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Article

A Hybrid Meta Model for Detecting Cotton Disease Employing an IoT-Based Platform and an Ensemble Learning Methodology

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Abstract: Every nation's development depends on its agriculture. "Cash crops" are important crops like cotton and others. Most pathogens that cause substantial crop damage also affect cotton. Many illnesses have an impact on yield through the leaf. Recognizing illnesses early causes additional damage to crops. Many diseases can harm cotton, including as powdery mildew, leaf curl, bacterial blight, leaf spot, target spot, and nutrient deficiencies. Accurate disease detection is necessary before the proper course of treatment can be taken. Accurate plant disease diagnosis depends on deep learning. With accuracy, the suggested model, which is based on meta-Deep Learning, can identify different cotton leaf diseases. When utilizing an Internet of Things (IoT)-based sensor technology to identify cotton plant diseases, prior information about soil moisture levels, relative humidity, temperature, leaf wetness, and rainfall is crucial. For this study in real time, we collected sensor-based information and 1956 pictures of cotton leaves that were cultivated in the field, showing both sick and healthy leaves. The data augmentation method increased the size of the dataset. The dataset was trained with Custom CNN to get good accuracy for cotton diseases prediction, And Classification is carried out using a stacking ensemble model, which combines, ResNet50, VGG16, and InceptionV3 models for more accurate Disease prediction.

Keywords: CNN; IoT; deep learning; hybrid classifier; ensemble learning; meta-model

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Introduction

The most important cash crop in India is cotton, which has a wide range of economic effects [4,10,11,12]. Much more people are dependent on the production of cotton [4]. In the modern world, several pests will impact the crops because of unpredictably changing weather patterns and other environmental problems. These problems may also have an impact on soil nutrition [1]. Many diseases may afflict the crops as a result of this nutritional shortage. Yet, the spread of several crop diseases may hinder the development of agriculture. The farmers either recognise the illness via experience or seek assistance from other professionals. In this case, the symptoms of these illnesses are typically assessed with just the naked eye. As a result, there are higher chances for diseases to be misdiagnosed because they share symptoms with one another. This could lead to errors in overuse of pesticides and incorrect illness diagnosis control [4]. Thus, it is essential to adopt a unique approach to illness control and early diagnosis [13–15]. Several diseases in cotton crops are a major warning sign that has an impact on both financial and commercial influence. If the disease is accurately diagnosed and discovered early, additional steps can be taken to save the crop.

Technology is advancing because there are so many intelligent systems (IS) and smart sensors around us that are connected to one another via the internet and cloud platforms. Cotton is among of the most significant crops produced in the state of Maharashtra. Many illnesses hinder plant growth in fields, potentially drastically lowering the quality of the end produce. Early fall off of leaves or diseased leaves cause damage to cotton crops. Plant illnesses are typically brought on by a variety of climatic factors, such as scorching temperatures in the crop fields or the need for pesticides soon after. There are various

methods for classifying and identifying various diseases, such as Bacterial Blight, Alternaria, and many others, in the soil for the purpose of detecting and controlling their spread on cotton leaves. Using a variety of machine learning algorithms and an IoT-based system, the farmers are then presented with information on the disease and potential treatments. Many and varied characteristics present in agricultural data must be gathered and analysed for the development of production techniques in order to address issues like environmental sustainability, undesired reduction, and topsoil optimization.

Scientists have recently focused on the agricultural industry to identify crop diseases through automated methods. Two examples of modern technologies that enable the automated identification of agricultural illnesses without human intervention are deep learning and computer vision. For the purpose of diagnosing plant disease, a computerised method would be quicker, less expensive, and more accurate. Plant diseases have a significant financial impact on the global agriculture sector. Management of crop diseases is crucial for ensuring the quantity and quality of food. Plant illnesses must be detected early in order to limit disease transmission and enhance effective treatment methods. Effective crop management depends on evaluating plant disease status, which involves predicting methods and models for treatment implementation.

