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IoT-Based System for Prediction of Fungal Disease Attack on Mango Leaves

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Abstract: Mango has significant commercial importance in Pakistan, as it is the world's sixth-largest mango supplier. However, mango is severely affected by fungal diseases due to variations in environmental parameters. These diseases are normally found in growing areas of mango worldwide; weather parameters such as humidity, temperature, and leaf wetness duration increase the probability of fungal infection on mango plants. Early prediction of fungal disease on mango leaves can help farmers prevent potential losses. The goal of the research was to use sensors based on Internet of Things (IoT) for the monitoring of mango orchards in real-time and collect environmental data from targeted areas for disease monitoring. The hardware was installed in the Mango Research Institute Multan (MRI) orchard to collect current data. The past data was collected from AWS-MNS University Multan. The study was then carried out by developing the logistic regression and random forest model for *Anthracnose* prediction using past and current weather data for predicting future *Anthracnose* infections. The accuracy of the logistic regression model was 96%, while the random forest achieved 99%. This study developed an IoT-based system to improve quality and quantity of mango production.

Keywords: Mango Leaves; Fungal Disease; IoT; Logistic Regression; Random Forest

1. Introduction

Mango is a delicious fruit that are high in vitamins, nutritious attributes, and minerals [1]. Mangoes are cultivated in over 160 varieties in the world, but the most famous varieties are grown in Pakistan [2]. After citrus, mango is the second most extensively produced fruit. It covers 420,079 acres and produces 1,727,000 tons per year, with huge potential for global income [3]. Pakistan's national fruit is Mango, and the country is the world's fourth-largest mango producer [1].

Unfortunately, mango plant fungal diseases such as powdery mildew and anthracnose are highly damaging, and the main reason of rapidly declining mango yields in countries like Pakistan [4], [5]. From agricultural research reports and field studies [4], [5], these infections are known to cause a decrease in yields by as much as 30-60% [6], [7] if not diagnosed at early stages. To overcome these farming issues, there is need of early detection and predictive solutions.

Mango trees were affected due to unfavorable weather conditions, which enhance the attack of *Anthracnose* present in the climate [8]. *Anthracnose* is a fungus that attacks a variety of plants in hot, humid areas. *Anthracnose* refers to a group of similar fungal infections that generate black lesions on leaves. The disease is also known as a leaf, shoot, or twig blight because it commonly begins on the leaves and twigs of trees. *Anthracnose* is caused by a variety of fungus. A system needed which can predict real-time climatic change conditions [9], [10].

During rainy conditions, the fungus attack leaves and severely damage the plant [11]. It causes floral and young shoot blight, as well as leaf spots and fruit rots. Flower blight causes reduced yield, and shoots die back in damp conditions [12]. Black dots appear on young diseased fruits, which shrink and fall off

[13]. Stamina generates black dots on the leaves that might meld together to form enormous black regions. The fungus can trigger leaf fall early in moist weather [14].

2. Related Work

Several studies have developed and applied IoT [15], [18], [19], [20], [24], [26], [28], [31], [32], [33], [34] image processing [16], [19] neural networks [17], [18], [21] machine learning [15], [21], [22], [24] deep learning [22], [23], [24], [29] sensor-based techniques [25], [28] and ensemble methods [33] for plant disease detection and prediction.

A machine learning-based methodology was proposed [15] based on IoT for the prediction of mango fruit disease. The historical weather data was utilized for disease and production forecasting, and current data was also employed through sensors. The random forest model worked effectively to achieve goal. In another study [16] an image processing system was proposed for the detection of pests on mango leaves and nine diseases were considered for identification among which 3 were identified accurately.

A neural network was applied [17] for the identification of mango leaf disease using union technique based on Canonical correlation analysis and features extraction. Ultrasonic technique was employed using sensors for the detection of canker and blight mango leaf disease. The methodology achieved 90% efficiency. The study [22] focused on anthracnose mango leaf disease forecasting using historical weather data and mango crop image data, machine learning (ML) and deep learning (DL) approaches. DL was aslo applied in another study [23] for the identification of mango leaf disease along with grapes leaf diseases using image dataset of healthy and diseases leaves collected from online freely available dataset repository. ALexnet was employed that resulted in disease identification with 89% accuracy for mango leaves and 99% accuracy for grapes leaf disease.

