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A Composite Meta Model for the Identification of Cotton Pathologies Utilizing an IoT-Enabled Framework and Stacked Generalization Learning Methodology

Bhushan V. Patil [a, *], Pravin S. Patil [b]

[a] Department of Electronics and Telecommunication, R. C. Patel Institute of Technology, Shirpur, Maharashtra-425405, India
[b] Department of Electronics and Telecommunication, S.S.V.P.S's BSD College of Engineering, Dhule, Maharashtra-424002, India.
* Corresponding Author Email: patilbhushan007@gmail.com
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Abstract: This research proposes a novel framework for predicting cotton plant diseases using IoT, deep learning, and meta-heuristic optimization techniques. High-definition images of cotton leaves are captured in the field, processed through IoT, and enhanced using a Probabilistic Hybrid Wiener Filter. The Modified Dilated U-Net segments pathological regions, while features are extracted using Improved Local Binary Pattern (LBP), Gray Level Co-Occurrence Matrix (GLCM), and Gray Level Run Length Matrix (GLRLM). Feature dimensionality is reduced by the Binary Guided Whale-Dipper Throated Optimizer. The classification uses an ensemble of deep learning models—EfficientNet-B7, ResNet50, VGG19, DenseNet121, and InceptionV3—optimized by Harris whale optimization to determine weight coefficients. The system accurately detects diseases like Army Worms, Powdery Mildew, and Bacterial Blight with 99.66% accuracy. This IoT-enabled framework provides efficient real-time disease detection, benefiting cotton farmers and the textile industry. A field study was conducted in the summer (Kharif) season of 2022–23 in North Maharashtra region to assess cotton cultivation utilizing IoT sensor data analyzed within the ThingSpeak IoT framework. The proposed methodology, leveraging a dataset of the images of cotton leaves demonstrate a remarkable precision rate of 99.66%. The amalgamation of IoT sensor data with deep learning methodologies enables the early prompt identification of diseases in cotton plant leaves. The suggested ensemble framework demonstrates enhanced efficacy in comparison to alternative models.

Keywords: Cotton disease prediction, IoT, Deep Learning, Meta-heuristic, Ensemble model, Harris whale optimization algorithm

1. Introduction

Traditional agricultural methodologies frequently depend upon manual labor and may not fully capitalize on resource efficiency, thereby presenting significant challenges in fulfilling escalating food requirements while sustaining productivity. Innovative farming practices are fundamental for addressing global issues linked to food security, agricultural output, and ecological integrity. As the world's population grows, increasing food production becomes critical, but it must be achieved without further harming natural ecosystems [1]. Consequently, there has been a notable surge in interest towards investigating avant-garde strategies aimed at augmenting agricultural productivity and sustainability [2].

In recent times, the adoption of Internet of Things (IoT) technology within the agricultural sector has gained considerable traction, proffering promising solutions to these obstacles. Smart agriculture utilizes sophisticated technologies, including the Internet of Things (IoT) and artificial intelligence (AI), and remote sensing to monitor and optimize agricultural practices [3].

The integration of these technologies enables the collection of real-time data concerning various environmental parameters such as soil moisture, temperature, humidity, and crop health, thus leading to more informed decision-making and efficient resource allocation. Through the implementation of IoT-based innovations, agronomists can partake in real-time surveillance and utilize data-driven insights to refine decision-making processes and judiciously allocate resources [4].

By harnessing sensors, connectivity, and advanced analytical methodologies, IoT-enabled agricultural applications possess the capacity to revolutionize conventional farming practices and markedly improve productivity. IoT-driven systems enable continuous monitoring of fields, crops, and livestock, allowing farmers to detect issues such as diseases, pests, or water shortages early. For example, autonomous drones and agricultural robots can perform tasks like spraying pesticides or harvesting crops with high precision. Remote sensing techniques, using satellites and drones, provide large-scale data on crop health and soil conditions, making it easier to predict yields and identify areas needing attention [5].

Cotton, recognized as one of the premier cash crops globally, occupies a pivotal position in the international economy, particularly within the textile sector [6]. Nevertheless, the cultivation of cotton is vulnerable to a myriad of diseases, including those that induce premature leaf abscission or foliar infections [7]. Predominantly, the afflictions observed on cotton crop foliage encompass white spot disease, Alternaria, red spot disease, bacterial blight, crumple leaf disease, among others [8]. The emergence of these pathologies is often correlated with various climatic conditions, such as elevated temperatures in agricultural regions, thereby necessitating timely pesticide interventions [9]. Mitigating the repercussions of diseases on plant vitality is paramount for optimizing crop yield and quality. Given the intrinsic vulnerability of plants to infectious diseases, early detection assumes critical importance in bolstering productivity and ensuring the production of high-quality yields [10]. In response to these challenges, a plethora of systems have been developed to identify and manage diseases afflicting cotton foliage [11]. These systems employ classification, soil monitoring, and the identification of specific maladies such as Alternaria, bacterial blight, and others [12]. Currently, substantial progress has been observed in the agricultural domain, attributed to the rising interest and implementation of IoT and deep learning (DL) technologies [13]. IoT plays a vital role in the acquisition of real-time data and facilitates the effective utilization of electricity, water, and fertilizers in agricultural practices [14]. Furthermore, IoT devices demonstrate proficiency in assessing both non-visual and visual manifestations of diseases at their incipient stages, identifying the necessity for insecticides, recognizing weeds, and detecting pest infestations [15].

The application of machine learning (ML) and deep learning (DL) algorithms considerably enhances the analysis of this dataset. They are increasingly used to diagnose crop diseases, predict weather impacts, and improve decision-making processes. For example, deep learning algorithms possess the capability to scrutinize satellite imagery to identify preliminary indicators of diseases in cotton agriculture, thereby facilitating prompt interventions that avert extensive harm. This not only increases productivity but also reduces the need for harmful chemicals, contributing to environmental sustainability. Moreover, smart agriculture supports the development of precision farming, where resources such as water, fertilizer, and pesticides are applied only where needed. This minimizes waste and enhances crop yield, addressing both food security and ecological conservation. By combining IoT, AI, and data analytics, smart agriculture offers a pathway to sustainable farming, helping to meet global food demands while preserving the environment.

1.1 Problem Statement

In contemporary agricultural practices, sophisticated computing technologies significantly enhance the monitoring of crop growth with efficacy. Nevertheless, conventional agricultural methods encounter challenges in the precise evaluation of crop health. An overdependence on visual assessments, without a comprehensive understanding of disease manifestations, may result in substantial crop degradation. Engaging with specialists incurs considerable expenses and demands significant time investments. Consequently, this research presents a novel methodology for the accurate identification and classification of cotton leaf spot diseases. The early detection of such diseases is imperative to alleviate potential losses.

The primary objective of this research endeavor is to formulate and enhance a refined stacking ensemble learning model with the intent of precisely categorizing the ailments afflicting cotton plant diseases.