The agronomist is helped by the computational approach to identifying and diagnosing plant diseases. The diagnosis of the condition might still be done subjectively using outdated methods. On the other hand, modern technologies offer a way that can be used to determine plant diseases objectively. Automated technologies, like Deep Learning, enable the precise and dependable identification of agricultural diseases while also reducing costs and time.

Literature Review

In this we present complete review on computational methods on cotton plant disease detection. Extensive literature survey of Cotton plant diseases detection methods was carried out, and more focus on what types of diseases occurred on cotton plant and what are the deep learning methods to detect cotton plant diseases. We studied, in the cotton plant, the occurrence of disease is reflected mainly through the symptoms on its leaves [10].

Some of the diseases identified in the cotton leaf spots are categorized and shown in below Table 1 as:[44]

Table 1. Categories of Diseases.

Sr. No.	Category of Diseases	Examples
1	Bacterial diseases	Bacterial Blight Crown Gall
2	Fungal diseases	Anthracnose Leaf Spot Alternaria
3	Viral diseases	Leaf Curl Leaf Crumple Leaf Roll
4	Diseases(Due to insects)	White flies Leaf insects

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Going through reviews and categories different research papers in terms of methods and features, dataset used, challenges etc. Below Table 2 shows overview of Literature in terms of Methods and Features is as shown below,

Proposed System

The Layers include convolutional, ReLU, fully connected, pooling, and activation layers are part of the supervised CNN technique. CNNs can use tens or hundreds of hidden layers to learn how to identify different features in an image. With every layer that is buried, the learnt visual aspects get increasingly complex. Depending on the geometry of the object that we want to detect, the final hidden layer may learn to recognize more complex forms, while that initial hidden layer may tend to recognize edges. The supervised CNN technique consists of pooling layers, activation layers, fully connected layers, ReLU layers, and convolutional layers.

In first phase the CNN model build using Keras framework, as shown in Figure 1.This implied work uses the real field image dataset and examined multiple parameters like learning rate, batch size, and number of epochs to preserve the functionality of model. There are 1956 images belonging to 4 classes such as diseased cotton leaf, diseased cotton plant, fresh cotton leaf, fresh cotton plant storing in separate folders. Pre-Processing the images through modifications of images using data augmentation for training. To avoid overfitting on the proposed training model, more data were generated by flipping the data vertically and horizontally, rotating it at four different angles, and creating their transformations and responses. This allowed for the acquisition of more images from the original cotton leaf class from the real field dataset. 10% was used for validation, 10% for testing, and 80% of the dataset was used for training. Next, a CNN architecture model along the hyper parameter suggested for training stages is suggested.

All of the experiments in this work were conducted with Google Colaboratory, a tool that comes with built-in GPU support from Google. The structure of the CNN model used to detect cotton plant leaf disease is shown in Figure 1 below,

Data availability

Dataset created from actual images from real cotton field through camera.

Data Augmentation

The process of creating new data points from preexisting data to train the model is known as "data augmentation," which increases the amount of data artificially. Rescale to 255, rotation range 450, width shift range 20 %, height shift range 20%, shear range 20%, zoom range 20 %.

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```
Layer (type)                Output Shape              Param #
=================================================================
conv2d (Conv2D)             (None, 148, 148, 32)      896

max_pooling2d (MaxPooling2  (None, 74, 74, 32)        0
D)

conv2d_1 (Conv2D)           (None, 72, 72, 64)        18496

max_pooling2d_1 (MaxPoolin  (None, 36, 36, 64)        0
g2D)

conv2d_2 (Conv2D)           (None, 34, 34, 128)       73856

max_pooling2d_2 (MaxPoolin  (None, 17, 17, 128)       0
g2D)

conv2d_3 (Conv2D)           (None, 15, 15, 256)       295168

max_pooling2d_3 (MaxPoolin  (None, 7, 7, 256)         0
g2D)