The authors of study work [24] demonstrated the application of IoT and ML for tea plant leaf disease prediction through environmental sensor data collection. The multiple linear regression algorithm achieved 91% accuracy when detecting blister blight as the target disease. The research work [18] applied IoT and neural network Resnet for the development of smart disease predictions system. The system achieved 99% accuracy.

Authors in the research [25], utilized Wetness Sensor for medical plant leaf disease detection. The manufactured LWS reacted in 10 seconds while maintaining a hysteresis range of ±3.8%. The sensor produced minimal capacitance changes of 6.2% as the temperature increased from 20°C to 65°C. The field tests of Tulsi plants using a commercial LWS and our LWS revealed leaf wetness detection deviations did not exceed 30 minutes.

IoT-based framework was developed and implemented for farmers [19] for the identification and classification of diseases of plants. The applied sensors were for real-time monitoring of water quality, soil fertility, and temperature. The decision was made through analyzing the plants image and sensor's data. Additionally, a robotic arm was also developed for automation of harvesting process. The applied system helped to improve crop health, quality, and paved the way for an efficient farming process.

Two types of technologies were integrated [26], one is IoT that collects real-time sensor data and second is deep learning that performs classification on plant images for disease detection. Developed system is used to analyze both types of data for potential disease prediction with high precision to improve agriculture industry. A web application was also developed.

The proposed system of study [27] monitors crop health by analyzing leaves, environmental stress, and soil fertility. Crop fields of Bottle Gourd, Maize, and Papaya leaves are monitored through Drones and digital images are captured which are then used for training process of CNN model to identify disease and apply classification. Weather changes are tracked via Web APIs, and results are compiled into reports for accurate monitoring.

IoT-based sensor networks was designed and deployed [28] for automated soil moisture and temperature and humidity monitoring instead of human inspection. The Raspberry Pi manages numerous farm sensors while a camera system identifies leaf diseases. Wi-Fi was used to send real-time sensor data to farmers, and monitor environmental conditions for crop health.

MMF-Net represents a CNN-based model which performs plant disease classification through utilization of multi-contextual features according to the proposed method [29]. The system analyzes images through RL and PL blocks at multiple levels while integrating actual environmental data. The model demonstrated its agricultural value by reaching 99% accuracy in its evaluation of corn leaf disease datasets. A deep learning-based cloud analytics system described in [30] allows farmers to interact with cloud processing in real-time through a head-mounted unit. The system was tested before implementation by means of user-interface friendliness, disease detection accuracy, and response-time. The results of these tests showed that system was effective for providing real-time plant disease inspections through augmented insights. The authors developed an IoT system which combined leaf wetness and soil moisture sensors [20] for testing with commercial environmental sensors to predict plant diseases. The field experiment on mango plants used an LSTM model to detect Powdery Mildew, Anthracnose, and Root Rot with 96% accuracy and 99% F1 score which surpassed conventional methods.

An IoT-based plant disease detection system was developed [31] which consists of semantic image segmentation methods including: SegNet, U-Net, and DeepLabv3, enhanced with CRFs for the localization of plant disease with more preciseness. The system performance evaluation uses F1-score and sensitivity and IoU to compare against current models. The experimental data demonstrates that SegNet with CRFs achieves superior performance compared to alternative methods, thus proving its effectiveness.

In a research work [32] demonstrated the integration of Parallel and Distributed Simulation Framework (PDSF) with IoT to monitor agriculture and manage pests. A Multi-threading approach was utilized to distribute workloads over several GPU's that ensures continuous data transmission. There were four functional-levels to process the tasks effectively, resulting improved performance with 98% accuracy.

A study [33] presented an IoT system which used sensor nodes to collect plant leaf images in a simulated environment before sending the data to a central sink node for disease detection. Images receive median filtering then segmentation and feature extraction operates at segment and pixel levels. The model: SCA-based RideNN classifier was used with its optimized weights for detection of plant leaf disease with 91.56% accuracy along with IoT data.

