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RESEARCH ARTICLE

Internet of Things Based Weekly Crop Pest Prediction by Using Deep Neural Network

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ABSTRACT Internet of Things (IoT) assisted application in agriculture shows tremendous success to improve productivity in agriculture. Agriculture is grappling with issues such as depleted soil fertility, climate-related hazards like intensified pest attacks and diseases. Accurate forecasting of pest outbreaks can play a vital role in improving agricultural yield. Utilizing IoT technology for environmental monitoring in crop fields to forecast pest attacks. The important parameters for pest predictions are temperature, humidity, rainfall, wind speed and sunshine duration. Directly sensed environmental conditions are utilized as input to a deep learning model, which makes binary decisions about the presence of pest populations based on the prevailing environmental conditions. The accuracy and precision of the deep learning model in making predictions are assessed through evaluation with test data. Five-year data 2028 to 2022 have been used for making prediction. The model of pest prediction generates weekly predictions. The overall accuracy of the weekly predictions is 94% and high F-measure, Precision, Recall, Cohens kappa, and ROC AUC for making to optimize the prediction. The accuracy of the pest prediction improves gradually with time. Weekly predictions are generated from the means of all environmental conditions from the last seven days. The weekly predictions are important for the short-term measures against pest attacks.

INDEX TERMS Internet of Things (IoT), deep learning model, pest predictions, weekly predictions.

I. INTRODUCTION

Pests are a common problem of agriculture with a severe threat to yield and production [1]. Pests are insects that can cause damage to the crops. Pests have serious damage to crop production and the environment. Pests can also have negative impacts on our lifestyle by direct and indirect means. Many solutions emerge to deal with the issue of pests in the crop. It is always very advantageous to predict the outcome of the attack above the threshold level to take preventive measures. Each pest has a certain threshold level of the population of pests from where it starts damaging the crop. The growth of the pests depends upon certain environmental conditions [2]. Under certain environmental conditions, each pest insect has different growth rates.

Pests' population growth rate depends upon many biotic and abiotic factors. The most important abiotic factors are temperature, humidity, rainfall, windspeed and sunshine hours as shown in Figure 1. These are important factors to determine the growth rate of the Pests and the population of pests. Under favorable conditions, the growth rate would be high, and there would be more population of the pests. The yield of crops is influenced by two kinds of pests. Insects can cause two types of harm to plants. The first is direct, where

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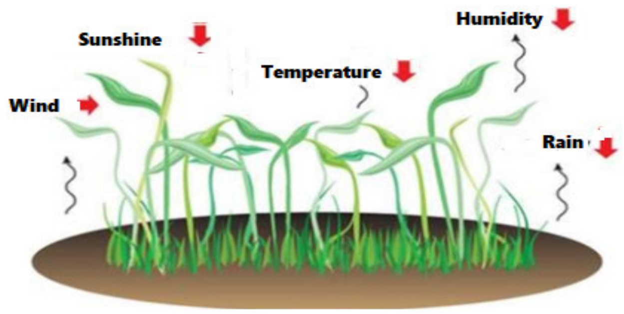

FIGURE 1. Abiotic factor affecting pest population.

they feed on leaves or burrow in stems, fruit, or roots. The second type is indirect, where the insect may not cause significant harm, but transmits bacterial, viral, or fungal infections to the crop. [3].

The population and growth rate of insect pests can be predicted by leveraging environmental conditions, as they are dependent on specific factors that influence their growth and proliferation [4]. The early prediction of insect's pest from the environmental conditions could be very advantageous for the use of inputs like pesticides, fungicides, and many other measures, before the set of attacks [5]. Early warning systems can help the farmers to cope with the issue in a better way. Early predictions of the pest level can help the farmers in choosing the crop, crop rotation policy, application of the inputs, and many others. Apart from the farmers, the government and agencies can actively take their part to impose a regulatory policy for the farmers for their better interest. Climate change poses multiple challenges for the agricultural sector [6], [7]. The current challenges of adverse climatic conditions amplify the risk of transboundary crop diseases, leading to decreased crop production, jeopardizing food security, and causing sub0stantial losses for farmers [8]. Along with a reduction in fertility, shortage of irrigation water, and many other issues, the pest is the major factor in reducing crop production. Pest attacks on certain crops have seriously damaged the production level in many crops. Cotton is the prime example in this case. The production of cotton in Pakistan has declined [9] as shown in Figure 2 to a large extent due to uncontrolled pest attacks. Cotton production has reduced. due to heavy attack of pest [10]. Figure 2 reflects the problem statement, and it shows that the production of cotton decreased year by year due to pest attack. Many other crops also suffered due to pest attacks.

The whitefly (Bemisia tabaci) as shown in Figure 3 is a common agriculture pest inhabitant of temperate regions. Whitefly causes significant losses to the farmers by sucking the plant nutrients, development of sooty molds on the plant surface, and carrier of the Cotton Leaf Curl Virus (CLCV). It can host many plants.

The population is increasing rapidly in the world, with 7.7 billion (2019) people [11]. With its large population, Pakistan ranks as the fifth most populous country globally. More population demands more resources like food. Using outdated and conventional farming methods can hinder meeting the basic needs of humans, such as food, due to increased labor requirements and lower efficiency, but the risks of less productivity of crops are still there.

The one reason for less productivity of crops is the heavy attack of insect pests, which may sometimes have a large influence on the country's socio-economic [12], [13]. Climate change has a great influence on crop production with a heavy attack on pests [6]. Therefore, continuous prediction of insect pests may result in better crop growth.

IoT is a stimulating discipline with successful applications in many areas of life. Smart cities, smart homes [14], and smart traffic management [15] are the core areas of the IoT applications. The IoT has shown tremendous success in many areas of life [16]. The IoT has also shown tremendous applications in agriculture for monitoring and control purposes [7]. IoT has ability to get the context and to adjust services according to the context has enabled to provide many successful applications to address the many issues in agriculture [17]. IoT has the capability to capture the environmental conditions and to make early predictions regarding inputs [18]. Due to the ability of the IoT for monitoring applications make it an ideal technology in agriculture to make predictions regarding input applications, yield predictions, soil predictions, and environment hazard detections [19]. IoT can play a key role in the capture of direct crop field environment conditions [20] for the prediction of whitefly pests according to the microenvironment conditions of the crop field.

Climate change is a global challenge that leads to many severe effects on crop production. The attack of insect pest without any prediction and control measure result into loss to the farmers due to severe impact of insect pest on crop productions [21]. Moreover, pest prediction cannot be achieved without environmental parameters may lead to the failure in achievements in required objectives. The objective is to propose a model IoT and deep learning based to address the problem of pest early prediction by using environmental parameters to effectively achieve the objective of pest early prediction. To evaluate and validate the proposed model with real time environmental parameters to check the effectiveness and efficiency.