dropout (Dropout)           (None, 7, 7, 256)         0

flatten (Flatten)           (None, 12544)             0

dense (Dense)               (None, 128)               1605760

dropout_1 (Dropout)         (None, 128)               0

dense_1 (Dense)             (None, 256)               33024

dropout_2 (Dropout)         (None, 256)               0

dense_2 (Dense)             (None, 4)                 1028

=================================================================
Total params: 2028228 (7.74 MB)
Trainable params: 2028228 (7.74 MB)
Non-trainable params: 0 (0.00 Byte)
```

Figure 1. Structure of Own CNN Model Employed for Cotton Plant Leaf Disease Detection.

Role of IoT (Internet of Things) for Cotton Plant Diseases Detection

The Proposed System Architecture is as shown in above **Figure 2**. To obtain greater development and productivity, cotton is the crop that needs to be watched over and managed. As a result, the IoT, which is a global trend today, has greatly penetrated the agriculture industry. IoT can help farmers overcome a variety of challenges in cotton production. The necessary secondary data were used as the foundation for the study. For the cotton crop, variables including temperature, humidity, soil moisture, soil temperature, etc., were also examined.

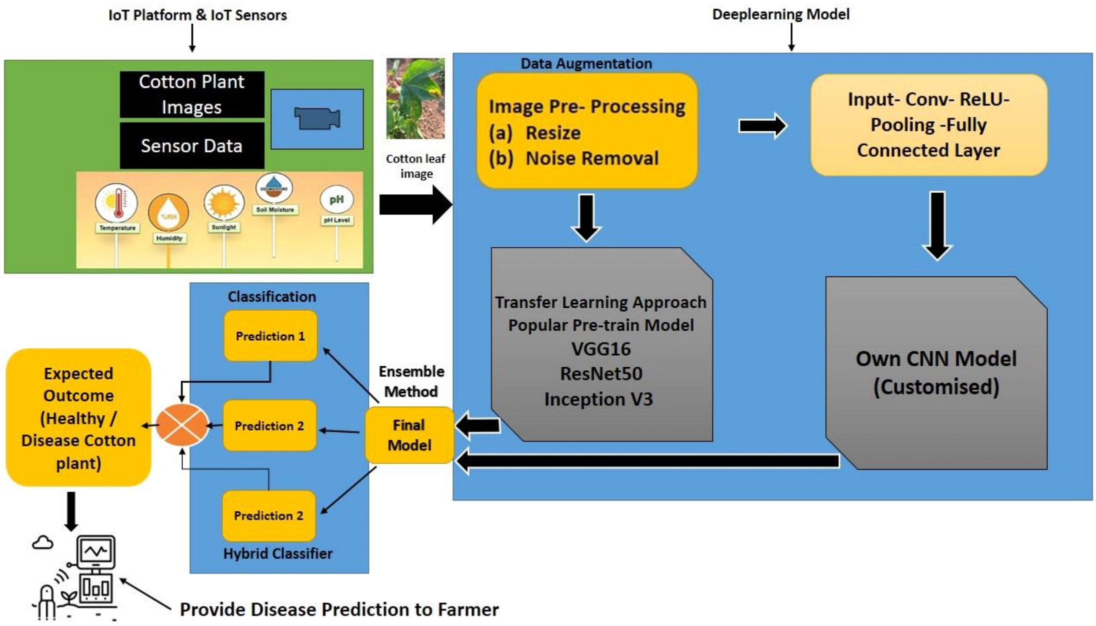


Figure 2. Proposed System Architecture.

Extensive survey on IoT based methods to collect Environmental data from Cotton farm field, and more focus on what types of diseases occurred on cotton plant and what are the symptoms and which environmental factors affecting cotton plant diseases.

We studied in the cotton plant, the occurrence of disease is reflected mainly through the symptoms on its leaves [10]. Implementing an IoT Based Live Environmental Parameters Monitoring System Using Node MCU ESP8266 on cotton crop field. Using several sensors, an IoT-based system will gather information about the soil and environment. In order to connect the NodeMCU ESP8266-12E Wi-fi Module with following components,

Components Details:

1. NodeMCU- ESP8266-12E Board,
2. BMP 180 Sensor- BMP 180 Barometric Pressure Sensor,
3. DHT11 Sensor- Humidity Temperature sensor,
4. FC-37 Sensor- Rain Sensor module

The below **Figure 3** represents IoT Based Live Environmental Parameters Monitoring System Using Node MCU ESP8266 as,

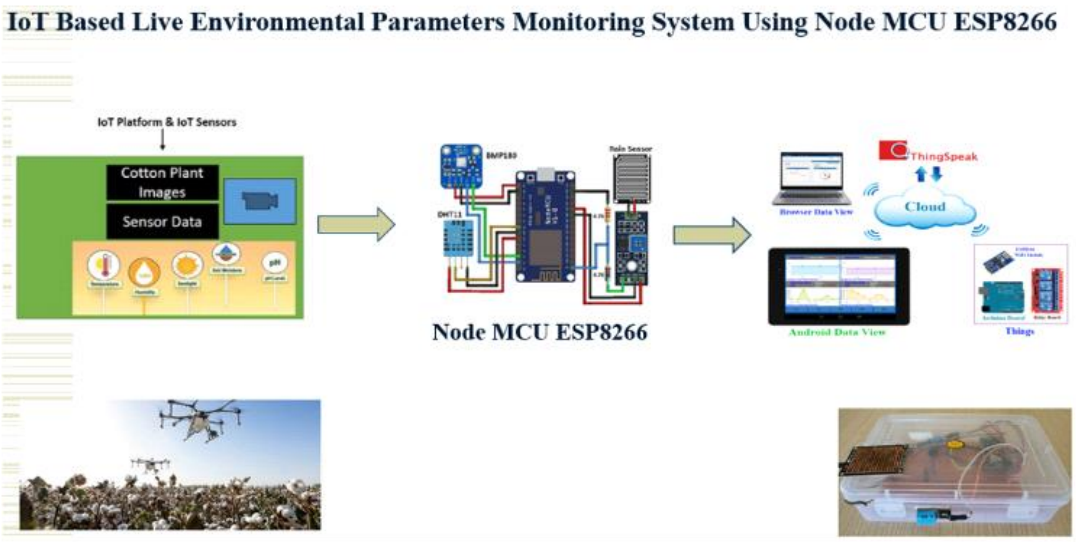


Figure 3. IoT Based Live Environmental Parameters Monitoring System Using Node MCU ESP8266.