IoT and machine learning techniques (i.e., SVM and CNN) were integrated [21] for plant health monitoring, identification of disease patterns, and to provide real-time information to IoT system for improved irrigation mechanism and plant nutrition. The ensemble classification system (ECPRC) uses ENSVM as a core component for detecting diseases at an early stage. The experimental data demonstrates that ECPRC achieves better accuracy and efficiency than Naïve Bayes, KNN,

In another similar study [34], machine learning was applied along with IoT to improve agriculture productivity and quality through real-time monitoring of environmental parameters including air temperature of crop area, humidity level of crops, and percentage of moisture in crop soil. This data was accessible to farmers through ThingSpeak. A TSPBO-based DQN method for plant disease detection in an IoT-simulated environment was presented in the study [35]. The sensor nodes gather plant images which get sent to the sink node for disease identification. The proposed approach achieves both high diagnostic precision and energy conservation with its sensitive and specific operation. A summary of previous studies is presented in Table 1.

Table 1. Review of previous studies.

Sr. No	Techniques and Algorithm	Results	References
1	Random Forest, IoT	Effective mango disease prediction using historical weather and sensor data	[15]
2	Image Processing	Accurately identified 3 out of 9 mango leaf diseases	[16]
3	Neural Network,	90% efficiency in mango leaf	[17]

	Canonical Correlation Analysis	disease detection	
4	ML, DL	Anthracnose disease forecasting using historical weather and image data	[22]
5	AlexNet (CNN)	89% accuracy for mango leaf, 99% for grapes leaf disease	[23]
6	IoT, Multiple Linear Regression	91% accuracy in tea plant leaf disease prediction	[24]
7	IoT, ResNet	The system achieves 99% precision for disease prediction.	[18]
8	Wetness Sensor	±3.8% hysteresis, 6.2% variance across 20°C-65°C, max 30 min deviation	[25]
9	IoT, Smart Sensors, Image Analysis	The automated harvesting system improved health of crops	[19]
10	IoT, Deep Learning, Crowdsourcing	Plant disease predictions with high accuracy	[26]
11	CNN, Web APIs, Drones	Image was used to diagnose disease for crop monitoring	[27]
12	IoT, Sensor Networks	Applied sensors for Real-time monitoring of soil moisture, temperature, and humidity	[28]
13	MMF-Net (CNN)	99% accuracy in corn leaf disease classification	[29]
14	Deep Learning,	It provides real-time augmented data for	[30]

	Cloud Analytics	detection of plant disease	
15	IoT, LSTM	Achieved 96% accuracy, and 99% F1-score	[20]
16	IoT, SegNet, U-Net, DeepLabv3, CRFs	SegNet with CRFs outperforms in disease localization	[31]
17	Parallel & Distributed Simulation Framework (PDSF), IoT	Showed 98% accuracy for monitoring of plants	[32]
18	IoT, SCA-based RideNN Classifier	91% detection accuracy	[33]
19	ML (SVM, CNN), IoT, ENSVM	Naïve Bayes, KNN, and standard SVM showed high performance	[21]
20	IoT, Azure Custom Vision	Enhanced accuracy for tomato disease detection	[34]
21	TSPBO-based DQN	Developed system with high accuracy, sensitivity, specificity, and energy efficient	[35]

There are various limitations in current researches for detection of disease on plant using ML and IoT. The authors ([15], [16], [17], [22], and [24]) have used precise datasets that results in low generalization ability of classification models. The studies ([23], [13], and [31]) applied pre-trained models that lack compliance with various environmental conditions, whereas IoT-based methodologies ([19], [26], [27]) do not presented valid real-time data. The studies ([28], [30], and [34]) utilized sensors and deep learning techniques ([18], [32], [35]) that requires high computational power for disease identification that is difficult to deploy. To resolve these problems a simple and computational-power efficient methodology is proposed in the current study based on IoT and ML techniques "IoT-Based System for Prediction of Fungal Disease Attack on Mango Leaves" that resulted in real-time detection, accuracy, and practical deployment.

3. Materials and Methods

The proposed study has two major steps; one is development of sensor module to collect dataset of mango orchard at real-time and second is application of machine learning algorithms to this collected data along with previous year's weather data. The proposed methodology is shown in Figure 1.