The key contributions of this scholarly analysis are presented as follows:

- To develop a system for the detection of diseases in cotton plants utilizing Internet of Things (IoT) technology and deep learning methodologies to facilitate the early identification of diseases in cotton plants with enhanced accuracy.
- To eliminate image noise through the application of the probabilistic hybrid Wiener filter-based preprocessing technique.
- To perform segmentation on the pre-processed images employing the Modified Dilated U-Net (MDU-Net) architecture.
- To extract various types of features utilizing the Improved Local Binary Pattern (ILBP), Gray Level Co-Occurrence Matrix (GLCM), and Gray Level Run Length Matrix (GLRM) methodologies.
- To identify optimal features through the implementation of a binary guided whale-dipper throated optimization algorithm.
- To categorize cotton plant diseases by leveraging optimized stacking ensemble learning algorithms, including EfficientNet-B7, ResNet50, VGG19, DenseNet121, and InceptionV3.

- To anticipate specific challenges, the calculation of weight coefficients using the Harris whale optimization algorithm is a critical factor in the ensemble techniques.
- To enhance predictive accuracy while minimizing error rates.

The subsequent sections of this manuscript are structured as follows: Section 2 presents a comprehensive review of pertinent methodologies pertaining to the detection of diseases in cotton plants. Section 3 delineates a concise overview, accompanied by illustrative images, of the complete procedure employed in the cotton plant disease detection model proposed herein. In Section 4, a thorough evaluation of the performance metrics attained by the proposed model is conducted, juxtaposed with the existing methodologies, supplemented with graphical representations. Finally, the overarching conclusions drawn from the proposed model are articulated in Section 5.

2. Related Work

The following is an overview that some of the strategies used in IoT-based DL models to identify cotton plant diseases. In table 1 the overview of diverse methodologies for the detection of diseases in cotton plants is as,

In this paper Lakshmi *et al*. [1], examines the Advanced Learning Model (ALM) in conjunction with ResNet50 for the purpose of cotton disease identification by achieving an accuracy rate of 98.45%. In this study Bhujade *et al.* [2], focuses on the application of CNN-Convolutional Neural Networks for the classification and severity estimation of diseases in cotton and soybean leaves. Li Bin *et al.* [3], employs a fuzzy logic control system to optimize irrigation timing for cotton crops, These methods collectively aim to enhance sustainable smart agriculture practices, particularly in cotton crop production, by optimizing irrigation and minimizing pest-related challenges. Adhao, A. *et al*. [4], used a SVM-Support Vector Machine classifier to identify five specific cotton leaf diseases like Bacterial Blight, Alternaria, Cereospra, Gray Mildew, and Fusarium wilt, on the features extracted from an images. Nagasubramanian, G. *et al.* [5], put forth a methodology to be utilized in the context of using Ensemble SVM-Support Vector Machines for detecting crop and leaf diseases at early stages with high accuracy. Islam, M. M *et al.* [6], a methodology has been articulated for the identification of diseases afflicting cotton leaves through the application of refined Transfer Learning algorithms with Xception model gets 98.70 % accuracy rate. Patki, S. S. *et al*. [7], performed segmentation of the images using Otsu's global thresholding method and highlights the use of the GLCM- Gray Level Co-occurrence Matrix for feature extraction for the early detection and classification of diseases in cotton leaves.

Rajasekar, V. [8], employs transfer learning methodologies to effectively identify and classify diseases affecting cotton crops with 95% accuracy. Kumari, C. U *et al*. [9], proposed automatic cotton disease detection using K-means clustering, and the categorization of cotton maladies employing Artificial Neural Networks (ANN) and Support Vector Machine (SVM) classifiers with 85.1% and 92.06% accuracy respectively. Naeem, A. B *et al.* [10], utilized the VGG-16 architecture for the diagnosis of cotton leaf diseases, achieving an impressive accuracy rate of 98%. Yanan Li *et al*. [11], devised an automated ground-based in-field cotton (IFC) segmentation methodology employing the 'UP' algorithm, which refines a coarse map and significantly enhances segmentation precision. Reddy *et al.* [12], applied Convolutional Neural Networks to forecast cotton leaf diseases and incorporated sophisticated image processing methodologies, including image segmentation and feature extraction to augment the accuracy of cotton disease classification. Shrivastava, A. [13], proposed CNN technique for early agricultural disease detection achieved 99.67% effectiveness in identifying cotton leaf diseases. Shafi, U. F. *et al.* [14], devised an advanced IoT-Internet of Things and machine learning-oriented methodology for the expedited identification of combustion phenomena within storage facilities, with an emphasis on safeguarding cotton quality during extended storage durations. The implementation of an IoT-integrated circuit, coupled with the proactive identification of combustion events through a robust artificial neural network (ANN) architecture, yielded an impressive accuracy rate of 99.8%.

Sarangdhar, A. *et al.* [15], introduced a support vector machine (SVM)-based regression model for the detection and classification of diseases utilizing IoT, achieving a classification accuracy of 83.26%. Quy, V. K. *et al.* [16], examined the prevailing trends and prospective applications of IoT within the domain of smart agriculture. Caldeira, R. F *et al.* [17], described leverages deep learning, specifically using GoogleNet and ResNet50 models with accuracy of 86.6 % and 89.2% respectively. Azath M. *et al.* [18], developed CNN model for cotton leaf disease and pest diagnosis Using 2400 images for training, focused on southern Ethiopia, Achieved 96.4% accuracy, feasible for real-time applications. Sandeep Kumar *et al.* [19], conducted a comparative analysis of machine learning methodologies for the identification of cotton diseases, employing Support Vector Machine, Random Forest, and Decision Trees for the classification of diseases. Mahadevan, K. *et al.* [20], concentrated on the identification of rice leaf diseases through deep learning techniques, utilizing ResNet152V2, which attained the highest recorded accuracy of 98.36%.

The study by Askr et al. introduces an explainable ResNet50 learning model utilizing copula entropy for predicting cotton plant diseases [21]. This approach enhances the interpretability of deep learning models, which is crucial for practical agricultural applications. The model's design aims to improve accuracy in disease detection while providing insights into the decision-making process of the algorithm. [22] The research by Gülmez Burak introduces a novel deep learning model enhanced by the Grey Wolf Optimization (GWO) algorithm for detecting cotton diseases with achieved an accuracy of 100%.

3. Materials and Methods

The proposed model aims to enhance the current methodologies utilized for the diagnosis of ailments in cotton plants via the integration of diverse algorithms, incorporating a hybrid deep learning strategy along with a meta-heuristic optimization method. This integration produces a solution distinguished by superior precision, efficiency, and reliability in the diagnosis of diseases impacting cotton plants. The model provides several advantages when contrasted with current systems. Firstly, it possesses the capability to detect pests affecting cotton plants utilizing a singular Internet of Things (IoT) sensor, thereby optimizing resource allocation. Secondly, the incorporation of a hybrid deep learning framework expedites the process of disease detection in cotton plants. Thirdly, the meta-heuristic optimization algorithm functions to enhance the parameters of the model, consequently reducing complexity. In addition, the model considers environmental influences, thereby decreasing the chances of misdiagnosis of diseases in cotton plants. In conclusion, the meta-heuristic optimization algorithm contributes to the enhancement of overall performance, thereby facilitating a reduction in the incidence of false positives.