We'll record the temperature, humidity, barometric pressure, and rainfall and upload the information to the cloud. So that we create "Krishimitra" Channel on ThingSpeak, to Monitor field sensor data and act on it immediately. Analyze, Process and store data from different environmental sensors on ThingSpeak Cloud. The below **Figure 4** shows IoT Based Circuit for collection of cotton field sensor parameters as,

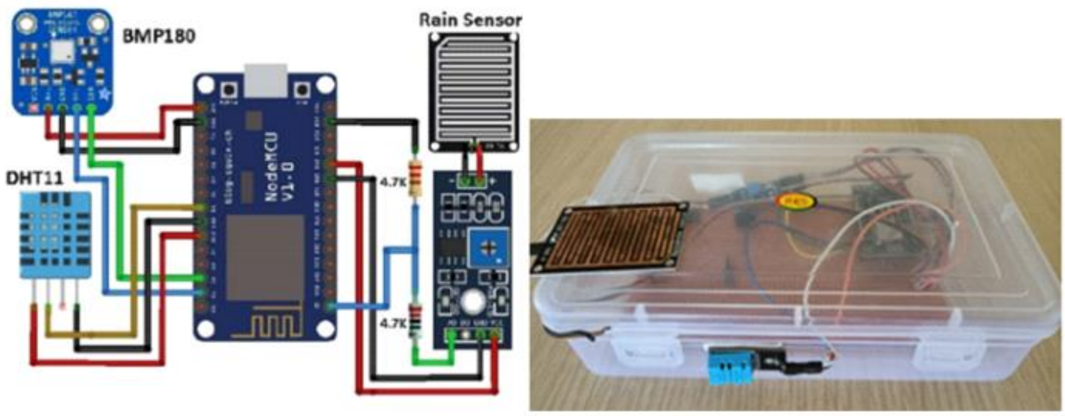
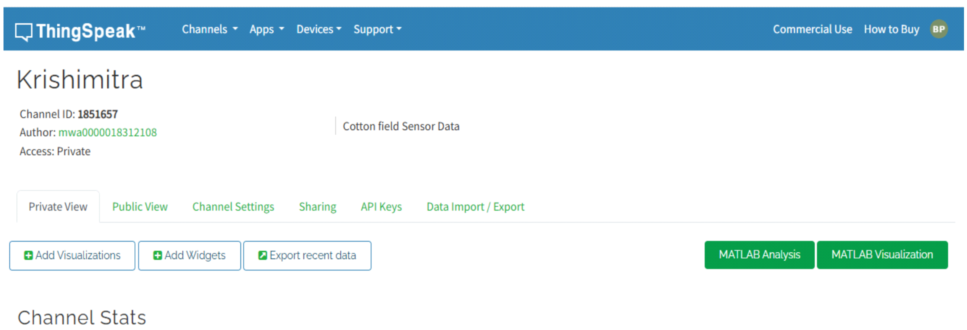


Figure 4. IoT Based Circuit for collection of cotton field sensor parameters.



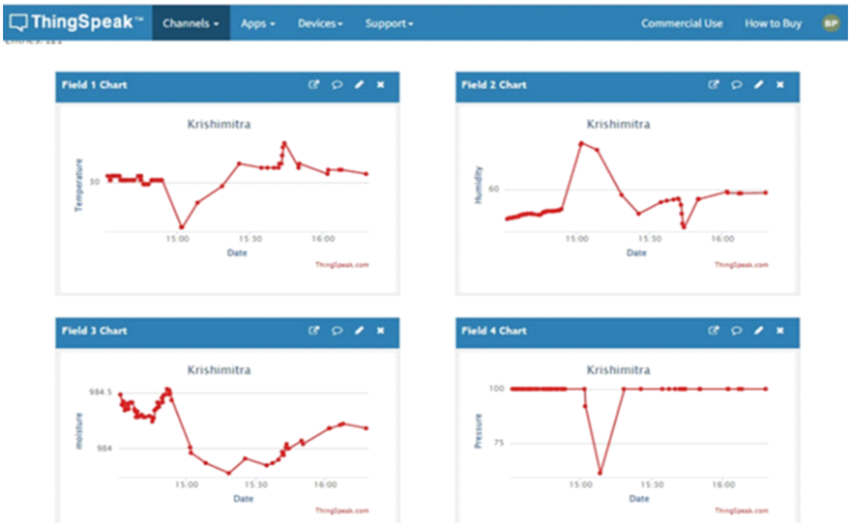


Figure 5. Krishi Mitra Channel on ThinkSpeak Open Access Cloud.

Table 2. Overview of Literature in terms of Methods and Features overview of Literature in terms of Methods and Features.

Sr. No.	Author [Citation]	Dataset Used	Adopted Methodology	Features	Challenges
1	Parul Sharma *et al.* [1]	PlantVillage database, field-based dataset, Internet image	Convolutional neural network (CNN)	High accuracy (>93%) was obtained with very noisy images	Required more disease coverage
2	Adhao and Pawar [2]	Images are Captured using digital camera	Support Vector Machine (SVM)	Cost-effective and independent	Lower overall accuracy for disease detection (83.26%) Highly prone to noise
3	Prashar *et al.* [3]	40 infected images capture through digital camera.	KNN and SVM	Accurately localize the disease region	Higher time complexity
4	Alves *et al.* [4]	Live field-based images & Internet image.	deep residual networks	Achieved the highest accuracy higher F1-Score	Lower learning rate
5	Afroze *et al.* [5]	Images of normal and diseased leaves are gathered from the Internet and used in the field.	Local Binary Pattern (LBP) is used to extract the gradient feature and texture of the K-Nearest neighbor classifier.	Reduced computing time and increased classification accuracy	Reduced specificity and sensitivity

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6	Nerkar and Talbar [6]	Images are Captured using digital camera	bio-inspired ML-based classification algorithm	Improved classification accuracy Increases the performance of system based on disease localization.	Higher computational complexity in terms of cost and time
7	Patki *et al*. [7]	103 infected images capture through digital camera	Multi SVM (Multi Support Vector Machine) classifier	Higher detection accuracy	Higher average recognition time
8	Bhong *et al*. [8]	images capture through digital camera	K-means technique for clustering	straightforward and precise	The identification procedure has a slower recognition rate.
9	Dubey et al. [9]	images capture through digital camera	Support Vector Machine (SVM)	Higher classification accuracy	Higher testing time
