Towards Sustainable Agriculture: A Stepwise Model Using Hybrid CNN Algorithms for Disease Detection

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ABSTRACT
Despite several obstacles including plant diseases, pollinator rise, and climate change, agriculture is vital to the economic growth of many nations and supports the worldwide population. Crop leaf diseases have grown to be a major worry for the agricultural sector, yet a lack of automated crop disease detection techniques makes prompt diagnosis and recognition difficult in many parts of the world. Plant diseases will increase food insecurity and have an impact on the nation's income if they are not recognized in a timely manner. The identification and control of crop diseases is essential for raising agricultural production, cutting expenses, and advancing ecologically friendly crop treatment practices. Crop disease detection systems that are automated have been developed using modern technology like machine learning algorithms and data mining. In order to build this system, three iterations of an improved Hybrid CNN algorithm were used, together with photos of crop pairings that were infected and healthy to create a stepwise disease detection model. The suggested model has been enhanced to maximize accuracy and speed of detection, and it has been used for plant leaf disease detection as well as multi-class crop identification. Two well-known publicly available dataset namely "PlantVillage '' and "CropImages" are used for experiment. The obtained findings showed higher accuracy (96.0%), precision (95.0%), F1-scores (96.0%), and recall (94.0%) when compared to state-of-the-art methods. The article offers a cutting-edge analysis, details our approach and experimental findings, and offers suggestions and future possibilities for our study on the use of hybrid CNN models to the categorization of crop and plant leaf diseases.

Keywords: crop disease detection, machine learning, deep learning, hybrid models, multi class classification.

1. INTRODUCTION
Agriculture, as the backbone of many economies, plays an indispensable role in global sustenance and economic development. Despite its significance, the agricultural sector faces formidable challenges such as climate change, pollinator decline, and the pervasive threat of plant diseases. Among these challenges, the increasing incidence of crop leaf diseases has emerged as a serious concern, posing a significant risk to agricultural productivity and food security worldwide. Plant diseases cause almost 30% of the world's agricultural output to be lost annually, with direct economic losses above $40 billion (Dong A et. al.) [1]. Numerous diseases can cause a range of losses; leaf spot and leaf rust are two prevalent ailments that frequently affect crops including rice, maize, and peanuts (Qi H et. al.) [2]. Plant protection thus depends on the prompt detection and precise identification of plant diseases.
Historically, plant pathologists and farmers have relied on their visual sense to identify disease and establish conclusions based on past experiences. However, this approach has sometimes been incorrect and misunderstood since several diverse circumstances first seem to be the same. The diversity of plants leads to a corresponding variation in disease traits in crops, further complicating the categorization of plant ailments. Furthermore, plant pathologists' and farmers' knowledge has to be passed down from one generation to the next. But the major method used in traditional field screening for plant disease identification is still visual examination of the color patterns and leaf crown structures. Based on their experience and close examination of the disease's symptoms on plant leaves, humans require time, effort,

and specific expertise to detect plant disease. The diversity of plants leads to a corresponding variation in disease traits in crops, further complicating the categorization of plant diseases.
Furthermore, abuse of pesticides results from inaccurate plant disease predictions, which drives up production costs. These characteristics make it imperative to develop a dependable disease diagnosis system that is linked to a specialized database in order to assist farmers—especially new and inexperienced ones. To solve these problems, researchers have created innovative methods for identifying plant diseases that make use of image processing. This is currently at the top of the scientific agenda. For the precision agriculture industry, it is still difficult to identify plant diseases intelligently and accurately without using labor (Donatelli M et al.) [3]. Utilizing machine learning and deep learning approaches, recent advancements in computer technology allow for object identification, image segmentation, and image classification (Otter D. W. et. al.)[4]. The majority of machine learning research has been on categorizing plant diseases based on traits seen in plant leaf photos, such as texture(Hossain, E et. al.) [5], color and kind (Mokhtar, U. et. al.) [6]. The main drawbacks of these techniques include poor performance and impracticability for real-time categorization in ML-based methods. Furthermore, manual feature extraction takes a lot of time and expertise and is challenging. Hand-crafted features, gradient histograms, shape-based extraction, and SIFT features are examples of basic feature extractors that are often used. It takes a lot of work to extract these characteristics, especially the scale-invariant transformation. Following feature training, various learning algorithms, such as SVM, are applied for information classification. Conventional methods often demand a substantial amount of image preparation, including scaling, de-noising with filters like Gaussian smoothing, and other processing techniques. These preprocessing steps contribute to an extended processing duration in the disease detection pipeline.

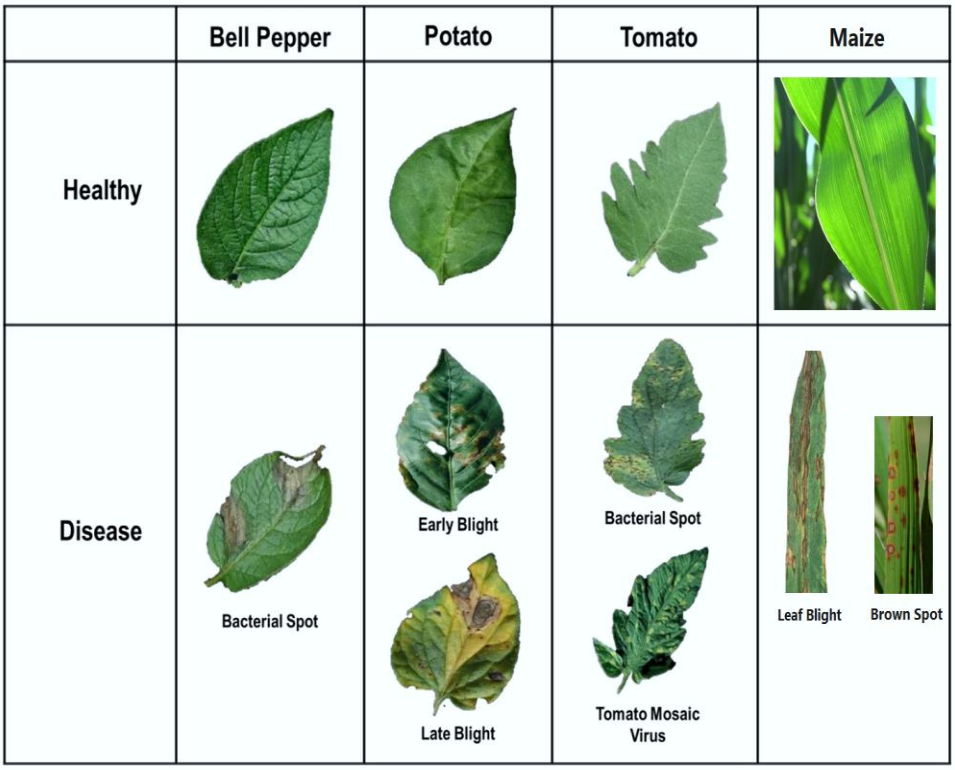

Figure 1. Healthy and Disease Plant and Crop Leaves.