So, these steps are explained in the following:

3.1. IoT-Based Sensor Module Development

This module was developed to collect mango orchard data including temperature of orchard, humidity of orchard, and rain sensor readings. The main components include:

1. NodeMCU/ESP8266 V2

2. DHT11
3. Rain fall Sensor
4. Solar Panel Plate

All these components were assembled using circuit and then coded using Arduino IDE software. The real-time data of mango orchard under the supervision of Mango Research Institute (MRI) Multan Pakistan, was collected through developed IoT system. This module is shown in Figure 2, and circuit diagram in Figure 3. The past data was collected from the Automatic Weather Station (AWS) of the MNS University of Agriculture Multan.

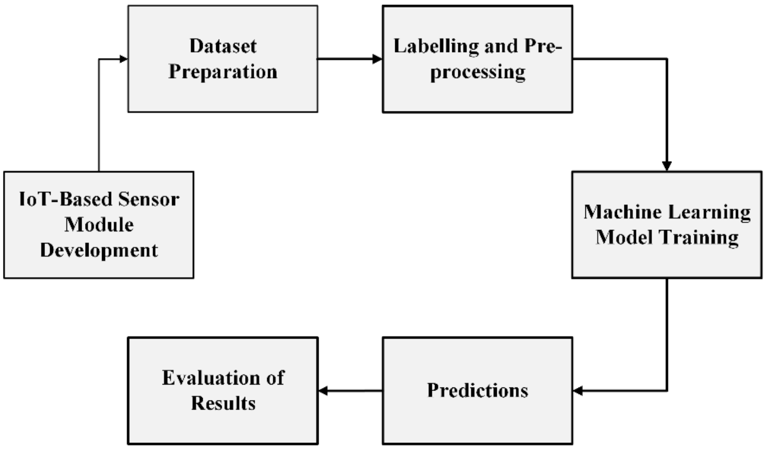

Figure 1. Proposed methodology

Figure 2. IoT-based sensor module developed for mango orchard.

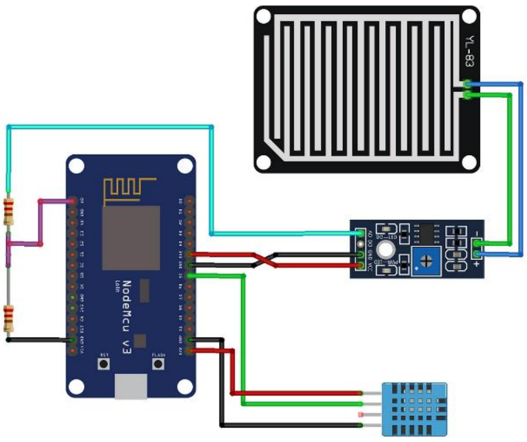

Figure 3. Circuit diagram of IoT-based sensor module.

3.2. Dataset Preparation

The real-time sensor data was collected and sent to Google Sheets for permanent storage. This dataset was then labelled as 0 for healthy and 1 for under anthracnose disease attack. The sample of dataset is presented in Table 2.

Table 2. Dataset sample.

Date	Air Temp	(oC)	Relative Humidity	Relative Humidity	Rain	Anthracnose
	Maxi	Mini	%		fall	
			8 A.M.	5 P.M.	(mm)	
12/1/2024	24	14	91	70	0	1
12/2/2024	25	9	88	70	0	0
12/3/2024	24	9	88	71	0	0
12/4/2024	24	10	87	70	0	0
12/5/2024	24	8	87	70	0	0
12/6/2024	23	12	100	65	0	1
12/7/2024	23	12	86	69	0	0
12/8/2024	24	12	87	65	0	0
12/10/2024	17	8	87	70	0	0
12/11/2024	18	11	87	69	2	0
12/12/2024	18	10	100	76	8	1
12/13/2024	17	11	100	70	0	1

The past dataset includes parameters such as maximum temperature (A-T), minimum temperature (a-t-min), maximum relative humidity (r-h-max), minimum humidity (r-h-min), and rainfall. It includes daily readings of all the parameters for about one year.