10	Bodhe et al. [10]	images capture through digital camera	Rule Based System	Higher detection and diagnosis Higher accuracy in classification	Very time-consuming and expensive
11	Jenifa et al. [11]	600 images capture through digital camera	Deep Convolution Neural Network	Improved classification rate	Highly prone to noise Higher misclassification
12	Jenifa et al. [12]	Real time images capture by camera	Multi-Support Vector Machine	less prone to over fits	suffers from multiple local minima
13	Dong et al. [13]	Own database formed for 5 diseases.	CBR and fuzzy logic	get a high success percentage for diagnostics	Inadequate database size and manual selection reduce the effectiveness of the diagnosis.
14	Kumari et al. [14]	plant village data base	K-means clustering and ANN	Improved average classification accuracy (92.5 %.)	Samples are misclassified
15	Sarangdhar and Pawar [15]	Images capture through Nikon digital camera	Support Vector Machine	Higher overall classification accuracy	Highly prone to noise

The Internet of Things (IoT) is a network of physical objects or objects with embedded software, sensors, or other technology. Sharing data and information through a connection or gadget on the

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internet is beneficial. The agricultural sector is attempting to adopt the technology for its application due to the rapid growth in IoT usage. IoT have the potential to boost and improve agriculture by looking at many farming-related parameters.

The following are the main obstacles to cotton farming:

- climatic circumstances;
- improper use of fertilizers and insecticides;
- pest and disease attacks;
- Minimal revenue for small-scale farmers
- Low cost because of problems with quality
- Increased labor costs
- Depletion of soil

IoT Plays Major role for Cotton Farming

1: To research the important function that IoT plays in cotton cultivation:

IoT is utilized in agriculture for a variety of tasks, including planting, harvesting, processing, and consumer delivery. The use of IoT in agriculture should be viewed as the best option for monitoring and controlling. An agriculturalist's ability to make decisions is aided by the analysis of remote data.

2: To explore how different parameters affect growth of cotton: [44]