Recently, DL-based research has been carried out in plants and DL analysis shown a high level of performance in plant disease detection. A wide range of applications, such as weed recognition by Yu, J., Sharpe et al.[7], crop pest classification by Ullah, N. et al. [8], and plant disease identification by Bansal, P. et al [9], are carried out in the agricultural sector using DL approaches. DL is one of ML's research interests. It has mainly tackled the problems associated with segmented operation, subpar performance, lengthy processing times, and manual feature extraction in typical ML techniques. The main advantage of deep learning models is their capacity to extract features with respectable performance even in the absence of segmentation operations. Automatic feature extraction is performed on the fundamental data for each individual item. Since the introduction of CNNs, plant disease categorization technologies have become more automated and efficient. CNN architectures exhibit a higher computational burden despite their remarkable efficacy in disease diagnosis. This means that a more efficient model that requires the development of fewer parameters must be developed.

The contribution of the plant leaf disease detection framework lies in its comprehensive approach to enhancing accuracy, robustness, and efficiency. Here are the key contributions:

- Integration of widely recognized datasets, "PlantVillage" and " CropImages" for model validation. This ensures the model's adaptability to diverse plant diseases and variations, enhancing its generalization capabilities.
- Using data augmentation methods, such as rotation, horizontal flipping, shear, zoom, and width and height changes, to reduce the effects of overfitting and underfitting. This diversifies the dataset, enabling the model to better generalize to unseen data and enhancing its robustness.
- Implementation of a fine-tuned CNN model optimized for both speed and accuracy. This involves a meticulous selection of hyper-parameters and activation functions, contributing to improved disease detection performance.
- Introduction of a novel hybrid model combining the strengths of CNN with Support Vector Machines (SVM) and XGBoost. The CNN algorithm is employed to extract features from the dataset, and these features serve as input to an SVM and XGB classifier. This hybrid approach aims to capitalize on the feature extraction capabilities of CNNs and the classification power of SVMs and XGB, contributing to a more accurate and refined disease detection process.

The article is divided into the following sections: The review of the literature is given in Section 2. A description of the dataset is given in Section 3. The anticipated work on Plant Disease Detection is then covered in great detail in Section 4. The results and performance evaluation of the suggested task are shown in Section 5. Lastly, the overall conclusion wraps up Section 6.

2. LITERATURE REVIEW

The literature review encompasses recent studies that contribute to the advancement of leaf disease detection and classification, employing various methodologies including CNN, machine learning, and computer vision.

Machine Learning Techniques for Plant / Crop Leaf Detection

Sunil S. Harakannanavar et. al. [10] performed the practical implementation of computer vision and ML algorithms for the detection of plant leaf diseases. Their study addressed real-world challenges associated with disease identification, showcasing the potential applications of these technologies in agricultural settings.

The work by Ahmed I et. al. [11] provides a methodical examination of deep learning and machine learning-based methods for recognizing and treating plant diseases. The study offers insight into the comparative effectiveness of various techniques for the diagnosis and detection of plant diseases. R K et. al. in [12] contributed to the advancement of smart agriculture by developing plant disease detection techniques. Their emphasis on technological progress underscored the significance of these methods in improving disease identification in agricultural contexts, aligning with the broader goal of enhancing efficiency in smart agricultural practices.

Yao, J., et. al.[13] conducted an extensive review, providing a comprehensive analysis of machine learning techniques employed in leaf disease classification. The review covered a wide range of methodologies and practical applications, serving as a valuable resource for understanding the evolving landscape of leaf disease classification.

Demilie, W.B. et. al. [14] conducted a comprehensive comparative study in plant disease detection and classification techniques, offering insights into their performances. This study contributes valuable knowledge for understanding the strengths and limitations of various methods in the field of plant pathology. A thorough research by Chaudhari, P. et al. [15] investigates the application of ML to agricultural disease extraction and detection. The research provides insights into disease patterns, emphasizing the importance of machine learning in precision agriculture for effective disease management.

Deep Learning-Based Method for Plant / Crop Leaf Detection

The research conducted by Hang J, et al. [16] centers on the utilization of an enhanced CNN in order to categorize plant leaf maladies. Utilizing architectural advancements from CNN, the initiative aims to improve the accuracy and efficiency of disease diagnosis in plant foliage.

With an emphasis on agricultural applications J., A.; Eunice et al. [17] offers a DL-based method for identifying leaf diseases in crops using photos. The project examines the application of cutting-edge DL methods for accurate and efficient disease identification in various crops. The application of DL approaches for agricultural disease identification based on photographs is examined by Deputy, K. V et al. [18]. The study employs advanced DL models to analyze images and identify patterns associated with various crop diseases. The goal of the research is to aid in the creation of precise and accurate systems for detecting crop diseases.

Adesh V. Panchal et al. [19] investigated the application of DL to image-based plant disease identification. This study looks into the ability of DL approaches to reliably and effectively diagnose plant diseases using leaf photos. Jung, M. et al. [20] created a DL-based algorithm for identifying plant diseases. The work investigates the use of DL techniques to develop an accurate and efficient model for diagnosing disorders in plant structures. Padshetty, S. et al. [21] proposed a Leaky ReLU-ResNet model for DL-based plant leaf disease detection. This model uses sophisticated neural network designs to improve illness classification accuracy, with an emphasis on the ResNet structure and Leaky ReLU activation.

Hybrid Techniques for Plant / Crop Leaf Detection

Singh, Ashutosh et. al. in [22] integrated CNN, Random Forest Classifier, and Bayesian-optimized Support Vector Machine (SVM) to offer a hybrid feature-based strategy for plant leaf disease identification. This hybrid model combines the strengths of different techniques, aiming for improved accuracy in identifying plant diseases.

A novel approach to botanical leaf disease detection by proposing a hybrid model is described by Mohapatra, Madhumini et. al. in[23]. This model combined CNN with metaheuristic techniques, offering a synergistic approach that improved the efficiency and accuracy of disease diagnosis in plant leaves.

