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An Artificial Intelligence and IoT Based Approach for the Pink Bollworm detection in Cotton Crop

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Abstract: The Internet of Things (IoT) is transforming agriculture by providing farmers with a range of innovative techniques to overcome field challenges, such as sustainable agriculture and precision farming. Agriculture is the foundation of Pakistan's economy and cotton has substantial contribution to GDP of state, the pest presents a significant threat to cotton, resulting in high costs and crop losses each year. Although pesticides are an effective method for controlling insect pests, they are costly, and farmers often use conventional pest detection methods to monitor fields and apply pesticides without knowledge of the required amount. To enhance agricultural productivity through technology, it is crucial to investigate a novel technique for detecting pests that can reduce costs and minimize pesticide use. This study is proposed to develop a sensor-based embedded system (SBES) that employs Artificial Intelligence (AI) based algorithms to detect pest damage on cotton due to pest attack. The SBES is utilized to collect data of various cotton boll parameters, and the suggested approach will detect the gases released, variation in temperature and humidity level in closed environment from cotton bolls. The classification models applied are Gaussian Naïve Bayes and Random Forest. Both of these resulted in high accuracy, whereas random forest outperformed in testing and prediction of damaged cotton bolls.

Keywords: Sensor-based embedded system (SBES); Cotton bolls; Pest attack; Gaussian naïve bayes; Random forest classifier.

1. Introduction

Cotton is the most significant crop worldwide for creating natural fiber, with commercial growth in approximately 111 nations, and is commonly known as "White Gold" or "King of Fibers" [1]. Of the 1326 species of insect pests that target cotton worldwide, roughly 130 different pest species have been reported to consume cotton at various stages of crop growth [2]. To preserve the benefits of cotton and reduce the need for excessive pesticide use, an improved pest attack measurement system is essential for accurately detecting and managing pests. This system would lead to pesticide application only in fields where pests exceed damage limits. However, obtaining necessary information for informed decision-making is a significant challenge in pest control. Current pest monitoring methods for cotton require field sampling to identify pest damage [2].

To cause bug infestation in cotton fields worldwide, a lack of consideration for control methods, the existence of pest-attack-prone types, a lack of crop rotation techniques, uneven fertilization, the improper use of pesticides, and other factors are primarily responsible. This approach may result in the uncontrolled presence of insects and pests in the field. Traditional methods, including mechanical, chemical, and biological controls, employ various tactics to keep pest densities below their natural enemies in the neighborhood. However, despite their ability to manage the pests, misapplication of these techniques frequently leads to unintended consequences [3].

Some agricultural techniques are labor-intensive, burdensome, and expensive, while others may only be effective on a limited scale. Consequently, recent studies in precision agriculture are exploring alternative methods that take a less direct and forceful approach to identifying crop damage. Remotely sensed data offers a promising solution to crop management because it allows for direct, non-contact, and continuous monitoring of pests and diseases across large areas. Based on the remote sensing concept, targets such as soil, plants, and water reflect and transmit electromagnetic radiation at specific wavelengths, which vary depending on their chemical composition, physical properties, and surface characteristics [4].

Singh [5] investigated the potential application of near-infrared hyperspectral (100–1600 nm) images generated through linear discriminant evaluation and quadratic discriminant assessment to detect insect-damaged wheat seeds. The methodologies employed by Singh successfully identified 100% of healthy and insect-damaged wheat seeds. Similarly, hyperspectral (400-720 nm) images were utilized to detect exterior insect damage in jujube fruits and utilized progressive regression techniques to process the images. The classification of Wang's method achieved a total accuracy of approximately 97% [6].

To safeguard cotton crops from the threat of insect overpopulation, comprehending the life cycle of pests is crucial. For example, the cotton bollworm undergoes a four-stage life cycle that is relatively fast. Female moths lay eggs, which can hatch within three days in favorable conditions. After hatching, the larvae enter their destructive stage, where they can cause harm to the crops. Then, they enter the pupal stage, which lasts for 10-15 days (about 2 weeks), during which the cocoon develops, and they are typically buried 4-10 cm (about 3.94 in) below the soil. Finally, the cocoon opens, and a new adult moth emerges, starting the reproduction cycle again. By understanding this cycle, farmers can take preventive measures to protect their crops before the pests cause significant harm [7].

