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Improving farming by quickly detecting muskmelon plant diseases using advanced ensemble learning and capsule networks

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ABSTRACT

In modern agriculture, ensuring plant health is essential for high crop yields and quality. Plant diseases pose risks to economies, communities, and the environment, making early and accurate diagnosis crucial. The internet of things (IoT) has revolutionized farming by enabling real-time crop monitoring and using drones and cameras for early disease detection. This technology helps farmers address challenges with precision and sustainability. This research proposes an ensemble learning model incorporating multi-class capsule networks (MCCN) and other pre-trained model with majority voting system is implemented to predict plant diseases and pests early. The research aims to develop a robust MCCN-based ensemble prediction model for timely disease identification. To evaluate the performance of the ensemble model, various key metrics, including accuracy, and loss value, are assessed. Furthermore, a comparative analysis is conducted, benchmarking the MCCN model against other well-known pre-trained models such as residual network-101 (ResNet101), visual geometry group-19 (VGG19), and GoogleNet. This research signifies a substantial stride towards the realization of IoT-driven precision agriculture, where advanced technology and machine learning contribute to the early detection and mitigation of plant diseases, ultimately enhancing crop yield and environmental sustainability.

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1. INTRODUCTION

In modern agriculture, plant health is crucial for achieving high crop yields, impacting both quality and quantity. Plant infections can threaten economies, communities, and the environment, highlighting the need for early and accurate disease diagnosis. In contrast, employing automated disease segmentation through plant leaf image analysis with soft computing techniques presents a more efficient alternative to the existing approach. The advent of the internet of things (IoT) has initiated a transformative era in agriculture, endowing farmers with the tools for precise and sustainable farming practices to address the multifaceted challenges in the agricultural landscape. The rapid evolution of technology is ushering in a shift from conventional practices towards cutting-edge methodologies. The automation of early-stage plant disease detection has become imperative, not only to streamline detection processes, enhance accuracy, but also to ensure consistent crop yields despite variations in climatic, soil, and environmental conditions. Manual pathogen detection in plants is burdened by its high costs, time intensiveness, and the necessity for specialized expertise.

2. LITERATURE REVIEW

The researchers primarily emphasize image processing techniques for extracting distinctive features, rather than concentrating on classifier systems. Recognizing the limitations of machine learning algorithms, the research direction has shifted towards deep learning algorithms. Deep learning models have gained prominence in image processing applications due to their ability to automatically extract features and train themselves. They have demonstrated significantly improved performance compared to traditional machine classification models, especially in tasks like plant leaf classification.

In 2015, Kawasaki *et al.* [1] introduced a three-layered convolutional neural network (CNN) structure designed to detect cucumber leaf diseases, achieving an impressive accuracy rate of 94.9%. Similarly, Lee *et al.* [2] presented a five-layer CNN model in 2015 for categorizing 44 different plant species. This model was tested using 2,816 images from the MalayaKew (MK) dataset, sourced from the Royal Botanic Gardens in New England, and achieved a remarkable accuracy of 99.7%. In 2016, Mohanty *et al.* [3] conducted experiments that explored the state-of-the-art techniques in plant disease identification and classification, marking a significant advancement in this field. Their research employed AlexNet and GoogleNet as integral components. The dataset was divided into three distinct categories: original color images, grayscale images, and segmented images. The model underwent training using each of these image sets, with the highest performance observed in the model trained on the original color images. Impressively, the proposed system achieved an average accuracy rate of 99.53%.

Transfer learning, a prevalent technique in deep learning, involves the utilization of pre-trained models as a foundational starting point, followed by fine-tuning through a classification algorithm. Several research studies have successfully applied this approach in conjunction with specific algorithms to classify plant diseases. Ramcharan *et al.* [4] employed an InceptionV3 pre-trained model for feature extraction, coupled with a support vector machine (SVM) classifier for classification purposes. They trained the model using 11,670 infected cassava leaves from image datasets, achieving a remarkable classification accuracy of 98%. Similarly, in 2017, Shijie *et al.* [5] implemented a technique merging visual geometry group-16 (VGG16) with SVM for tomato leaf disease identification, attaining an accuracy of 89% in tests conducted with 440 infected images, spanning 11 different class labels.