It is suggested by C. R Dhivyaa et al. [24] that to find diseases in cassava plant leaves, expanded convolution should be combined with a residue dense block network and a multi-level feature recognition network. The study looks into ways to make feature recognition better in systems that find plant leaf diseases.

A hybrid model for classifying leaf diseases was described by Saberi Anari M.et al. [25]. It made use of ensemble methods and improved deep transfer learning. This model is specifically intended to improve the robustness of disease categorization within the framework of agricultural monitoring systems, namely for use in Agricultural Internet of Things (AIoT)-based monitoring.

R. Arumuga Arun et. al. [26] introduces an effective approach for pruning a whole concatenated deep learning model in order to detect multi-crop diseases. The study focuses on enhancing the efficiency of disease identification across multiple crops through advanced model architecture.

Mamba Kabala, et al [27] explore the application of federated learning for image-based crop disease detection. Federated learning, a decentralized machine learning approach, is employed to collectively train a model across multiple devices without exchanging raw data. The study focuses on enhancing privacy and efficiency in crop disease detection systems.

SOFUOĞLU, C. İ. et al [28] addresses the detection of potato plant leaf diseases using a deep learning method. The research investigates the application of deep learning techniques for accurate disease identification in potato plants, contributing to advancements in agricultural disease management.

Table 1. Comparative Analysis of researcher's work.

Reference No.	Authors	Method	Algorithms Used	Dataset Used	Accuracy
[10]	Sunil S. Harakannanavar et al. (2022)	Image processing and machine learning	KNN,SVM,CNN	Plant Village dataset	99.6%
[11]	Ahmed I & Yadav P K (2023)	Review of Machine Learning and Deep Learning methods	SVM, CNN, Gray-level co-occurrence matrices	public dataset of 8350 images of damaged and healthy plants	99.0%
[12]	R, K., T, S. (2023)	Plant disease detection for smart agriculture	Image processing and machine learning	-	99.0%
[15]	Chaudhari et al. (2024)	Diverse crop disease patterns using ML and DL techniques	CNN, RNN	PlantVillage dataset, Tomato Disease, Cassava Leaf Disease, Paddy	-

				Crop Disease	
[16]	Hang et al. (2019)	CNN uses a squeeze-and-excitation (SE) module in combination with an inception module's structure.	Improved Convolutional Neural Network (CNN)	plant leaf disease dataset.	91.71%
[17]	Jayaprakash et al. (2022)	Pre-trained models are used for effective plant disease detection	DenseNet-121, ResNet-50, VGG-16, and Inception V4	PlantVillage dataset	99.1%
[18]	Deputy et al. (2023)	Training from scratch and transfer learning approaches ware used	GoogleNet , InceptionV3	PlantVillage dataset	98.73%
[19]	Panchal et al. (2023)	Pixel based operations and segmentation are applied on leaf images	Convolutional Neural Network (CNN)	PlantVillage dataset	90.50%
[20]	Jung et al. (2023)	Data Augmentation techniques and pre-trained model are used	AlexNet, VGG19, GoogLeNet, ResNet, and EfficientNet	ILSVRC2012 dataset	97.09%
[21]	Padshetty et al. (2023)	Three main components of the LRRN model are used: feature extraction, classification, and data pre-processing.	Leaky ReLU-ResNet	PlantVillage dataset	92.20%
[22]	Singh, Ashutosh &Sreenivasu, (2022)	Combining Random Forest Classifier, Bayesian Optimized SVM, and CNN for Hybrid Based on features Disease Detection in Plant Leaf	CNN, Bayesian Optimized SVM, Random Forest Classifier	Plant Village	96.1%
[23]	Mohapatra, Madhuminiet al. (2022)	A Hybrid CNN Approach Facilitated by Metaheuristics	CNN, Black Widow Optimization Algorithm	Real Time Mango Tree Leaves Dataset	98.75%
[24]	C. R Dhivyaa,et al. (2022)	Identification of cassava plant leaf diseases by the integration of residual dense block network, multi-level feature detection network,	Dilated convolution, Residual dense block network, Multi-level feature detection network	Cassava Leaf Disease Dataset	99.22%

		and dilated convolution			
[25]	Saberi Anari M.	Hybrid Model for Classifying Leaf Diseases Using Ensemble Approach and Modified Deep Transfer Learning for Agricultural AIoT-Based Monitoring	Modified Deep Transfer Learning, Ensemble Approach	PlantVillage and UCI datasets	98.5%
[26]	R. Arumuga Arun, S.	Multi-crop disease detection with a concatenated DL model that is trimmed entirely	Pruned Complete Concatenated Deep Learning Model	PlantVillage	98.14%
[27]	Mamba Kabalaet al.	Federated learning	Federated Learning	PlantVillage	98.57%

These studies collectively contribute to the field by exploring and implementing diverse techniques, ranging from comparative analyses to hybrid models, all aimed at advancing the accuracy and efficiency of plant leaf disease detection systems.

3. Dataset Description

Two Publicly available dataset are used namely “PlantVillage” and “CropImages”.

PlantVillage [29]: With 61,486 photos of plant leaves and backdrops, this dataset attempts to address the efficient diagnosis of 39 different plant diseases. Six different augmentation strategies were used in the creation of the dataset in order to enhance its diversity and robustness. These enhancements consist of picture flipping, gamma correction, scaling, rotation, noise injection, and PCA color augmentation, ensuring a varied set of background conditions for more comprehensive and accurate disease detection solutions.

CropImages [30]: A comprehensive crop dataset encompassing images of jute, maize, rice, sugarcane, and wheat, download from "https://www.kaggle.com/code/aman2000jaiswal/crop-images-classification/input." This dataset, totaling 27 MB in size, offers a valuable resource for researchers, enthusiasts, and practitioners in the field of agriculture.

4. METHODOLOGY

Figure 1 depicts the overall architecture of the suggested strategy, which consists of many modules to precisely accomplish plant leaf disease. The workflow for the methodology encompasses several key steps to facilitate efficient disease detection in crops. Initially, the Input Dataset is curated, laying the foundation for subsequent processing. Image Preprocessing follows, incorporating crucial steps like Image Resizing to standardize dimensions, RGB to Gray Color Conversion for simplifying data, and LabelBinarizer for categorical label transformation. To enhance the model's robustness, Data Augmentation techniques are employed, introducing changes including zoom, shear, rotation, shifts in width and height, and horizontal flips. By diversifying the dataset, these augmentations enhance the algorithm's capacity to generalize to other contexts.

