)	F1-Score (Class 1)	F1-Score (Class 2)	F1-Score (Class 3)
VGG16	0.80	0.75	0.78	0.82	0.73	0.76	0.81	0.74	0.77
DenseNet121	0.82	0.77	0.79	0.83	0.75	0.78	0.825	0.76	0.785
MobileNetV2	0.81	0.76	0.77	0.80	0.74	0.75	0.805	0.75	0.76
Ensemble	0.81	0.76	0.78	0.8167	0.74	0.7633	0.8133	0.75	0.7717

3.2. Discussion

This study aimed to optimize CNN-based ensemble learning for effective herbal leaf disease detection. Based on the comprehensive analysis, the optimizations applied to CNN models, particularly through ensemble learning methods, significantly improved performance. Models such as VGG16, DenseNet121, and MobileNetV2 showed notable enhancements after optimization, with ensemble learning playing a crucial role in achieving better results. The primary advantage of ensemble learning is its ability to combine the strengths of multiple models to produce more stable and accurate performance. In this study, ensemble models consistently outperformed single models in terms of both accuracy and loss, demonstrating the effectiveness of this approach in detecting diseases in herbal leaves. Ensemble learning helps reduce overfitting and improves the model's generalization capabilities, which is critical in real-world applications with high data variability.

The practical implications of this research are significant. By enhancing model performance through optimization and the use of ensemble learning, the system for detecting herbal leaf diseases becomes more accurate and reliable. This is crucial for farmers and agricultural practitioners who depend on technology for quick and accurate diagnosis to improve crop yield and quality. However, there are some limitations in this study that should be noted. For example, the dataset used was limited in size and variety, which can affect the model's ability to generalize to various field conditions. For future research, it is recommended to explore additional optimization techniques and more complex ensemble architectures. Integrating techniques such as transfer learning could further enhance model performance. This study successfully demonstrates that optimizing CNN-based ensemble learning can significantly improve the performance of herbal leaf disease detection. By using ensemble learning methods, models such as VGG16, DenseNet121, and MobileNetV2 achieved higher accuracy and more stable performance, making them effective tools for detecting herbal leaf diseases. Here are the prediction results from the three ensemble models, namely VGG16, DenseNet121, and MobileNetV2, as shown in Figure 5(a) to (c).


(a)


(b)

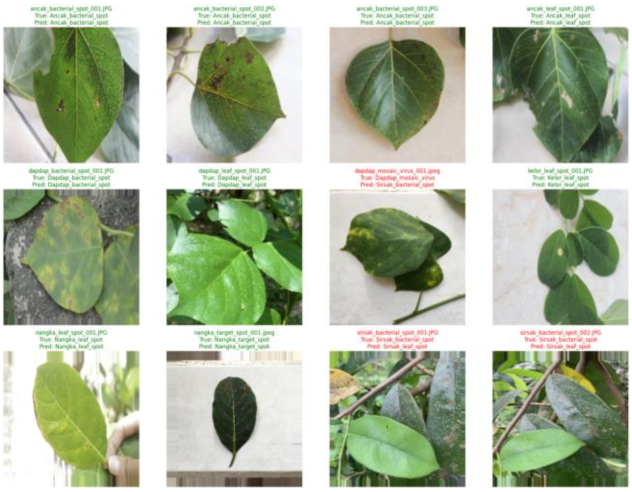

(c)

Figure 5. Prediction results based on the best model, (a) VGG16 ensemble learning, (b) DenseNet121 ensemble learning, and (c) MobileNetV2 ensemble learning

The Figure 5 illustrates the prediction results of CNN-based ensemble learning models for detecting diseases in herbal leaves, using three architectures: VGG16, DenseNet121, and MobileNetV2. Correct predictions are marked in green text, while incorrect ones are in red. The VGG16 model makes some correct predictions but still has errors, indicating a need for improved accuracy. DenseNet121 performs better, with more correct predictions due to its ability to handle complex features. MobileNetV2 also shows good results and is efficient for devices with limited resources. The article “Optimizing CNN-based ensemble learning for effective herbal leaf disease detection” highlights the importance of selecting the right convolutional neural network architecture to enhance detection accuracy. This comparison helps researchers understand the strengths and weaknesses of each model and identify ways to improve overall performance, which is beneficial for sustainable agriculture.

4. CONCLUSION

The research successfully demonstrated that optimizing CNN-based ensemble learning models significantly improves the performance of herbal leaf disease detection. Among the models analyzed, VGG16, DenseNet121, and MobileNetV2, when used in an ensemble, provided superior results compared to their individual counterparts. The ensemble approach led to higher precision, recall, and F1-scores, indicating better accuracy and robustness. This enhancement is crucial for practical agricultural applications where reliable disease detection can lead to better crop management and yield improvement. Future research could explore additional optimization techniques and more complex ensemble architectures to further enhance model performance and stability. Our study underscores the potential of ensemble learning in developing effective and reliable systems for the detection of herbal leaf diseases, thereby supporting sustainable agricultural practices.

