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Fusion of AI Techniques: A Hybrid Approach for Precise Plant Leaf Disease Classification

Abstract: **-** Classification of plant leaf diseases is an important step in protecting the world's food supply and agricultural yields. There has been encouraging progress in improving the efficiency and accuracy of plant leaf disease diagnosis via the combination of deep learning methods with artificial intelligence (AI) in recent years. This research introduces a new hybrid strategy, CNN+SVM and CNN+RF, that uses deep learning techniques like Convolutional Neural Networks (CNN) in conjunction with more traditional machine learning algorithms like Random Forest (RF) and Support Vector Machine (SVM). Moreover, two hybrid variants, CNN + RF and CNN + SVM, are proposed to exploit the strengths of both paradigms synergistically. To further improve classification accuracy, the study employs Particle Swarm Optimization (PSO) as a feature selection technique. PSO optimizes the feature subset for each classification model, facilitating the extraction of the most informative features, which leads to better discrimination between healthy and diseased plants. The dataset used for experimentation consists of a comprehensive collection of plant leaf images representing various diseases across multiple plant species. Experimental results demonstrate the efficacy of the proposed hybrid approach compared to individual classification methods. The hybrid models achieve higher accuracy rates and improved generalization performance, showcasing the synergistic benefits of combining AI and deep learning techniques. Furthermore, the feature selection process through PSO contributes significantly to enhancing the classification outcomes, providing insights into the discriminative power of selected features. This research contributes to the advancement of plant leaf disease classification methodologies by offering an innovative hybrid approach that leverages the complementary strengths of AI, deep learning, and feature selection techniques. The study's findings underscore the potential for improving plant leaf disease management strategies, ultimately leading to enhanced crop productivity and sustainable agriculture. The proposed hybrid framework can serve as a blueprint for similar classification tasks in other domains, demonstrating the broader impact of synergizing different AI techniques for improved accuracy and performance. CNN+RF gives 95% accuracy, 93% precision, 96% recall and 94% F1 score, whereas CNN+SVM gives 93% accuracy, 91% precision, 94% recall and 92% F1 score.

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

I. INTRODUCTION

Agriculture serves as the bedrock of human civilization, providing sustenance and nourishment to a growing global population. However, the challenges confronting modern agriculture are formidable, none more critical than the effective management of plant diseases. Plant diseases, caused by an assortment of pathogens, environmental stressors, and genetic factors, have the potential to decimate crops, disrupt ecosystems, and undermine food security. Timely and accurate identification of these diseases is imperative for devising targeted interventions that safeguard crop health and ensure an uninterrupted supply of food.

The conventional methods of diagnosing plant leaf diseases often rely on labour-intensive and subjective assessments, requiring expert knowledge and extensive manual observation. These approaches, while foundational, are hindered by their time-consuming nature, potential for human error, and limited scalability. In recent years, the convergence of artificial intelligence (AI) and deep learning has breathed new life into disease identification and classification [1]. This research delves into an innovative hybrid approach that synergizes the capabilities of machine

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learning (ML) algorithms with the transformative power of deep neural networks to create a comprehensive and precise framework for plant leaf disease classification [2].

Intricacies abound within the realm of plant diseases, encompassing a diverse array of conditions that affect various plant species. Fungal diseases, bacterial infections, viral outbreaks, and physiological disorders are just a few examples of the challenges that plague crops worldwide. The hybrid classification framework proposed in this study is designed to accommodate this diversity, offering a unified solution that transcends the limitations of single-method approaches. This versatility ensures that the methodology can be applied across a multitude of agricultural contexts and geographic regions, fostering a holistic approach to disease management.

The study harnesses the capabilities of two distinct paradigms: traditional ML and deep learning. The former, represented by RF and SVM algorithms, excels in feature extraction and decision boundary delineation. The latter, embodied by CNN, exhibits remarkable proficiency in image analysis and pattern recognition. By fusing these techniques, the research seeks to create a hybrid model that capitalizes on the strengths of both methodologies, enhancing classification accuracy and robustness.