Rainfall: Expect a modest amount, between 50 and 75 cm. Early growth of the cotton plant requires sufficient moisture, but after flowering it needs a bright, dry climate. Rainfall is not necessary during the early stages of germination, but it may reduce output if it occurs later. Rainfall can seriously harm crops, especially during the harvest season. Sowing at the appropriate period is therefore advised. In India, it is sown between April and May, and harvested between December and January, just before winter, because the latter can harm the crops.

pH of soil: For best development, In general, cotton requires a deep, productive sandy loam soil with adequate drainage. Problems arise when seeds germinate in sandy or clayey soil. Neither, According to their pH value, soils can be categorized as neutral (6.5 to 7.5), alkaline (above 7.5), acidic (less than 6.5), or extremely acidic (5.5 or below). It is advised to cultivate cotton in soil with a pH of 6.0 to 8.0. The pH of the soil has a significant impact on cotton yield when it rises over 8.5 or falls below 5.5.

Moisture of the Soil: Cotton has a wide range of soil moisture requirements because it is a drought-tolerant crop. Because of this, the amount of water needed varies depending on the conditions, from 400 to 800 mm. A high soil moisture content increases fruit shedding because the earth's oxygen content is reduced. Moreover, a decrease in soil moisture causes the leaves to mature and shed more leaves. The **Table 3** shows soil type and their moisture level as below,

Table 3. Moisture Level.

Soil Type	Soil Moisture Level
Fine (Clay)	Below 60%
Medium (Black & loamy)	Below 70%
Coarse (Sandy)	Below 80%

Temperature of the Soil: The germination of seeds is greatly influenced by soil temperature. Early germination can be achieved with a higher soil temperature, but cotton's growth stages are ruined. Similar to that, if the soil temperature is kept low, it may take longer for the plant to emerge. As a result, the soil temperature must be kept above 64°F (18°C) during the germination period. The ideal temperature range for cotton is between 21°C and 30°C. Cotton balls ripen and burst more

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quickly in the sunshine when the daytime temperature in October is over 26 degrees Celsius. The plant must also grow for at least 200 frost-free days in order to develop. 21°C to 37°C is the ideal soil temperature for cotton.

Air Humidity: Cotton's color and quality are mostly impacted by humidity. As is well known, bacteria thrive in humid environments, which can cause cotton fiber to deteriorate and becoming discolored. Moreover, it may intensify pest and disease attacks. Thus, the air's relative humidity must be lower than 70%.