Zhang *et al.* [6] in 2018 proposed an improvised GoogLeNet model and Cifer 10 model for maize leaf disease classification top identification accuracy of about 98%. The research by Singh *et al.* [7] in 2019 proposed a multi-layer CNN structure for identification of mango leaves affected by the anthracnose fungal infection. In this work, they have conducted a rigorous evaluation using a real-time dataset collected at Shri Mata Vaishno Devi University, Katra, Jammu and Kashmir, India. This dataset comprises a total of 1,070 images depicting the leaves of mango trees. It encompasses a diverse range of images, including those of both healthy leaves and leaves that have been infected by various diseases. The outcomes of their study demonstrate a notable improvement in classification accuracy achieved by the multi-layer convolutional neural network (MCNN) model in comparison to existing state-of-the-art approaches.

Sun *et al.* [8] in 2020 used an improvised RPN model for detection of northern maize leaf blight in challenging field conditions and achieved an accuracy of 91.8% after 6,000 iterations. In 2020, Hu *et al.* [9], introduce the multidimensional feature compensation residual neural network (MDFC-ResNet) model designed for precise disease identification within the system.

Zinonos *et al.* [10] in 2021, presents the practical outcomes of a combined long range (LoRa) and deep learning-powered computer vision system, designed for efficient identification of grape leaf diseases utilizing low-resolution images. In this research, they employ the grad-CAM method to visualize the judgments made by the CNN’s output layer. The visualization results highlight significant activation in the disease’s affected region, elucidating how the network effectively discriminates between various grape leaf diseases. A comprehensive evaluation was conducted using a total of 1,296 bean leaf images by Elfatimi *et al.* [11] in 2022. The results obtained through this approach demonstrated the remarkable performance of our MobileNet model in classifying bean leaf diseases. Specifically, the proposed model exhibited impressive average classification accuracy, surpassing 97% on the training dataset and exceeding 92% on the test dataset, encompassing the two unhealthy classes and one healthy class. These findings underscore the potential of deep learning techniques in the realm of bean leaf disease detection and classification, offering robust and accurate results.

The research by Vishnoi *et al.* [12] in 2023, proposed an improvised CNN model for detecting apple leaf diseases and achieved an accuracy of 98%. In the same year, Farah *et al.* [13], proposed a transfer learning based VGG19 model for classification of soybean leaf diseases and achieved an accuracy up to 94.16%. For a comprehensive overview of existing research in leaf disease identification using deep learning algorithms, please refer to Table 1, summarizing the recent efforts of various researchers in this field from the year 2020 [14], [15].

Table 1. Previous studies conducted by diverse researchers on leaf disease recognition utilizing deep learning algorithms from the year 2020

Author	Algorithm used	Dataset	Prediction accuracy
Tetila *et al.* [14]	Deep neural network (DNN) with fine turned transfer learning	UAV images of soybean	99.04%
Li *et al.* [15]	Faster recurrent-CNN (RCNN)	Sea cucumber videos	99%
Liu *et al.* [16]	generative adversarial network (GAN) based Xception network	8,124 images of grape leaves	98.70%
Zeng *et al.* [17]	GAN based deep CNN model	14,056 images of citrus leaves	92.60%
Ai *et al.* [18]	Inception-ResNet-v2	27 disease images of 10 crops	86.1%
Pham *et al.* [19]	Enhanced transfer learning	450 images of mango leaves	Up to 89.41%
Zhou *et al.* [20]	Restructured deep residual dense network	AI challenger 2018 datasets for tomato leaf diseases	95%
Zhou *et al.* [21]	Fine grained-GAN with ResNet	1,500 images of grape leaves	96.27%
Zinonos *et al.* [10]	LoRa with deep learning	Grape leaves	-
Hassan and Maji [22]	CNN with inception layer and residual connection	Plantvillage dataset rice disease dataset cassava dataset	99.39%, 99.66%, and 76.59% respectively
Amin *et al.* [23]	ResNet152 and InceptionV3	15,408 images of corn leaf	98.37% and 96.26% respectively
Chen *et al.* [24]	Lightweight M-Inception	PlantVillage dataset	99.21%
Liu and Zhang [25]	PiTLiD based Inception-V3	Apple leaf imags	98.65%
Masood *et al.* [26]	MaizeNet	2,112 images of mize leaf	97.89%
Hosny *et al.* [27]	CNN based on local binary pattern (LBP)	Apple leaf, tomato leaf, and grape leaf	98.8%, 96.5%, and 98.3% respectively
Alharbi *et al.* [28]	EfficientNet	CGIAR dataset	98.5%
Abinaya *et al.* [29]	Residual U-net	54,303 images of corn leaf	95.26%
Farah *et al.* [13]	Transfer learning based VGG 16 model	6,410 images soybean leaves	94.16%

Presently, there is a notable scarcity of systems for monitoring and forecasting crop conditions. Muskmelon, a lucrative crop, hinges its productivity on optimal farming practices, careful management, and disease-free plant growth. With a relatively short lifespan of 55 to 65 days, any disease outbreak during this period results in complete losses for farmers. Moreover, there is a dearth of comprehensive information on fine-grained plant disease prediction that incorporates additional deep learning layers.