The selection of plant leaf diseases covered in this research mirrors the diversity found in the natural world. From the conspicuous symptoms of powdery mildew to the insidious attacks of bacterial blight, the gamut of diseases encompasses a spectrum of visual manifestations and underlying biological mechanisms. Figure 1 shows the various diseases of plant leaves [4]. Noteworthy examples include:

Downy Mildew: A formidable fungal disease considered by the appearance of fuzzy growth on the undersides of leaves, leading to discolouration and wilting.

Anthracnose: A group of fungal infections that result in sunken lesions on various plant parts, affecting both aesthetic appeal and yield.

Cucumber Mosaic Virus: A notorious viral pathogen with the potential to distort leaves, stunt growth, and compromise 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.

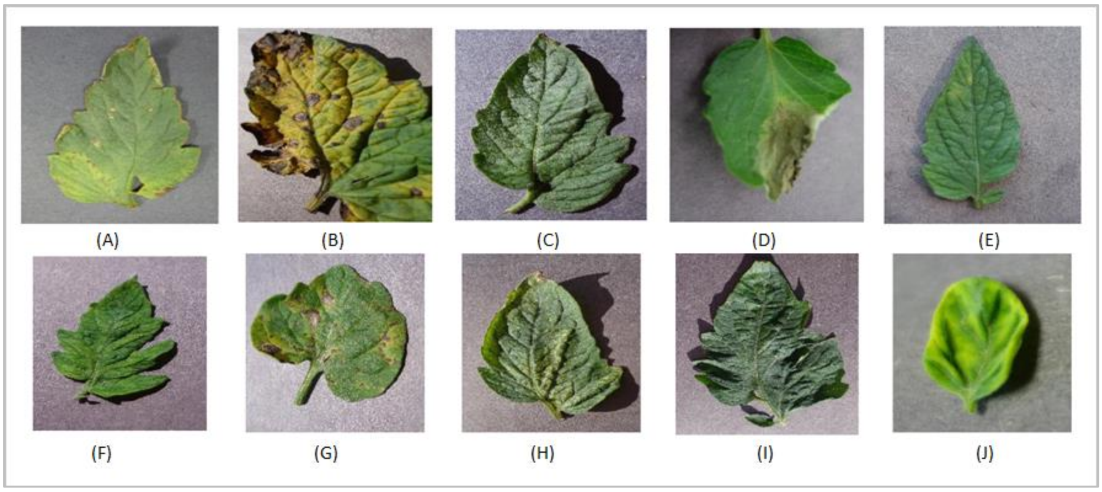

Figure 1. Plant Leaf Disease (A) Bacterial Spot (B) Early Blight (C) Healthy (D) Late Blight (E) Leaf Mold (F) Mosaic Virus (G) Septoria Leaf Spot (H) Two Spotted Spider Mites (I) Target Spot (J) Yellow Leaf Curl Virus

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 subsequent sections, this research unveils the intricate details of the hybrid methodology, outlines the experimental design, presents compelling results, and engages in insightful discussions. By pioneering an innovative synthesis of AI, deep learning, and feature selection techniques, this study aims to redefine the landscape of plant disease classification, ultimately fostering more resilient agricultural systems, reduced crop losses, and a more sustainable future for global food production.

II. LITERATURE REVIEW

A thorough summary of current developments is provided by the literature review in the field of plant leaf disease identification and monitoring, incorporating diverse methodologies ranging from machine learning models to deep learning and transfer learning approaches.

Saleem et al. [3] conducted a review of the application of DL models for plant leaf disease visualization. They emphasize the need for in-depth investigations into variables influencing disease identification, calling for a better understanding of factors like dataset classes, quantity, and illumination.

Guo et al. [5] propose a mathematical model based on DL for accurate plant leaf disease detection. The model combines a region proposal network (RPN) to locate leaves and transfer learning to classify diseases, achieving an experimental accuracy of 83.57% for diseases like black rot, bacterial plaque, and rust.

Saberi Anari et al. [6] introduce an efficient structure for leaf disease classification by employing TL and SVM models. Their method enhances SVM performance using feature extraction and kernel parameter optimization, achieving high accuracy across six different plant types.

E. Elfatimi et al. [7] present a DL-based approach utilizing the MobileNet model to detect bean leaf diseases. They attained an impressive 97% average accuracy on the training dataset and 92% on test data by comparing and testing models to optimise the network architecture.