A. CONTRIBUTION OF THE STUDY

The study proposed a model that identifies the important environmental parameters that are considered for the development rate of a pest and proposed pest prediction on the environmental conditions. The unique feature of the study is that the model is flexible to be applied to any pest prediction on any crop. The study puts forward a pest prediction model that is based on the direct sensing of environmental conditions. The proposed model stands out due to its distinctiveness in considering multiple parameters during predictions and its utilization of directly sensed environmental conditions.

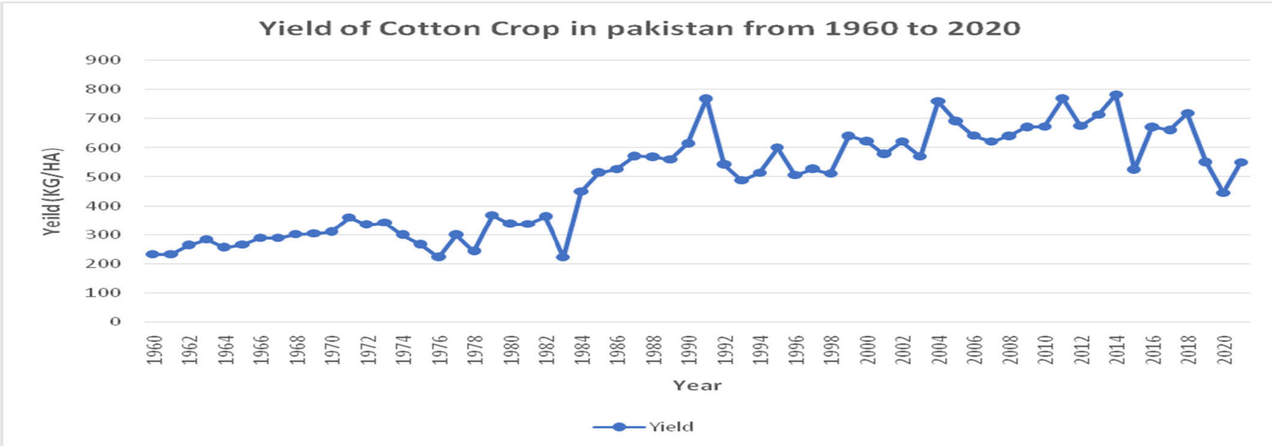

FIGURE 2. Cotton production in pakistan.

FIGURE 3. Whitefly on cotton.

II. RELATED WORK

Marković et al. [22] proposed pest prediction by temperature and humidity. The proposed solution also compared the performance of the model. According to the study the neural network-based accuracy is best in prediction of pest attack. Latif et al. [23] A suggested method for predicting pest infestations in rice crops involves utilizing the Internet of Things (IoT) in combination with a Feedforward Neural Network. Nanushi et al. [24] proposed a pest (bollworm) prediction for cotton crop using meteo-climatic and vegetation conditions. Tamoghna Ojha et al. [25] elaborated on the potential of IoT for agriculture applications to address agricultural issues. The authors proposed a framework for the solution of agricultural challenges. The authors also focused on energy optimization in this framework. Christopher Brewster et al. [26] explored the opportunities, challenges, and prospectus of IoT in agriculture applications. The authors also focused on environmental issues and effects on food. The use of IOT technologies is a successful domain in agricultural issues. Uddin et al. [27] suggested IoT assisted Decision Support System (DSS) for the farmers. The authors proposed a new dynamic clustering and data gathering with IoT technique in the agriculture sector.

Srbinovska et al. [28] proposed a vegetable greenhouse environment monitoring system for smooth control of the environmental conditions. The authors have used low cast wireless sensor technique to monitor the humidity, illumination, and temperature parameters. Changqing et al. [29] proposed a greenhouse environment monitoring solution for continuous provisions of environment conditions desired for the crop. The authors have used layered technologies to monitor the environmental parameters. Talavera et al. [30] suggested IoT architecture for IoT assisted monitoring and control of agriculture applications. The authors studied the peer review of 10 years from 2006-2016. IOT has great influence in agriculture fields. Ramos-Fernández et al. [31] proposed temperature and humidity monitoring systems in a protected environment by using fuzzy logic algorithm and observing the Vapor Pressure Deficit (VPD).

Ojha et al. [32] proposed real-time sensed data using the IoT for different applications to effectively manage different operations in agriculture. IoT can play significant contributions from sowing to harvest to support farmers' decisions. Soto-Silva et al. [33] proposed a model of supply chain management for fresh horticulture products. The proposed solution seeks to minimize spoilage by effectively managing environmental conditions and closely monitoring them to ensure optimal conditions for storage and transportation of perishable goods. Shi et al. [34] presented different prospects of IoT applications for protected agriculture. Popovic et al. [35] suggested IoT assisted ecological monitoring system. Ecological monitoring is very important to support sustainable developments in agriculture with minimum impacts on environments. ecological monitoring is the observation of environmental monitoring for lengthy time.

Ahmed et al. [36] proposed a smart farm solution for monitoring of crop from remote areas. Remote monitoring is very important for agriculture applications. Many solutions in agriculture demands for remote monitoring. The proposed solution addresses the issue of latency in the network for IoT devices in remote monitoring of the environment. Ramachandran et al. [37] recommends IoT assisted monitoring of the environmental conditions for the optimal amount of irrigation recommendations according to the directly sensed environment conditions. Bertha Mazon-Olivo et al. [38] proposed a solution for automatic actuator decisions by directly real-time sensed data from the environmental conditions. Ray Mulenga et al. proposed IoT enabled crop environment monitoring to recommend irrigation water based on directly sensed data [39].

Goa et al. [40] shows the concerned about disease detection through spectrum analysis technology which is based on Unmanned Aerial Vehicles (UAVs). The suggested solution is deployed in the field of wheat for recognition of disease attack. Dai et al. [41] shows the new (YOLOv5) deep learning technique for pest detection. The authors have achieved high precision and robustness for identifying the pest.

In table 1 the emphasis in previous studies was primarily on detecting insect pests rather than predicting their occurrence. Previous studies placed greater emphasis on pest prediction using image processing techniques. Prediction purposes in previous studies did not incorporate intelligent decision-making.