3.3. Application of Machine Learning Algorithms

Two machine learning algorithms namely Logistic Regression and Random Forest were applied to this labelled dataset. The major steps and these machine learning algorithms are defined in the following:

3.3.1. Pre-processing weather data

The pre-processing applied are Label-encoding and dataset division. The labels were encoded into numerical values using Label-encoder from Scikit-Learn library. After this, the dataset was divided such that 80% was used for training and remaining 20% was utilized for testing purpose.

3.3.2. Logistic Regression Model

Suppose x denotes independent variables, the dependent variable Y can be calculated by combining x (inputs) in linear-way. The divided dataset consists of train(x) and test(Y) sets. The concept behind this study is that disease is dependent (Y) on weather parameters (x). The logistic regression identifies connection between input (weather parameters) and output (Anthracnose disease forecasting). The input parameters include maximum temperature, minimum temperature, maximum humidity, minimum humidity, and rainfall. The conditional probability (P) of Y is denoted as follows:

$$P(Y = 1|x) \text{ or } P(Y = 0|x) \quad 1$$

Here, P is probability of anthracnose disease attack, x denotes independent variables, and Y denotes dependent variables. P(Y |X) is estimated as a sigmoid function is utilized to a linear combination of input features

hence, we can write:

$$P(\text{default} = \text{yes}|\text{disease}) \quad 2$$

When the P(default=yes)≥0.5, then we say there will be anthracnose attack.

When the P(default=yes)<0.4, then we say there will not be anthracnose attack.

The range of probability will remain in 0-1 range. The sum of the probability of a disease attack and no attack will be up to 1 always. The equation of logistic regression will be:

$$\ln\left(\frac{P}{1-P}\right) = \theta_1 + \theta_2 y + e$$

Equation 3

p is the possibility that event Y occurs.

$$P(Y = 1) \quad 4$$

The equation for exponential will be:

$$\frac{P}{1-P} = e^{\theta_1 + \theta_2 y + e} \quad 5$$

P/(1-P) is the odds ratio and θ is a parameters of length n. The representation for function of sigmoid is calculated as:

$$P = \frac{1}{1+e^{-}} (\theta_1 + \theta_2 y) \quad 6$$

The sigmoid function estimates probabilities between 0 and 1, and hence logistic regression is a non-linear transformation, as given:

$$\sigma(z) = \frac{1}{1+e^{-z}} \text{ where } z = \theta^T y \quad 7$$

The features are combined as follows:

$$\theta^T y = \sum_{i=1}^{m} \theta_i y_i = \theta_1 y_1 + \theta_2 y_2 + \cdots + \theta_n y_n \quad 8$$

3.3.3. Random Forest Model

The random forest is a supervised ML model, applied in this study work for forecasting anthracnose disease attack on mango leaf. A decision tree is created from several samples and then voting is applied based on majority method. The nodes on decision tree are decided by the following formula:

$$gini_{node} = 1 - \sum_{i=1}^{c} (p_i)^2 \quad 9$$

This formula uses the class and probability to determine the $gini_{node}$ of each branch on a node, determining which of the branches is more likely to occur. Here, p_i represents the relative frequency of the class under observation in the dataset and c represents the number of classes.

The nodes branch is decided through entropy formula as follows:

$$f_{entropy} = \sum_{i=1}^{c} - p_i * log_2(p_i) \quad 10$$

Entropy uses the probability of a certain outcome in order to make a decision on how the node should branch. Unlike the Gini index, it is more mathematical intensive due to the logarithmic function used in calculating it. A single decision tree holds properties such as low bias and high variance. After aggregating a pack of trees, bias remains but variance goes down. A constant bias is achieved that is as low as possible by constructing a large enough random forest.

4. Results

The applied models are logistic regression and rando forest. The highest accuracy is achieved by Random Forest model that can predict anthracnose disease attack on mango leaf with 99% accuracy using developed IoT-based sensor system. The results of both models are explained in detail in the following:

4.1. Logistic Regression Results

This model achieved 96% accuracy in detecting anthracnose disease in mango leaves. It demonstrated a precision of 96% for healthy leaves and 100% for diseased leaves, while the recall was 100% and 73%, respectively. The model achieved 98% F1-score for healthy mango leaves and 84% for diseased leaves ensuring high performance. However, the recall value could be improved and optimized to reduce misclassification. These results are shown in Figure 4.