This proposed model introduces a meta-heuristic-assisted hybrid deep learning framework for the prediction of cotton diseases within an IoT-based application. This model seeks to address the shortcomings of contemporary disease detection systems for cotton plants by delivering a solution that is significantly more accurate, efficient, and reliable in comparison to traditional methodologies. This analysis delineates an advanced meta-heuristic-integrated hybrid deep learning framework for the assessment of cotton diseases within Internet of Things (IoT) applications. The proposed framework is structured into a sequence of methodical phases. The below Figure 1 illustrates the overarching architecture of the proposed research is as,

Table 1. Summary of related work on IoT-based DL models for detecting cotton plant diseases

Author and References	Technique Used	Limitations Occurred	Accuracy (%)
Azfar *et al.* [23]	IoT-based smart response system	Requirement for different IoT sensors to identify various cotton pests	99.8
Patil *et al*. [24]	IoT-based CNN	A large amount of time is required for cotton plant disease detection	98.34
Puri *et al*. [25]	A hybrid approach combining sensors and DL models	High model complexity	99.19
Saleem et *al.* [26]	IoT-based RBFN algorithm	Misclassification of cotton plant diseases	98.54
Azfar *et al.* [27]	IoT-based system for real-time detection of CFMs	High false positive rate	99.11
Kathole *et al.* [28]	Metaheuristics DL approach	Need for a large and diverse dataset of pest images	97.91
Tsai *et al*. [29]	DNN using MobileNetV3 model	High model complexity	92.6
Kathole *et al*. [30]	Meta-heuristic-based DL framework	Reliance on a single dataset for evaluation purposes	91.7
Ananthi *et al.* [31]	ADHCNet with an attention mechanism	Designed for leaf-level disease detection	98.9
Saini *et al.* [32]	DL-based ensemble method using leaf wetness sensor	High training time	99.17

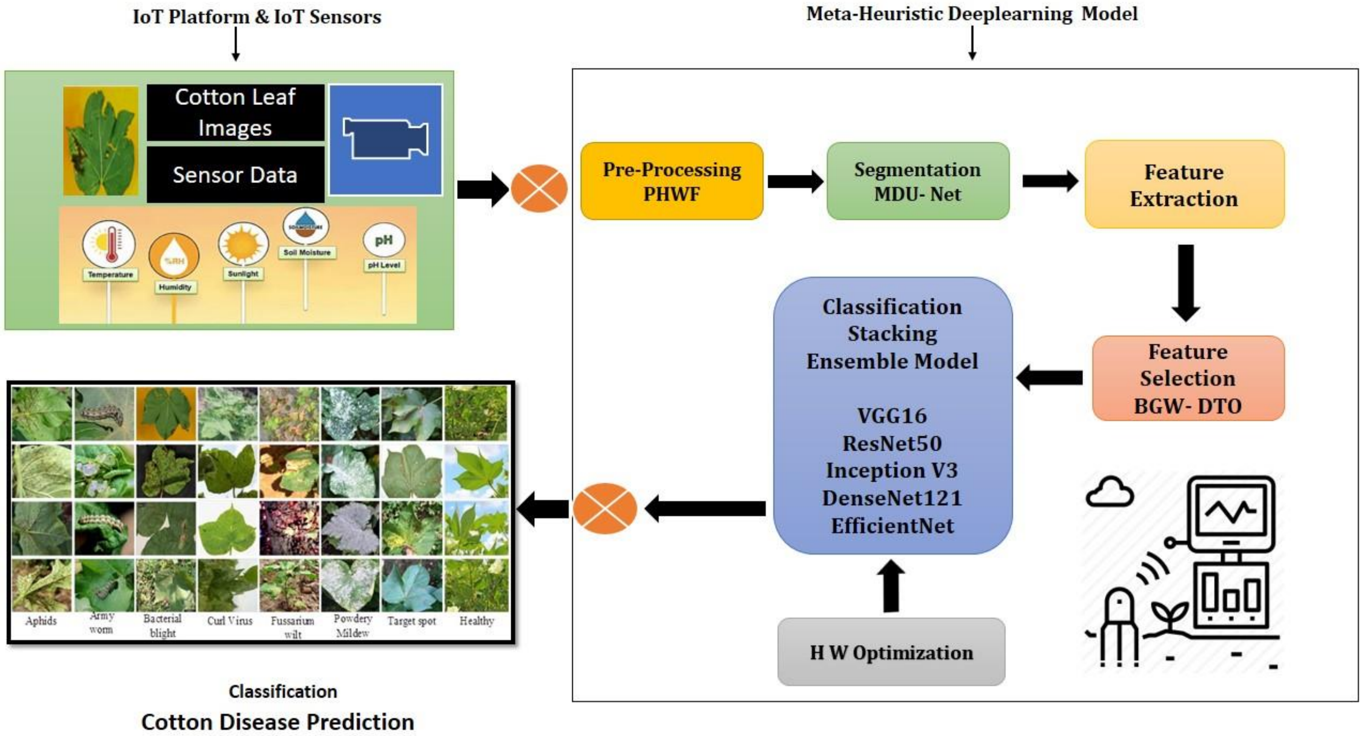


Figure 1. Architecture of the proposed work

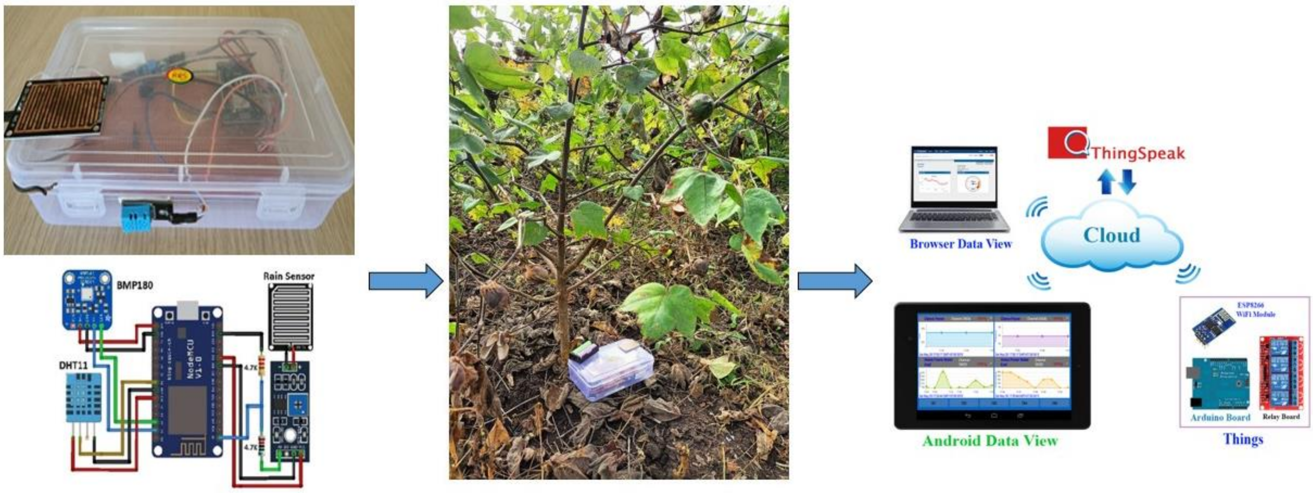


Figure 2. IoT Based System implemented on cotton field

Following the processing phase, the obtained images are processed through pre-processing using a Probabilistic Hybrid Wiener Filter (PHWF) to reduce irrelevant noise and enhance the overall quality of the images. The Modified Dilated U-Net (MDU-Net) configuration is applied to distinctly segment the important disease regions depicted in the images. Subsequently, essential features are extracted from the segmented images through the application of Improved Local Binary Pattern (ILBP), Gray Level Co-Occurrence Matrix (GLCM), and Gray Level Run Length Matrix (GLRM). In order to mitigate feature dimensionality, optimal features are chosen via a Binary Guided Whale-Dipper Throated Optimizer (BGW-DTO). Finally, an optimized stacking ensemble learning model is constructed for the classification task, facilitating the identification of various plant diseases, including Army Worms, Powdery Mildew, Bacterial Blight, Aphids, Target Spot, among others. Through the implementation of these procedures, the proposed methodology aspires to accurately detect and classify a diverse array of diseases afflicting cotton plants, thereby contributing to effective agricultural management strategies. With an emphasis on cotton plants, this study uses IoT devices and image processing to track crop health. Digital cameras are used to take pictures of the leaves of cotton plants, which are then sent to Internet of Things sensors. In addition to gathering visual data, these sensors also measure environmental variables such soil moisture, humidity, temperature, and rainfall. The above Figure 2 shows the IoT Based System implemented on cotton field is as,