Ashtagi Rashmi et al. [8] proposed a system to identify different melanoma types, utilizing pre-trained models from ImageNet. The research also focuses on accurately identifying irregular borders, which is a significant clinical challenge. The study utilized 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]

III. PROPOSED SYSTEM

A. System Architecture

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

1. Data Collection and Pre-processing:

The first step involves assembling a comprehensive dataset comprising high-resolution images of various plant species afflicted by a diverse range of diseases. These images serve as the foundational input for the classification framework. To ensure data integrity, images may be sourced from reputable agricultural databases, research institutions, and field surveys. Once collected, the images undergo pre-processing to standardize size, color, and resolution, mitigating variations that may hinder accurate classification.

2. Feature Extraction and Selection using PSO:

In this phase, the PSO algorithm is applied to select the most relevant features from the pre-processed images. PSO operates by iteratively optimizing a population of feature subsets, seeking the combination that maximizes classification performance. The selected features represent distinct visual characteristics and patterns indicative of various plant diseases.

3. Machine Learning Model Integration:

Traditional ML algorithms, including RF and SVM, are integrated into the framework. The pre-processed and feature-selected data are used to train these models. RF excels in capturing complex interactions within the data and constructing an ensemble of decision trees, while SVM effectively identifies optimal decision boundaries.

4. Deep Learning Model Integration:

Convolutional Neural Networks (CNN) are introduced to the hybrid approach. CNNs have demonstrated exceptional prowess in image analysis and pattern recognition. These neural networks comprise multiple layers, including convolutional, pooling, and fully connected layers, enabling the extraction of hierarchical features from the input images.

5. Hybrid Model Creation - CNN + RF:

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

6. Hybrid Model Creation - CNN + SVM:

Similar to the previous step, the hybrid framework is extended to encompass a fusion of CNN and SVM. The predictions from each model are harmonized, amplifying 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 may be employed to estimate model performance across various subsets of the dataset, enhancing generalization capabilities.

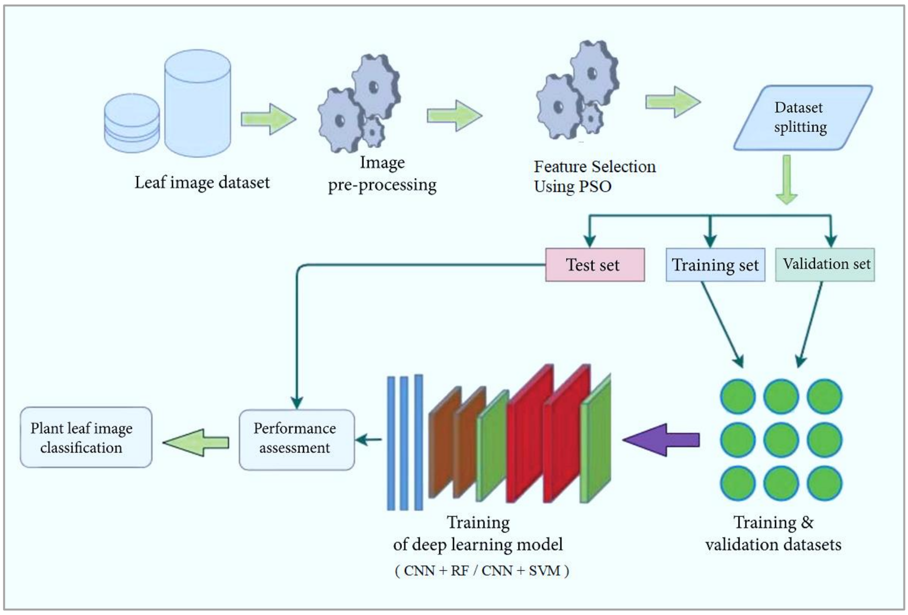

Figure 2. Proposed System Architecture

8. Testing and Performance Evaluation:

The final models, including RF, SVM, CNN, and the hybrid CNN + RF and CNN + SVM variants, are tested on a separate set of unseen images. Classification accuracy, precision, recall, F1-score, and other relevant metrics are computed to assess the models' performance and robustness.

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.

