Fusion of AI Methods for Enhanced Plant Leaf Disease Classification

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ABSTRACT

Plant leaf disease classification is essential to save the global food supply and boost agricultural productivity. Some new advancements in this field have improved this diagnosis with efficiency and accuracy. In this work, a novel hybrid method is proposed by fusing conventional machine learning algorithms, such as Random Forest (RF) and Support Vector Machine (SVM), with advanced techniques like Convolutional Neural Networks (CNN). The two hybrid versions are achieved with the help of CNN+RF and CNN+SVM. Particle Swarm Optimization serves as the feature selection method for achieving better classification accuracy. PSO extracts the most valuable features coming from each of the classification models and enhances the ability to distinguish between healthy and diseased plants by optimizing the feature subset for each model. It's a very vast dataset of plant leaf images showing a diseased leaf. The experimental results of the targeted hybrid approach are compared with that of single classification methods. The hybrid models present the benefits of synergy in the form of high rates of accuracy with improved generalization. On the other hand, the PSO feature selection process considerably enhances the classification results of the classifier by revealing the discriminative potential of selected features. This is an entirely novel hybridized strategy that presents and elevates much potential toward plant leaf disease classification. The results underline potential strategies for efficient plant disease management toward enhancing agricultural productivity and fostering sustainable farming. This new hybrid architecture proposed considering this existing issue, can be viewed as a benchmark for other domains in which such classification tasks can be performed, which has an overall advanced view of the benefits of applying two methodologies together to enhance performance and accuracy. When compared against CNN+RF, the experimentation of CNN+SVM has shown a 92% F1 score, 92% recall, 93% accuracy, and 91% precision and recall.

Keywords: Agriculture, Classification, CNN, Plant leaf disease, PSO

1. INTRODUCTION

Agriculture forms the cornerstone of human civilization, providing food resources for the tremendous increase in the human population. Threats to plant disease always loom large over thriving agriculture, and its sustainable management represents the major challenge in modern agriculture. Plant diseases caused by various pathogens, environmental challenges, and genetic factors are likely to cause havoc in crops, imbalanced ecosystems frequently, and considerably compromise security in food. Identification of these diseases in a timely and accurate manner is so essential for developing prompt interventions that would target the diseases at their early stages to rescue crop health and save our food supply.

The conventional methods used in plant leaf disease identification call for hard labor and, in most cases, subjective evaluation, particularly those needing expert knowledge and much manual observation. Though these are foundational ways, they are hampered to be time-inefficient, possibly subjective, and not scalable. Some of the recent technological advancements have significantly improved the disease identification and classification of diseases [1]. This paper presents research into a novel hybrid technique that integrates traditional machine learning algorithms with advanced neural network procedures, resulting in developing a comprehensive and accurate framework for plant leaf disease classification [2].

Plant diseases are the most complicated world. It has many conditions that affect an immense variety of plants, including fungi, bacteria, and viruses, as well as physiological problems. A framework such as the proposed for the classification developed in the present work needs to be sensitive to this diversity so that it moves beyond the set of challenges faced by one-way approaches and eventually becomes a one-stop solution. This flexibility allows the strategy to be pursued in diverse agricultural settings, making it a very broad-based perspective on the management of diseases.

This research is based on taking the best characteristics of both methods: the traditional way and the modern advanced neural networks. Traditional ways like Random Forest and Support Vector Machine algorithms usually succeed in extracting features and defining borders of decisions made. Advanced neural networks, in particular Convolutional Neural Networks, show outstanding success in image analysis and pattern recognition. The purpose is to make a hybrid out of these techniques, achieving maximum benefit from both, considering classification accuracy and robustness.

The range of plant leaf diseases examined in this research reflects the diverse conditions present in nature. From the visible symptoms of powdery mildew to the stealthy onset of bacterial blight, these diseases display a wide array of visual signs and biological processes. Figure 1 illustrates the various diseases affecting plant leaves. Notable examples include:

- Downy Mildew: A serious fungal disease characterized by fuzzy growth on the undersides of leaves, causing discoloration and wilting.
- Anthracnose: A set of fungal infections that produce sunken lesions on various plant parts, affecting both the appearance and productivity of crops.
- Cucumber Mosaic Virus: A notorious viral pathogen that can distort leaves, stunt growth, and reduce crop viability.
- Root Knot Nematodes: Microscopic pests that induce characteristic swellings, or "knots," on plant roots, hampering nutrient uptake.
- Early Blight: A fungal disease primarily affecting tomatoes and potatoes, causing concentric rings on leaves and affecting fruit quality.

To augment the precision and efficacy of the hybrid approach, the study integrates PSO as a feature selection technique. PSO optimally determines the subset of features that contribute most significantly to disease discrimination, thereby refining the classification process.