The dataset is split into 80% for training and 20% for testing in order to ensure the model's effectiveness and performance. This segmentation makes it easier to evaluate the model's accuracy and capacity for generalization in a trustworthy manner.

The heart of the methodology lies in the Deep Learning Algorithm, where a CNN is employed. Various activation functions, including Sigmoid and Softmax, are considered for the hidden and output layers. A meticulous selection process identifies the best activation functions, optimizing the overall performance of the model.

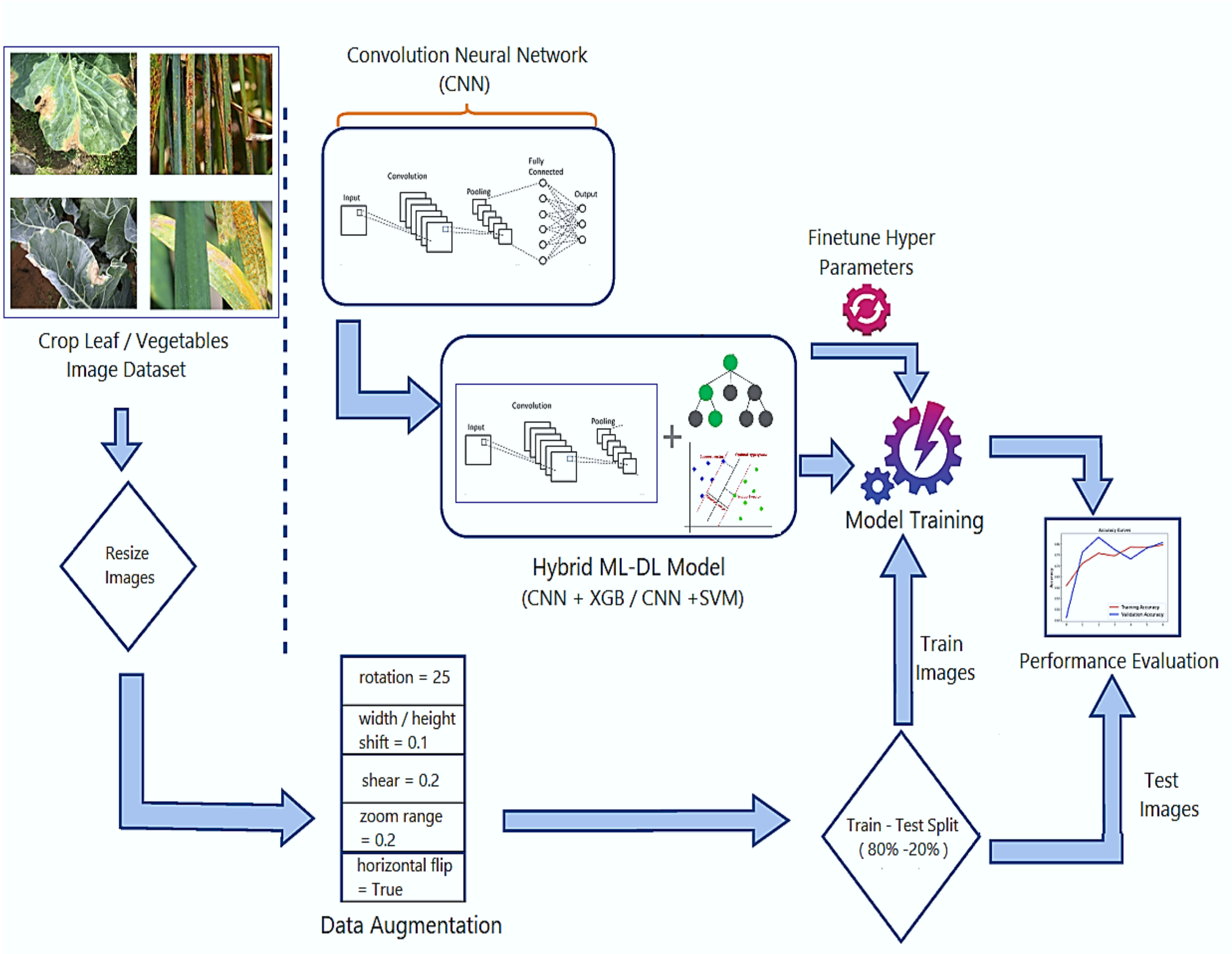

Figure 2. System Architecture

Taking the approach, a step further, a **hybrid model**, CNN + SVM, CNN + XGB are introduced. Initially, the CNN algorithm is applied to the dataset, extracting features from the Dense Layer. These extracted features serve as input to an SVM / XGB classifier, performing additional classification to refine the disease detection process. This hybrid approach harnesses the strengths of both CNN and SVM / XGB, contributing to a comprehensive and effective solution for crop disease detection. The detail flow is explained below;

Data Collection

Acquire a diverse collection of pictures showing leaves afflicted with different diseases. The publicly available dataset “PlantVillage '' and “CropImages” are used as input. The suggested hybrid model is trained and assessed using this dataset as the foundation.

Phase of Pre-Processing Data

This method improves the quality of the photos and prepares them for additional processing by the model. On occasion, the leaf disease patches might not be apparent due to the dataset photos' inadequate illumination. The following is a description of a few techniques used in data pre-processing:

Scaling and Resizing: Sometimes, the non-uniformity of the photos leads to computational difficulty; to resolve these issues, the dataset's uniformity is preserved while the images are downsized to a standard size. The scaling technique is used to keep the value of pixels within a specific range.

RGB to Gray Color Conversion: Convert the images from the RGB color space to grayscale, reducing computational complexity while preserving essential features.

Label Binarizer: Apply label binarization to convert categorical labels into binary vectors, enabling the model to handle multi-class classification tasks effectively.

Data Augmentation
A big dataset is required since the tiny training set overfits. This approach is used to increase the training set. Following are various data augmentation technique applied for input dataset. Table 2 shows the parameters value used for data augmentation.
Rotation Range: Introduce random rotations within the specified range to enhance the model's ability to recognize variations in leaf orientations.
Width Shift Range: To simulate variations in leaf positions within the frame, periodically change the width of pictures.
Height Shift Range: To simulate variations in leaf positions within the frame, periodically change the height of pictures.
Shear Range: Apply shearing transformations to simulate deformations in leaf shapes.
Zoom Range: Introduce random zooming to simulate variations in the scale of the leaves.
Horizontal Flip: Perform horizontal flips to augment the dataset and enhance the model's robustness to mirror-reversed leaf images.
Fill Mode: Specify the fill mode for pixel values during image transformations.