3. PROPOSED METHOD

This research proposes an ensemble learning model incorporating multi-class capsule networks (MCCN) and other pre-trained model with majority voting system is implemented to predict plant diseases and pests early. The research aims to develop a robust MCCN-based ensemble prediction model for timely disease identification. The architecture of the proposed methodology is shown in Figure 1.

3.1. Capsule network

A capsule is like a group of specialized neurons, where each neuron is tuned to recognize different characteristics of an object, like its position, size, or color. Capsule networks aim to predict these features, including the object's orientation, based on the information they receive. This loss of spatial information can be detrimental when dealing with diseases in plants, which require preserving even more information. To address this issue, capsule networks are used for infection classification in leaf images, as they maintain more spatial information, leading to improved accuracy.

3.2. Architecture of multi-class capsule network

We have made a notable change by eliminating the standard max-pooling layers that usually follow each convolutional layer. Furthermore, we've adapted the loss function within the capsule network to a multi-class entropy loss function, which is tailored to identify a network with six distinct classes. In this setup, one class signifies a healthy condition, while the remaining five classes represent different disease labels.

The architecture of the MCCN is illustrated in Figure 2. This comprehensive structure comprises ten convolutional layers for extracting essential features, followed by a single primary capsule layer and a single disease capsule layer responsible for the classification process. In addition, there are three fully connected layers, which play a role in decoding the image segments and are crucial for reconstructing the loss function. This reconstruction process measures how effectively the algorithm models the provided data.

The process of feature extraction from the input image is achieved through convolutional layers. In our proposed structure, there are a total of ten convolutional layers. To facilitate a meaningful comparative analysis with the benchmarked dataset, the input image is resized to 256×256 pixels. It’s worth noting that the benchmarked dataset for comparison is the PlantVillage dataset, where all images share the same dimensions of 256×256 pixels.