The proposed system leverages the synergy between traditional machine learning, deep learning, and feature selection techniques to create a holistic and effective framework for plant leaf disease classification. By intelligently combining the capabilities of these diverse methodologies, the approach aims to enhance accuracy, robustness, and versatility in tackling the complex challenges posed by plant leaf diseases, thereby contributing to the advancement of agricultural practices and global food security.

B. Algorithms

Support Vector Machine (SVM):

Support Classification and regression are two areas where the robust supervised machine learning method Vector Machine shines. The goal of a SVM is to maximise the margin between data points belonging to distinct classes so that the hyperplane may be found. The process begins by projecting the data points into a higher-dimensional space. From there, a decision boundary, also called a hyperplane, is found by maximising the distance between the nearest points of each class. SVMs are great at dealing with complicated datasets and can use kernel functions to handle linear and non-linear separations.

Random Forest (RF):

Among its many applications, RF is an ensemble learning technique for regression and classification. In order to generate predictions, it builds a network of decision trees during training and then merges their results. Every decision tree is constructed with a different selection of features and original data, chosen at random. Data sampling and feature selection are both made more random, which improves the model's accuracy and resilience by reducing the likelihood of overfitting. Random Forest is a popular option for many ML [17] applications because of its reputation for handling high-dimensional data and capturing complicated correlations within the data.

Particle Swarm Optimization (PSO) [3]:

In order to find the best possible solutions in a given problem space, Particle Swarm Optimisation (PSO) mimics the cooperative behaviour of swarms of small, autonomous particles, much like birds or fish. It is particularly effective for optimization tasks where the solution space is complex, and the optimal solution is not easily determined. Particle swarm optimisation (PSO) works by continuously learning from its neighbours' and individual experiences to fine-tune a pool of potential solutions (particles). In PSO, every particle stands in for a possible answer to the optimisation issue. As they traverse the solution space, these particles constantly refine their placements by taking into account both their own past best positions and the best positions discovered by particles nearby. An ideal or nearly ideal solution is converged upon as a result of this cooperative behaviour.

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:

- Assess the fitness of every particle according to 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 for convergence based on predefined criteria (e.g., maximum number of iterations, target fitness value).

Step 7. Iterate:

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

Step 8. Output Result:

- Once the algorithm converges or reaches the maximum iterations, return the best solution found (gbest).

PSO leverages the exploration capabilities of particles moving through the solution space and the exploitation of good solutions found by individual particles and their neighbors. The algorithm's dynamics enable it to efficiently navigate complex solution spaces and converge towards optimal or near-optimal solutions. PSO has found applications in various domains, including optimization problems, feature selection, parameter tuning, and more. Its ability to efficiently explore and exploit solution spaces makes it a versatile and effective optimization technique.

CNN [2] Algorithm:

CNNs are tailor-made for visual data processing and analysis. Image classification, object recognition, and segmentation are just a few of the many computer vision applications that have benefited greatly from CNNs’ ability to automatically acquire hierarchical features from raw pixel values.

CNN + RF / CNN + SVM

The CNN + RF algorithm is a hybrid approach that combines the strengths of CNNs and RF to create a powerful framework for accurate and robust classification tasks, such as plant leaf disease identification. 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, assessing metrics like accuracy, precision, recall, and F1 score. Performance is compared to individual CNN, RF, and other baseline models.

9. Model Interpretability:

- The hybrid model's interpretability can be enhanced by examining feature importances from the RF component. These importances provide insights into which extracted CNN features contribute most to accurate classification.

The CNN + RF CNN +SVM hybrid algorithm seeks to exploit the complementary strengths of CNNs and RFs, enhancing the accuracy, generalization, and interpretability of the classification process. This approach addresses challenges in image-based classification tasks by combining deep learning's feature representation with ensemble learning's robust decision aggregation. Table 2 shows hyperparameters chosen for training, such as the number of epochs, activation function, batch size, learning rate, dropout and optimizer used.

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

After the successful implementation of the proposed system, the next crucial phase involves evaluating its performance and effectiveness. In the upcoming section, we will delve into the results obtained from the system implementation. This analysis will provide valuable insights into how well the proposed solution addresses the identified challenges or requirements.