Table 2. Data Augmentation parameters and their values

Parameters	Value
Rotation Range	25
Width Shift Range	0.1
Height Shift Range	0.1
Shear Range	0.2
Zoom Range	0.2
Horizontal Flip	True
Fill Mode	nearest

Train Test Split
Train Test Split involves partitioning a dataset into two subsets: a training set and a testing set. In this specific case:
Split Ratio: The dataset is divided with a ratio of 80:20, with 80% of the data being used for training and the remaining 20% being set aside for evaluating the model's performance.
Training Set: The machine learning model is trained using the 80% of the dataset that has been set aside for training. To provide predictions or classifications, the model analyses the data to find patterns, characteristics, and correlations.
Testing Set: The reserved 20% of the dataset serves as a separate subset for evaluating the model's performance. This set is not used during the training phase.Instead, it serves as a standard by which to measure how effectively the model extrapolates to novel, unobserved data.
A crucial stage in the creation of machine learning models is the train-test split, which makes sure that the model's performance is evaluated on data that it has never seen before and gives information about how well it can predict outcomes on new, unknown instances. This practice aids in gauging the model's overall effectiveness and generalization capabilities.

Deep Learning Classifier
1. Convolutional Neural Network (CNN) Algorithm
CNNs are made to automatically learn hierarchical features by using convolutional layers to interpret structured grid data, like photographs.
Step 1: Input Layer
Begin with the raw input data, typically representing an image.
Step 2: Convolutional Layer
Apply convolutional filters to capture spatial hierarchies and detect features within the input data.
Step 3: Activation Function, such as ReLU, etc.
Give the model non-linearity by applying the Rectified Linear Unit activation function.
Step 4: Pooling Layer
Down sample the feature maps' spatial dimensions as determined by the convolutional layer to reduce computation and retain important information.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_36 (Conv2D)          (None, 64, 64, 32)        896

 batch_normalization_36 (Bat  (None, 64, 64, 32)       128
 chNormalization)

 conv2d_37 (Conv2D)          (None, 64, 64, 32)        9248

 batch_normalization_37 (Bat  (None, 64, 64, 32)       128
 chNormalization)

 max_pooling2d_18 (MaxPoolin  (None, 32, 32, 32)       0
 g2D)

    ⁞    ⁞        ⁞    ⁞        ⁞    ⁞        ⁞    ⁞

 conv2d_41 (Conv2D)          (None, 16, 16, 128)       147584

 batch_normalization_41 (Bat  (None, 16, 16, 128)      512
 chNormalization)

 max_pooling2d_20 (MaxPoolin  (None, 8, 8, 128)        0
 g2D)