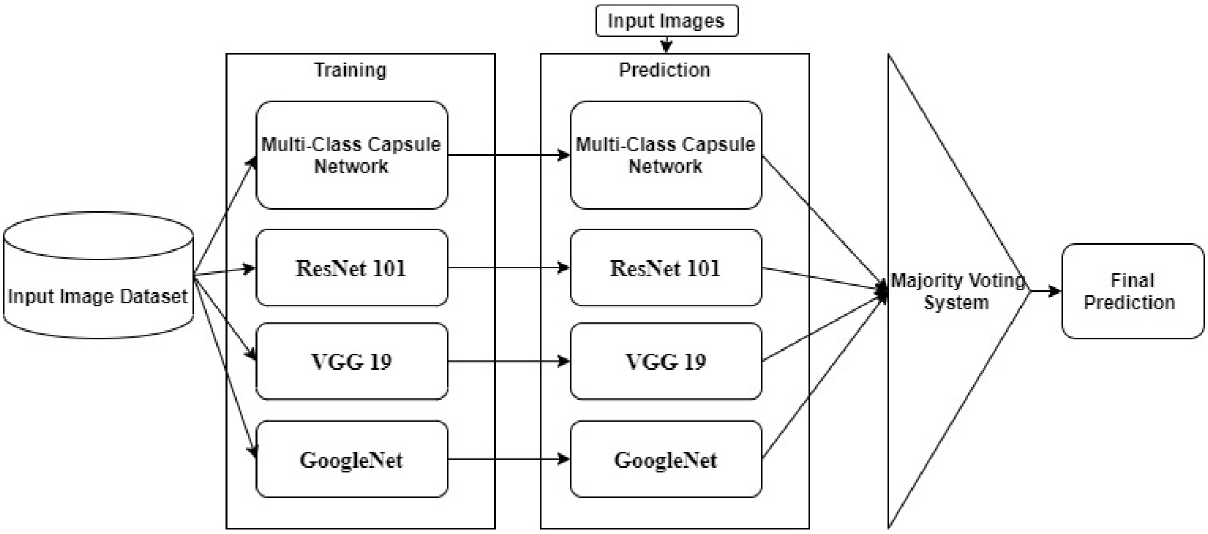

Figure 1. Architecture of ensemble model prediction

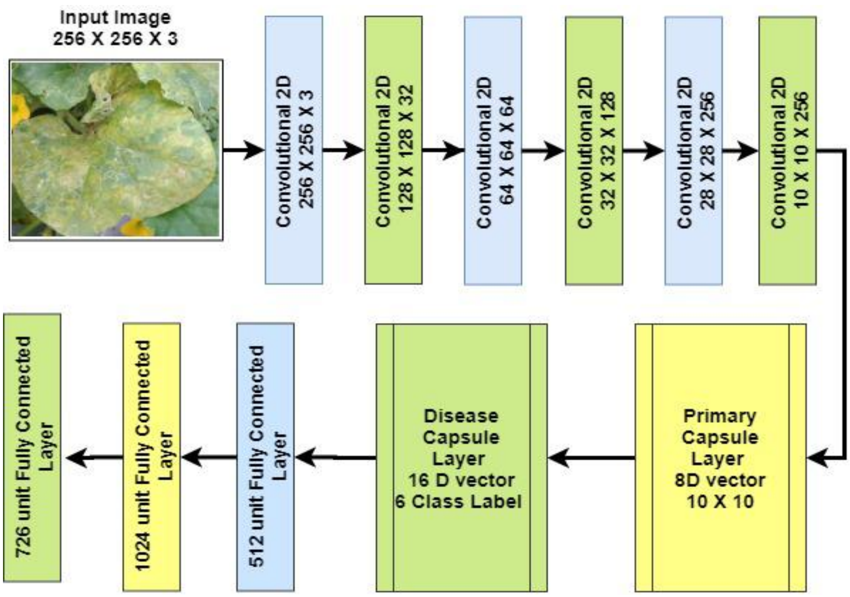

Figure 2. Architecture of MCCN

3.3. Capsule layer

The primary capsule layer contains a total of 53,08,672 learnable parameters, and these parameters are then passed on to the disease capsule layer, serving as the higher capsule layer. In the transition, the 3,200 eight-dimensional vectors are meticulously mapped into the disease capsule layer, resulting in 3,200 capsules, each comprising eight neurons arranged in a 1×1 structure, as described in reference [30].

These eight-dimensional vectors are further transformed into six class labels, expanding their vector size to sixteen dimensions. These six class labels represent five distinct disease categories and one for the category of healthy leaves. The link weights connecting the DisiCaps layer with the preceding layer encompass two vital parameters: C_{ij}, which pertains to each capsule's connection to all six class labels, and W_{ij}, which signifies the connection between specific neurons in the output layer.

The total number of learnable C_{ij} parameters amounts to 19,200 parameters (3,200 capsules×6 class labels). Similarly, the total number of learnable W_{ij} parameters stands at 24,57,600 parameters (8 dimensions ×16 dimensions×32,00 capsules×6 class labels). In this setup, the primary capsule layer consists of eight capsules labeled as u_i, and these capsules are interconnected with sixteen capsules labeled as v_j in the DisiCaps layer. A squashing function, as described in [31], [32], is applied to ensure that the output falls within the range of zero to one. The final step entails assessing the results from both low-level capsules and high-level capsules and making any required adjustments.

3.4. Final layers

This process generates a vector with dimensions of 16×512, where 16 corresponds to the dimension of the DisiCaps layer. Subsequently, the fully connected layer is further extended to encompass 1,024 neurons, utilizing the rectified linear unit (ReLU) activation function. Eventually, this expanded fully connected layer contains 784 neurons, aligning with the input dimensions of the last CNN layer, which measures 28×28 pixels.

3.4.1. VGG19

VGG19 derives its name from its structure, consisting of 19 layers, including 16 convolutional layers and 3 fully connected layers. The repeated pattern of small-sized kernels (3×3) for convolutional layers contributes to its distinctive design. While VGG19 exhibits remarkable performance, its main drawback lies in its resource-intensive nature due to a large number of parameters. This can lead to challenges in deploying the model on resource-constrained devices.

