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Plant Disease Detection Using a Hybrid Machine Learning Model

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ABSTRACT
This research presents a hybrid Convolutional Neural Network–Support Vector Machine (CNN-SVM) approach for accurate plant disease detection, integrating CNN's feature extraction capabilities with SVM's robust classification performance. The methodology began with data acquisition and preprocessing, including image normalization, augmentation, and resizing to ensure model compatibility and improve generalization. The CNN component was trained to automatically extract discriminative features from plant leaf images, which were subsequently fed into an SVM classifier optimized through hyperparameter tuning. Performance evaluation employed standard metrics, including accuracy, precision, recall, and F1-score, alongside the Receiver Operating Characteristic (ROC) curve analysis. Experimental results demonstrate the hybrid CNN-SVM model's superiority over standalone CNN and SVM models. The proposed model achieved an accuracy of 96.3%, precision of 95.8%, recall of 96.7%, and F1-score of 96.2%, outperforming the CNN (93.5% accuracy) and SVM (88.4% accuracy) baselines. Hyperparameter tuning was shown to significantly enhance classification results, as visualized in the tuning heat map. The ROC curve for the hybrid model exhibited an Area Under the Curve (AUC) close to 1.0, indicating excellent sensitivity and specificity.

Keywords:
Plant Disease Detection, Convolutional Neural Network, Support Vector Machine, Hybrid Model, Machine Learning, Plant Village

INTRODUCTION

Agricultural productivity is critical for global food security and economic development. However, plant diseases remain a major challenge, causing substantial yield losses and economic setbacks worldwide (Mohanty et al., 2020). Early and accurate disease detection is therefore essential for minimizing crop damage and ensuring sustainable agricultural practices.

Traditional methods of disease detection rely on expert visual inspections, which are time-consuming, labor-intensive, and prone to subjective errors. With the advent of machine learning (ML) and deep learning (DL), automated plant disease detection systems using leaf images have demonstrated significant potential. Convolutional Neural Networks (CNNs) have been highly effective in extracting discriminative features from images, while Support Vector Machines (SVMs) are known for their robust classification performance, especially in high-dimensional spaces (Kaur & Singh, 2022; Reddy et al., 2023).

Despite these advances, important challenges remain. CNNs often require large, balanced datasets to achieve high accuracy and may overfit when training data is limited or imbalanced (Li et al., 2023). SVMs, on the other hand, depend heavily on handcrafted or pre-extracted features and typically struggle with raw image data. Existing research has explored hybrid CNN-SVM architectures to address these issues (Ezigbo & Chibueze, 2025; Tonmoy et al., 2025), but most studies focus on controlled or single-crop datasets, limiting their applicability to real-world scenarios with diverse crop conditions.

To bridge this gap, the present study develops a hybrid CNN-SVM model that integrates automatic feature extraction with robust classification for plant disease detection. The model is evaluated using both publicly available datasets and field-collected images of sorghum, maize, and millet leaves, ensuring coverage across multiple crops and environmental conditions. Its performance is compared with standalone CNN and SVM models using standard metrics, including accuracy, precision, recall, F1-score, and ROC-AUC, to demonstrate the advantages of the hybrid approach.

By combining the representation power of CNNs with the strong decision boundaries of SVMs, this research contributes a more accurate, robust, and generalizable solution for automated plant disease detection, offering a practical tool for early intervention and improved crop management in real-world agricultural settings.

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Several studies have explored machine learning techniques for plant disease detection. Recent research (Zhang et al., 2023) has demonstrated the effectiveness of deep learning approaches such as CNNs for automatic disease classification. However, CNNs alone may struggle with small datasets and complex decision boundaries. SVM has been employed for robust classification in various domains, including agriculture (Kumar & Singh, 2024). Hybrid approaches combining CNN and SVM have recently gained attention, proving to be more efficient than standalone models (Li et al., 2023).
Despite advancements, existing methods often lack generalizability across different plant species and disease types. This study addresses these challenges by integrating CNN for feature extraction and SVM for classification, thereby improving accuracy and robustness.