Using pest traps, such as pheromone, light, sticky, and other varieties [8], enables quantification of the problem, shifting the focus from identifying the pest or damage to estimating its abundance. There are two available methods for predicting pest incidence: i) physical models [11], and ii) data-driven models that use in-situ measurements and distant sensing [8, 12]. It is worth noting that most relevant research relies on meteorological data, with distant Earth observations rarely used to document changes caused by pests and favorable planting conditions for their existence [12]. Recurrent Neural Networks (RNN) [21, 22] have been employed to analyze time-series of meteorological data, preserving the cyclic pattern of pest prevalence and compensating for secular characteristics [13]. In other words, when predicting pest incidence at a particular time, it is important to consider the weather and vegetation status from the preceding days [14].

The study extensively utilizes conventional machine learning, particularly regression analysis. In [15], the authors perform multivariate regression studies and observe a significant correlation between the populations of cotton bollworms and temperature. Likewise, [16] emphasizes the importance of wind speed, temperature, and solar radiation. Furthermore, they employ relative temperature and humidity in [17] for classifying the detection of pest presence.

2. Literature Review

Ramos and co-authors [9] developed a theoretical methodology to simulate the spectral response of cotton plants to armyworm infestations. They collected hyperspectral radiance data over an eight-day period using both healthy and damaged cotton plants and a portable spectroradiometer with a range of 350-2500 nm. Several algorithms were compared using a ranking technique to determine the most useful wavelengths for identifying damage.

Ahmad and colleagues [2] applied several machine learning models to predict plant infestation by cotton leafworm using a dataset collected over two years from a hydroponic greenhouse. The study recorded two parameters: relative humidity and temperature. The XGB algorithm was found to have the highest accuracy of 84%. To determine correlations between environmental variables and the prevalence of cotton pests, author Qingxin [10] used the popular Apriori technique. They defined the issue of predicting pest and disease appearance as a time series prediction and created an LSTM-based approach to address it. According to their association study, the probability of cotton pest attack is high in environments with moderate humidity, temperature, rainfall, and wind speed in winter. This research was later used to accurately predict the prevalence of pests and diseases in cotton fields, producing an accuracy of 0.97 with LSTM.

Puig et al. [11] proposed a methodology for the management of pest damage to cotton crops that consisted of machine learning practices and an unnamed aerial system. The system used a UAV equipped with a high-quality camera to follow predefined flight patterns over the cotton field. The damage was visualized and monitored using image processing, and an automatic machine learning-based algorithm was deployed to cluster the images. This study opened doors for automated damage detection, crop protection, and pest quantification. Hu et al. [12] proposed a novel approach for quantifying the severity levels of cotton aphid infestations using a spectral index reconstruction methodology. They defined a severity scale to measure the disease level due to cotton aphids and achieved a performance of OA=0.94.

Alves [13] introduced a new method to classify primary and secondary cotton pests by utilizing deep residual networks. RGB images of cotton fields were used to create an image dataset, and a residual network was developed to classify the pests. The highest accuracy of 0.98 using ResNet34* was achieved. Nanushi et al. [14] presented a machine learning classifier to predict bollworms in cotton fields, using vegetation indices, insect traps, and weather prediction data. The results showed the effectiveness of the proposed study. Pattnaik et al. [15] employed texture features and machine learning algorithms such as decision tree, support vector machine, and K-nearest neighbor to classify tomato pests. The highest accuracy of 81% was achieved using the SVM algorithm with local binary pattern.

Kasinathan et al. [16] used shape features and machine learning algorithms including artificial neural network, convolutional neural network, k-nearest neighbor, support vector machine, and naïve bayes to identify different categories of insects. The CNN model achieved the best performance with a highest classification rate of 91%. Gomes et al. [9] proposed a machine learning approach for detecting fall armyworm attack on cotton plants using the spectral response calculated with a spectroradiometer. Orbital sensors were utilized to detect the damage, and the proposed methodology achieved high accuracy.

Garcia et al. [17] utilized hyperspectral data and machine learning algorithms to detect insect damage in maize and predict the type of insect. The random forest algorithm achieved the highest accuracy of 96% in detecting the insect type. Pechuho et al. [17] introduced a machine learning algorithm with the TensorFlow python library to detect disease in cotton crops and recommend suitable pesticides, aiming to assist farmers in achieving high yields at a low cost. Zhang et al. [18] presented a remote sensing technique for monitoring plant diseases and detecting pests using various sensors and machine learning and regression-based methods. The study demonstrated the detection of unknown pests and diseases through statistical analysis of multiple features extracted from the remote sensing dataset.