3.4.2. ResNet101

While ResNet101 addresses challenges related to training deep networks, its computational complexity may pose challenges for deployment on resource-constrained devices. Model compression techniques are often explored to mitigate this issue.

3.4.3. GoogleNet

The standout feature of GoogleNet is the use of the inception module, which employs multiple convolutional filters of different sizes (1×1, 3×3, and 5×5) and a pooling layer in parallel. This allows the network to capture features at various spatial scales within the same layer.

3.4.4. Dataset description

For our experimental work, we've assembled a real-time dataset comprising six distinct class labels. This dataset encompasses various categories, specifically, "Disinfected leaf," "Early Blight," "Mosaic virus," "Leaf spot," "Bacterial Spot," and "Powdery Mildew." Our research primarily focuses on addressing the five most common diseases that typically afflict muskmelon plants. The images utilized in this study have been sourced from a one-acre agricultural plot situated in Sathappadi Village, Attur Taluk, Salem District, Tamil Nadu. This location's geographic coordinates are approximately 11° 35' 53.2176'' N for latitude and 78° 35' 48.4872'' E for longitude [30], [32].

Muskmelon, known for its profitability, has a relatively short lifespan, typically around 65 days. During this brief period, any outbreak of disease can have a devastating impact on the entire crop, leading to significant yield losses. Consequently, there is a pressing need for the development of an early disease prediction system to mitigate these risks. From this vast repository, we extracted images relevant to the five major diseases that commonly affect plants, and these images were employed as a benchmark dataset for our disease classification efforts. As a standard practice, all the images in this dataset have been uniformly resized to dimensions of 256×256.

4. RESULTS AND DISCUSSION

The model's performance is evaluated using a range of key metrics, focusing on accuracy and loss. During 50 epochs, training and validation accuracies and loss values are recorded for each model. After training, models are tested on 30% of the unused dataset to measure their accuracy. For predictions, an ensemble learning model is used with majority voting to select the most accurate model. The training and validation accuracy and loss function of ResNet101 is shown in Figure 3. The training accuracy of the ResNet101 model exhibits a progressive increase from an initial accuracy of 62.53% to a peak of 98.59%. The validation accuracy of the ResNet101 model follows a similar increasing trend, starting at 66.41% and reaching 92.37% in the final epoch.

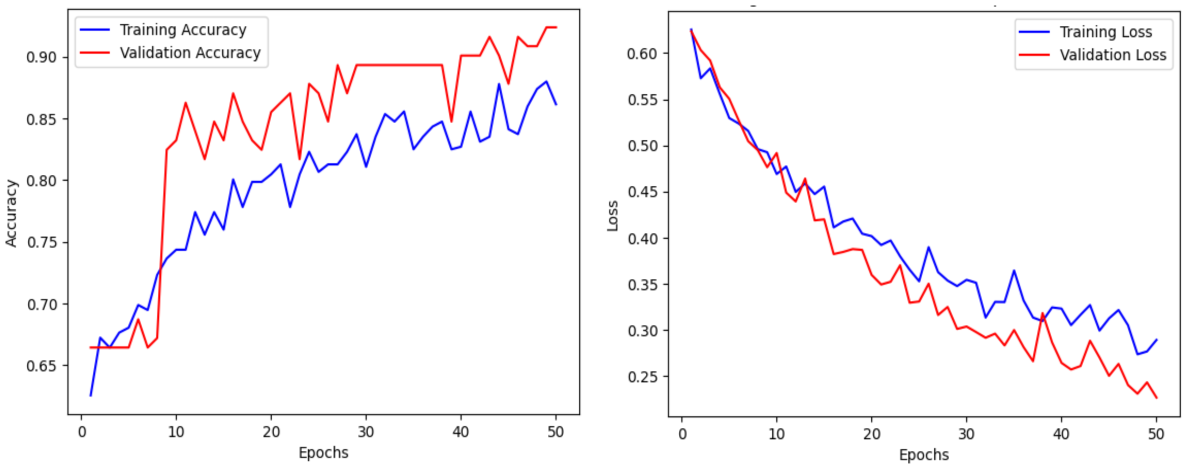

Figure 3. Training and validation accuracy and loss values ResNet101

The training and validation accuracy and loss function of VGG19 is shown in Figure 4. The training accuracy of the VGG19 model steadily increased with each epoch, reaching a peak of 98.57% in the final epoch. The validation accuracy of the VGG19 model followed a similar positive trajectory. Starting at 66.41%, the accuracy steadily increased and reached 96.95% in the final epoch. This alignment with the training accuracy demonstrates the model's ability to generalize well to data it has not seen during training.