In table 1 outlines previous studies that have examined the techniques/sensors and objectives of pest monitoring and prediction systems. Through a comprehensive literature review, it is evident that IoT technology has been extensively utilized to monitor weather and environmental conditions in crop fields. Based on the directly sensed parameters, different decisions are proposed like irrigation management, growth detection, yield predictions, site-specific inputs applications. Pest attacks are a serious problem that needs attention in this regard. Many images processing-based pest detections solutions are proposed, and some solution environment based are proposed with limited environmental parameters. Early prediction of the pest population can be very useful for pest management strategies. A significant correlation exists between the population of pests and weather conditions. The prevailing weather-based conditions are help full in the determination of the insect pest population. No solution emerged up to the knowledge that ascertains the pest population based on the prevailing weather conditions of the crop field.

III. METHODOLOGY

This section represents the architecture and design of the proposed solution and Deep learning algorithm for whitefly insect pest prediction.

A. ARCHITECTURE OF PEST PREDICTION APPROACH

The proposed model for predicting pest infestations is built on an architecture that includes environmental conditions, an IoT server, sensors, a gateway, and an application. The proposed architecture helps to manage the context of each sensor by separate concern. The different sensors (temperature, humidity, rainfall, sunshine and windspeed) are responsible for sensing important climate conditions directly from the field. The internal field environment is different from the area environment. It's better to use field sensors to get accurate environmental data. The gateway is used to transfer data from the sensors to the IOT server. The IOT server manages the data at the server. The heart of the proposed architecture lies in the use of a deep neural network for predicting pests, which is where the data processing takes place. The results of the predictions are stored and transferred to the end-user through the application. The detail of the architecture in Figure 4 represents that five sensors temperature, humidity, sunshine, wind speed and rainfall in the mean while Arduino have been also used in the field and get sensed data from the field to the IOT server. The sensed data have been applied on Deep Neural Network algorithm to get the prediction of pest attack which is shown at android application. The farmers get alert through an android application.

Figure 4 illustrates how the IoT is utilized to capture environmental conditions directly from the crop field, which are then used to train the DL model and make predictions about future pest infestations. The data from the sensors is sent to the server application to be processed for making predictions. The deep learning model relies on directly sensed environmental conditions to make precise predictions. Along with environmental conditions the field observation for pest population is also carried out to validate the predictions and for training the deep learning model. Once the model is trained, the directly sensed environmental conditions are input to the DL model for prediction.

B. PROPOSED PEST PREDICTION MODEL

The proposed pest prediction model is shown in figure 5. The proposed model is based on IoT assisted environment monitoring. The directly sensed environmental conditions are processed to determine the mean weekly environmental conditions. These conditions are used to train the deep learning algorithm. The deep learning algorithm is evaluated for its accuracy against the test data set. The prediction made by the proposed model are also compared against the field observations. The model is improved with time to improve the performance of the model.

C. DNN FOR PREDICTION OF WHITEFLY PEST

The Deep Learning model is shown in Figure 6. It stat by acquiring the initial data set from the expert opinions. To evaluate the performance of deep learning, the original dataset is divided into two sets: the training set, which is utilized to train the model, and the test set, which is utilized to compare the predicted and actual outcomes. The loss function is also determined from the test data set. The cost function is determined from the complete dataset. The effectiveness of deep learning is evaluated on various criteria, such as precision, recall, and f-measure. The predictions of deep learning for the input data are also evaluated against the field.

Observations. If any problem arises, the result is incorporated into the deep learning model, which is then retrained, resulting in an improved model. This cycle of retraining

TABLE 1. Related to sate of the art prediction methods.

Publish Year	Sensor used/Approaches	Goal
[5] 2018	No Sensor/Combination of Artificial Neural Network and Genetic Algorithm	Predict the Insect Pest of Fruit Trees
[42] 2018	No Sensor/Linear Regression and Natural Spline Algorithm	Prediction for corn crop
[43] 2018	Temperature, Humidity, Co2 Concentration, light intensity/Regression analysis Machine Learning Algorithm	IoT based Strawberry Disease Prediction
[19] 2018	Temperature and Humidity/ Classification and regression algorithm machine learning	Prediction of Frost Events
[44] 2019	Air temperature, air humidity, and soil moisture /Machine learning	Prediction of Disease before first occurrence Potatoes and Tomatoes
[45] 2017	Proposed Model of pest prediction	Pest and disease predictions
[46] 2014	Photoelectric Sensor	WSN based snail pest detection to reduce the pesticide usage
[47] 2016	Acoustics	Palm Tree Pest Detection
[48] 2014	Weather base Disease prediction	WSN assisted weather base disease prediction
[40]2020	UAV and Image processing-based disease detection/ Vision and Weather sensors	To detect disease in wheat crop
2022[24]	Machine learning can be employed to predict the presence of pests.	To detect bollworm pest in cotton pest
2022[23]	Utilizing IoT and a Feedforward Neural Network can facilitate the prediction of pests in rice crops.	To predict the pest in rice crop with environmental conditions
2021[22]	The forecast of pest emergence can be achieved through the implementation of sensors and machine learning techniques.	Pest detection using Machine Learning
2022 [2]	Only three parameter used temperature, humidity, and rainfall	Predict the stem borer using machine learning with low 83% accuracy.

continues to enhance the performance of the deep learning model, as illustrated in Figure 6.

The Deep Neural Network (DNN) is utilized to predict pest infestations based on environmental conditions. Deep Neural Network is applied due to the following reasons.

- It has a high performance for binary predictions.
- The Deep Neural Network (DNN) achieves its peak performance when the input variables are correlated with each other.
- High Accuracy with the large data set.
- Reliable for large data processing.
- High accuracy with complex problems.

The Economic Threshold Level (ETL) of the pest population is utilized to make predictions for the given problem. The output of the proposed model involves making binary decisions about whether the pest population is above or below the Economic Threshold Level (ETL). The input of the model is the crop, pest type, maximum temperature, minimum temperature, maximum humidity, win speed, rainfall, and sunshine duration. All these inputs are independent of each other. Apart from these conditions, the Deep Neural Network (DNN) could process large data sets and shows more accuracy with a large data set. For the problem on hand, sufficient data is selected to achieve a reasonable accuracy in pest prediction. Moreover, each year observations would add up the more data set and more accuracy of the model. The mathematical form of deep neural network is represented in Equation 1. Y is output prediction, x is input environmental parameters, w is weight for calculation at hidden layer and b is constant value as shown in Equation 1.

The Deep Neural Network operates in layers and consists of one input layer, multiple hidden layers, and one output layer. At input layer it takes input parameters which is sensed data that is gathered from the field. The 2nd layer is a hidden layer which is called a processing layer to train and predict pest attack according to data. Lat output layer is used to get output as a prediction of pest attack in binary form. The first layer is input represented as xi and 2nd is multiple layer which is called hidden layer represented as wi and the last layer is output layer represents as y as output as shown in Figure 7.