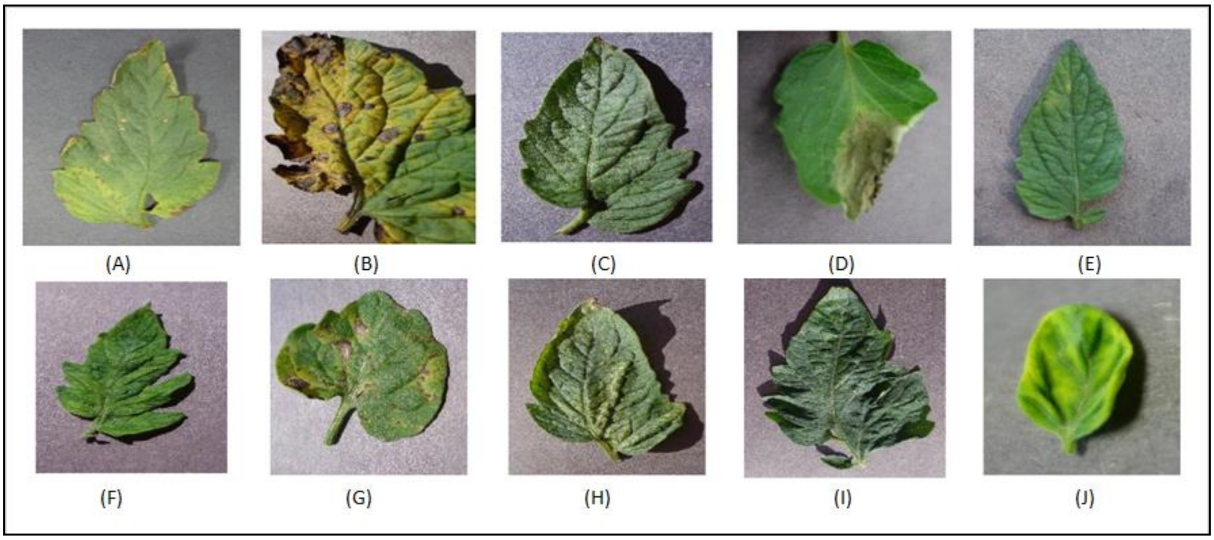

Figure 1. Plant Leaf Disease (A) Bacterial Spot (B) Early Blight (C) Healthy (D) Late Blight (E) Leaf Mold (F) Mosaic Virus (G) Septoria Leaf Spot (H) Two Spotted Spider Mites (I) Target Spot (J) Yellow Leaf Curl Virus

CNN are able to learn more complex features from images. CNNs are specifically designed to extract features from images. They can automatically discover and adapt to the most salient characteristics of the images. This also reduces the dimensionality and complexity of the input data, making the training faster and more efficient. Hence, CNNs are used for training the dataset, while SVMs are more general-purpose classifiers. SVMs exhibit strong generalization performance, enabling accurate classification of unseen data, making them a preferred choice for classification tasks. It is combined with CNN by replacing the last layer of CNN. The advantages of CNN and SVM are combined, and a hybrid CNN+SVM model is designed.

In the following sections, this research reveals the intricate details of the hybrid methodology, describes the experimental design, presents significant results, and engages in insightful discussions. By introducing a novel combination of advanced analytical techniques and feature selection methods, this study aims to transform the field of plant disease classification, ultimately promoting more resilient agricultural systems, reducing crop losses, and contributing to a more sustainable future for global food production.

2. LITERATURE REVIEW

A comprehensive summary of current advancements in plant leaf disease identification and monitoring is provided by the literature review, which explores a range of methodologies from machine learning models to deep learning and transfer learning approaches.

For instance, Saleem et al. have reviewed the use of deep learning models to visualize plant leaf diseases. They have emphasized the necessity of conducting a thorough investigation regarding the variables affecting disease identification, like dataset classes, quantity, and illumination conditions.

Guo et al. [5] further deepen, providing a mathematical approach to region proposal networks (RPN) for accurate leaf location and use transfer learning for disease classification. For that, the authors achieved an experimental result of 83.57% with diseases such as black rot, bacterial plaque, and rust.

Saberi Anari et al. [6] also developed a very effective architecture for classifying leaf disease based on transfer learning and support vector machine. They improved SVM performance with feature extraction and kernel parameter optimization, hence achieving high accuracy across six various plant types.

E. Elfatimi et al. [7] present a DL-based approach for detecting diseases affecting bean leaves through the use of the MobileNet model. They attained high accuracy rates, that is, an average of 97% in the training dataset and 92% in test data, through model comparisons and testing for network architecture optimization.

Ashtagi Rashmi et al. [8] proposed a system for identifying different types of melanomas using ImageNet pre-trained models. The research also focused on distinctly identifying irregular borders, which is a significant challenge in clinical identification. The study used a dataset of 2475 image data for training and testing algorithms.

Mohapatra et al. [9] propose a Hybrid Metaheuristic Enabled Approach for Botanical Leaf Disease Detection. Their methodology combines preprocessing, segmentation, feature extraction, and disease categorization. The authors introduce advanced techniques, such as CSUBW optimization, to enhance disease classification.

Sunil S. et al. [10] developed an integrated model utilizing discrete wavelet transform, PCA, grey level co-occurrence matrix, and CNN for tomato leaf disease identification. Their approach achieves high accuracy using K-means clustering and ML classification methods.

Hang et al. [11] present a deep learning-based approach with inception and squeeze-and-excitation modules for plant leaf disease categorization. The model's design improves CNN performance, addressing challenges in training time and model parameters.