Light Intensity: High light intensity is necessary for cotton to grow well at all stages, according to research on light intensity. Sugars are produced by high levels of sunshine and aid in the growth of foliage and bolls. Low light levels, on the other hand, may retard the growth of bolls and ultimately produce low-quality fruit.

The below Table 4 summarizes cotton plant diseases with different environmental parameters as,

Table 4. Cotton plant Diseases with different environmental Parameter [69].

Temperature	Humidity	Soil Moisture	Rail fall	Symptoms	Disease type
24^{0}-28^{0} C	High	80-90%	YES	Yellow to brown colored cotyledon leaves turn brown and drop off	Fussarium wilt
35^{0}-43^{0} C	High	50-60%	YES	Sudden and complete wilting of the plant	Root rot
29^{0}-33^{0} C	High	80-90%	YES	Small reddish-colored spots and cotyledons. Water soaked small	Boll spotting
25^{0}-30^{0} C	Very high	60-70%	25.4 to 76.2 mm	Angular leaf spots on leaf on steam and leaf-lesions on young leaves	Angular leaf spots
Temperature	**Humidity**	**Soil Moisture**	**Rail fall**	**Symptoms**	**Disease type**
10^{0}-30^{0} C	Very high	80-90%	YES	Brown rounded or irregular spots on leaf cracked centres cause canker on steam	Alternaria leaf spot
25^{0}-30^{0} C	Very high	60-70%	YES	Irregular translucent spots on leaf- leaves become yellowish brown and finally fall off	Bacterial blight
35^{0}-43^{0} C	High	50-60%	NO	Purple dark brown or blakish borders and white centers	Cercospora

Classification using the Ensemble Learning Model

The proposed Stacking ensemble Learning Model for categorizing diseases in cotton plant leaves utilizes several components, including Popular Pre-train model such as Inception V3, ResNet50, and

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VGG16. Each of these models has a unique design that captures various aspects of the input data, providing a diverse range of predictions. When an image is input into each model, they generate predictions regarding the probabilities of the image belonging to different classes in our task. These predictions reflect the confidence of each model in the image's classification.

Result And Performance Analysis

The CNN model's performance on a dataset encompassing 100 epochs, along with the accuracy and loss analysis conducted for the proposed CNN model, yielded the findings depicted in below **Table 5** and overall classification performance in **Table 6** shows the proposed ensemble model and existing model.

Table 5. Result and Performance of Own CNN Model.

Parameters	Proposed Own CNN model
Training Accuracy	**0.92**
Training Loss	**0.209**
Testing Accuracy	**0.95**
Testing Loss	**0.132**