This methodology facilitates the continuous observation of agricultural health, thus empowering cultivators to execute timely interventions upon the identification of irregularities, consequently enhancing both the yield and quality of the crops. The below Table 2 presents the data collected by the IoT sensors [33].

3.1. Dataset Description

A dataset pertaining to leaf diseases in cotton plants, specifically designed for the classification and identification of various cotton leaf ailments, is utilized in this research. Each of the eight classes is represented in the 3784 captioned photos of cotton plant leaves in this collection. Table 3 provides a detailed overview of the composition of this dataset. By using this specialized dataset,

Table 2. Analysis of measurements taken by the IoT sensors

Temp.	Atmospheric moisture content	Soil moisture content	Precipitation	Factors favoring infection	Clinical manifestations
24^0-28^0 C	High	80-90%	YES	Excessive soil moisture, soil temperature range 24^0-28^0 C	Cotyledon leaves exhibiting a yellow to brown pigmentation undergo desiccation and subsequently abscise.
36^0-44^0 C	High	50-60%	YES	High soil temperature	The plant experiences an abrupt and total wilting phenomenon.
29^0-33^0 C	High	80-90%	YES	Warm and humid weather (29^0-33^0 C)	Observations reveal diminutive reddish-hued spots accompanied by water-soaked small cotyledons.
24^0-29^0 C	Very high	60-70%	25.4 to 76.2 mm	Seed-borne bacteria- Secondary infection through natural openings or inset-caused wounds	The presence of angular leaf spots manifests on both the leaf and stem, alongside lesions observed on the juvenile leaves.
10^0-30^0 C	Very high	80-90%	YES	High humidity- intermittent rains and moderate temperature are congeners	The leaf exhibits brown, rounded or irregular spots with fissured centers, potentially leading to the development of cankers on the stem.
25^0-30^0 C	Very high	60-70%	YES	Low-lying moist localities-25^0-30^0 C is a favourable temperature for conidia germination	The leaf surface displays irregular translucent spots, with the leaves transitioning to a yellowish-brown hue, ultimately culminating in their abscission.
35^0-43^0 C	High	50-60%	NO	Favorable conditions crop environment	The appearance of dark purple, brown, or blackish margins with white centers is noted.

Table 3. Analysis of our dataset

Classes	Images	Classes	Images
Aphids	520	Fussarium Wilt	419
Army Worm	520	Healthy	422
Bacterial Blight	448	Powderly mildew	520
Curl Virus	417	Target Spot	518

3.2. Pre-processing using Probabilistic Hybrid Wiener Filter (PHWF):

The PHWF model is often employed to improve the quality of captured images, particularly in the reduction of noise. In this methodology, Gaussian mask kernels are utilized to effectively eliminate noise from the images. An original image is split up into several pixel groups in the PHWF [34] process.

The initial input photos and the output images after pre-processing for cotton leaf dataset are shown in below figure 3,

3.3. Segmentation

The MDU-Net model [35-37], created especially for plant leaf disease segmentation, and receives the pre-processed image as input.

The unhealthy areas on cotton plant leaves are precisely detected and identified using this model.

The organizational framework of the MDU-Net model is depicted in Figure 4. The below Figure 5 shows the image after pre-processing together with the anticipated segmentation of the image is as,