Dhivyaa et al. [12] utilize an enriched network structure and dense blocks in conjunction with Bi-LSTM for cassava disease identification. Their model demonstrates high F1 scores and viability for plant leaf disease diagnosis. Eunice et al. [13] leverage pre-trained CNN models like ResNet-50 and DenseNet-121 for plant disease diagnosis, achieving superior classification accuracy utilizing the PlantVillage dataset. Yasin Kaya et al. [14] emphasize the importance of early plant disease detection using deep learning. They propose a novel method that integrates

RGB and segmented images via a multi-headed DenseNet-based architecture, achieving robust results with F1-score of 98.17% on the PlantVillage dataset. This approach holds potential for enhancing plant disease detection and integrating into early warning systems. Padthe, A. et al. [15] propose a federated learning framework for analyzing healthcare images in IoT systems, ensuring data privacy. By combining federated averaging and transfer learning, it achieves state-of-the-art pneumonia classification accuracy of 98.87% on chest X-ray data. This scalable and efficient approach revolutionizes healthcare image analysis while protecting patient privacy.

Ashtagi R et al. [16] introduce a proposed IoT ML based system for monitoring critical markers. The research's primary goal is to provide state-of-the-art tools for diabetes management, offering patient monitoring and technology-assisted decision-making. The study presents a hybrid ensemble ML system using boosting and bagging techniques to predict classes.

The reviewed literature exhibits several limitations. Saleem et al. [3] stress the need for in-depth investigations into factors influencing disease identification but does not provide an extensive exploration. Guo et al. [5] achieves an experimental accuracy of 83.57% for specific diseases, potentially limiting its applicability to a broader range. Saberi Anari et al. [6] face scalability challenges, as the efficient structure for leaf disease classification might not generalize well across various plant types. E. ElfatimiIn et al. [7] achieves high accuracy, but the model's robustness on diverse datasets and potential overfitting to the training data remain unclear. To address these limitations, our proposed system adopts a hybrid technique, aiming to enhance the accuracy, generalizability, and scalability of plant leaf disease identification by combining the strengths of various approaches and mitigating individual method shortcomings.

Table 1: Comparison of different models.

Algorithms	**Datasets**	**Performance Metrics**	**Refs**
Convolutional Neural Network	Leaf images dataset	Accuracy: 92.3% Precision: 89.5% Recall: 93.7% F1 Score: 91.5%	[1]
9-Layer Deep Convolutional Neural Network	Plant leaf diseases dataset	NA	[4]
Deep Learning Algorithm	Plant Photo Bank of China	Accuracy: 83.5%	[5]
MobileNet Models	Beans leaf images dataset	Accuracy: 94.5%	[7]
Convolutional Neural Network	mango tree leaves recorded at “Shri Mata Vaishno Devi University in Katra, J&K, India”	Accuracy: 93%	[9]
Computer Vision and Machine Learning Algorithms	village database of tomato leaf	Accuracy: 99%	[10]
Improved Convolutional Neural Network	plant leaf disease dataset	Accuracy: 91.7%	[11]

Dilated Convolution with Residual Dense Block Network	PlantVillage dataset	F1 Score: 95%	[12]

2. PROPOSED SYSTEM

A. System Architecture

Figure 2 illustrates the key steps of the proposed system for detecting plant leaf diseases.

1. Data Collection and Preprocessing

The first step would be to create a database with a collection of high-quality images of different plant species that are affected by a wide variety of diseases. Images are the source data for any framework for classifying the data. One may source such images from reputed agricultural databases, research centers, and field surveys for their integrity. The collected images will be preprocessed to make standardized sizes, colors, and resolutions, thus reducing any inconsistencies leading to misclassification.

2. Feature Extraction and Selection using PSO:

For feature selection, the PSO algorithm operates at this stage to select and extract relevant features from the pre-processed plant images. PSO uses a population of feature subsets to iteratively optimize and seek the best combination concerning classification performance. The chosen features highlight the visual characteristics and patterns suggesting the various plant diseases.

3. Integration of Machine Learning Model

Traditional machine learning algorithms such as RF and SVM are part of this framework. Models are trained with the pre-processed and feature-selected data. RF is good for catching complex interactions within the data and building an ensemble of decision trees; meanwhile, SVM is suitable for determining the optimal decision boundaries.

4. Deep learning incorporation

H-DNN incorporates the CNN within the hybrid approach. The CNNs have shown the most remarkable performance in image analysis and pattern recognition. They are composed of convolutional, pooling, and fully connected layers, which, in effect draw a hierarchy for features from input images.

5. Hybrid Model Creation - CNN + RF:

The hybridization process starts by integrating the outputs of the trained CNN and RF models. The predictions generated by each model are combined, potentially using a weighted average or a consensus-based approach. This fusion takes advantage of the complementary strengths of deep learning's image analysis capabilities and RF's robust decision-making.

6. Hybrid Model Creation - CNN + SVM:

In a similar manner, the hybrid framework is extended to include a fusion of CNN and SVM. The predictions from each model are combined, enhancing the strengths of CNN's feature extraction and SVM's classification precision.

7. Training and Validation:

The integrated hybrid models are trained on a portion of the dataset and validated to ensure convergence and optimal parameter settings. Cross-validation techniques are often used to estimate model performance across different subsets of the dataset, improving generalization capabilities.