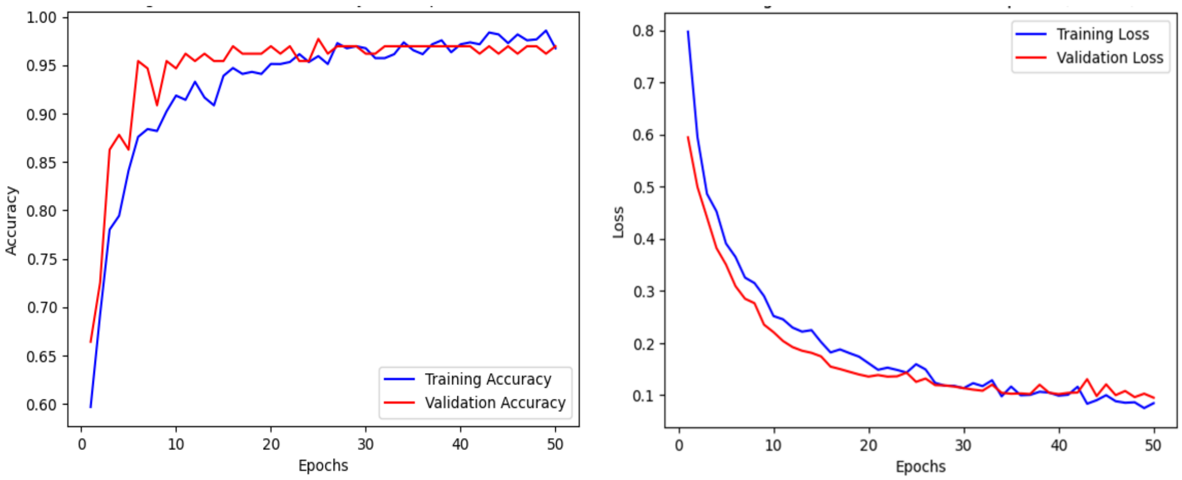

Figure 4. Training and validation accuracy and loss values VGG19

The training and validation accuracy and loss function of GoogleNet is shown in Figure 5. The training accuracy of the GoogleNet model exhibits a progressive increase from an initial accuracy of 62.53% to a peak of 98.13%. The validation accuracy of the GoogleNet model follows a similar increasing trend, starting at 66.41% and reaching 92.37% in the final epoch. The training and validation accuracy and loss function of MCCN is shown in Figure 6.

The MCCN exhibited noteworthy performance during both training and validation phases, as depicted by the evolving accuracy values over the course of 50 epochs. The training accuracy consistently improved throughout the epochs, starting at 85.997% and reaching an impressive 99.1%. This progressive increase underscores the model's capability to effectively learn and adapt to the complexities of the dataset. The validation accuracy mirrored the training accuracy trend, demonstrating a parallel increase from an initial 72.95% to a peak of 98.74%. This synchronization indicates that the model not only performed well on the training set but also maintained its effectiveness when confronted with previously unseen data during validation. The consistent rise in validation accuracy signifies the robustness of the MCCN in making accurate predictions on diverse data, reinforcing its potential for real-world applications. The testing accuracy of the models is shown in Table 2. The experimental results unequivocally demonstrate the superiority of the MCCN-based ensemble learning model. This model surpasses its counterparts, achieving an outstanding accuracy rate of 99.54%.