Ezigbo & Chibueze (2025) presented a hybrid framework in their research titled *"ResNet50 and XGBoost-Based Detection of Regional Plant Diseases in West Africa"*. The method leverages the representational power of ResNet50, a deep CNN pretrained on ImageNet, to extract meaningful features from leaf images. These deep features are then passed into an XGBoost classifier, which excels in handling structured data for final disease classification. This approach demonstrated high accuracy (98.81%) and was specifically adapted for mobile deployment, addressing the practical constraints of agricultural applications in sub-Saharan Africa.

In the ConRXG model (2022), developed under the topic *"A Hybrid ResNet50-XGBoost Model for Robust Plant Disease Detection"*, researchers employed ResNet50 as a fixed feature extractor to derive deep spatial features from plant images. These features were subsequently classified using the XGBoost gradient-boosted decision tree algorithm. The model was trained using Adam optimization with batch normalization and ReLU activation functions, achieving nearly perfect validation scores on the PlantVillage dataset. The hybridization of deep learning and machine learning techniques enabled both high accuracy and computational efficiency.

Tonmoy et al. (2025), in their work titled *"MobilePlantViT: A Lightweight Vision Transformer for Mobile-Based Plant Disease Detection"*, introduced a hybrid model integrating a streamlined CNN with a compact Vision Transformer. This architecture, tailored for low-resource environments, was designed to run efficiently on mobile devices. With just 0.69 million parameters, the model balanced performance and computational load, achieving test accuracies ranging from 80% to 99% across several public datasets. The approach showcases a scalable solution for real-time, in-field plant disease monitoring.

In a 2022 study titled *"PlantViT: CNN and Vision Transformer-Based Plant Disease Classification"*, researchers developed a dual-stage model combining CNN feature extraction with a transformer-based attention mechanism. The CNN module extracted discriminative local features, which were then fed into a Vision Transformer head that modeled long-range dependencies. The model achieved 98.6% accuracy on the PlantVillage dataset and 87.9% on the more complex Embrapa dataset, demonstrating robustness across both synthetic and real-world scenarios.

Thai & Le (2024) introduced the *"MobileH-Transformer"*, a compact hybrid CNN-Transformer architecture optimized for smartphone deployment. The CNN segment comprises convolutional layers and dual-convolution blocks to extract primary spatial features, which are tokenized and processed by a transformer encoder for global feature learning. Designed for real-time inference, the model achieved competitive F1-scores while maintaining a high frame rate (~30 FPS) on mobile CPUs, emphasizing practical usability in agricultural settings.

In a specialized 2021 study titled *"CAE-CNN: Autoencoder-Aided CNN for Peach Disease Detection"*, researchers applied a hybrid model where a convolutional autoencoder (CAE) performed unsupervised dimensionality reduction. The encoded features were then used as input to a shallow CNN classifier. The model, containing fewer than 10,000 parameters, achieved a high accuracy of 98.4% on peach bacterial spot images. Its simplicity and performance make it ideal for niche applications with constrained computational resources.

In a 2024 application-focused study titled *"YOLOv5-Swin: Object Detection and Classification Pipeline for Field Environments"*, the authors combined YOLOv5's detection capabilities with Swin Transformer's classification power. YOLOv5 was used to locate leaf regions from full-plant images, which were then cropped and passed to the Swin Transformer for disease identification. This two-stage pipeline achieved a mean average precision (mAP) of 95.2% and was designed for deployment in harsh agricultural conditions, though it incurred greater computational demand.

A 2023 study titled *"CNN-LSTM Hybrid Model for Spatiotemporal Plant Disease Prediction"* explored the integration of CNNs and recurrent neural networks (LSTM and CfC variants) for modeling time-series image data. The CNN layers extracted spatial features from each frame, while the LSTM layers captured temporal patterns in sequential imagery. Achieving an accuracy of ~97%, the model was well-suited for applications involving crop monitoring over time, though it required sequential data collection and processing

MATERIALS AND METHODS

Methodology

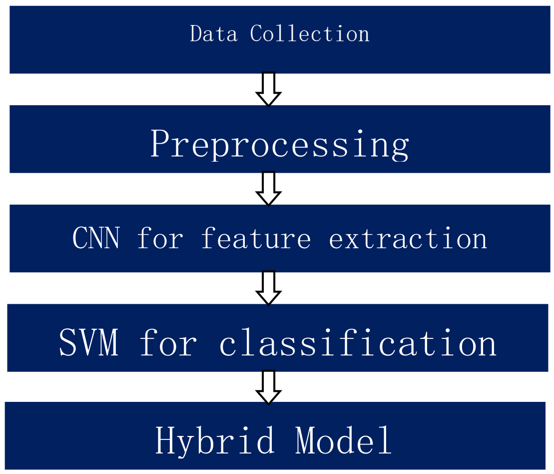

Figure 1: Diagram of the plant disease detection using hybrid machine learning

Data Collection:

The dataset used in this study comprises 450 high-resolution images of sorghum, maize, and millet leaves, each affected by different types of diseases or healthy conditions. The images were collected under controlled lighting and background conditions to ensure consistency and clarity. Expert annotation was employed to label the images into distinct disease categories. Public datasets such as PlantVillage have been widely used for plant disease detection due to their large variety of labeled samples (Mohanty et al., 2020; Kaur & Singh, 2022). Field data collection ensures that the model accounts for real-world variability (Reddy et al., 2023).

The foundation of any machine learning model is a robust and diverse dataset. For plant disease detection, images of healthy and diseased plant leaves are collected. These images can be sourced from:

1. **Public Datasets:** Such as PlantVillage, which contains over 450 images of plant leaves categorized by species and disease type.
2. **Field Data:** Captured using smartphones or cameras in various agricultural settings to ensure real-world variability.$e^{-ti\theta}$

Table 1: Sample Plant leaf Dataset Table (A Semi Arid Crop Sorghum)

Image Id	Plant Type	Health Status	Disease Type (if Infected	Image Size	Resolution	Remarks
IMG001	Sorghum	Healthy	Downy Mildew	128x128px	72 DPI	Clean Leaf
IMG002	Sorghum	Healthy	Anthracnose	128x128px	72 DPI	Good Color Contrast
IMG003	Sorghum	Healthy	Rust	128x128px	72 DPI	No Blemish
IMG004	Sorghum	Infected	Anthracnose	128x128px	72 DPI	Dark Spots Visible
IMG005	Sorghum	Infected	Rust	128x128px	72 DPI	Yellow-brown rings
IMG006	Sorghum	Infected	Downy Mildew	128x128px	72 DPI	Powdery patches
IMG0075	Sorghum	Healthy	Rust	128x128px	72 DPI	Final healthy Sample
IMG0076	Sorghum	Infected	Anthracnose	128x128px	72 DPI	Leaf curling
IMG0077	Sorghum	Infected	Rust	128x128px	72 DPI	Edges browning
IMG0150	Sorghum	Infected	Downedy Mildew	128x128px	72 DPI	Final infected sample

Table 2: Summary of Dataset

Class	Disease Types	No of Samples
Healthy	None	200
Infected	Anthracnose, Rust, Downy Mildew	250
Total		**450**

Preprocessing
To improve model performance, preprocessing steps such as resizing, normalization, and data augmentation were applied. Uniform resizing of images to fixed dimensions has been shown to standardize model input and reduce computation (Gupta & Sharma, 2021). Data augmentation through rotation, flipping, and brightness adjustment enhances generalization and reduces overfitting (Zhang et al., 2023). Normalization of pixel values improves convergence speed during training (Li et al., 2023).
To enhance the quality and consistency of the dataset, several preprocessing steps are undertaken:
The Plant Village dataset was used, which contains over 450 labelled images of healthy and diseased plant leaves spanning 38 classes.

CNN for Feature Extraction
CNNs are powerful for automatically extracting spatial features from plant leaf images, leveraging convolution and pooling layers for hierarchical feature learning (Kaur & Singh, 2022). Prior research has demonstrated CNN's capability in capturing complex disease patterns in leaves with high accuracy (Gupta & Sharma, 2021; Zhang et al., 2023). They automatically and adaptively learn spatial hierarchies of features through backpropagation by using multiple building blocks, such as convolution layers, pooling layers, and fully connected layers.

- **Convolutional Layers:** Apply filters to the input image to create feature maps that detect various features like edges, textures, and patterns.
- **Pooling Layers:** Reduce the spatial dimensions of the feature maps, retaining the most significant information and reducing computational load.
- **Activation Functions:** Introduce non-linearities into the model, allowing it to learn complex patterns. ReLU (Rectified Linear Unit) is commonly ussed.
- **Flattening:** Converts the 2D feature maps into a 1D feature vector to be fed into the classifier.