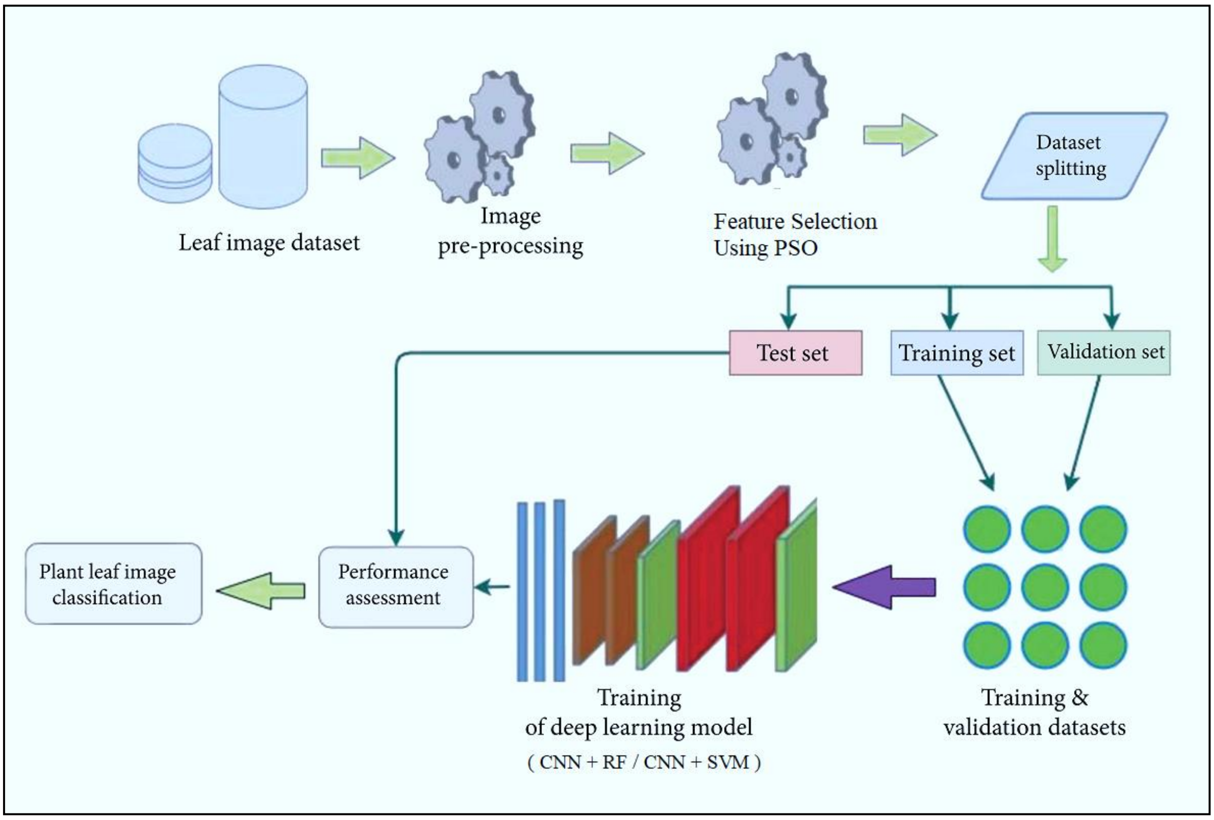

Figure 2. Proposed System Architecture

8. Testing and Performance Evaluation:

The final models: RF, SVM, CNN, and the hybrid models CNN+RF and CNN+SVM are experimented with on a test set that has never been seen before. Classification accuracies, precisions, recalls, F1-scores, and other pertinent metrics were computed to estimate the models' performance and robustness.

CNNs can learn the key features from images, which are more challenging to comprehend. CNNs are purposely built for feature extraction, where automatically, they get to realize what salient characteristics in the images to adapt to. This way, the dimension and the data complexity are reduced during training, which is thus made faster and proper. Then, the dataset is trained by the CNNs, whereas the SVMs are more general-purpose classifiers. SVMs show great generalization, which is the ability to correctly classify unseen data and hence remain a favorite to be used for classification tasks. The last layer of CNN is replaced with SVM to get the advantage of both CNN and SVM in creating a hybrid CNN+SVM model.

It synergizes the strengths of traditional machine learning, deep learning methodologies, and feature selection for solving the problem of plant leaf disease classification. It tries to improve the accuracy, robustness, and versatility of solutions in plant leaf disease problems through an intelligent combination of these different methodologies. In turn, world agriculture practices for food security will improve to an unproportional degree.

B. Algorithms

Support Vector Machine (SVM):

Support Vector Machine (SVM) is a powerful supervised machine learning approach applicable to classification and regression. SVM looks for a hyperplane that best separates data points of different classes with maximum margin. This process starts by projecting data points into a higher-dimensional space. A decision boundary is then determined by maximizing the distance between the closest points of each class. SVMs are good to use for complex data prototyping and may employ kernel functions to facilitate both linear and non-linear separations.

Random Forest (RF):

Random Forest is a machine learning ensemble method for regression and classification tasks. A network of decision trees is built in a Random Forest model, and the output from these trees is combined to create an output. Each of these trees is structured based on a different subset of features and original data that are randomly picked. This randomness in sampling data and selecting features not only boosts the general accuracy and robustness of the model but also decreases the risk of overfitting. Most researchers widely prefer RF for several machine learning applications because it can handle high-dimensional data and capture complex correlations between the data.