The DNN algorithm is written in python language with keras library. The input variables are environmental

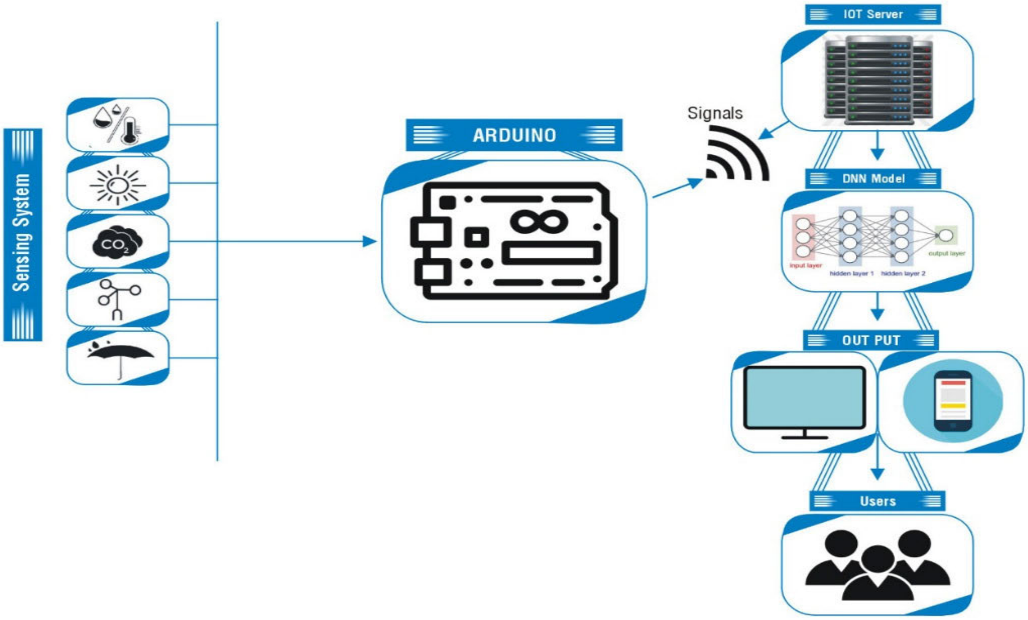

FIGURE 4. Architecture of the Insect pest prediction model.

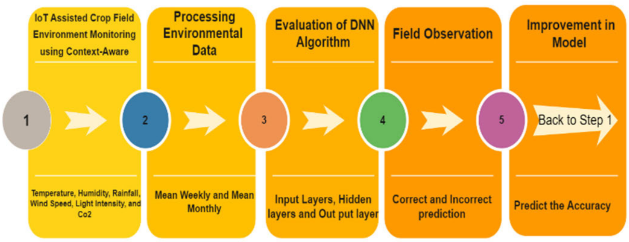

FIGURE 5. Deep learning model of pest prediction.

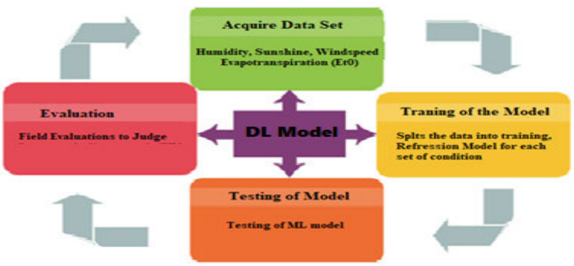

FIGURE 6. Deep learning model of pest prediction.

parameters (temperature, Humidity, Rain, Wind speed and Sunshine) and the target output variable is pest population prediction.

$$Y = \sum_{i}^{n} x_i * w_i + b \tag{1}$$

Calculate the linear and non-linear/activation function of the first hidden layer.

$$y_1^{[1]} = w_{11}x_1 + w_{12}x_2 + w_{13}x_3 + \ldots + w_{1n}x_n + b_1^{[1]} \tag{2}$$

$$a_1^{[1]} = ReLu(y_1^{[1]}) \tag{3}$$

$$y_2^{[1]} = w_{21}x_1 + w_{22}x_2 + w_{23}x_3 + \ldots + w_{2n}x_n + b_2^{[1]} \tag{4}$$

$$a_2^{[1]} = ReLu(y_2^{[1]}) \tag{5}$$

$$y_n^{[1]} = w_{n1}x_1 + w_{n2}x_2 + w_{n3}x_3 + \ldots + w_{nn}x_n + b_n^{[1]} \tag{6}$$

$$a_n^{[1]} = ReLu(y_n^{[1]}) \tag{7}$$

linear function can be written in matrix form.

$$\begin{bmatrix} \mathrm{w}_{11} & \mathrm{w}_{12} & \mathrm{w}_{13} & \cdots & \mathrm{w}_{1n} \\ \mathrm{w}_{21} & \mathrm{w}_{22} & \mathrm{w}_{23} & \cdots & \mathrm{w}_{2n} \\ \mathrm{w}_{31} & \mathrm{w}_{32} & \mathrm{w}_{33} & \cdots & \mathrm{w}_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathrm{w}_{n1} & \mathrm{w}_{n2} & \mathrm{w}_{n3} & \cdots & \mathrm{w}_{nn} \end{bmatrix} \begin{bmatrix} \mathrm{x}_1 \\ \mathrm{x}_2 \\ \mathrm{x}_3 \\ \vdots \\ \mathrm{x}_n \end{bmatrix} + \begin{bmatrix} \mathrm{b}_1 \\ \mathrm{b}_2 \\ \mathrm{b}_3 \\ \vdots \\ \mathrm{b}_n \end{bmatrix} = \begin{bmatrix} \mathrm{y}_1^{[1]} \\ \mathrm{y}_2^{[1]} \\ \mathrm{y}_3^{[1]} \\ \vdots \\ \mathrm{y}_n^{[1]} \end{bmatrix} = \mathrm{Y}^{[1]} \tag{8}$$