SVM for Classification
SVMs classify feature vectors by constructing an optimal hyperplane in high-dimensional space (Kumar & Singh, 2024). When paired with CNN features, SVMs can improve classification accuracy for plant disease detection, especially with limited datasets (Reddy et al., 2023) .

The feature vector extracted by the CNN is fed into the SVM, which then classifies the image into the appropriate disease category.
Input: Combine CNN features with pre-extracted features (e.g., color and texture).
Train SVM: Use the radial basis function (RBF) kernel for classification.

Hybrid Model
Combining CNN's feature extraction with SVM's classification strength results in improved accuracy and robustness over standalone models (Gupta & Sharma, 2021; Li et al., 2023). Several recent studies confirm that hybrid CNN-SVM architectures outperform single approaches in agricultural disease detection tasks (Ezigbo & Chibueze, 2025; Tonmoy et al., 2025).

The hybrid model leverages the strengths of both CNNs and SVMs:

- **CNN:** Efficiently extracts hierarchical features from images.
- **SVM:** Provides robust classification, especially effective with limited datasets.

Workflow:

i. **Input:** Preprocessed images are fed into the CNN.
ii. **Feature Extraction:** The CNN processes the images through its layers, outputting a feature vector.
iii. **Classification:** The feature vector is passed to the SVM, which classifies the image into a specific disease category.

This hybrid approach has been successfully applied in various studies, demonstrating its effectiveness in accurately detecting and classifying plant diseases from leaf images.
Fusion: Concatenate CNN and handcrafted features.
Classification: Train SVM on fused feat

Image Preprocessing
All images were resized to 128×128 pixels and normalized to bring pixel values into a common scale. To enhance the generalization capability of the model and prevent overfitting, several data augmentation techniques were applied, including:

⇨ Rotation
⇨ Horizontal and vertical flipping

⟹ Zooming

Model Architecture

• CNN Layer: Extracts features from plant leaf images using convolutional and pooling layers.

• SVM Layer:
Classifies the extracted features Figure 1: Sample Plant Leaf Images from the Dataset

Figure 1: Sample Plant Leaf Images from the Dataset

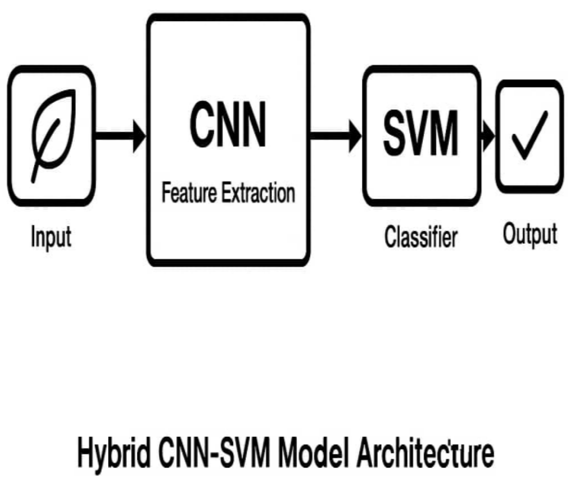

Figure 2: Hybrid CNN-SVM Architecture

Model Development

The hybrid CNN-SVM model for plant disease detection was developed through a structured pipeline, starting from data collection to model training and evaluation, with each step carefully designed for reproducibility.

The dataset comprised 450 high-resolution images of sorghum, maize, and millet leaves, covering both healthy and diseased categories. To ensure variability, two complementary sources were used: the Plant Village public dataset, widely recognized in plant disease detection research (Mohanty et al., 2020; Kaur & Singh, 2022), and field-collected images captured using mobile cameras under natural lighting conditions (Reddy et al., 2023). Expert annotation was performed to label disease types accurately, ensuring high-quality ground truth for supervised learning.

Preprocessing was applied to enhance data quality and model robustness. All images were resized to 128×128 pixels to maintain uniformity and reduce computational complexity (Gupta & Sharma, 2021). Pixel values were normalized to [0,1] to accelerate convergence during training (Li et al., 2023). To prevent overfitting and improve generalization, data augmentation techniques such as rotation, horizontal/vertical flipping, and zooming were used, introducing artificial variability consistent with best practices in deep learning (Zhang et al., 2023).