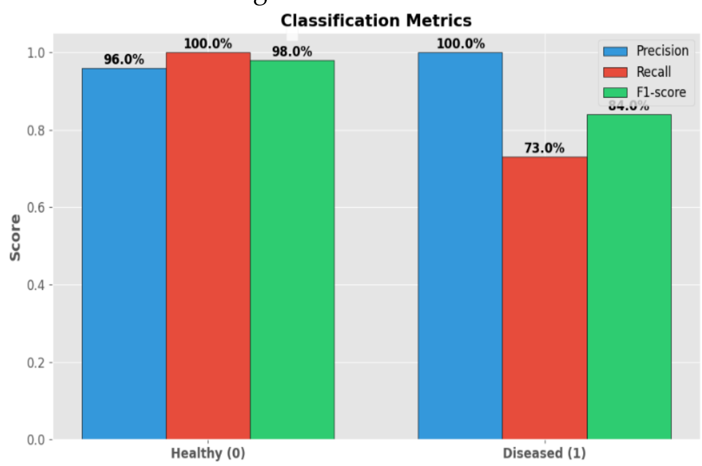

Figure 4. Accuracy metrices of logistic regression model.

The confusion matrix over test dataset shown in Figure 5, indicates that 69 healthy leaves were correctly classified, while 3 were misclassified as diseased. For anthracnose-infected leaves, 8 were accurately identified, but 3 were incorrectly classified as healthy.

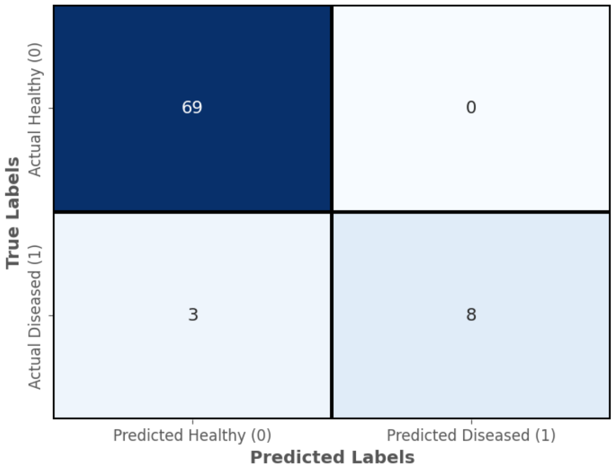

Figure 5. Confusion matrix of logistic regression model.

4.2. Random Forest Results

This model resulted in high accuracy gain as shown in Figure 6, the precision for healthy (class 0) and diseased (class 1) leaves reached 99% and 100%, respectively, confirming nominal false positives. The recall was 100% for healthy leaves but slightly lower at 91% in case of diseased, indicating some misclassification. The F1-score was 99% for healthy and 95% for diseased leaves which indicates model's reliability.

In the confusion matrix (Figure 7) all 69 healthy leaves were correctly classified, while 10 out of 11 diseased leaves were accurately identified, with only one misclassification. The macro-averaged precision, recall, and F1-score were 99%, 95%, and 97%, respectively.

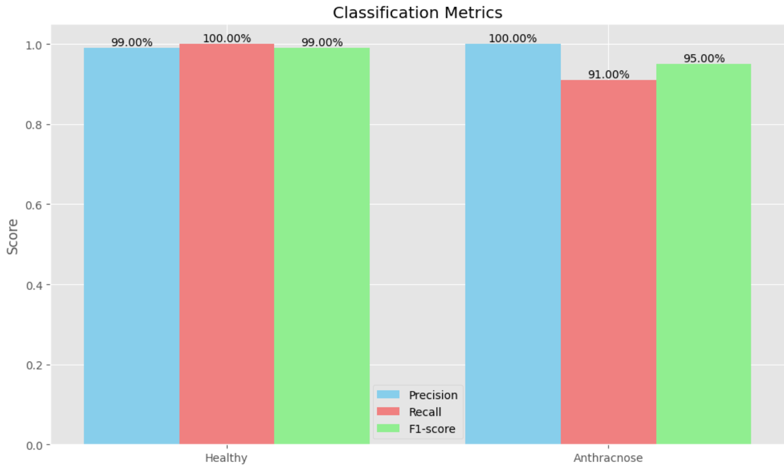

Figure 6. Accuracy metrices of Random Forest model.