Non-linear or activation function can be written as

$$A^{[1]} = \begin{bmatrix} a_1^{[1]} \\ a_2^{[1]} \\ a_3^{[1]} \\ \vdots \\ a_n^{[1]} \end{bmatrix} = \begin{bmatrix} ReLu(y_1^{[1]}) \\ ReLu(y_2^{[1]}) \\ ReLu(y_3^{[1]}) \\ \vdots \\ ReLu(y_n^{[1]}) \end{bmatrix} \tag{9}$$

$$A^{[1]} = ReLu(Y^{[1]}) \tag{10}$$

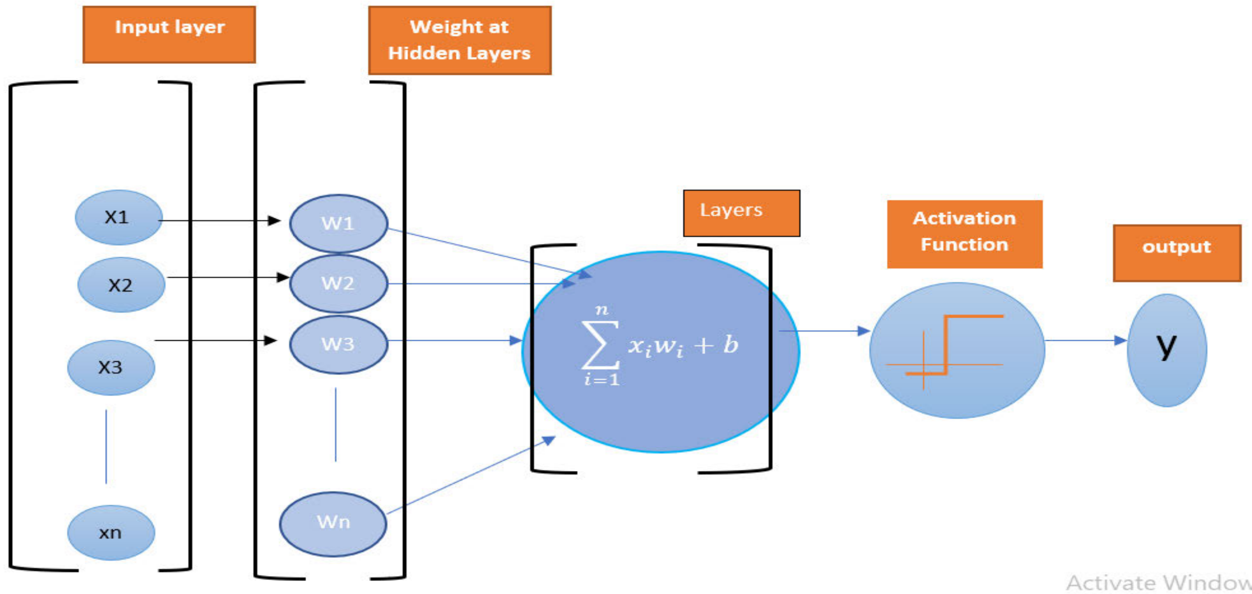

FIGURE 7. Deep neural network.

The general form of linear and nonlinear/Activation function at any layer is given below.

$$Y^{[layer]} = W^{[layer]} * A^{[layer-1]} + b^{[layer]} \tag{11}$$

$$A^{[layer]} = ReLu(Y^{[layer]}) \tag{12}$$

Equation 2 to 12 is computation process to convert into generalized form of DNN. The Deep Neural Network (DNN) is composed of six layers, comprising one input layer, four hidden layers, and one output layer. ReLu serves as the activation function.

IV. IMPLEMENTATION

The implementation section describes the sensors, hardware, and software developed for the implementation of the proposed model of pest predictions. Initially, an introduction is given about eh sensors and nodes used for the implementation purpose. Then the hardware prototypes are described with their purpose and deployment in the field. The server application to capture, store, and for prediction purposes are also elaborated in this section. The software, libraries, and tools used for the purpose are also described in this section.

A. SENSORS AND HARDWARE

DHT-22 Sensor for Humidity and temperature, Anemometer for windspeed, LM393 Light Sensor to record the sunshine duration, Rain Sensor and Arduino UNO have been used for sensing environmental data.

B. PROTOTYPE AND DEVELOPMENT

The prototypes are developed using modern sensing technologies. The Arduino platform is used for the development of hardware prototype. Figure 8 shows the complete hardware prototype with different sensors and the Arduino board.

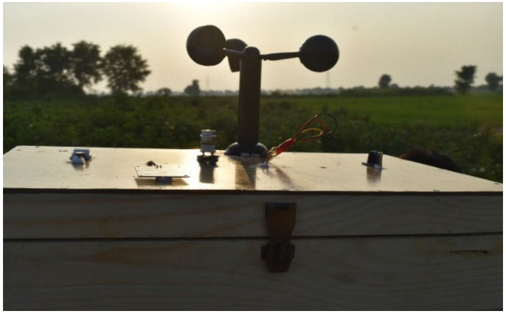

FIGURE 8. Hardware prototype in the field.

FIGURE 9. Implementation of the prototype in the field.

The main sensor is wind speed, rain, temperature, humidity, and light sensor for sunshine observation.

Figure 9 shows the field snapshot. Data is processed and stored at the IOT server. The mobile application accesses the data from the server to intimate the user about conditions of pest attack in the field.

V. RESULTS AND DISCUSSION

Temperature is an important parameter on which the population of the pest is heavily dependent. Many pest-like hot conditions, with a temperature near 40 C or above 40 C. Temperature is captured using the DHT-22 sensor from the selected area. The temperature is given in degree centigrade scale. The data from the year 2018 to the year 2022 is observed and stored. Temperature is monitored between February and November, which coincides with the cotton crop season and the whitefly attack period. Temperature data from the year 2018 to the year 2022 is observed. The daily maximum and minimum temperature of the selected area is observed, stored to predict the pest population accordingly. The daily maximum and minimum temperature of the selected area is shown in Figure 10 and Figure 11. It is observed that April to September are hot months and from October to March are relatively cooler months with the lowest values of temperature.

In Figure 10, the daily maximum temperature of each year is shown with a different color. Temperature tends to increase from April and maximum in May, June, July, in August. The months are favorable for the whitefly life cycle. In Figure 11, the daily minimum temperature is shown that also shows a similar pattern with May, June, July, and August with higher values of daily minimum temperature. This is the duration of the growth of the cotton crop, with the high temperature in the field that favors the development of the whitefly populations.