The Internet and sensors play a major role in providing a solution to a wide range of everyday issues in IoT. Smart agriculture, smart cities, smart buildings, smart environments, and smart transportation are a few examples of these uses [19]. By eliminating human interaction through automation [24], IoT [23] may make farming and agricultural industry operations more effective [20].

3. Materials and Methods

The field of technology and research are known as smart embedded systems uses smart computers, sensors, microcontrollers (Arduino, esp32, raspberry pi), computer-based programs, and apps to perform tasks that normally require human intelligence. This study is based on applying an IoT-based architecture and performance evaluation to determine the intended concept. It is a conceptual description of dataset abstraction and algorithm. The capability for computers to effectively predict the forthcoming based on preceding learning has just shown momentous development for to the rapid increase in computer processing power and storage. Nevertheless, the notion that a computer may learn a theoretical notion from data and then apply it to as-yet-unknown scenarios is not new and has at least been around since the 1950s [1].

Our goal is to utilize a microprocessor and sensor nodes to categorize pests present in a field, allowing for the detection of all pests in cotton bolls and the implementation of specific actions to prevent crop damage through AI. Early identification of pests is crucial for reducing the need for pesticides and improving production, especially for large crops where traditional monitoring methods are ineffective. Recent advancements in AI can significantly enhance dependability and productivity. Our primary focus is to select the optimal pest detection strategy, with particular emphasis on the most dangerous pests affecting cotton bolls. To design and evaluate AI models, we have created a dataset comprising a substantial number of both healthy and infected cotton bolls. Early detection of pests using proposed methodology can help to prevent significant losses.

The objective was to develop an affordable and easily accessible sensor-based embedded system that uses an AI algorithm to identify pest damage in cotton bolls. This system aims to efficiently detect damaged bolls, replacing the current time-consuming manual process of hand-counting bolls and insects. By identifying the optimal parameter compositions for detecting damaged cotton, our sensor arrangement requires less training and reduces the total sampling duration. Consultants and growers can utilize this system to make quick in-field decisions.

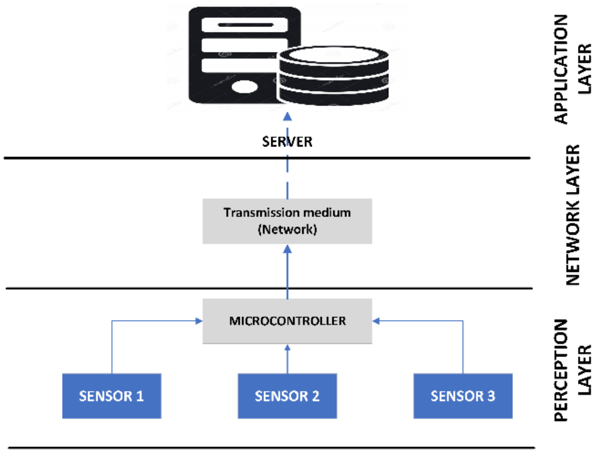

Figure 1. Layered architecture of proposed SBES.

The proposed SBES consists of three layers: perception, network, and application layers as shown in Figure. 1. The current focus was on developing this system and compiling it accordingly. The necessary sensors were connected to a microcontroller, such as Arduino, esp32, NodeMCU, using a high-level programming language C. Once configured, the microcontroller transmits the data to the network using communication network as transmission medium, which sends it on application layer, i.e., server for future use and permanent storage. The AI model utilizes the saved data as input.

3.1. Dataset

Data generated by the perception layer is configured and stored in the database (e.g., cloud) by the microcontroller. A sample image of the data head is shown in Figure 2-3. It consists of humidity, temperature, and gases. These parameters are labeled according to their values as 0 represents "healthy" and 1 represents "unhealthy or damaged" cotton bolls. A significant difference can be seen in these parameters for both conditions. The total number of entries is 1623.

The compatibility of the algorithm with the implemented hardware is determined by validation of results. Monitoring parameters in different environments (e.g., a box with healthy cotton bolls and a box with unhealthy cotton bolls) can help improve the results, and we can test the SBES for this purpose.

	humidity	temperature	gases	label
0	99	34	80	1
1	99	34	80	1
2	99	34	69	1
3	99	34	65	1
4	99	34	73	1

Figure 2. Dataset Head

	humidity	temperature	gases	label
1619	99	33	317	0
1620	99	33	321	0
1621	99	33	319	0
1622	99	33	320	0
1623	99	33	321	0

Figure 3. Dataset Tail

The methodology is presented in Figure 4. for pest attack detection using SBES data. Major steps include pre-processing, feature extraction, AI model training, and pest attack detection. To avoid overfitting and apply the artificial intelligence algorithm, we use the best subset of attributes from SBES input data. The algorithm determines whether cotton bolls are damaged or undamaged. To train the model, we provide the corresponding SBES data and labels, which will affect the output.