 dropout_20 (Dropout)        (None, 8, 8, 128)         0

 flatten_6 (Flatten)         (None, 8192)              0

 dense_6 (Dense)             (None, 15)                122895

=================================================================
Total params: 411,695
Trainable params: 410,799
Non-trainable params: 896
_________________________________________________________________
```

Figure 3. CNN Model Architecture

Step 5: Fully Connected Layer (Flattening)
To get the data ready for the fully linked layers, flatten the 2D feature maps into a 1D vector.
Step 6: Fully Connected Layer
To identify global patterns and correlations in the data, connect each neuron in one layer to each neuron in the one below.
Step 7: Output Layer
Produce final predictions based on the learned features. For classification tasks, use activation functions like Softmax.
Step 8: Loss Calculation
Compute the variation between the actual and anticipated values to measure the model's performance. Here categorical cross-entropy is used as loss function.

$$\text{Categorical Crossentropy} = -\sum_{i} y_i . \log(\hat{y}_i)$$

Where:
y_i is the true probability distribution (i.e., the ground truth), typically represented as a one-hot encoded vector where y_i=1 for the true class and y_i = 0 for other classes.
$(\hat{y}_i)$is the predicted probability distribution, typically outputted by the softmax function in the final layer of a neural network. It represents the model's confidence scores for each class.
i iterates over all the classes.
Step 9: Backpropagation

Update the model's parameters using the calculated gradients to minimize the loss. This step involves adjusting the weights and biases.
Step 10: Training
Repeat Steps 2-10: Iteratively train the model on the training dataset, adjusting the weights and biases to improve performance.
Step 11: Evaluation
Assess the trained model's performance on a separate set of unseen test data to ensure generalization.

Activation Functions
Sigmoid: The sigmoid function is commonly used in binary classification problems to squish the output of a linear transformation into the range [0, 1], representing a probability. The formula for the sigmoid function is:

$$\mathrm{Sigmoid}\ (x) = \frac{1}{1 + e^{-x}}$$

Where:
x is the input to the function.
e is Euler's number (approximately equal to 2.71828).
Softmax: The softmax function multiplies each raw score to produce non-negative values before normalising them by dividing by the total of all exponentiated raw scores. This normalisation assures that the resultant probabilities total up to one, rendering them interpretable as probabilities.

$$\mathrm{softmax}\ (Z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_i}}$$

Where:
e is Euler's number, approximately equal to 2.71828.
Z_i is the raw score (logit) for class.
K is the total number of classes.

CNN + SVM / XGB
CNN Architecture:
- Convolutional Layers: Detect local features using convolutional filters.
- Pooling Layers: Downsample to reduce spatial dimensions.
- Fully Connected Layers: Capture global patterns and relationships.
- Output Layer: Produces feature vectors.

Feature Vectors from CNN:
- Flattening and Fully Connected Layers: After the CNN architecture processes the input, the feature vectors are obtained by flattening the final layer or extracting from fully connected layers.

SVM for Classification (M1):
- SVM Utilization: The feature vectors obtained from the CNN are then used as input to an SVM for classification.