IV. RESULTS

A. Dataset Description:

The PlantVillage dataset [4] is a widely recognized and extensively used dataset in the field of plant pathology and agriculture. It is a comprehensive collection of images depicting various plant leaf diseases and other health-related conditions across a diverse range of plant species. The dataset was created to aid researchers, practitioners, and AI developers in advancing the accuracy of plant leaf disease detection and classification 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

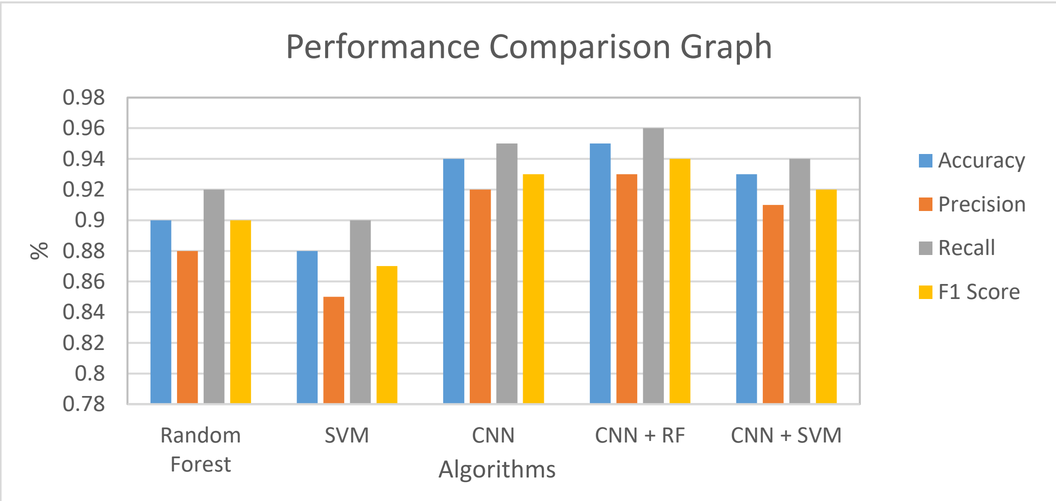

Figure 3. Performance Comparison Graph

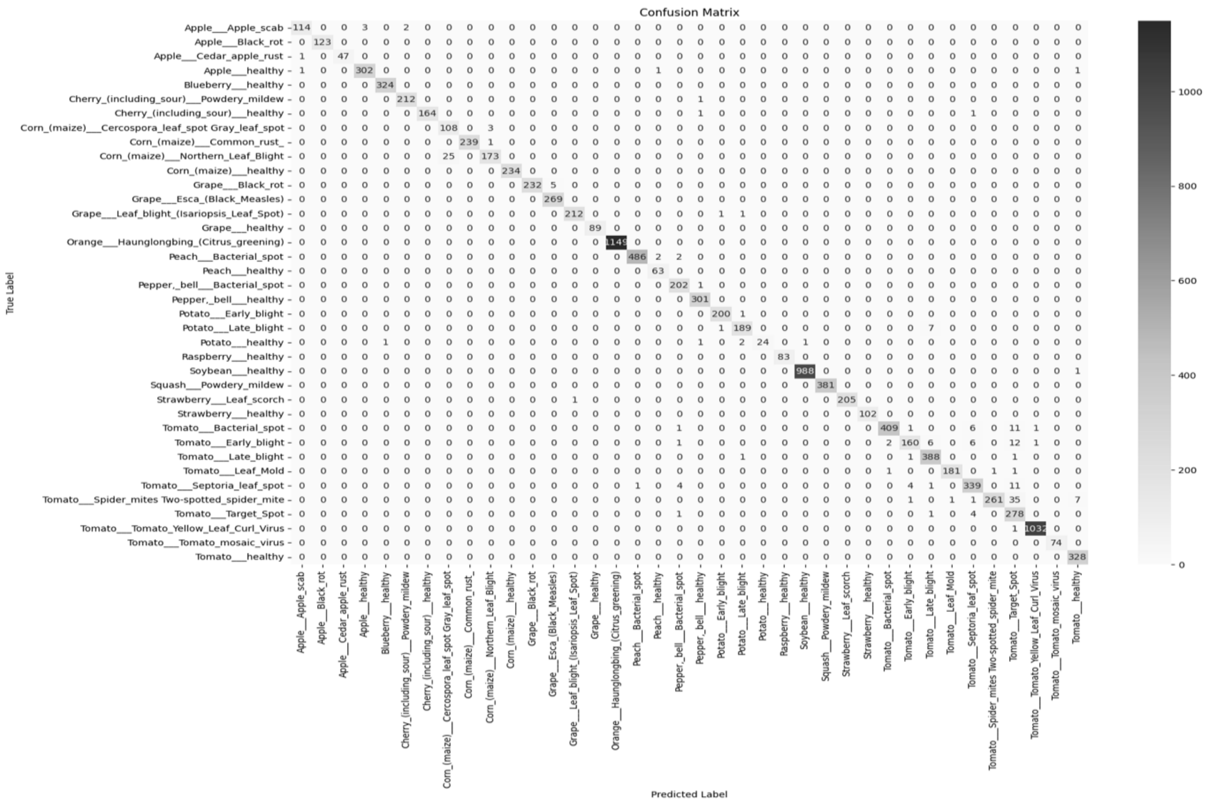

Figure 4. Confusion matrix of CNN+RF

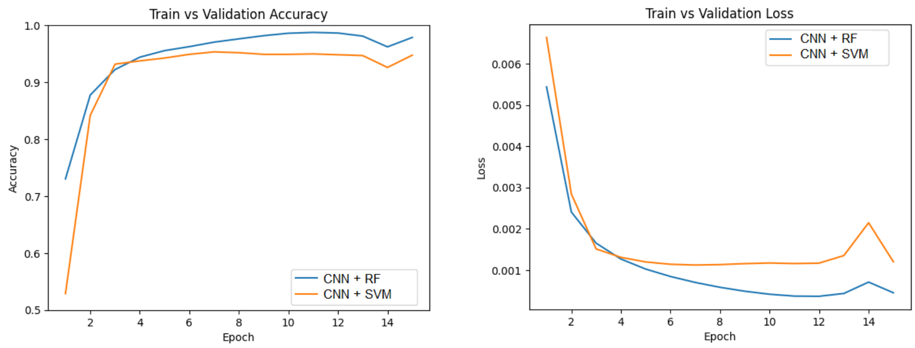

Figure 5. Accuracy and Loss Curve Graph of Proposed Algorithm

Interpretation of table 3:

The algorithm CNN + RF achieves the highest accuracy, recall, and F1 score, indicating its superior performance in correctly classifying and capturing instances of plant diseases.

CNN + SVM achieves slightly lower scores than CNN + RF but outperforms individual SVM and CNN models in most metrics.

RF and SVM demonstrate competitive results, with RF excelling in recall and SVM showing relatively high precision.

V. CONCLUSION

The fusion of AI and deep learning techniques, exemplified by the hybrid approach of combining CNNs with RF or SVM, presents a promising avenue for addressing the intricate challenges of accurate plant leaf disease classification. The overarching objective of this hybrid methodology is to harness the unique strengths of each component to create a more resilient and effective model for identifying and categorizing plant leaf diseases. The intricate landscape of plant leaf diseases, encompassing fungal infections, bacterial pathogens, viral outbreaks, and physiological disorders, demands a comprehensive approach that transcends the limitations of standalone algorithms. The integration of CNNs, proficient in capturing complex visual patterns and features, with the ensemble learning capabilities of RF and SVM, equips the hybrid model with the capacity to make well-informed decisions that combine high-level abstract representations and robust classification boundaries. The proposed hybrid methodology is not confined solely to its technical prowess; rather, it offers profound implications for agricultural systems and food security. However, it is essential to acknowledge that this hybrid approach is not devoid of challenges. The fusion of disparate techniques necessitates careful parameter tuning, model selection, and validation to ensure optimal performance. Additionally, the availability and quality of training data play a crucial role in the model's efficacy. As AI and deep learning continue to advance, the hybrid approach exemplified by CNN + RF or CNN + SVM stands as a testament to the potential of interdisciplinary collaboration. The integration of image analysis, feature extraction, and ensemble learning exemplifies the synergy that can be harnessed to tackle complex real-world challenges. Moving forward, further research and experimentation are needed to refine this hybrid methodology to transform plant disease classification into a powerful tool for promoting sustainable agriculture, safeguarding global food supply, and contributing to a more resilient and food-secure future.

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