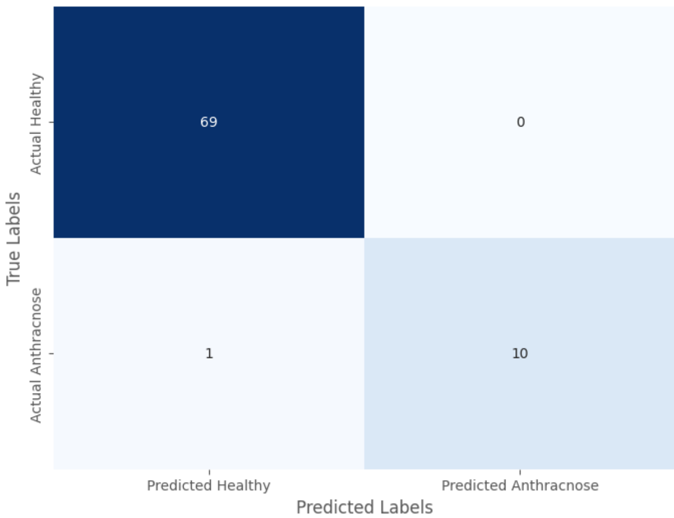

Figure 7. Confusion matrix of Random Forest model.

5. Discussion

The IoT-based system for mango leaf fungal disease prediction reached 99% accuracy through Random Forest modeling which outperformed existing studies in their effectiveness. The accuracy rate for mango leaves using traditional image-processing methods reached 89% through CNN-based approaches but proved less effective than the proposed system. The integration of neural networks and Canonical Correlation Analysis had slightly better results gaining 90% accuracy. The combination of IoT with LSTM and ResNet networks delivered precision results of 96% and 99% accuracy respectively. Real-time monitoring is integrated in current study to enhance reliability of model's predictions and it resulted in high accuracy as compared to historical weather data and image classification techniques. The model uses IoT sensor data to deliver an adaptable early fungal disease detection system which helps farmers reduce potential losses through scalability.

5.1. Comparative Analysis of ML Models

The results of the study reveal that Random Forest has a better accuracy than Logistic Regression in predicting anthracnose disease. This is because Random Forest has a higher accuracy of 99% compared to 96% of the decision tree due to its ability to capture the non-linear relationship between the weather conditions and the development of the fungi. Random Forest was also noted to have a high recall in identifying diseased leaves compared to Logistic Regression, which is important for farmers who cannot afford to overlook any diseases. It also proved to be more effective in handling the natural variability in the sensor data, which made it suitable for real-world agricultural applications.

A comparison table of current study with previous related studies has been presented in the following table 3:

Table 3. Comparison table of current work with state-of-the-art studies.

Sr. No	Techniques and Algorithm	Results	References
1	Neural Network, Canonical Correlation Analysis	90% efficiency in mango leaf disease detection	[17]
2	AlexNet (CNN)	89% accuracy for mango leaf, 99% for grapes leaf disease	[23]
3	IoT, ResNet	99% accuracy in smart disease prediction system	[18]
4	IoT, LSTM	96% accuracy, 99% F1-score for plant disease prediction	[20]
5	ML, DL	Anthracnose disease forecasting using historical weather and image data	[22]
6	**IoT, Random Forest**	**98.75% accuracy in anthracnose disease prediction**	**Proposed Work**

This comparison highlights the effectiveness of combining IoT-based sensor data with machine learning for disease prediction. While deep learning models like ResNet [18] and LSTM [20] show high accuracy, the proposed study achieves competitive results.

Supplementary Materials: The following are available online at www.jcbi.org/xxx/s1, Figure S1: title, Table S1: title, Video S1: title.

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Data Availability Statement:

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Conflicts of Interest: The authors declare no conflict of interest.

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