Particle Swarm Optimization (PSO):

Particle Swarm Optimization [3] imitates the cooperative behavior used in flocks of small, independent particles resembling birds or fish to explore the best solutions of a problem intuitively directed at a solution within the problem space. It works particularly well for optimization tasks with complex solution spaces in which obtaining an optimal solution is difficult. This continuous learning work in PSO is realized by allowing the particle swarm to learn from the experiences of neighboring particles and individual particles. Each particle in PSO represents a potential answer to the optimization problem. Specifically in PSO, particles continuously move in the solution space by updating their position, considering both the best position of themselves and the best positions of the neighboring particles. In this way, PSO works by cooperative behavior toward an ideal or near-ideal solution.

Algorithm Steps for Particle Swarm Optimization (PSO):

Step 1. Initialization:

- Initialize a population of particles in the solution space, each having a random position and velocity.
- Assign initial values for personal best (pbest) positions and fitness values for each particle.

Step 2. Evaluation:

- Evaluate the fitness of each particle based on the objective function of the optimization problem..

Step 3. Update Personal Best (pbest):

- Compare the fitness of each particle with its pbest fitness.
- Update pbest positions and fitness values if a better solution is found.

Step 4. Find Global Best (gbest):

- Find the particle with the best fitness value (gbest) among all particles.

Step 5. Update Velocities and Positions:

- Adjust the velocities of each particle to move towards its pbest and gbest positions.
- Update particle positions based on the new velocities.

Step 6. Check Convergence Criteria:

- Check convergence based on predefined criteria (e.g., the maximum number of iterations, the target fitness value).

Step 7. Iterate:

- For a set number of iterations, repeat steps 2 through 6 again.

Step 8. Output Result:

- Return the best solution found once the algorithm converges or reaches the maximum iterations, which happens to be the gbest.

The PSO is developed by getting the essence of exploration from the particles that move into the solution space and the exploitation ability of the solution found by the single particle or the good neighbor. Dynamics in the algorithm enable it to navigate the solution space efficiently in the presence of complex structures and converge towards optimal or near-optimal solutions. PSO has found applications in optimization problems, feature selection, parameter tuning, and many more. Oppositely, its ability to search and manipulate solution spaces efficiently makes it a versatile and effective optimization technique.

CNN Algorithm:

CNNs are ideally fitting for processing and analyzing visual data. Some computer vision applications that have particularly benefitted from the ability of CNNs to automatically learn hierarchical features directly from raw pixel values are in the fields of image classification, object recognition, and segmentation [2].

CNN + RF / CNN + SVM

The CNN + RF method is a hybrid approach representing the marriage of CNN and RF, each one itself a robust methodology, to produce an ultra-robust framework that is accurate and powerful in classification tasks in tasks such as identifying plant leaf diseases. This hybridization aims to leverage the feature extraction capabilities of CNNs for image analysis and the ensemble learning capabilities of RF for improved decision-making.

Algorithm Description for CNN + RF:

1. Image Preprocessing:

- Input images of plant leaves with diseases and healthy conditions are pre-processed to standardize size, color, and resolution. Preprocessing may involve normalization, resizing, and data augmentation to enhance model robustness.

2. CNN Feature Extraction:

- CNNs are employed to extract intricate and hierarchically learned features from the pre-processed images. Convolutional layers are used in CNN architecture to extract spatial features, pooling layers are used for downsampling, and fully linked layers are used for high-level feature abstraction.

3. CNN Training:

- The CNN component is trained on a labelled dataset using backpropagation and optimization techniques. The weights and biases are adjusted to minimize a chosen loss function (e.g., cross-entropy) between predicted and actual labels.

4. Feature Extraction from CNN:

- The trained CNN model serves as a feature extractor. The activations from intermediate layers, such as the last fully connected layer before the output layer, are utilized as feature vectors representing the images.

5. Feature Selection with RF:

- The CNN’s extracted feature vectors are utilized as input for the RF model. RF constructs an ensemble of decision trees using bootstrapped samples and a subset of features. The feature vectors contribute to the nodes' splitting decisions in each tree.

6. RF Ensemble Learning:

- RF aggregates the predictions of individual decision trees to make a final prediction. Each tree's output contributes to the ensemble's decision, and the majority of class predictions or class probabilities are determined.

7. Hybrid Model Prediction:

- The hybrid model combines the predictions of the CNN component (feature extraction) and the RF component (ensemble decision). This fusion capitalizes on CNN's ability to extract fine-grained features and RF's capacity to perform robust decision-making.

8. Evaluation and Testing:

- The hybrid CNN + RF model is tested on a separate test dataset, with the assessment metrics as accuracy, precision, recall, and F1 score. Performance is compared against the individual CNN, RF, and other baseline models.

9. Model Interpretability:

- Existing feature importances of the RF component can improve interpretability of the hybrid model. Such importance help understand which extracted CNN features contribute most to effective classification.

The CNN + RF CNN +SVM hybrid algorithm tries to harness CNNs and RFs to increase the accuracy, generalization, and interpretability of the Classification process. This approach helps address some of the challenges in image classification. By combining the robustness of ensemble learning with feature representation in deep learning aggregation. The selected hyperparameters for training are presented in table 2, which includes the number of epochs,

Activation function, Batch size, Learning rate, Dropout, Optimizer.