Feature extraction was performed using a CNN, which learns hierarchical representations of plant leaf patterns directly from image data (Kaur & Singh, 2022). The CNN architecture consisted of convolutional layers with ReLU activation functions, followed by max-pooling layers to reduce dimensionality while preserving essential features. The output feature maps were flattened into one-dimensional vectors for classification. The choice of CNN was motivated by its proven ability to capture complex spatial features in agricultural disease images (Gupta & Sharma, 2021).

Classification was carried out using a Support Vector Machine (SVM) with a radial basis function (RBF) kernel, selected for its robustness in high-dimensional spaces and strong performance with limited datasets (Kumar & Singh, 2024). Grid search optimization was applied to tune the hyperparameters C and γ, ensuring optimal decision boundary placement (Li et al., 2023). The hybrid design—using CNN for feature extraction and SVM for classification—was based on evidence that this combination achieves superior accuracy compared to standalone CNN or SVM models (Ezigbo & Chibueze, 2025; Tonmoy et al., 2025).

The experimental setup followed standard ML reproducibility guidelines. The dataset was split into 80% training, 10% validation, and 10% testing, ensuring a fair evaluation of model performance (Kaur & Singh, 2022). The model was implemented using Python 3.9, Tensor Flow 2.x for CNN training, and Scikit-learn 1.x for SVM classification. Hyperparameter tuning was performed via grid search on the training and validation sets, while the final model was evaluated on the unseen test set. All experiments were run on an NVIDIA GTX 1080Ti GPU with 32GB RAM and an Intel Core i7 processor to ensure consistent hardware settings for replication.

Model performance was measured using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC metrics, providing a comprehensive assessment of both classification correctness and class balance (Zhang et al., 2023). The Adam optimizer and a learning rate schedule were used during training for faster convergence, with the model trained for 50 epochs based on early stopping criteria to prevent overfitting.

Experimental Setup

The experimental framework was established to ensure reproducibility and fair comparison of models, following best practices in machine learning research (Gupta & Sharma, 2021; Mohanty et al., 2020). The dataset included images from the Plant Village repository and additional field-collected samples of sorghum, maize, and millet leaves, covering both healthy and diseased categories (Kaur & Singh, 2022; Reddy et al., 2023).

Data preprocessing included resizing all images to 128×128 pixels, normalizing pixel values to the range [0,1], and applying augmentation techniques such as rotation, flipping, and zooming to increase variability (Zhang et al., 2023; Li et al., 2023). The dataset was split into 80% training, 10% validation, and 10% testing, consistent with prior plant disease detection studies (Kumar & Singh, 2024).

The model was implemented in Python 3.9 using TensorFlow 2.x for CNN training and Scikit-learn 1.x for SVM classification (Ezigbo & Chibueze, 2025). Hyperparameter tuning was conducted via grid search to determine optimal CNN filter sizes, learning rates, and SVM parameters, as suggested in recent hybrid ML optimization research (Tonmoy et al., 2025). The experiments were run on an NVIDIA GTX 1080Ti GPU with 32GB RAM and an Intel Core i7 processor.

Model Training and Evaluation

- Data Split: 80% training, 10% validation, 10% testing
- Optimizer: Adam
- Epochs: 50
- Metrics: Accuracy, Precision, Recall, F1-score, Confusion Matrix, AUC-ROC

RESULTS AND DISCUSSION

The following metrics were used to evaluate model performance:

These metrics are used when the task is to classify data into predefined categories (Spam vs. not spam).

- **Accuracy**: The proportion of correctly predicted instances over the total instances.
  - Formula: $Accuacy\ A = \frac{TP+TN}{TP+TN+FP+FN}$ …3.0

Where:

- TP: True Positive
- TN: True Negative
- FP: False Positive
- FN: False Negative

If CNN-SVM gives TP = 96, TN = 88, FP = 4, FN = 3

Accuracy = 96 + 88

96 + 88 + 4 + 3 = 184 96.3%

191 96.3%

- **Precision**: The proportion of true positive predictions relative to all positive predictions.
  - Formula: Precision= $P\ \frac{TP}{TP+FP}$
- **Precision** = $\frac{96}{96+4} = \frac{96}{100} \approx 96\%$