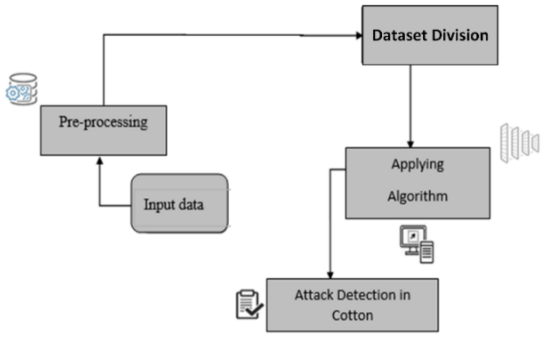

Figure 4. Pest attack prediction using AI

3.2. Pre-processing

For the pre-processing of this data, Label Encoder is applied to transform humidity, temperature, and gases values using Panda's data frame. Label Encoder converted these categorical values into numerical values. This method made data to fit the machine learning model and analyze in various aspects. The bar graph is shown in Figure 5-7, which is plotted using Seaborn library on data frame. The blue color combination, which classifies data into two specified classes dark blue representing unhealthy whereas light blue is for healthy cotton bolls. Bar graph is used to show data in graphical representation. This graph is used to make the dataset more informative and visualized.

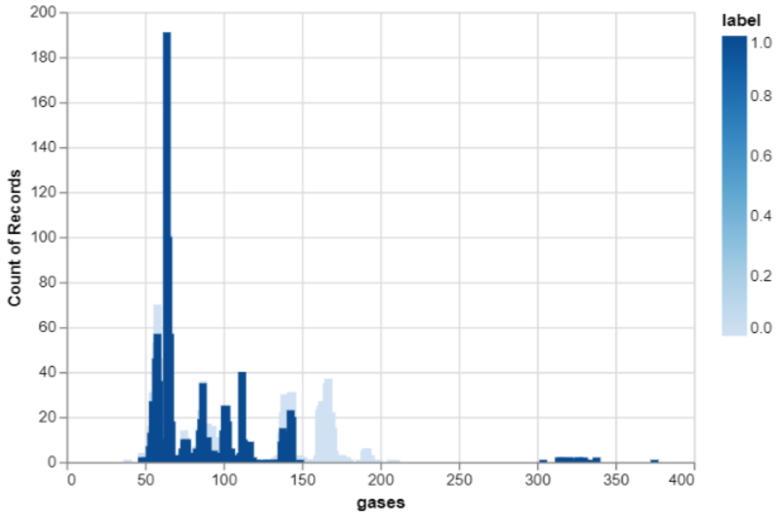

Figure 5. Bar graph representation of independent features.