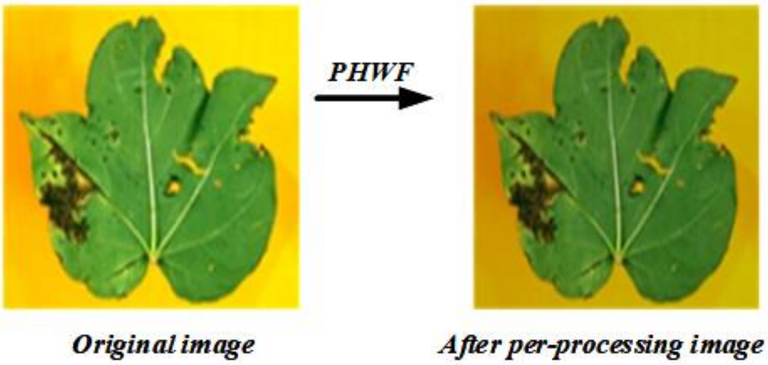


Figure 3. Pre-processing of the cotton leaf dataset using input photos

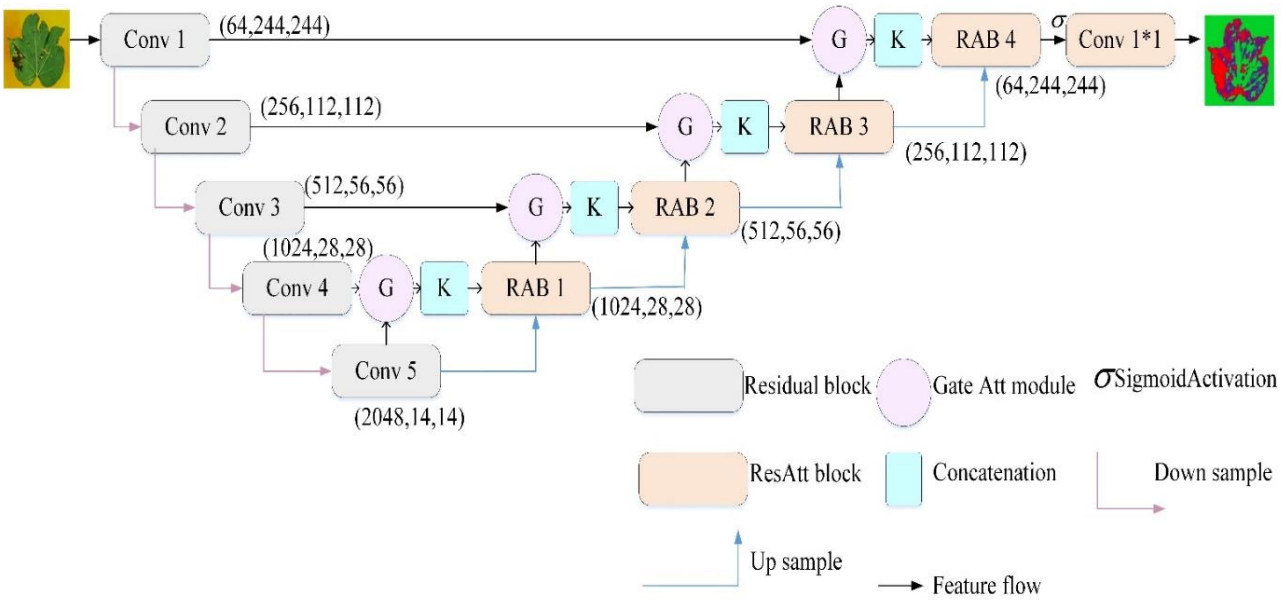


Figure 4. MDU-Net model

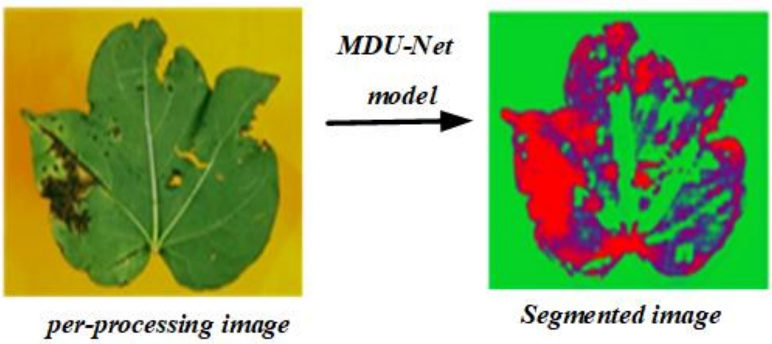


Figure 5. Segmentation from the anticipated picture

The results of the suggested segmentation technique successfully pinpoint the precise area of cotton leaf disease.

3.4. Feature extraction

Three different feature extraction models—ILBP, GLCM, and GLRLM—are used to the segmented image. These models use the segmented images to extract several kinds of features.

3.4.1. Local Binary Pattern (ILBP)

A texture descriptor known as Local Binary Patterns [38] (LBP) is used in computer vision. In order to identify the pixels in an image and interpret the output as a binary number, the region surrounding each pixel is threshold. The fundamental LBP operator is extended by the ILBP, which improves performance in applications involving face recognition and texture categorization.

3.4.2. Gray Level Co-Occurrence Matrix (GLCM):

A grid of grayscale changes called the GLCM [39] is used to recognize textures in segmented pictures.

3.4.3. Gray Level Run Length Matrix (GLRLM)

To prevent pixel information from being redundant, GLRLM [40] features are stripped. The image was often reduced by preceding re-quantizing in maximum grey dimensions in order to construct the network.

3.5. Feature selection

By processing the extracted features, the Binary Guided Whale-Dipper Throated Optimizer (BGW-DTO) feature selection model [41] finds the best features for selection. This framework aims to enhance the overall efficacy of the classification paradigm, mitigate the occurrence of over fitting, and decrease the dimensionality of the dataset.

Table 4 illustrates the BGW-DTO algorithm for feature selection. This technique transforms the obtained solution into a binary format through the application of the sigmoid function. The K-nearest neighbor algorithm is employed to evaluate the efficacy of the selected features, which have been refined for specific applications, such as the identification of diseases in cotton plant foliage.

$$\vec{K}^{(m+1)} = \begin{cases} 0 & f\ Sigmoid(K_{best}) < 0.5 \\ 1 & Otherwise \end{cases}$$

$$Sigmoid(K_{best}) = \frac{1}{1+z^{-10(K_{best}-0.5)}} \quad (1)$$

Table 4. BGW-DTO for feature selection

Initialize population $\vec{K}_n (n = 1,2,..., N)$ with size N, maximum iterations $Max iter$, fitness function G_n
Initialize GW parameters $\vec{S}$, $\vec{A}$, $\vec{t}_1$, $\vec{k}_1$, $\vec{k}_2$, $\vec{k}_3$
Initialize the DTO parameters and bird velocities $\vec{L}_1$, $\vec{L}_2$, $\vec{t}_2$
Set $m = 1$
Evaluate the fitness of every $\vec{K}_n$
Find the best solution
While $m \le Maxiter$ do
If $(m\%2 == 0)$ then,
For $(n = 1; n < N + 1)$ do
If $(t_1 < 0.5)$ then
If $(\lvert\vec{S}\rvert < 1)$ then
Update the position of the current search agent
Else
Select three random search agents
Update $\vec{z}$ by the exponential form of $\vec{z} = 1 - \left(\frac{m}{\max iter}\right)^2$
Update the position of current search agents
End if
Else
Update the velocity of the DTO agent
Update the position of the DTO agent
End if
Evaluate fitness G_n for every $\vec{K}_n$ from GW
Else
Evaluate the fitness G_n of every $\vec{K}_n$ from DTO
End if
Update t_1, t_2 $\vec{S}$, $\vec{A}$, $\vec{L}_1$, $\vec{L}_2$
Find the best individual $\vec{K}^*$
Set $m = m + 1$
End while
Convert the best solution $\vec{K}^*$ to binary using
$\vec{K}^{(m+1)} = \begin{cases} 0 & f\ Sigmoid(K_{best}) < 0.5 \\ 1 & Otherwise \end{cases}$
$Sigmoid(K_{best}) = \frac{1}{1+z^{-10(K_{best}-0.5)}}$
Return

3.6. Cotton Plant Disease Classification through the Utilization of an Ensemble Learning Framework:

The suggested stacked generalization learning Model aims to facilitate the categorization of ailments that impact the foliage of cotton plants incorporates a variety of components, such as EfficientNet-B7, ResNet50, VGG19, DenseNet121, and InceptionV3. The Harris whale optimization algorithm is utilized to ascertain the weight coefficients pertinent to each learning algorithm, which is essential for the efficacy of the ensemble methodologies.