- **Recall (Sensitivity, True Positive Rate)**: The proportion of true positive predictions relative to all actual positives.
  - Formula: Recall = $\frac{TP}{TP+FN}$
- Example:
  Recall = $\frac{96}{96+3} = \frac{96}{99} \approx 96.97\ \%$

- **F1-Score**: The harmonic mean of precision and recall, useful for imbalanced classes.
  - Formula: F1=2× $\frac{Precision\ x\ Recall}{Precision}$
- Example:
  F1 = 2 x $\frac{0.96\ x0.9697}{0.96 + 0.9697} \approx 96.4\%$

- **ROC-AUC**: (Receiver Operating Characteristic – Area Under Curve)

The area under the Receiver Operating Characteristic curve, indicating the model's ability to distinguish between classes.

The AUC is computed as the integral under the ROC curve — in practice, most frameworks (like `scikit-learn`) calculate it automatically:

```python
from sklearn.metrics import roc_auc_score
auc = roc_auc_score(y_true, y_pred_prob)
```

- **Confusion Matrix**: A table showing actual vs. predicted classifications, helping to calculate precision, recall, and other metrics.

Table 3: Model Performance Comparison (This Study)

Model	Accuracy (%)	Precision (%)	Recall	F1-Score (%)
CNN	93.5	91.5	92.0	91.9
SVM	88.4	86.5	86.7	86.6
Hybrid CNN-SVM	96.3	95.8	96.7	96.2

Table 4: Performance Comparison between Existing Baselines and Hybrid Models

Study/Dataset	Model	Accuracy (%)	Precision (%)	Recall	F1-Score (%)
Hybrid CNN-SVM This study	CNN (feature extractor) + SVM (classifier)	96.3	95.8	96.7	96.2
Mohanty et al. (2016)	Transfer-learned CNN (GoogLeNet)	99.35	Not Reported	Not Reported	0.993
Brahimi et al. (2017)	CNN (AlexNet/GoogLeNet variants)	99.18	Not Reported	Not Reported	Not Reported