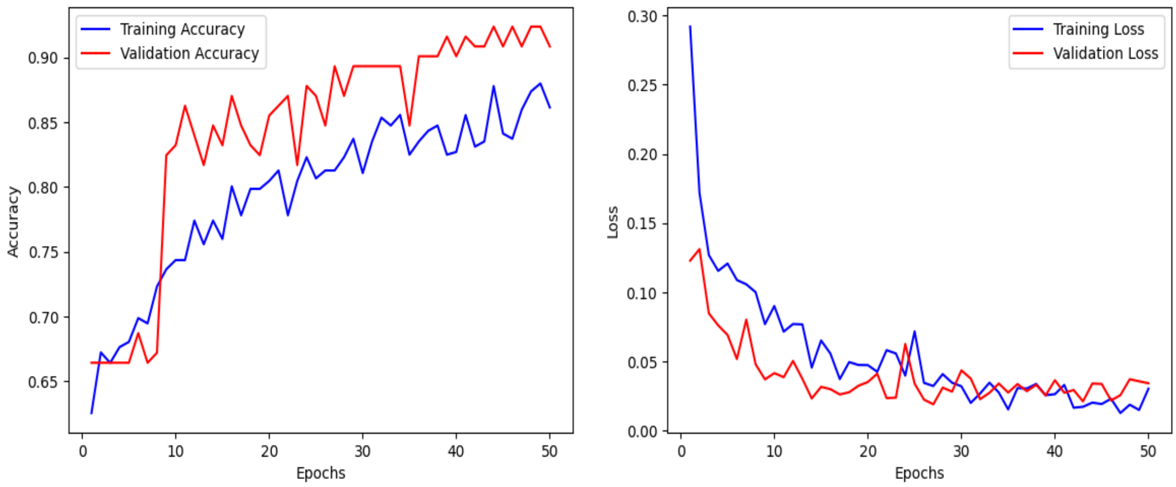

Figure 5. Training and validation accuracy and loss values GoogleNet

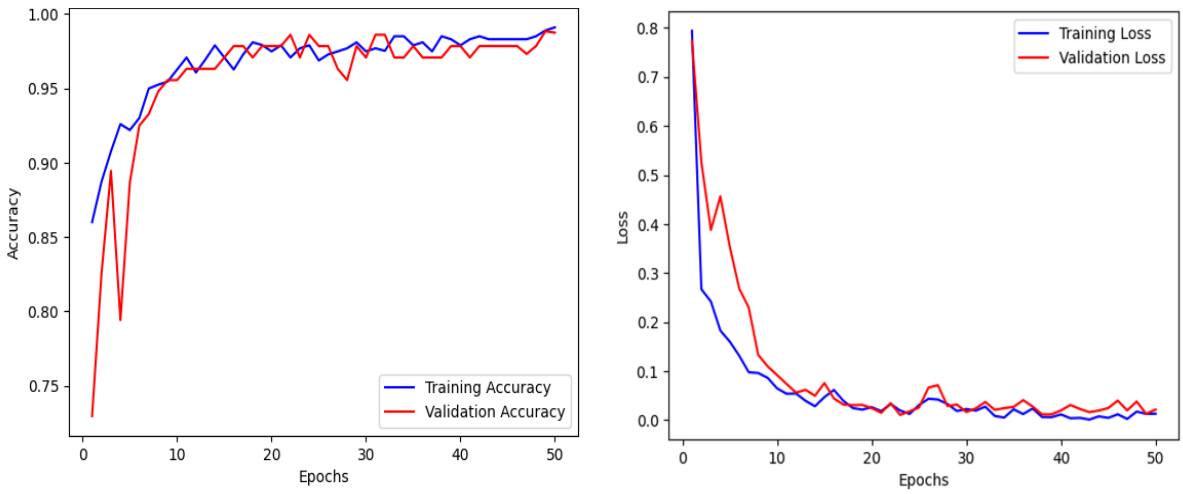

Figure 6. Training and validation accuracy and loss values MCCN

Table 2. Testing accuracy of different models

Models	ResNet101	VGG19	GoogleNet	MCCN	Ensemble model
Testing accuracy	98.67%	98.73%	98.36%	99.25%	99.54%

5. CONCLUSION

This research presents an ensemble learning model combining MCCN with pre-trained models and a voting system for early detection of plant diseases and pests, achieving an impressive 99.54% accuracy. The model surpasses established architectures like ResNet101, VGG19, and GoogleNet, promoting IoT-driven precision agriculture to enhance crop yields and environmental sustainability. Future work includes field trials to validate real-world applicability, optimizing the MCCN architecture, and integrating additional data sources like meteorological and soil information. Scalability for large-scale farming and compatibility with IoT systems are key areas for practical deployment. This approach aims to revolutionize proactive disease control in agriculture.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Deeba Kannan	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Nagamuthu Krishnan Sundarasrinivasa Sankaranarayanan		✓				✓		✓	✓	✓	✓	✓		
Shanmugasundaram Venkatarajan	✓		✓	✓		✓			✓		✓		✓	
Rashima Mahajan	✓				✓		✓	✓	✓					
Brindha Gunasekaran					✓		✓			✓		✓		✓
Pandi Maharajan Murugamani	✓		✓			✓		✓		✓				
Karthikeyan Dhandapani	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT:

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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