In the next section, the mean temperature on a weekly basis is given to make predictions based on temperature. The Mean weekly maximum and mean weekly minimum temperature is obtained by Equation 13 and Equation 14.

$$Mean\ weekly\ Temp = \frac{\sum(daily\ max.\ temp)}{7} \tag{13}$$

$$Mean\ weekly\ Min\ Temp = \frac{\sum(daily\ min.\ temp)}{7} \tag{14}$$

Humidity refers to the proportion of moisture present in the air, relative to its maximum capacity at a given temperature. High humidity in the air with hot conditions favors the high growth rate of the pest, especially the whitefly. Humidity is an important parameter on which the population of the pest is also dependent. The humidity is given in relative percentage. The data from the year 2018 to the year 2022 is observed and stored. The humidity is measured from February to November, which corresponds to the cotton crop season and the whitefly infestation period. Humidity data from the year 2018 to the year 2022 is observed. The daily maximum humidity of the selected area is observed, stored to predict the pest population accordingly. The daily maximum humidity of the selected area is shown in Figure 12. It is observed that April to September are hot months and from October to March are relatively cooler months with the lowest values of temperatures. Humidity is low in April, May, and June as compared to other months. The humidity level is high in July and August. Mean weekly humidity are obtained from the daily maximum level of humidity data by using Equation 15. The mean weekly humidity are used in making weekly humidity.

$$Mean\ weekly\ Humidity = \frac{\sum(daily\ Humidity)}{7} \tag{15}$$

High Windspeed with hot and humid conditions favors the high growth rate of the pest, especially the whitefly. Windspeed is an important parameter on which the population of the pest is also dependent. Windspeed is observed in kilometer per hour (Km/h). The data from the year 2018 to the year 2022 is observed and stored using a reliable wind speed sensor. The period for which wind speed is measured is from February to November, which coincides with the cotton crop season. Windspeed data from the year 2018 to the year 2022 is observed. The daily maximum Windspeed of the selected area is observed, stored to predict the pest population accordingly. The daily maximum wind speed of the selected area is displayed in Figure 13.

Mean weekly wind speed is obtained from the daily maximum level of windspeed data by using Equation 16. The mean weekly windspeed is used in making weekly pest prediction.

$$Mean\ weekly\ Windspeed = \frac{\sum(daily\ Windspeed)}{7} \tag{16}$$

Rainfall duration is an important parameter on which the population of the pest is also dependent. The Rainfall is observed in kilometer millimeters per inch. The data from the year 2018 to the year 2022 is observed and stored using the rainfall detection sensor. The duration of rainfall is measured between February and November, which corresponds to the cotton crop season. Rainfall duration data from the year 2018 to the year 2022 is observed. The daily maximum Rainfall duration of the selected area is observed, stored to predict the pest population accordingly. The daily maximum Rainfall duration of the selected area is shown in Figure 14. It is observed that the rainfall level is high in July and August in selected areas for the experiment. The mean weekly rainfall is obtained by Equation 17. The mean weekly rainfall is important for generating weekly predictions accordingly.

$$Mean\ weekly\ Rain\ fall = \frac{\sum(daily\ Rain\ fall)}{7} \tag{17}$$

Sunshine duration is also an important parameter by which the population of the pest is also dependent. The Sunshine duration is observed in hours. The data from the year 2018 to the year 2022 is observed and stored using a reliable light sensor with processing. The duration of sunshine is measured from February to November, which aligns with the cotton crop season. The daily sunshine duration of the selected area is observed to predict the pest population. The daily sunshine duration of the selected area is shown in Figure 15.

Mean weekly sunshine duration are obtained from the daily maximum level of sunshine duration by using Equation 18. The mean weekly sunshine duration is used in making the weekly prediction of pest attack.

$$Mean\ wkly\ Sunshine = \frac{\sum(daily\ sunshine)}{7} \tag{18}$$

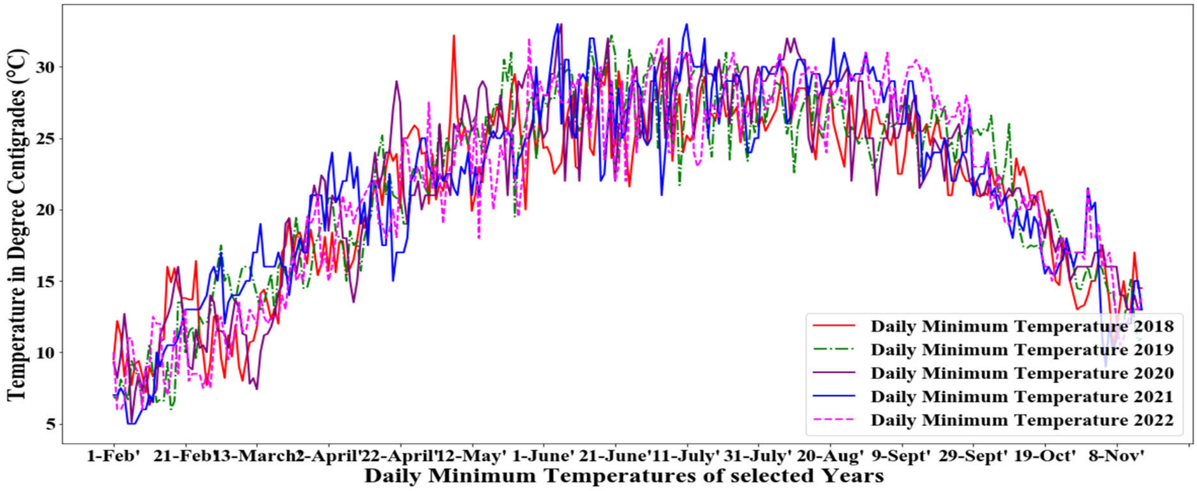

FIGURE 10. Five year data analysis daily minimum temperature.

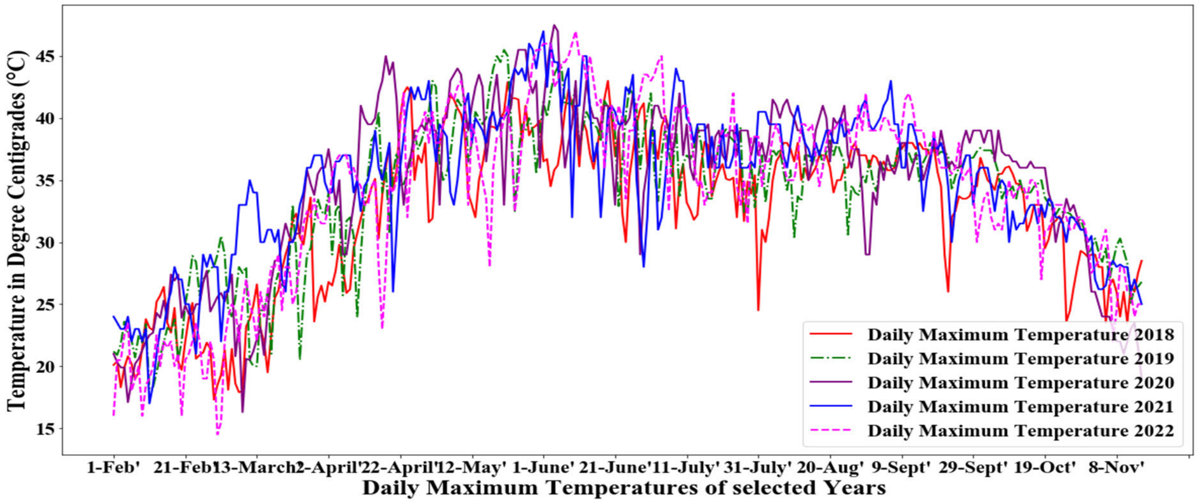

FIGURE 11. Five year data analysis of maximum temperature.