XGB for Classification(M2):
- XGB Utilization: The feature vectors obtained from the CNN are then used as input to an XGB for classification.

Training and Fine-Tuning:
- Training Process: The CNN is initially trained to learn features from labeled data.
- Fine-Tuning with SVM / XGB: The SVM / XGB is then trained on the feature vectors extracted by the CNN, optimizing its parameters for the classification task.

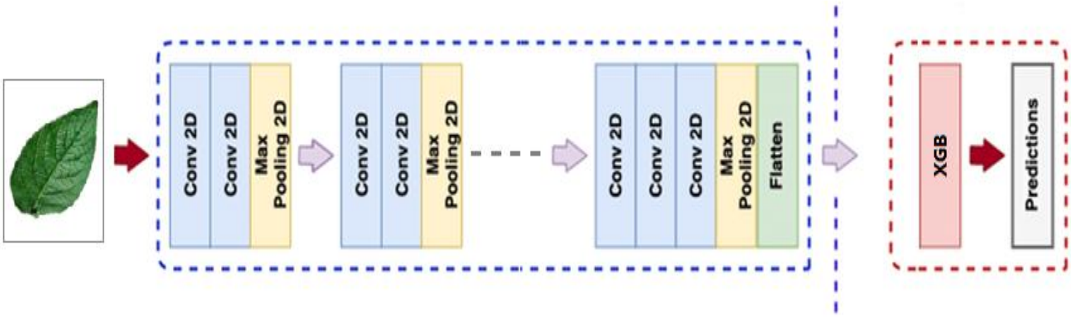

Figure 4. CNN + XGB Model Architecture

Performance Evaluation
After applying Fine-tune CNN and Hybrid CNN +SVM, CNN + XGB to validate the effectiveness of the hybrid approach for disease diagnosis in leaves, analyse the performance of the hybrid model on the test dataset by assessing and analysing the accuracy, precision, recall, and other pertinent metrics.

5. RESULT AND DISCUSSION
Operating environment and parameter setup
The experimental setup utilizes cloud-based computing on Google Colab, providing access to GPU acceleration for efficient model training. Essential Python libraries are employed for model development and data processing. These include TensorFlow and Keras for deep learning, scikit-learn for machine learning algorithms, and additional libraries such as OpenCV, Matplotlib, and Seaborn for image processing and visualization. Google Drive is mounted onto the Google Colab environment, enabling seamless access to the dataset and other relevant files stored in Google Drive. Metrics like accuracy are used to evaluate the performance of the model. Confusion matrices and visualizations, generated with libraries like Seaborn and Matplotlib, aid in analyzing the effectiveness of both the deep learning and machine learning models. We also attempted to standardize the hyper-parameters throughout all of the experiments to allow for a fair comparison of the outcomes of each experimental configuration. The following hyper-parameters were employed in each experiment:

Table 3. Hyper-parameters Tuning

Parameters	Value
loss	binary_crossentropy
Optimizer	Adam
Epoch	300
Dropout	0.1
batch size	32
learning rate	1e-3

This experimental setup provides a comprehensive framework for plant disease leaf detection, combining the advantages of machine learning and deep learning algorithms on a cloud-based platform for efficient computation.

Results Analysis
The section conducts a thorough analysis of the hybrid DL models that have been used for the detection of plant leaf diseases and crop disease detection. The experiments are conducted on the Plant Village and Crop datasets using various algorithms, including fine-tuned CNN, and hybrid approaches such as CNN+XGB (XGBoost) and CNN+SVM (Support Vector Machine), yielded insightful results. We used performance measures like F1 score, accuracy, precision, and memory to check how well each programme worked. The fine-tuned CNN demonstrated robust performance across both datasets, achieving high accuracy rates. However, when augmenting the CNN architecture with additional classifiers like XGBoost or SVM, further improvements were observed, particularly in precision and recall metrics. The CNN+XGB and CNN+SVM combination methods were better at finding real positive cases while reducing the number of fake positives and false negatives. Furthermore, the loss curve graphs provided valuable insights into the training progression, illustrating the convergence and stability of the models over epochs. Overall, the comparative analysis revealed the efficacy of hybrid algorithms in leveraging the strengths of both DL and traditional ML techniques, showcasing their potential for achieving superior performance in plant disease classification tasks.