- **EfficientNet-B7**: EfficientNet constitutes a collection of models that surpasses its antecedents in diverse computational and memory prerequisites. It employs compound scaling methodologies to construct the models, thereby facilitating the augmentation of the ConvNet baseline to any desired target with constrained resources while maintaining efficacy on transfer learning datasets**.** It utilizes a sophisticated architecture that balances depth and width, enhancing feature extraction capabilities [42].
- **ResNet50:** ResNet50 a 50-layer residual network is a widely acknowledged model employed in the domains of image categorization, auto-encoding, and recognition. This architecture effectively mitigates the issue of gradient vanishing while enhancing the efficiency of network training, rendering it appropriate for participation in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). ResNet50 underwent training to classify images into 1000 distinct categories of objects found within the ImageNet database, encompassing items pertinent to the classification of cotton plant leaf diseases, including various insects and agricultural tools. The architecture of ResNet-50 delineates the specifications for the residual units, the dimensions of the filters, and the outputs associated with each convolutional layer. Furthermore, the terminal convolutional layer of this network incorporates a Dense Random Forest (DRF). Known for its stability and ability to handle vanishing gradient problems, ResNet50 provides reliable performance in disease classification [43].
- **VGG19**: The third architectural model, VGG19, is widely recognized as an exemplary framework for tasks pertaining to image classification. It encompasses six fundamental components, each comprising multiple interrelated convolutional layers and fully connected layers [44]. The convolutional kernel utilized in VGG19 is characterized by a dimension of 3x3, while the input dimension is specified as 224x224x3. VGG19 is typically structured with 16 to 19 layers. In comparison to conventional convolutional neural networks (CNNs), VGG19 exhibits enhanced efficacy attributed to its layered architecture, which integrates convolutional layers alongside non-linear activation functions. This architectural design facilitates the extraction of supplementary features from images, subsequently followed by downsampling through Max pooling and activation via a rectified linear unit (ReLU). The principal aim of the downsampling layer is to reduce the parameter count, preserve essential features, and augment the network's robustness against visual distortions. It offers a straightforward architecture that is effective for image classification tasks, also its depth allows for detailed feature extraction, beneficial for identifying subtle disease symptoms.
- **DenseNet121:** DenseNet represents an innovative convolutional neural network (CNN) architecture that enhances network profundity through the interconnection of every layer in a sequential feed-forward configuration. Specifically, DenseNet 121 is a variant of this architectural framework, which comprises several dense blocks with repetitions of 6, 12, 24, and 16 iterations distributed across the four distinct dense blocks. Combines feature reuse and efficient gradient flow, leading to high accuracy rates also particularly effective in classifying multiple disease types due to its dense connectivity [45].
- **InceptionV3:** The final model discussed is InceptionV3 [46], which signifies the most recent advancement of the Inception architecture. This particular model facilitates the expansion of the deep learning network in both its dimensional width and depth while maintaining a constant computational expense, thereby rendering it an adaptable multi-level feature extractor. It executes convolutional operations of 1×1, 3×3, and 5×5 at various hierarchical levels, culminating in a sophisticated architecture comprising 42 layers. This architectural design permits the model to implement varying kernel sizes on the input image, thus facilitating the acquisition of a diverse range of information from each respective scale. The results generated from these convolutional operations are consolidated along the channel dimension and subsequently utilized as input for the ensuing layers. Its ability to handle varying scales of features effectively, also the model's inception modules allow for a diverse range of

feature extraction, enhancing its adaptability to different disease symptoms.

The evaluation of various deep learning models for cotton plant disease detection reveals distinct advantages for EfficientNet-B7, ResNet50, VGG19, DenseNet121, and InceptionV3. Each model demonstrates unique strengths in accuracy, efficiency, and adaptability, contributing to improved disease management in cotton agriculture.

3.7. Stacked Generalization Model

In the proposed stacked generalization model [47], five distinct pre-trained deep learning architectures are employed: EfficientNet-B7, ResNet50, VGG19, DenseNet121, and InceptionV3. All these models represent different features that help them capture various dimensions of the input data and thus produce multiple types of predictions. Upon the acquisition of an image, each model generates prognostications that signify the probability of the image being classified into various categories pertinent to the specific task. These predictions serve as indicators of the degree of confidence each model has regarding the classification of the image. Figure 6 illustrates the structural framework of the proposed stacked generalization model, elucidating its operational mechanics and the methodology employed for output classification.

3.7.1. Harris whale optimization

The proposed Harris Whale Optimization (HWO) [48] approach aims to find the best weights for improving the ensemble classifier for cotton plant disease classification. A basic description of the algorithm is provided. The optimal weight is calculated using the proposed Harris whale optimization algorithms, which aid in tuning the proposed classification model for optimal classification results.

Table 5. Pseudocode of Harris whale optimization algorithm

Input: Whale population G, iteration k, coefficient vector u, best solution G^*

Start
Set up the whale position G.
Calculate each search agent's error
While $(k < k_{\max})$
For each search agent
Update u
If $r < 0.5$
Update the position of current search agent using the $G(k+1)\left[\dfrac{-u_1}{1-u_1}\right] = -\dfrac{2u_1u_2G(k)}{(1-u_1)} - KS$ equation.
Else if
Check if any search agent goes beyond the search space
End for
Calculate each search agent's error
Update G if there is best solution
$k = k+1$
End while
Return G^*

Output: Best search agent

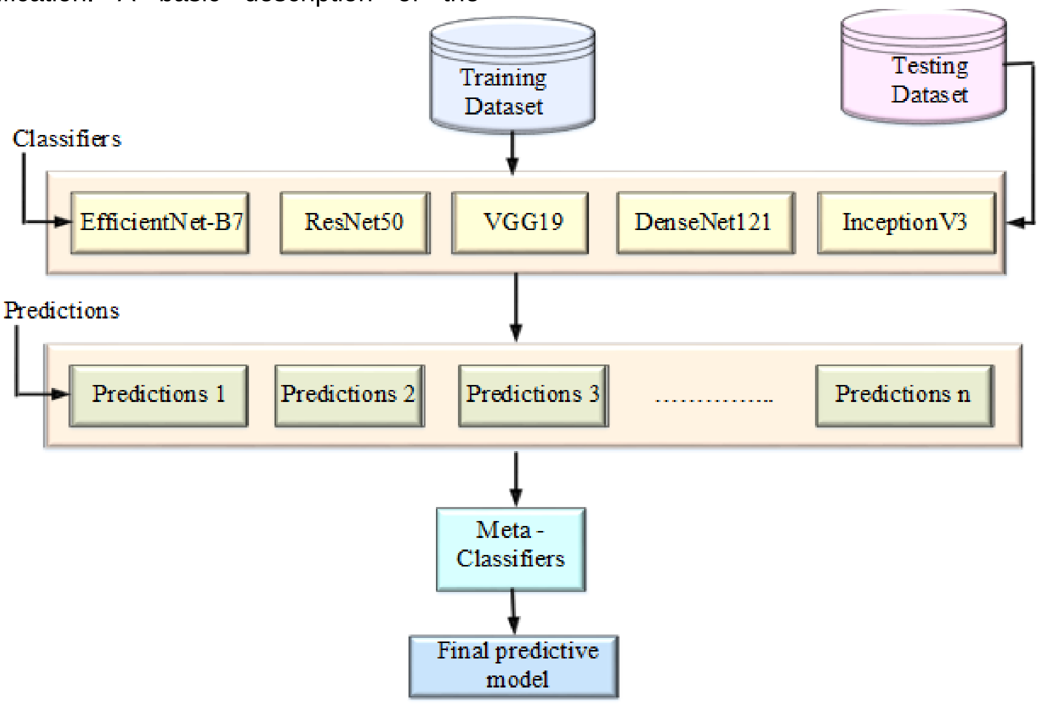


Figure 6. Stacked generalization model

The assault detection adapts the proposed classification model to deal with new data from remote sources. Table 5 shows the pseudocode for the proposed Harris whale optimization algorithm.

4. Results and Discussion

This segment conducts empirical investigations on both the proposed model and existing frameworks, methodically contrasting and evaluating their effectiveness through the application of imagery derived from the cotton leaf disease dataset with the intent of classifying plant leaf diseases. Performance of proposed model is calculated using error matrix for each respective model. Subsequently, the performance accuracy of the proposed model is compare with that of established architectures such as VGG16, ResNet50, EfficientNetB7, MobileNet, Inception V3, and DenseNet121.

The Figure 7 (a) and (b) shows that proposed model attains training and testing loss metrics, illustrating a heightened performance relative to contemporary models.

The evaluation of the confusion matrix for the different classes found in our dataset such as the Aphids, Armyworm, Curl virus, Bacterial blight, Fussarium wilt, Healthy, Powdery Mildew, and Target spot classes. Figure 8 (a) to (g) displays the confusion matrix for the proposed and existing model classification.