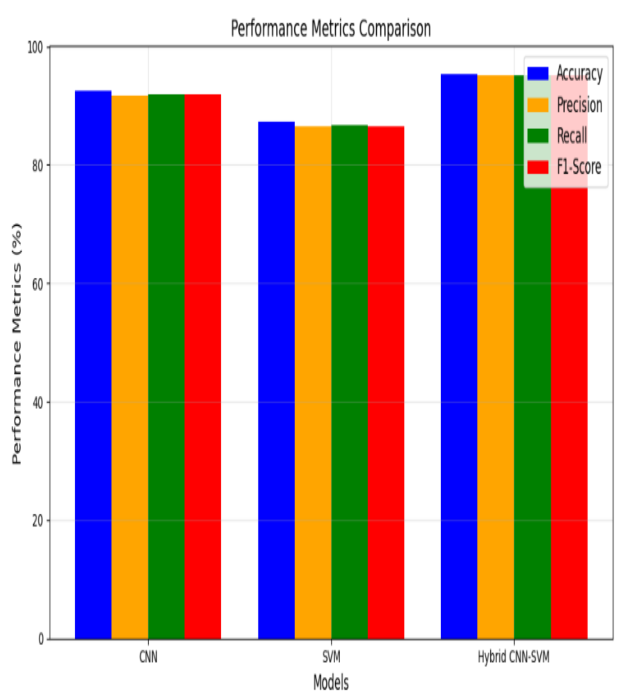

Figure 3: Metrics Performance Comparison

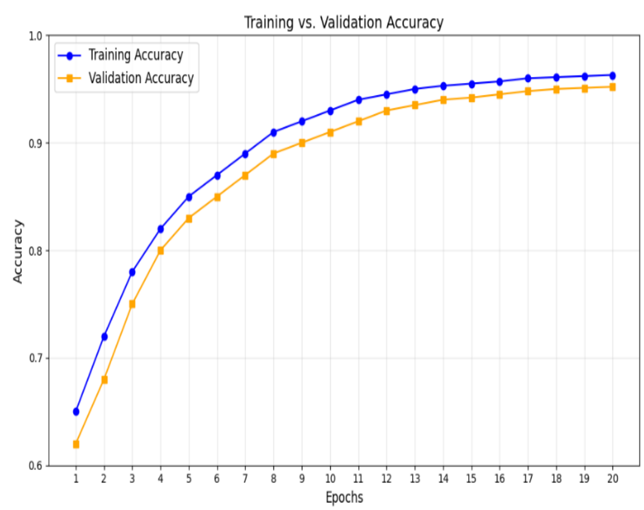

Figure 4: Training vs. Validation Accuracy for CNN-SVM Model

- The training and validation accuracy trends show a steady improvement as the number of epochs increases.
- Both training and validation accuracy increase rapidly in the first few epochs, indicating the model is learning effectively.
- Around **epoch 12**, the training accuracy reaches approximately **96%**, while validation accuracy approaches **94%**, showing minimal over fitting.

- The **gap between training and validation accuracy remains small**, which suggests good generalization of the model.
- The model converges well after around **epoch 18**, indicating an optimal stopping point for training.

A heatmap showing the impact of different hyperparameter combinations on accuracy