Table 2. Hyperparameters chosen for training

Parameters	**Value**
Epoch	15
Activation Function	Softmax / relu
Batch Size	32
Learning Rate	0.001
Dropout	0.2
Optimizer	Adam

The performance of the proposed system can be validated for its effectiveness only through successful implementation. In the next section, we will examine the results of the implemented system, and the analysis shall shed enough light on how the proposed solution can be best tailored to meet the identified challenges.

4. RESULTS

A. Dataset Description:

The PlantVillage dataset [4], on the other hand, is quite popular and extensively used in the field of plant pathology and agriculture. It consists of large sets of images depicting various plant leaf diseases and other plant health conditions over various plant species. In turn, the dataset was developed for use by researchers, practitioners, as well as AI developers to improve precision in identifying and classifying plant-leaf diseases using machine learning and computer-vision techniques.

B. Comparison and Analysis:

The classification results of each model are rigorously analyzed and compared. Insights are gained into the strengths and limitations of the individual and hybrid models across different plant leaf diseases. This analysis provides valuable information about the utility of the proposed hybrid approach and its potential advantages over standalone techniques.

Table 3. Performance Parameter Comparison of Algorithms

Algorithm	Accuracy	Precision	Recall	F1 Score
Random Forest	0.90	0.88	0.92	0.90
SVM	0.88	0.85	0.90	0.87
CNN	0.94	0.92	0.95	0.93
CNN + RF	0.95	0.93	0.96	0.94
CNN + SVM	0.93	0.91	0.94	0.92