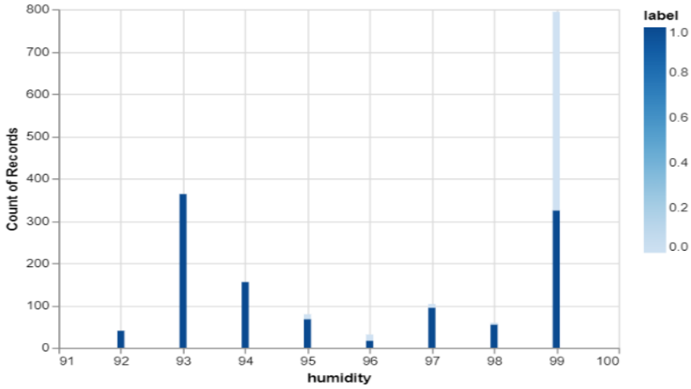

Figure 6. Bar graph representation of independent features

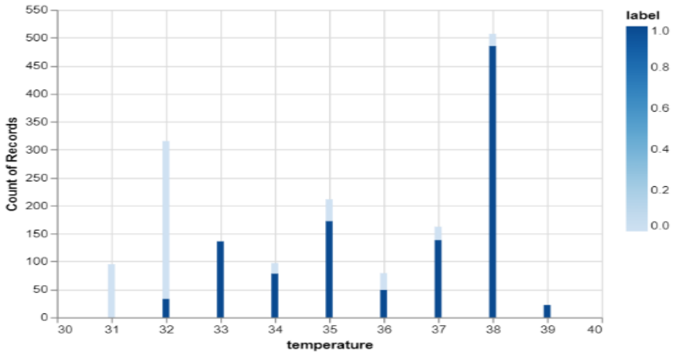

Figure 7. Bar graph representation of independent features

3.3. Dataset Division

The dataset is divided into training and testing with 80% and 20% ratio respectively as shown in Figure 8. The accuracy of training data is essential for the categorization process, enabling machine learning models to effectively identify and categorize similar items in the future. Conversely, inaccurate data can negatively affect model outcomes, leading to the failure of artificial intelligence projects. To mitigate the impact of data inconsistencies, it is crucial to use the same dataset for both training and testing. This approach improves the understanding of the model's properties. After the model is trained, the test set is used to generate predictions. In summary, the accuracy and consistency of data used for training and testing are critical to the success of machine learning projects.

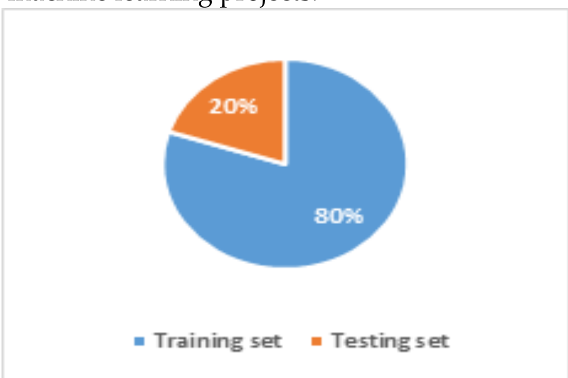

Figure 8. Dataset division

3.4. Machine Learning Algorithms

Two machine learning classification algorithms namely Gaussian naïve bayes and random forest are applied for classification and prediction. Naive Bayes classifiers rely on the Bayes Theorem and assume strong independence between features, as illustrated in Figure 9. This means that each feature's value is considered independent of the values of other features. Due to their simplicity and broad applicability to real-world situations, Naive Bayes classifiers are widely used in supervised learning scenarios. Gaussian Naive Bayes is a variant of Naive Bayes that assumes continuous variables follow a Gaussian normal distribution and can handle complete data. It distributes the actual values for each category according to a normal distribution.

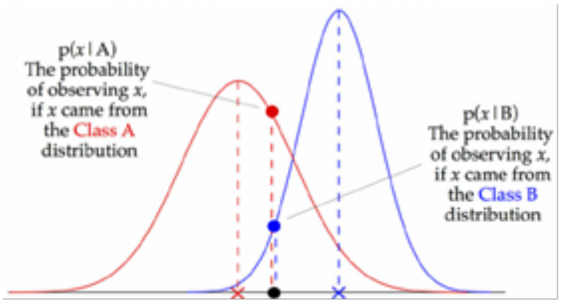

Figure 9. Gaussian naïve bayes algorithm working principal illustration

Suppose D is the training dataset with "a" datapoints.

$$a = a1,\ a2,\ a3, \ldots., an \tag{1}$$

Each datapoint belongs to kth class, the goal of this algorithm is to predict class label b based on new datapoint value a by following equation:

$$P\left(bi \mid a\right) = \frac{P(a \mid bi) * P(bi)}{P(a)} \tag{2}$$

Random Forest is a machine learning method that employs multiple decision trees, which are constructed using random subsets of the dataset and limited features, to make predictions. By combining the predictions of all trees, it achieves superior accuracy, avoids overfitting, and handles high-dimensional datasets. This algorithm is applied for classification task. The strength of Random Forest stems from its collective decision-making by uncorrelated models (trees) as shown in Figure 10, which leads to better performance compared to individual models.

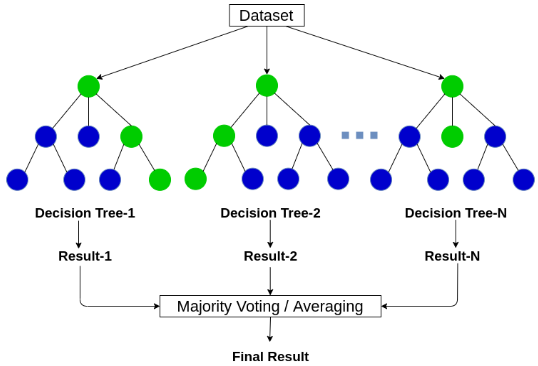

Figure 10. Random forest classification algorithm visualization

Suppose df is dataset frame with n number of samples, each sample a has m features, (a1, a2, a3,…..,am) and associated with one of kth classes (b1,b2,b3,….,bk), here algorithm will create t decision trees (t>1). The jth decision tree is denoted by fj(a) where j=1,2,3,…,t.