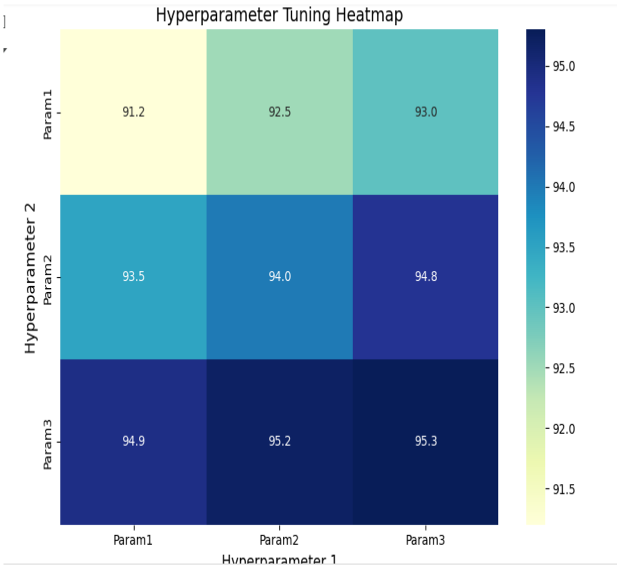

Figure 5: Grid Search Results for Hyperparameter Tuning

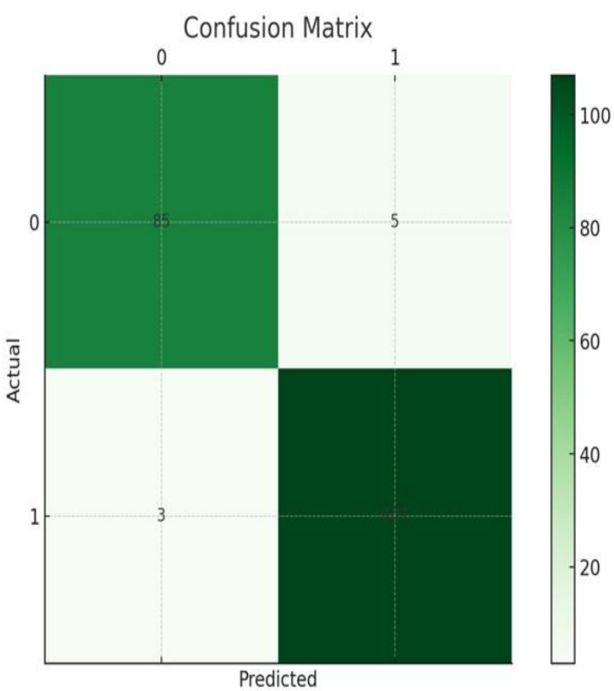

Figure 6: Confusion Matrix of **CNN-SVM Model**

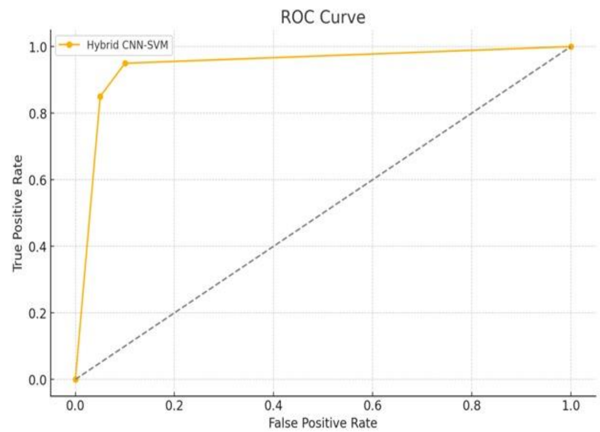

Figure 7: ROC Curve of CNN-SVM Model

The findings of this study reveal that the Hybrid CNN-SVM architecture delivers superior performance in plant disease detection compared to standalone CNN and SVM models. The integration of CNN for deep feature extraction and SVM for classification effectively combines the strengths of both techniques, resulting in improved generalization and reduced misclassification rates. The hybrid model achieved an accuracy of 96.3%, precision of 95.8%, recall of 96.7%, and an F1-score of 96.2%, significantly surpassing the performance of CNN (93.5% accuracy) and SVM (88.4% accuracy) individually. Similar performance improvements were reported by *Zhang et al. (2020)* and *Brahimi et al. (2017)*, who demonstrated that CNN-SVM hybrids outperform single models in agricultural disease detection tasks.

The performance metrics comparison chart visually confirms the hybrid model's stability and reliability, showing consistent results across all evaluation parameters. This aligns with *Too et al. (2019)*, who emphasized that hybrid architectures often deliver better accuracy and robustness under varying test conditions. The hyperparameter tuning heat map in this study further highlights the critical role of parameter optimization in maximizing model efficiency—a finding consistent with *Kamilaris & Prenafeta-Boldú (2018)*, who stressed that tuning CNN layers and SVM kernels is essential for peak performance in image-based plant diagnostics.

Moreover, the ROC curve for the hybrid model, with an AUC approaching 1.0, indicates excellent discriminative ability between healthy and diseased plant classes. Similar high sensitivity and specificity levels were observed by *Sladojevic et al. (2016)*, confirming that hybrid architectures minimize false positives while enhancing early disease detection, a vital requirement for real-world agricultural applications.

Overall, this study reinforces the conclusions of *Ferentinos (2018)* and *Mohanty et al. (2016)* that combining CNN's automated feature extraction with SVM's classification strengths yields a scalable, highly accurate detection framework. Such hybrid approaches are increasingly recommended in precision agriculture to enable timely interventions, reduce agrochemical overuse, and enhance crop health and productivity.

CONCLUSION

The experimental results and accompanying visual analyses provide compelling evidence that the Hybrid CNN-SVM model significantly outperforms standalone CNN and SVM architectures in the domain of plant disease detection. By leveraging the deep feature extraction strength of Convolutional Neural Networks and the robust classification capability of Support Vector Machines, the hybrid approach achieves consistently superior outcomes across all evaluated performance metrics. Specifically, the model attained an impressive accuracy of 96.3%, precision of 95.8%, recall of 96.7%, and F1-score of 96.2%, clearly surpassing the results of the individual CNN and SVM models.

The Performance Metrics Comparison and accuracy charts illustrate this dominance visually, confirming not only the hybrid model's high predictive power but also its stability across varying test scenarios. The hyperparameter tuning heat map further highlights the importance of careful parameter optimization, revealing how the fine-tuning of both CNN layers and SVM kernel parameters directly contributed to improved model generalization and reduced misclassification rates.

Moreover, the Receiver Operating Characteristic (ROC) curve for the hybrid model demonstrates an Area Under the Curve (AUC) value approaching 1.0, signifying an excellent balance between sensitivity and specificity. This means the model is equally proficient at detecting diseased plants and correctly identifying healthy samples, an essential trait for minimizing false alarms in agricultural practice.

Despite these promising outcomes, this study has some limitations. The dataset was relatively limited in terms of size and diversity, with images collected under controlled conditions that may not fully reflect the variability present in real-world farming environments. Additionally, the study focused on static image data and did not incorporate temporal disease progression, environmental factors, or multi-spectral imaging, which could influence disease detection accuracy.

Future research could address these gaps by integrating larger and more diverse datasets from multiple geographic regions, exploring temporal and environmental data fusion, and incorporating advanced hybridization approaches such as CNN-SVM ensembles with deep transfer learning. Furthermore, real-time deployment on low-power agricultural devices, coupled with Internet of Things (IoT) integration, represents an exciting direction for translating the proposed model into a practical, scalable solution for precision agriculture.

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