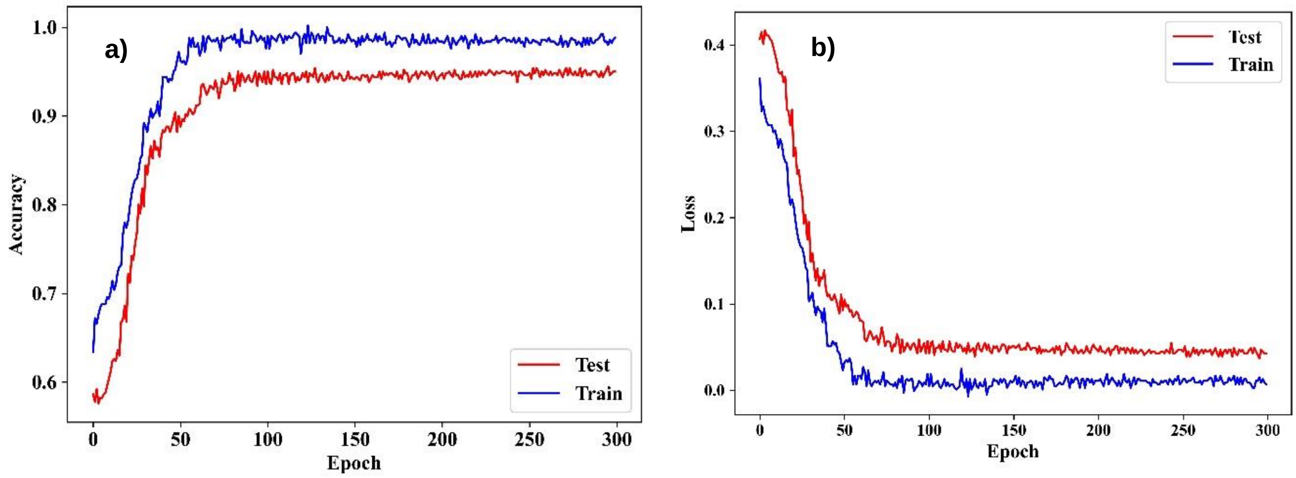
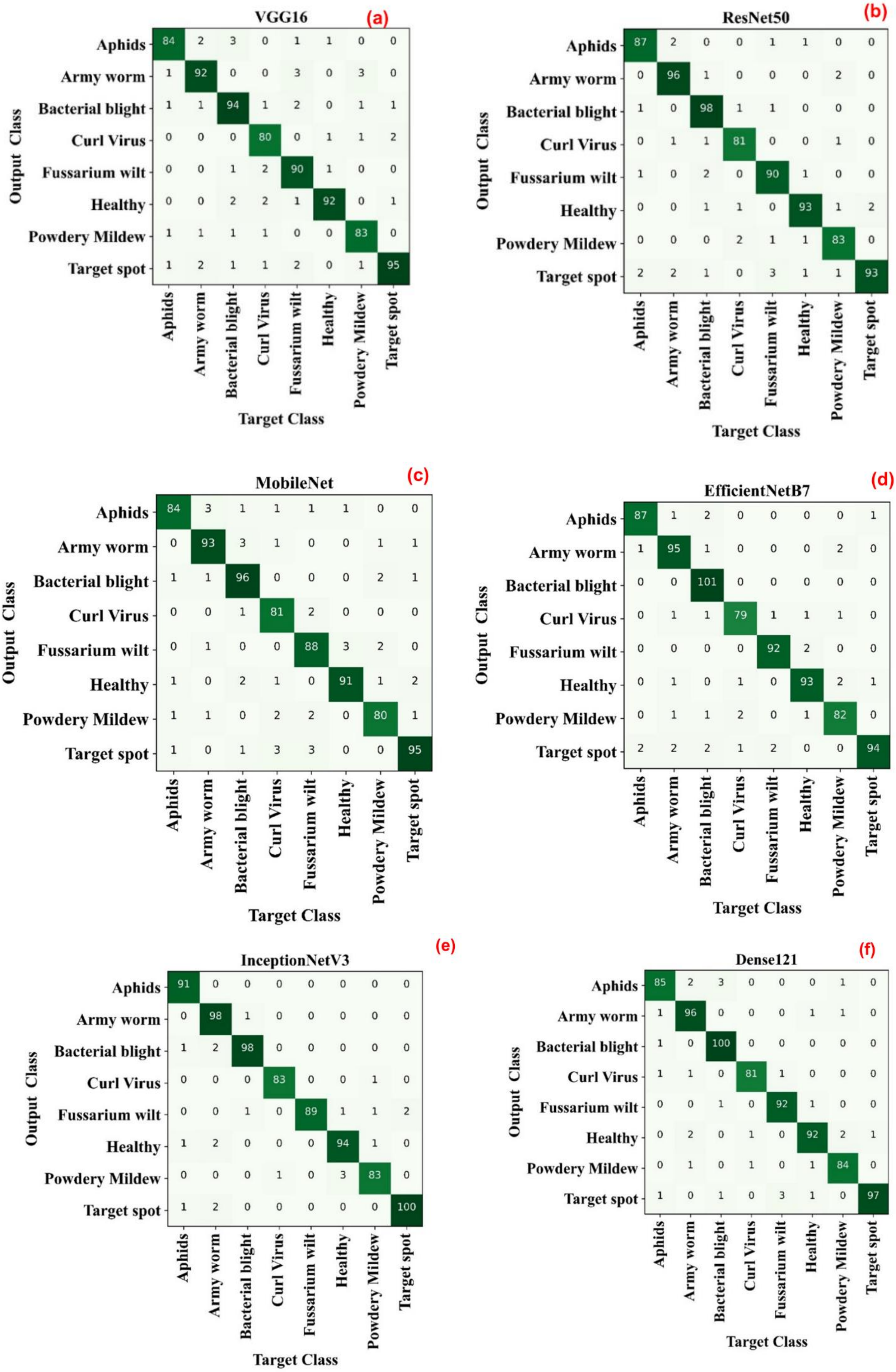


Figure 7 (a) Analysis of Accuracy curve, (b) Analysis of Loss curve

Table 6. Overall Classification Performance of Existing Model with the Stacked Generalization Model

Performance (%)	Methods						
	VGG 16	ResNet 50	EfficientNet B7	MobileNet	Inception V3	DenseNet 121	stacked generalization Method
Accuracy	0.9844	0.9881	0.9887	0.9838	0.9930	0.9900	**0.9966**
Precision	0.9380	0.9525	0.9553	0.9352	0.9728	0.9606	**0.9866**
F1-score	0.9382	0.9527	0.9551	0.9353	0.9726	0.9605	**0.9869**
MCC	0.9290	0.9457	0.9487	0.9260	0.9683	0.9547	**0.9849**
Specificity	0.9911	0.9932	0.9935	0.9907	0.9960	0.9943	**0.99811**
Sensitivity	0.9380	0.9529	0.9548	0.9354	0.9723	0.9603	**0.9871**
RMSE	0.0704	0.060	0.0644	0.0665	0.0453	0.0511	**0.0346**
MSE	0.0049	0.0036	0.0041	0.0044	0.0020	0.0026	**0.0422**
MAE	0.1889	0.1373	0.1413	0.1783	0.0766	0.1070	**0.0422**
PPV	0.9380	0.9525	0.9553	0.9352	0.9728	0.9606	**0.98662**
NPV	0.9911	0.9932	0.9936	0.9907	0.9960	0.9943	**0.99810**
FPR	0.0088	0.0067	0.0064	0.0092	0.0039	0.0056	**0.99818**
FNR	0.0614	0.0470	0.0451	0.0645	0.0276	0.0396	**0.01280**