Final prediction is based on majority of votes by these trees:

$$f(a) = argmax_i \sum j = 1^t \left[fj(x) = bi\right] \tag{3}$$

And prediction can be calculated as:

f(a)=(1/t) ∑j= 1^t fj(a) (4)

4. Results

The effectiveness and accuracy of the applied methodology is assessed by feeding new data to these algorithms. A comparison of applied models is presented as a bar graph in Figure 11 and accuracy results are shown in Table 1.

Table 1. This is a table. Tables should be placed in the main text near to the first time they are cited.

Model name	Precision	Recall	F1 Score	Accuracy
Gaussian Naïve Bayes	85%	81%	88%	83%
Random Forest	79%	84%	82%	82%

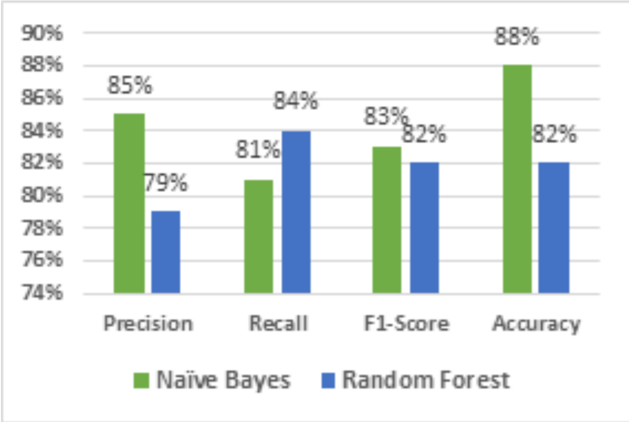

Figure 11. Comparison of evaluation metrices of applied algorithms

The Confusion matrix of naïve bayes and random forest are presented in Figure 12 and Figure 13 respectively. A confusion matrix is a table used to estimate performance of algorithms for classification.

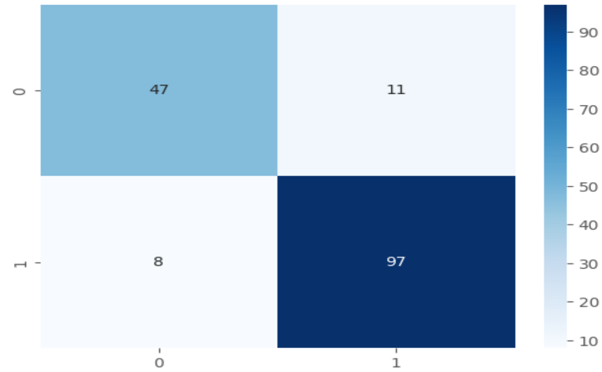

Figure 12. Confusion matrix using Naïve bayes classification algorithm indicating true and predicted labels

And prediction can be calculated as:

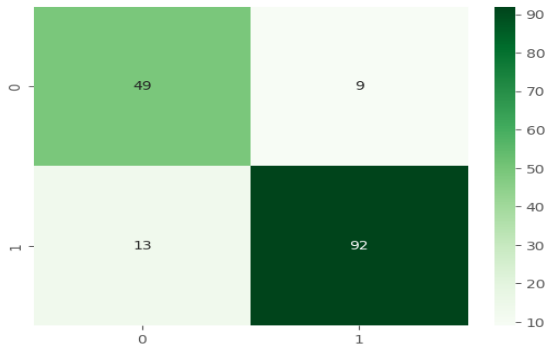

Figure 13. Confusion matrix using Random Forest classification algorithm.

5. Discussion

The proposed methodology effectively implements AI algorithms. We utilized these algorithms to predict the health status of cotton bolls, whether they are healthy or unhealthy, by analyzing sensor data collected from the developed SBES. The independent features considered in this controlled environment were temperature, humidity, and gases. The outcomes of the proposed SBES demonstrated state-of-the-art performance in detecting and classifying damaged cotton bolls. This compelling performance of SBES not only showcases its effectiveness but also paves the way for AI novices to easily apply AI principles to various other domains.

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

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