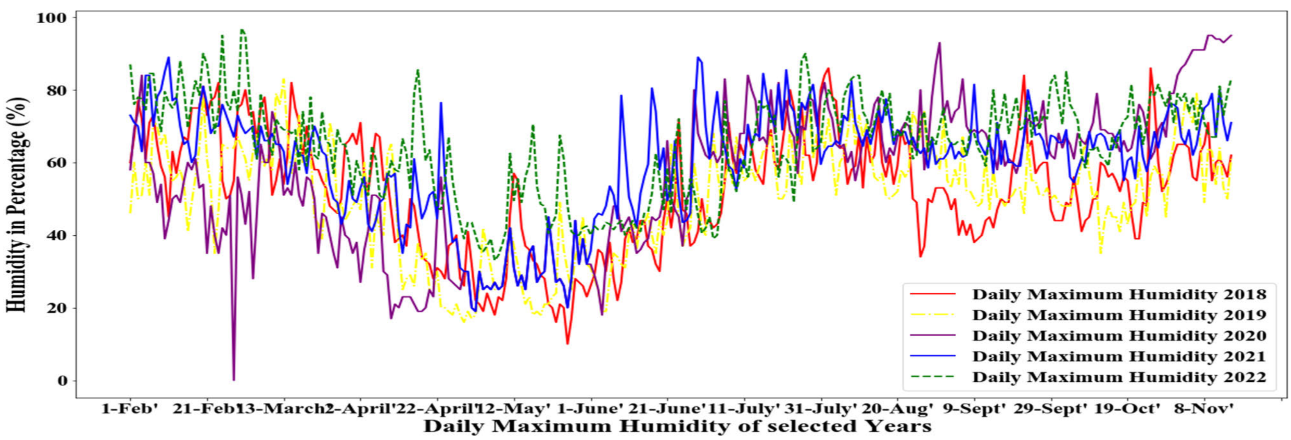

FIGURE 12. Five Years Data Analysis of daily maximum humidity.

A. PERFORMANCE OF DEEP NEURAL NETWORK MODEL

The evaluation of the proposed Deep Neural Network (DNN) model for pest prediction includes measuring its accuracy, precision, and F1-Measure. Precision is calculated by determining the ratio of accurate predictions to the total number of predictions made. [49]. It means precision is based on

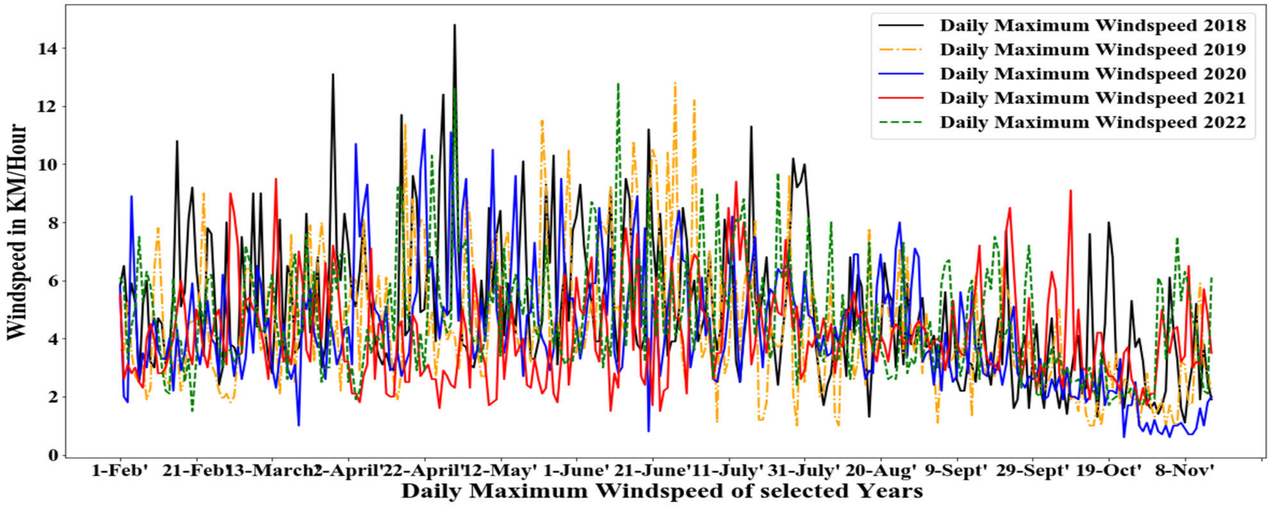

FIGURE 13. Five years data analysis of windspeed daily observations.

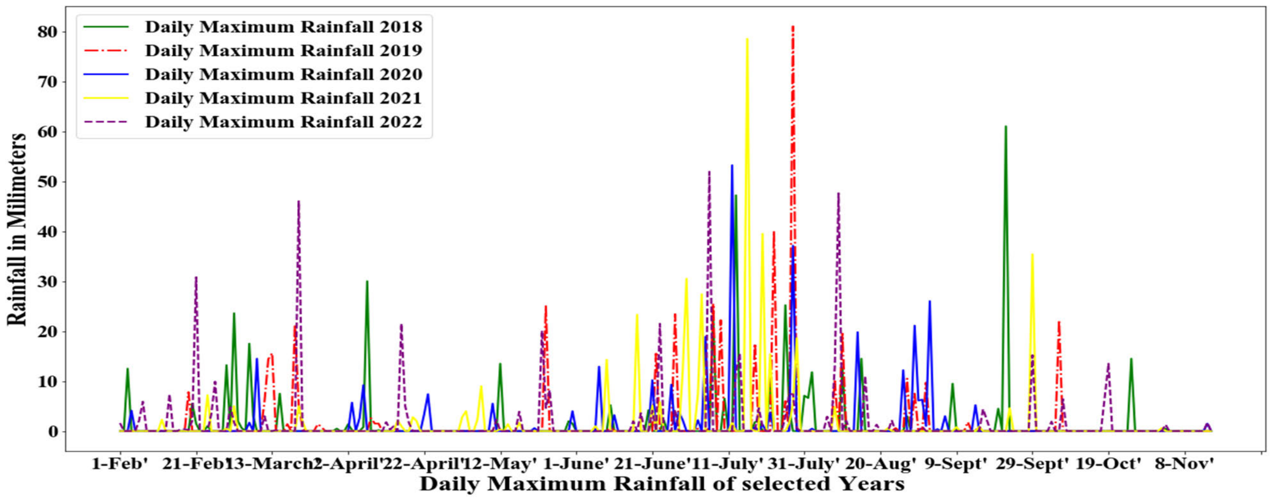

FIGURE 14. Five years data analysis of daily rainfall.