VGG16
(a)
ResNet50
(b)
MobileNet
(c)
EfficientNetB7
(d)
InceptionNetV3
(e)
Dense121
(f)
Output Class
Target Class
Aphids
Army worm
Bacterial blight
Curl Virus
Fussarium wilt
Healthy
Powdery Mildew
Target spot

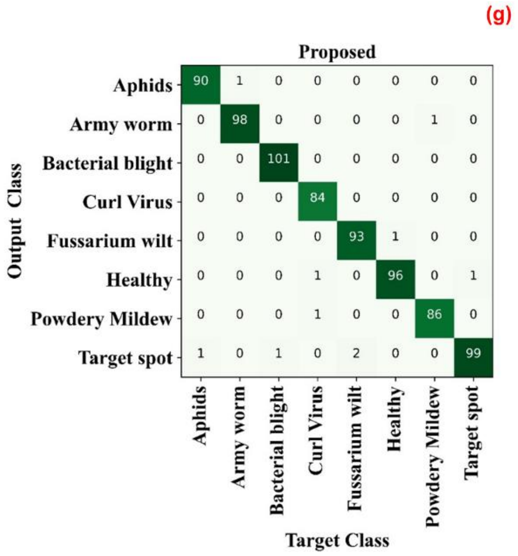


Figure 8. (a) VGG16, (b) ResNet50 (c) MobileNet, (d) EfficientNet (e) InceptionNet, (f) Dense121, (g) Proposed Model: Analysis of proposed and existing classification model confusion matrix

Table 7. Accuracy comparison of proposed and existing literature work

Author and Ref. No.	Method used	Accuracy (%)
Azfar *et al.* [23]	IoT-based smart response system	99.8
Patil *et a.* [24]	IoT-based CNN	98.34
Puri *et al*. [25]	A hybrid approach combining sensors and DL models	99.19
Saleem *et al.* [26]	IoT-based RBFN algorithm	98.54
Azfar *et al*. [27]	IoT-based system for real-time detection of CFMs	99.11
Kathole *et al.* [28]	Metaheuristics DL approach	97.91
Tsai *et al.* [29]	DNN using MobileNetV3 model	92.6
Kathole *et al.* [30]	Meta-heuristic-based DL framework	91.7
Ananthi *et al.* [31]	ADHCNet with an attention mechanism	98.9
Saini *et al.* [32]	DL-based ensemble method using leaf wetness sensor	99.17
Proposed Method	**Stacking Ensemble model**	**99.66**

When compared to other models currently in use, the suggested model exhibits a better degree of prediction accuracy. The suggested strategy can produce a more effective classification model for cotton plant leaf disease by forecasting the classes represented as numbers based on our dataset.

The overall classification performance of existing model with the stacked generalization model is shown in above Table 6.

The proposed model demonstrates a marked enhancement in comparison to the current classification model, achieving an overall accuracy rate of 99.66%, a precision rate of 98.66%, an F1-score of 98.69%, an MCC rate of 98.49%, a specificity rate of 0.9981%, and a sensitivity rate of 98.719%. The existing model exhibited suboptimal performance attributable to constraints such as prolonged computation times, diminished recall values, and impaired accuracy in the identification of cotton plant leaf diseases. Conversely, the proposed classification approach proficiently addresses these shortcomings, culminating in a more accurate and precise classification of cotton plant leaf diseases by exceeding the efficacy of prior methodologies.

The classification outcomes obtained using the proposed model are summarized in the table below. This research demonstrates improved precision and efficiency in diagnosing cotton plant leaf diseases, leading to higher accuracy and reduced time consumption. The performance of the cotton plant leaf disease classification model is compared in Table 7, showcasing the performance of the proposed stacking ensemble model in contrast to the top existing literature related to fusion of deep learning and IoT systems.

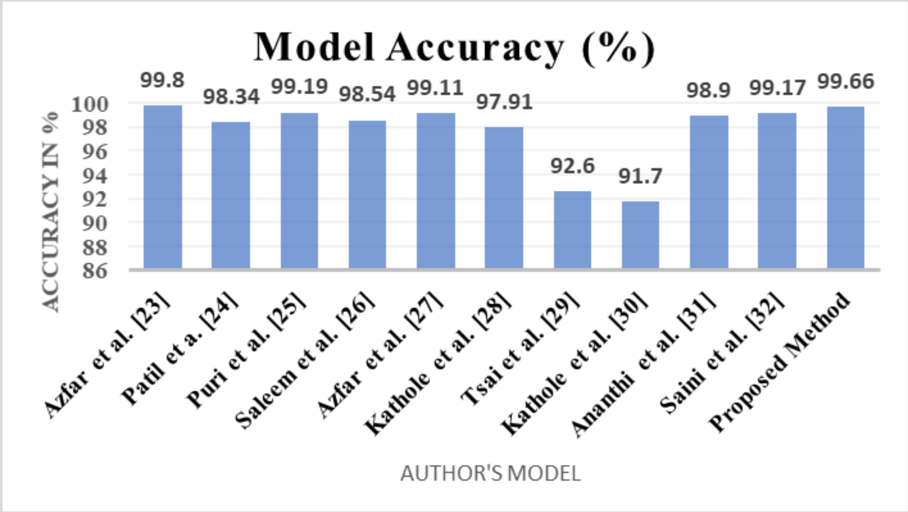


Figure 9. Comparison of proposed ensemble model with existing models

The proposed ensemble model exhibits superior performance compared to other models in the literature, as shown in above Figure 9.

5. Conclusion and Future Work

This study presents an innovative methodology that integrates Internet of Things (IoT) technology, deep learning algorithms, and meta-heuristic strategies to proficiently and precisely identify and categorize diseases affecting cotton plants, thereby providing advantages to agricultural practitioners and the textile sector. A stacked generalization model is articulated for the purpose of classifying diseases afflicting cotton plant leaves, incorporating several phases: data pre-processing, segmentation, feature extraction, and feature selection.

The effectiveness of the proposed model is assessed by employing a bespoke dataset of cotton plant leaf diseases and juxtaposed with established methodologies. In comparison to prevailing methodologies, the proposed strategy exhibits enhanced performance and precise categorization of cotton plant leaf diseases. Prospective research endeavors will encompass the examination of additional datasets pertaining to cotton plant leaves to further substantiate the effectiveness of the proposed model.

In subsequent research endeavors, we aspire to investigate the incorporation of additional sophisticated attention frameworks and optimization methodologies to augment the resilience and efficacy of our approach.

We intend to enhance the model to integrate more intricate activities and multi-sensor fusion, thereby augmenting its efficacy in a variety of real-world contexts. Future applications include automation in agriculture and disease detection.

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Authors Contribution Statement

Bhushan V. Patil: Conceptualization, Investigation, methodology, data collection, Paper formulation and Writing original draft. Dr. Pravin S. Patil Supervision.

Additional Information

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Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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Has this article screened for similarity?

Yes

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