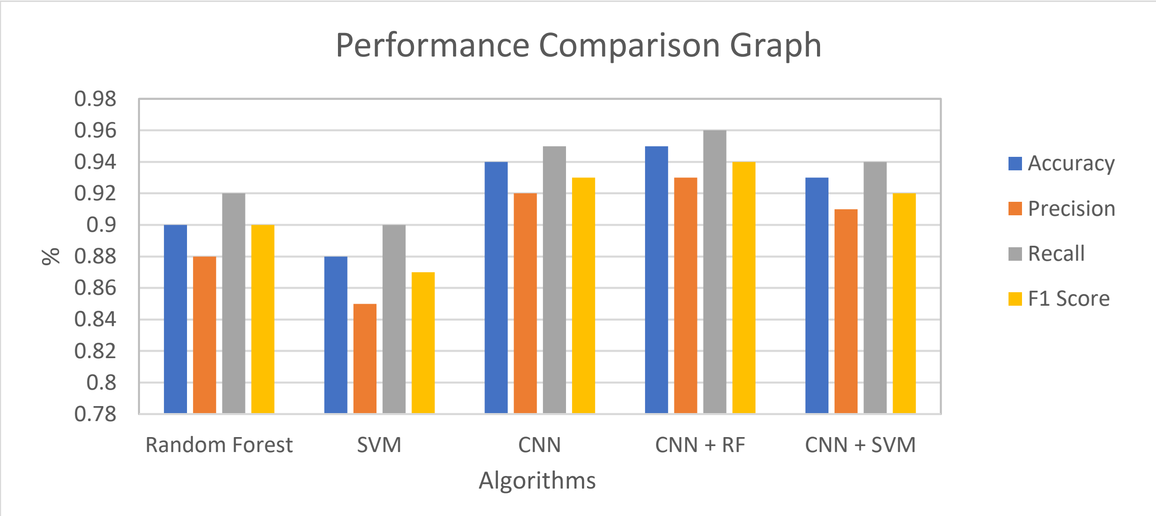

Figure 3. Performance Comparison Graph

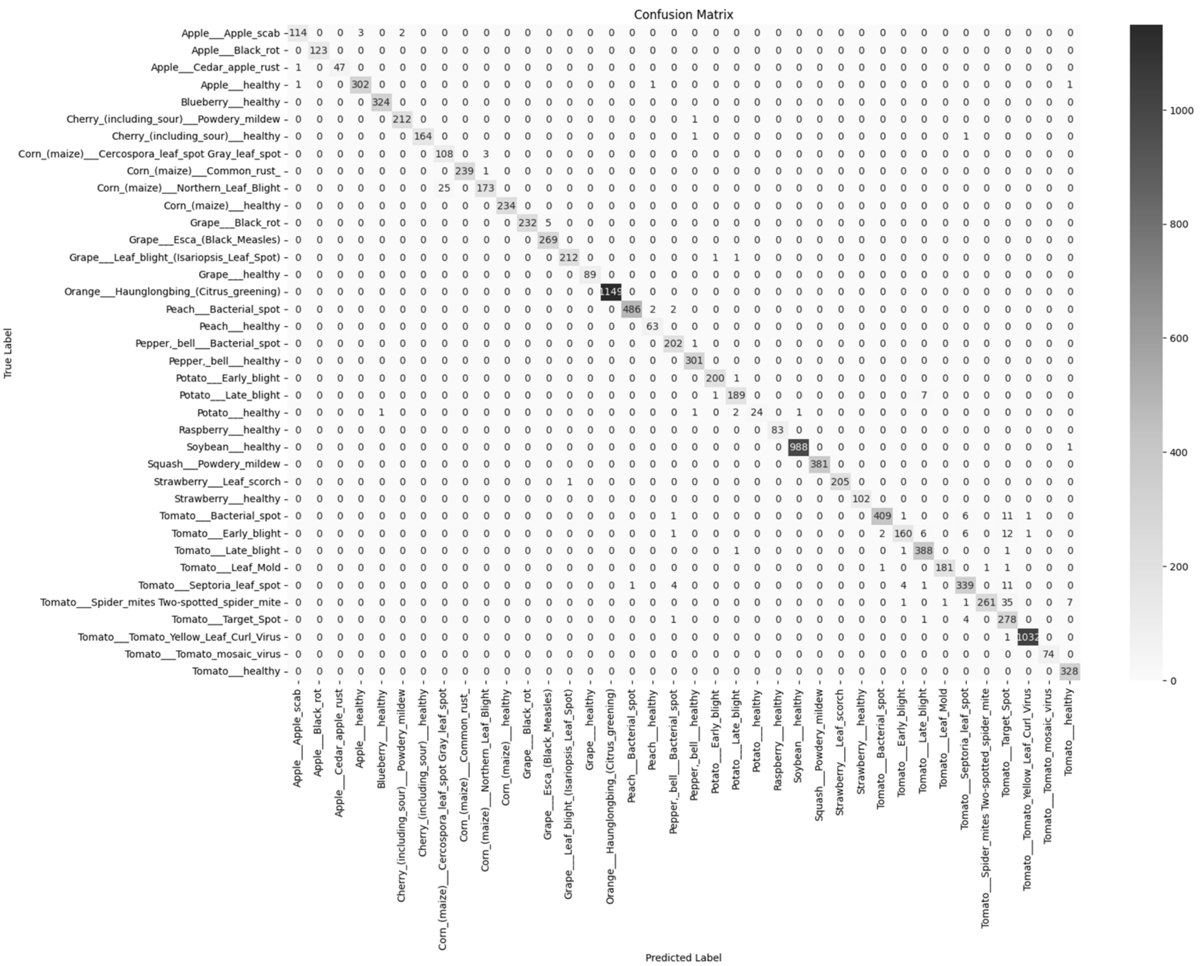

Figure 4. Confusion matrix of CNN+RF

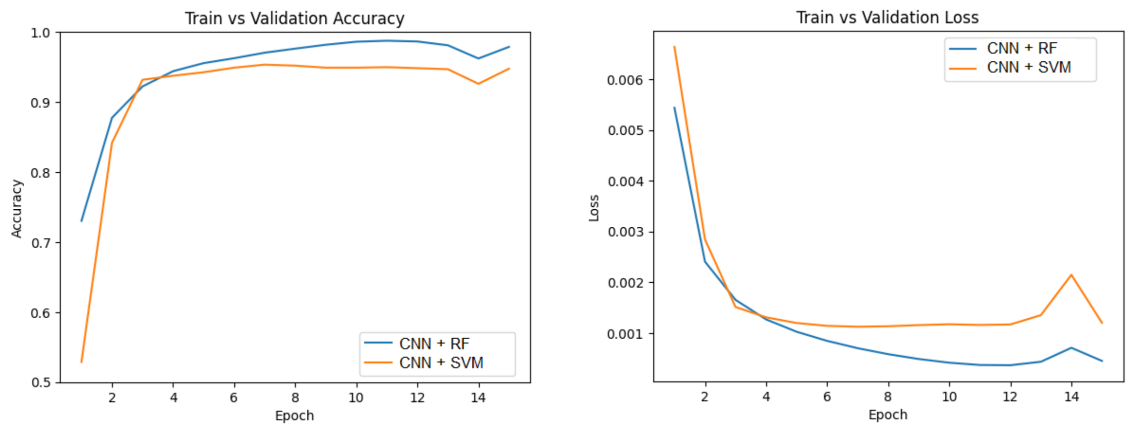

Figure 5. Accuracy and Loss Curve Graph of Proposed Algorithm

Interpretation of table 3:

The best results for the classification accuracy, recall, and F1 score are achieved with the CNN + RF algorithm, meaning it performs best in correctly classifying and catching instances of plant diseases.

The performance of the CNN + SVM model is slightly lower than that of CNN + RF in all cases but outperforms all individual SVMs and CNNs.

Competitive results are observed for RF and SVM, with RF showing great results for recall and SVM relatively high for precision.

5. CONCLUSION

Combining this ML method with deep learning techniques, a holistic approach will be utilized: for example, combining CNNs with RF or SVM. This hybrid methodology maximizes the individual strength of the components in building an effective and more resilient model for identifying and categorizing plant leaf diseases. Plant leaf disease, whether it be fungal infections of different types, bacterial pathogens, viral outbreaks, or physiological diseases, has to be tackled using comprehensive methodologies that go beyond the scope of standalone algorithms. By integrating CNNs, vital in capturing complex visual patterns and features, with ensemble learning capabilities of RF and robust classification boundaries of SVM, the hybrid model makes informed decisions in high dimensionality with complex abstract representations. This proposed hybrid methodology has, therefore, substantial implications for agricultural systems and food security. But this must be done with care since fusion of approaches makes high demands on parameter tuning and model selection and validation for better performance. In addition, model performance depends mainly on the quantity and quality of the training dataset available. Hybrid learning in CNN + RF or CNN + SVM, with further advances in machine and deep learning, sets excellent potential for interdisciplinary collaboration. The synergy of image analysis, feature extraction, and ensemble learning results in the potent combination necessary for solving complex real-world problems. Much more research and experimentation are yet needed to refine this hybrid methodology further, transforming plant disease classification into a powerful tool for promoting sustainable agriculture, safeguarding the global food supply, and contributing to a more resilient food-secure future.