The analysis of the fine-tuned CNN model on the Plant Village dataset and Crop dataset reveals compelling results. Figure 5 and Figure 6 displays the loss and accuracy curves of plant village dataset and crop dataset respectively across 300 epochs of training. The loss curve demonstrates a steady decrease, indicating effective convergence of the model during training. Simultaneously, the accuracy curve exhibits consistent improvement, culminating in an impressive accuracy rate of 80% (plant village dataset) and 89% (crop dataset) by the conclusion of the training process.

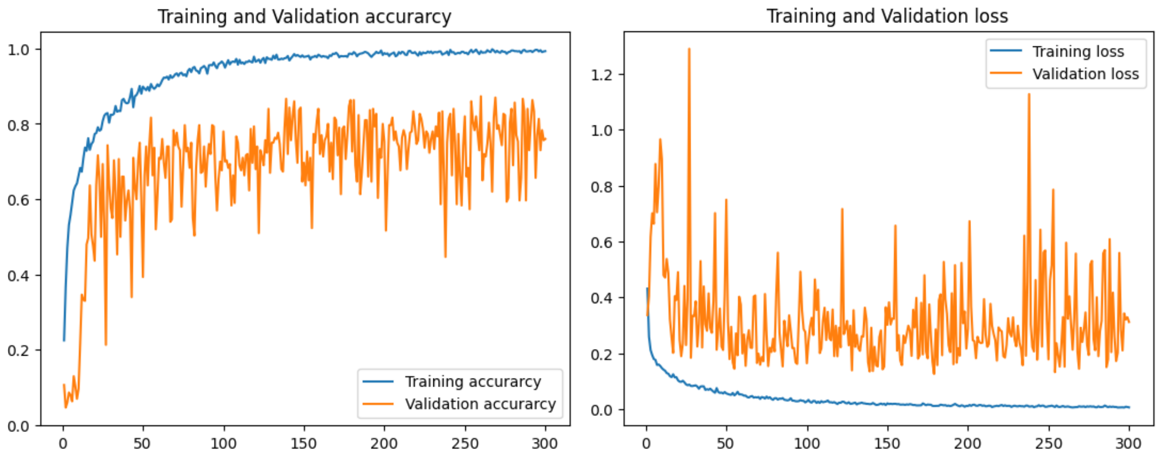

Figure 5. Plant Village Dataset (A) Accuracy Curve (B) Loss Curve graphs

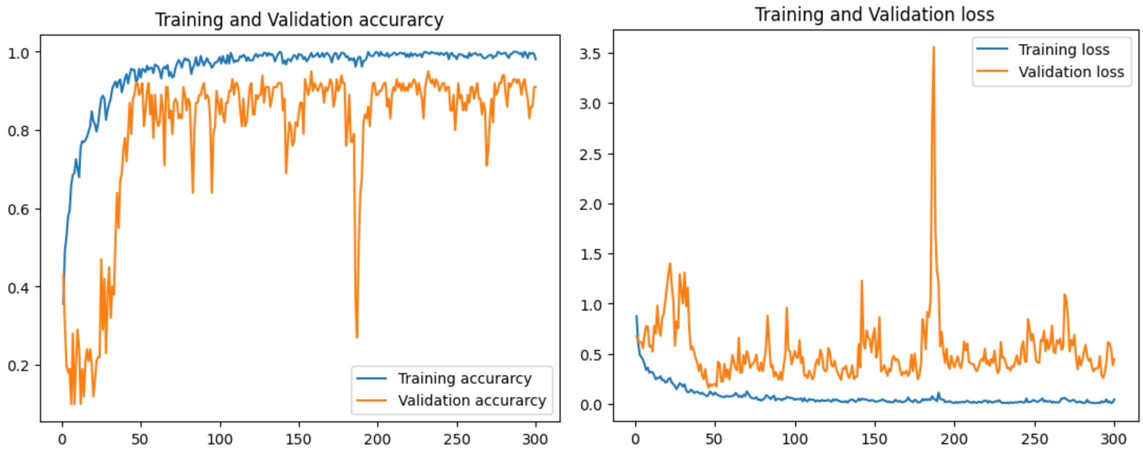

Figure 6. Crop Dataset (A) Accuracy Curve (B) Loss Curve graphs

The confusion matrix of Hybrid technique CNN +XGB for plant village and crop dataset is shown in Figure 7 and Figure 8 respectively which provides valuable insights into the model's classification performance. Notably, the model demonstrates robust performance across various disease categories, effectively distinguishing between different plant diseases with minimal misclassifications. The hybrid model outperforms fine tune CNN model achieving accuracy of 84.8 % (CNN + SVM) and 87.1% (CNN +XGB) for plant village dataset and 93.3% (CNN +SVM) and 96.2 % (CNN +XGB) on crop dataset. Overall, these results underscore the effectiveness of the fine-tuned Hybrid CNN +XGB model in accurately classifying disease plant leaf within both datasets. The comparative analysis graph and respective table shown in Figure 9 and Figure 10 Respectively.

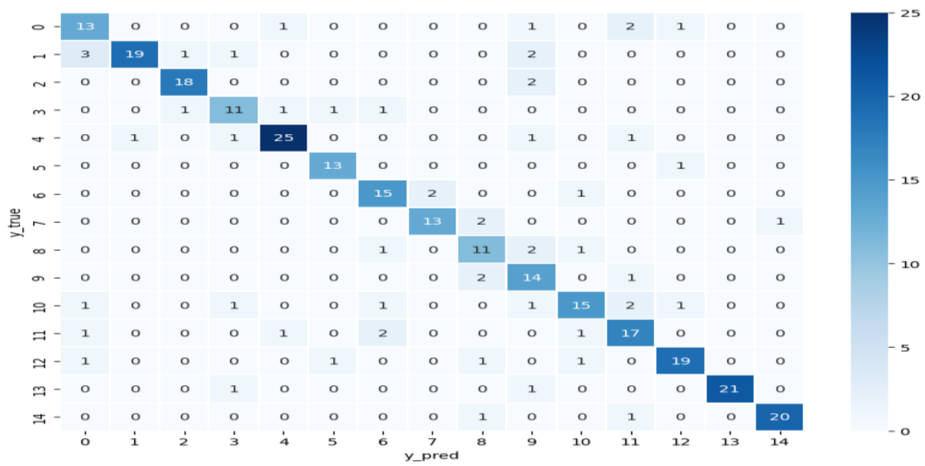

Figure 7. Confusion Matrix using Hybrid CNN + XGBoost Classifier for Plant Village Dataset

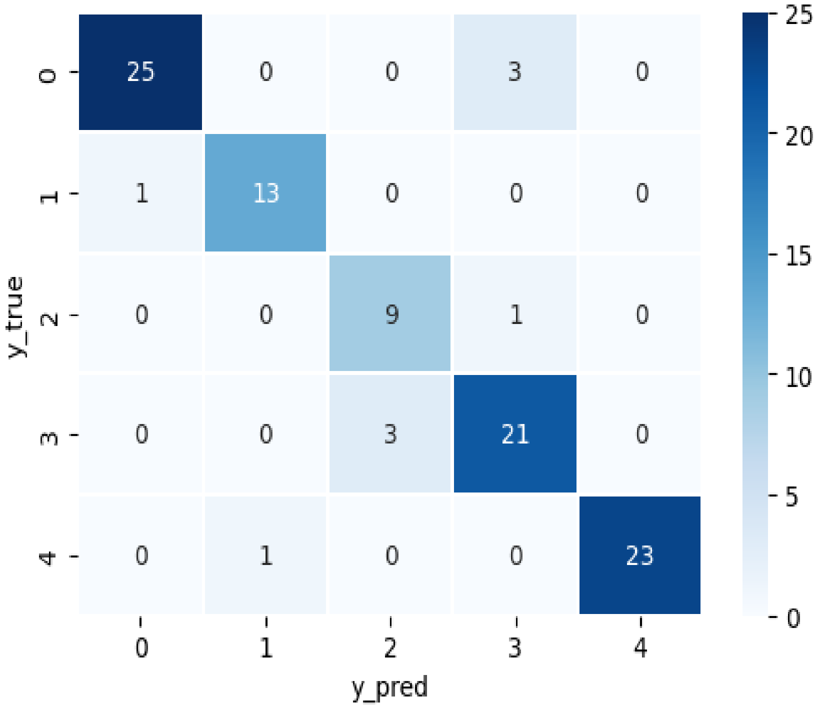

Figure 8. Confusion Matrix using Hybrid CNN + XGBoost Classifier for Crop Dataset

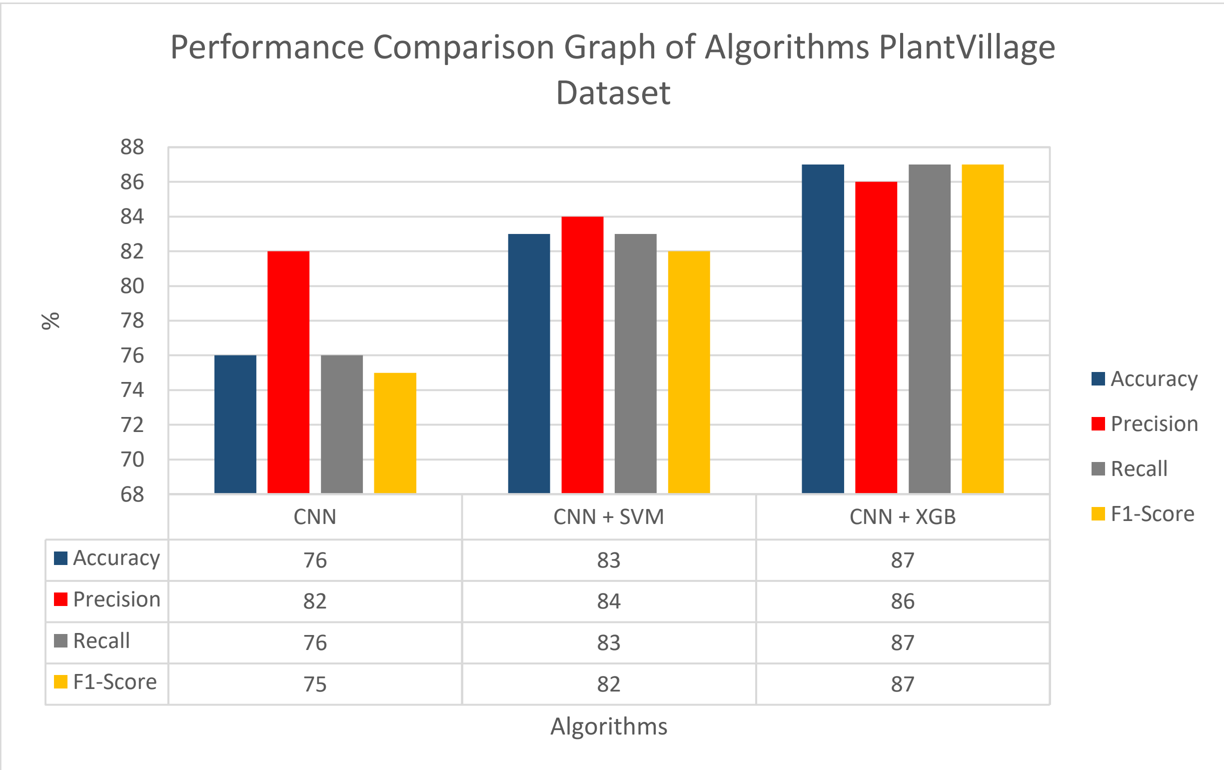

Figure 9. Performance Comparison Graph of Algorithms Plant Village Dataset

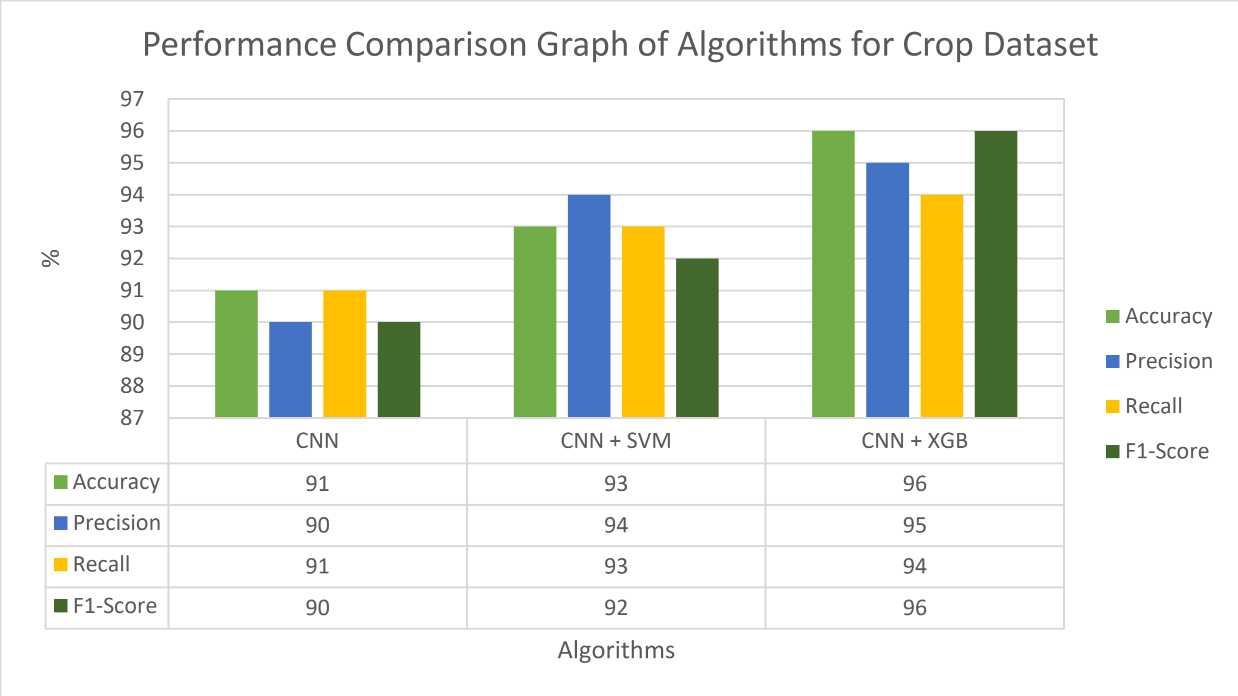

Figure 10. Performance Comparison Graph of Algorithms for Crop Dataset

6. CONCLUSION

The study represents a significant stride towards sustainable agriculture through the development of a stepwise model utilizing hybrid CNN algorithms for precise disease detection in plants. Our experimentation focused on harnessing the capabilities of hybrid CNN+XGB (XGBoost) and CNN+SVM (Support Vector Machine) models for plant leaf disease classification on both the Plant Village and Crop datasets. Moreover, our findings reveal that the hybrid CNN+XGB model surpasses the performance of the fine-tuned CNN model and Hybrid CNN +SVM model achieving remarkable accuracy rates. Specifically, on the Plant Village dataset, the hybrid CNN+XGB model achieves an accuracy of 87.1%, while on the Crop dataset, it achieves 96.2%. These results underscore the effectiveness of the hybrid CNN+XGB model in accurately classifying diseased plant leaves within both datasets. Overall, our study demonstrates the promising prospects of hybrid CNN algorithms for enhancing disease diagnosis in plants, thereby contributing to the pursuit of sustainable agricultural practices.

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