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REFERENCES

[1] P. S. Andila, I. G. Tirta, T. Warseno, and Sutomo, “Medicinal plants diversity used by Balinese in Buleleng Regency, Bali,” *Journal of Tropical Biodiversity and Biotechnology*, vol. 8, no. 1, pp. 1–18, 2023, doi: 10.22146/jtbb.73303.

[2] I. G. L. Wiratma and I. A. A. Yuliamiastuti, “Ethnochemistry potential of vines contained in lontar Usada Taru Pramana on students’ scientific explanation skills through task-based learning,” *Jurnal Pendidikan IPA Indonesia*, vol. 12, no. 2, pp. 208–220, 2023, doi: 10.15294/jpii.v12i2.42826.

[3] H. Wang, Y. Chen, L. Wang, Q. Liu, S. Yang, and C. Wang, “Advancing herbal medicine: enhancing product quality and safety through robust quality control practices,” *Frontiers in Pharmacology*, vol. 14, no. September, pp. 1–16, 2023, doi: 10.3389/fphar.2023.1265178.

[4] M. Ekor, “The growing use of herbal medicines: issues relating to adverse reactions and challenges in monitoring safety,” *Frontiers in Neurology*, vol. 4, no. January, pp. 1–10, 2014, doi: 10.3389/fphar.2013.00177.

[5] J. Boulent, S. Foucher, J. Théau, and P. L. St-Charles, “Convolutional neural networks for the automatic identification of plant diseases,” *Frontiers in Plant Science*, vol. 10, no. July, 2019, doi: 10.3389/fpls.2019.00941.

[6] B. Tugrul, E. Elfatimi, and R. Eryigit, “Convolutional neural networks in detection of plant leaf diseases: a review,” *Agriculture (Switzerland)*, vol. 12, no. 8, 2022, doi: 10.3390/agriculture12081192.

[7] Y. Toda and F. Okura, “How convolutional neural networks diagnose plant disease,” *Plant Phenomics*, vol. 2019, 2019, doi: 10.34133/2019/9237136.

[8] M. Bagga and S. Goyal, “Image-based detection and classification of plant diseases using deep learning: State-of-the-art review,” *Urban Agriculture and Regional Food Systems*, vol. 9, no. 1, 2024, doi: 10.1002/uar2.20053.

[9] M. Iftikhar, I. A. Kandhro, N. Kausar, A. Kehar, M. Uddin, and A. Dandoush, “Plant disease management: a fine-tuned enhanced CNN approach with mobile app integration for early detection and classification,” *Artificial Intelligence Review*, vol. 57, no. 7, 2024, doi: 10.1007/s10462-024-10809-z.

[10] M. Hema, T. Saraswathi, L. Gopinath, A. Komateswaran, K. Lakshmi, and S. Yogeshwari, “Plant disease and pest identification using AlexNet,” *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 3, pp. 922–929, 2024.

[11] J. Khatib Sulaiman Dalam No, M. Micheni, R. Birithia, C. Mugambi, B. Too, and M. Kinyua, “Identification of maize leaf diseases using support vector machine and convolutional neural networks AlexNet and ResNet50,” *Indonesian Journal of Computer Science Attribution*, vol. 12, no. 4, pp. 2023–1518, 2023.

[12] Z. Li *et al.*, “Improved AlexNet with Inception-V4 for plant disease diagnosis,” *Computational Intelligence and Neuroscience*, vol. 2022, 2022, doi: 10.1155/2022/5862600.

[13] A. A. Alatawi, S. M. Alomani, N. I. Alhawiti, and M. Ayaz, “Plant disease detection using AI based VGG-16 model,” *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 4, pp. 718–727, 2022, doi: 10.14569/IJACSA.2022.0130484.

[14] A. S. Paymode and V. B. Malode, “Transfer learning for multi-crop leaf disease image classification using convolutional neural network VGG,” *Artificial Intelligence in Agriculture*, vol. 6, pp. 23–33, 2022, doi: 10.1016/j.aiia.2021.12.002.