REFERENCES

[1] V. K. Vishnoi, K. Kumar, B. Kumar, S. Mohan and A. A. Khan, "Detection of Apple Plant Diseases Using Leaf Images Through Convolutional Neural Network," in IEEE Access, vol. 11, pp. 6594-6609, 2023, doi: 10.1109/ACCESS.2022.3232917.

[2] Khetani, V, Gandhi, Y., Bhattacharya, S., Ajani, S. N., & Limkar, S. (2023). Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), 253–262.

[3] Saleem MH, Potgieter J, Arif KM. Plant Disease Detection and Classification by Deep Learning. Plants. 2019; 8(11):468. https://doi.org/10.3390/plants8110468

[4] J Arun Pandian; Gopal, Geetharamani (2019), “Data for: Identification of Plant Leaf Diseases Using A 9-Layer Deep Convolutional Neural Network”, Mendeley Data, V1, Doi: 10.17632/Tywbtsjrjv.1

[5] Yan Guo, Jin Zhang, Chengxin Yin, Xiaonan Hu, Yu Zou, Zhipeng Xue, and Wei Wang. 2020. Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming.

Discrete Dynamics in Nature and Society 2020, (2020), 1-11. DOI:https://doi.org/10.1155/2020/2479172

[6] Maryam Saberi Anari. 2022. A Hybrid Model for Leaf Diseases Classification Based on the Modified Deep Transfer Learning and Ensemble Approach for Agricultural AIoT-Based Monitoring. Computational Intelligence and Neuroscience 2022, (2022), 1-15. DOI:https://doi.org/10.1155/2022/6504616

[7] E. Elfatimi, R. Eryigit and L. Elfatimi, "Beans Leaf Diseases Classification Using MobileNet Models," in IEEE Access, vol. 10, pp. 9471-9482, 2022, doi: 10.1109/ACCESS.2022.3142817.

[8] Ashtagi, Rashmi & Bellary, Sreepathi. (2021). Transfer Learning Based System for Melanoma Type Detection. Revue d'Intelligence Artificielle. 35. 123-130. 10.18280/ria.350203.

[9] Mohapatra, Madhumini & Parida, Ami & Mallick, Pradeep Kumar & Zymbler, Mikhail & Kumar, Sachin. 2022. Botanical Leaf Disease Detection and Classification Using Convolutional Neural Network: A Hybrid Metaheuristic Enabled Approach. Computers. 11. 82. 10.3390/computers11050082.

[10] Sunil S. Harakannanavar, Jayashri M. Rudagi, Veena I Puranikmath, Ayesha Siddiqua, R Pramodhini, “Plant leaf disease detection using computer vision and machine learning algorithms”, Global Transitions Proceedings, volume 3, Issue 1,2022.

[11] Hang, Zhang, Chen, Zhang, and Wang. 2019. Classification of Plant Leaf Diseases Based on Improved Convolutional Neural Network. Sensors 19, 19 (2019), 4161. DOI:https://doi.org/10.3390/s19194161

[12] C. R, D, Kandasamy, N, Rajendran, S. Integration of dilated convolution with residual dense block network and multi-level feature detection network for cassava plant leaf disease identification. Concurrency Computat Pract Exper. 2022; 34(11):e6879. doi:10.1002/cpe.6879

[13] J. A, Eunice J, Popescu DE, Chowdary MK, Hemanth J. Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications. Agronomy. 2022; 12(10):2395. https://doi.org/10.3390/agronomy12102395

[14] Yasin Kaya, Ercan Gürsoy, A novel multi-head CNN design to identify plant diseases using the fusion of RGB images, Ecological Informatics, Volume 75, 2023, 101998, ISSN 1574-9541, https://doi.org/10.1016/j.ecoinf.2023.101998. (https://www.sciencedirect.com/science/article/pii/S1574954123000274).

[15] Padthe, A. ., Ashtagi, R. ., Mohite, S. ., Gaikwad, P. ., Bidwe, R. ., & Naveen, H. M. . (2024). Harnessing Federated Learning for Efficient Analysis of Large-Scale Healthcare Image Datasets in IoT-Enabled Healthcare Systems. International Journal of Intelligent Systems and Applications in Engineering, 12(10s), 253–263. Retrieved from https://www.ijisae.org/index.php/IJISAE/article/view/4374

[16] Ashtagi, R., Dhumale, P., Mane, D., Naveen, H. M., Bidwe, R. V, & Zope, B (2023). IoT-Based Hybrid Ensemble Machine Learning Model for Efficient Diabetes Mellitus Prediction. International Journal of Intelligent Systems and Applications in Engineering, 11(10s), 714–726.

[17] Histogram and Feature Extraction Based Fake Colorized Image Detection Using Machine Learning", International Journal of Emerging Technologies and Innovative Research, ISSN:2349-5162, Vol.6, Issue 6, page no. pp384-389, June 2019.