Training Time	**29s 466ms/step**
Testing Time	**29s 467ms/step**
Epoch	**100**

Table 6. Overall classification performance in the proposed ensemble model and existing model.

Performance (%)	VGG 16	ResNet 50	Inception V3	Proposed (Stack ensemble)
Accuracy	0.9844	0.9881	0.9930	**0.9966**
Precision	0.9380	0.9525	0.9728	**0.9866**
F1-score	0.9382	0.9527	0.9726	**0.9869**
MCC	0.9290	0.9457	0.9683	**0.9849**
Specificity	0.9911	0.9932	0.9960	**0.99811**
Sensitivity	0.9380	0.9529	0.9723	**0.9871**
RMSE	0.0704	0.060	0.0453	**0.0346**
MSE	0.0049	0.0036	0.0020	**0.0422**
MAE	0.1889	0.1373	0.0766	**0.0422**
PPV	0.9380	0.9525	0.9728	**0.98662**
NPV	0.9911	0.9932	0.9960	**0.99810**
FPR	0.0088	0.0067	0.0039	**0.99818**
FNR	0.0614	0.0470	0.0276	**0.01280**

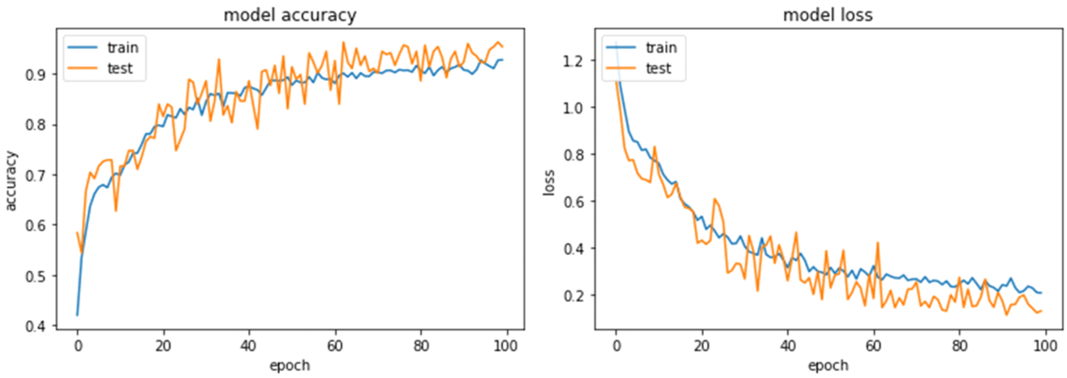

Figure 6. Result of Own CNN Model in terms of Accuracy and loss.

Conclusion

It is crucial for cotton growers to be aware of the illnesses that affect the crop, the organisms that cause them, when the diseases are most likely to strike, and how to combat them using integrated disease management strategies that include cultural, biological, and environmental approaches. Convolutional neural network and IoT based detection techniques have been developed in our proposed model and have been utilized extensively in cotton crop production loss reduction efforts in recent years due to crop disease outbreaks. CNN is the most dependable tool for diagnosing and forecasting cotton plant diseases. For a number of diseases, we use field-based images that must be assessed in order to identify the contaminated area and identify the type of disease present in the target area. A Stacking Ensemble model is introduced for cotton plant leaf disease classification, our focus should be on showcasing the various automated systems that have the potential to transform our daily lives, since technology is advancing at an exponential rate and reducing the need for human labor through the use of automated devices to execute certain tasks. Cotton illness is predicted by our suggested method with a good degree of accuracy. Our next task is creating an intuitive application that offers solutions for the farmers. Enhancing the capabilities of the robot or automated car that is used to diagnose plants. This research proposes a novel method that combines IoT, deep learning, Hybrid Meta Model for Cotton disease detection Using IoT based platform and Ensemble learning Approach.

Availability of data and materials: Real time dataset data collection from cotton field.

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