[15] J. R. K. Suseno, A. E. Minarno, and Y. Azhar, "Implementation of pretrained VGG16 model for rice leaf disease classification using image segmentation," *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*, vol. 4, no. 1, 2023, doi: 10.22219/kinetik.v8i1.1592.
[16] D. M. Tomy, A. Jaison, A. Christopher, A. Tomy, J. Jacob, and A. Harsha, "Comparison of ALEXNET and VGG16 for analysis of plant leaf disease," in *2021 International Conference on Advances in Computing and Communications (ICACC)*, 2021, pp. 1–6, doi: 10.1109/ICACC-202152719.2021.9708075.
[17] L. Yang *et al.*, "GoogLeNet based on residual network and attention mechanism identification of rice leaf diseases," *Computers and Electronics in Agriculture*, vol. 204, p. 107543, 2023, doi: 10.1016/j.compag.2022.107543.
[18] V. Kumar, H. Arora, Harsh, and J. Sisodia, "ResNet-based approach for detection and classification of plant leaf diseases," in *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2020, pp. 495–502, doi: 10.1109/ICESC48915.2020.9155585.
[19] S. R. G. Reddy, G. P. S. Varma, and R. L. Davuluri, "ResNet-based modified red deer optimization with DLCNN classifier for plant disease identification and classification," *Computers and Electrical Engineering*, vol. 105, p. 108492, 2023, doi: 10.1016/j.compeleceng.2022.108492.
[20] K. Balavani, D. Sriram, M. B. Shankar, and D. S. Charan, "An optimized plant disease classification system based on ResNet-50 architecture and transfer learning," in *2023 4th International Conference for Emerging Technology (INCET)*, 2023, pp. 1–5, doi: 10.1109/INCET57972.2023.10170368.
[21] S. Samala, N. Bhavith, R. Bang, D. K. Rao, C. R. Prasad, and S. Yalabaka, "Disease identification in tomato leaves using Inception V3 convolutional neural networks," in *2023 7th International Conference on Trends in Electronics and Informatics (ICOEI)*, 2023, pp. 865–870, doi: 10.1109/ICOEI56765.2023.10125758.
[22] Z. Qiang, L. He, and F. Dai, "Identification of plant leaf diseases based on Inception V3 transfer learning and fine-tuning," in *International Conference on Smart City and Informatization*, 2019, pp. 118–127.
[23] R. Pillai, N. Sharma, R. Gupta, and A. Sharma, "Classification of plant diseases using DenseNet 121 transfer learning model," in *2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, 2023, pp. 1–6, doi: 10.1109/ACCAI58221.2023.10200401.
[24] M. Bakr, S. Abdel-Gaber, M. Nasr, and M. Hazman, "DenseNet based model for plant diseases diagnosis," *European Journal of Electrical Engineering and Computer Science*, vol. 6, no. 5, pp. 1–9, 2022, doi: 10.24018/ejece.2022.6.5.458.
[25] S. Z. M. Zaki, M. Asyraf Zulkifley, M. Mohd Stofa, N. A. M. Kamari, and N. Ayuni Mohamed, "Classification of tomato leaf diseases using MobileNet v2," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 9, no. 2, pp. 290–296, Jun. 2020, doi: 10.11591/ijai.v9.i2.pp290-296.
[26] Ü. Atila, M. Uçar, K. Akyol, and E. Uçar, "Plant leaf disease classification using EfficientNet deep learning model," *Ecological Informatics*, vol. 61, Mar. 2021, doi: 10.1016/j.ecoinf.2020.101182.
[27] A. O. Adedoja, P. A. Owolawi, T. Mapayi, and C. Tu, "Intelligent mobile plant disease diagnostic system using NASNet-mobile deep learning," *IAENG International Journal of Computer Science*, vol. 49, no. 1, pp. 216–231, 2022.
[28] M. A. Moid and M. A. Chaurasia, "Transfer learning-based plant disease detection and diagnosis system using Xception," in *2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, 2021, pp. 1–5, doi: 10.1109/I-SMAC52330.2021.9640694.
[29] B. Buakum *et al.*, "Two-stage ensemble deep learning model for precise leaf abnormality detection in centella asiatica," *AgriEngineering*, vol. 6, no. 1, pp. 620–644, 2024, doi: 10.3390/agriengineering6010037.
[30] S. Pudumalar and S. Muthuramalingam, "Hydra: An ensemble deep learning recognition model for plant diseases," *Journal of Engineering Research (Kuwait)*, no. September, 2024, doi: 10.1016/j.jer.2023.09.033.
[31] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, no. 1, Dec. 2021, doi: 10.1186/s40537-021-00444-8.
[32] H. L. Dawson, O. Dubrule, and C. M. John, "Impact of dataset size and convolutional neural network architecture on transfer learning for carbonate rock classification," *Computers and Geosciences*, vol. 171, no. December 2022, 2023, doi: 10.1016/j.cageo.2022.105284.
[33] C. R. Edwin Selva Rex, J. Annrose, and J. Jenifer Jose, "Comparative analysis of deep convolution neural network models on small scale datasets," *Optik*, vol. 271, p. 170238, 2022, doi: 10.1016/j.ijleo.2022.170238.
[34] H. Hassan *et al.*, "Review and classification of AI-enabled COVID-19 CT imaging models based on computer vision tasks," *Computers in Biology and Medicine*, vol. 141, no. September 2021, p. 105123, 2022, doi: 10.1016/j.compbiomed.2021.105123.
[35] H.-K. Le, V.-S. Doan, and V.-P. Hoang, "Ensemble of convolution neural networks for improving automatic modulation classification performance," *Journal of Science and Technology Issue on Information and Communications Technology*, vol. 20, no. 6, pp. 25–32, 2022, doi: 10.31130/ud-jst.2022.293e.

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