the test data set. The number of correct predictions. Accuracy is the accuracy of all the predictions made. The Deep Learning Model is evaluated using the "Keras" library of python programming language. The performance is evaluated by using Deep Neural Network on five-year data from 2018 to 2022 during the month of February to October. 70 % of captured data is used as trained dataset and 30% is used for test dataset. The performance of the deep learning model is shown in table 2. In table 2 the term Precision, also called "specificity," is the fraction of the true positive by the sum of a truly positive and false positive. It can be said that the true positive is the prediction of the pest population when the population is above the Economic Threshold Level (ETL). Predicting the pest population above the ETL when it is not present in the case of a false negative. Precision is obtained by the ratio of the true positive and sum of the true positive and false positive, as shown in Equation 19 Precision is also called "specificity" or "negative rates."

$$Percision = \frac{True\ Positive(tp)}{(True\ Positive\ (tp) + False\ Positive(fp)} \tag{19}$$

In table 2 the term Recall, also known as "sensitivity," is the ratio of the true positive to the sum of a truly positive and false negative. True positive is the prediction of the pest population when the population is also above the Economic Threshold Level (ETL). When conditions are favorable for pest development and the pest population is above the Economic Threshold Level (ETL), a false-negative prediction occurs if the model incorrectly predicts that the pest population is not above the ETL. Recall values are in the range of 0 to 1. Zero means no true prediction is made, and recall one means all positive predictions are made. The recall is also called "sensitivity" or a positive rate. recall is determined

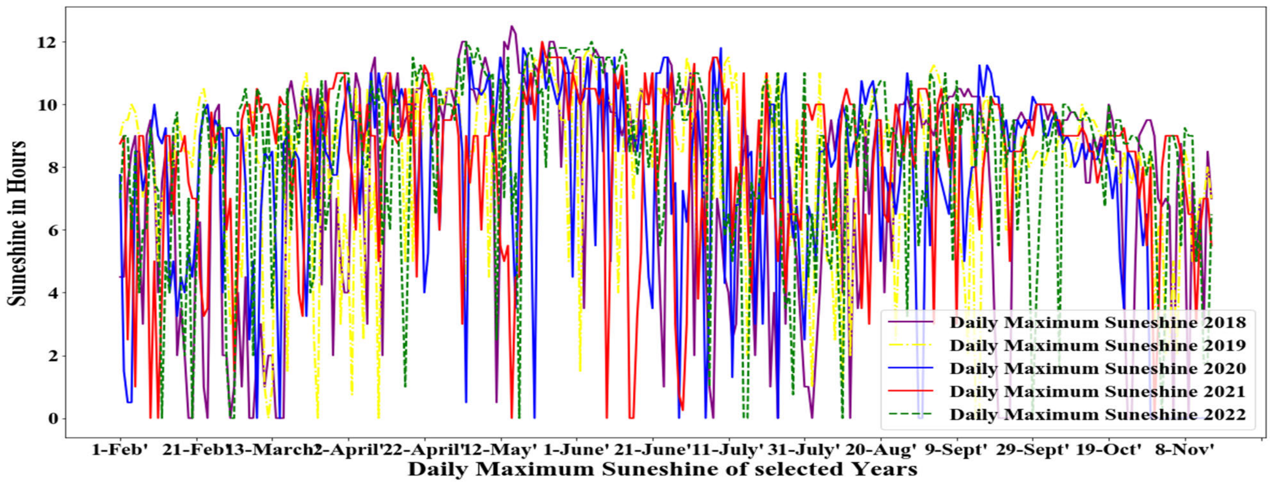

FIGURE 15. Five years data analysis of daily sunshine duration.

TABLE 2. The metrics employed for evaluating the results.

B-Class	F1	Recall	Precision	Support
0.0	0.53	0.38	0.94	27
1.0	0.91	0.97	0.92	83
Macro Avg	0.71	0.68	0.94	111
Weighted Avg	0.81	0.84	0.92	111

by Equation 20.

$$Recall = \frac{True\ Positive(tp)}{True\ Positve\ (tp) + False\ Negative(fn)} \tag{20}$$

Precision and recall are inversely proportional to each other. Sometimes a tradeoff is required to balance these measures. The F1-measure, as given by Equation 21, represents the harmonic mean of precision and recall.

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{21}$$

The accuracy of deep learning performance is determined by dividing the number of correct predictions by the total number of data points in the test dataset. The accuracy of the deep learning model is determined by Equation 22.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ test\ Data\ set} \times 100 \tag{22}$$

Table 3 displays additional relevant model attributes, including Cohen's Kappa, ROC AUC, log loss, and confusion matrix. Cohens Kappa calculates the value based on confusion matrix. Cohen's kappa says little about the expected accuracy of a single prediction. Cohen's kappa says little about the expected accuracy of a single prediction. ROC is used to model the probability distribution of predictive

TABLE 3. Metrics for predictive features measured by Cohen's Kappa, ROC AUC, Log Loss, and confusion matrix.

B-Class	Cohens kappa	ROC AUC	Log Loss	confusion matrix
Binary Class	0.486058	0.942434	0.43	[[10 6] [2 94]]

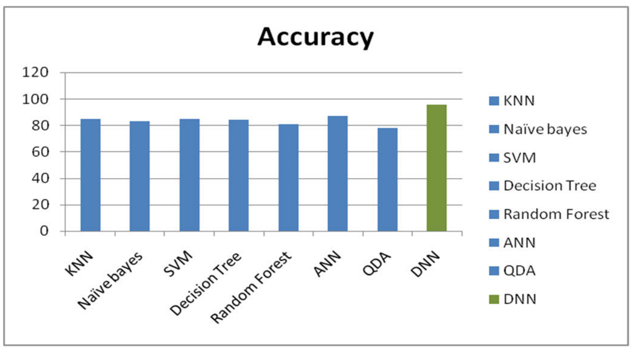

FIGURE 16. Comparison of machine learning algorithms in term of accuracy.

classes. In table 3 the loss function determines what loss has been in the output. Equation 23 is used to calculate the log loss, which measures the difference between the predicted output and the actual output.

$$\mathrm{L.F} = -(\mathrm{y}\log \mathrm{y}^\wedge + (1-\mathrm{y})\log(1-\mathrm{y})^\wedge) \tag{23}$$

B. COMPARISON OF MODEL ACCURACY WITH OTHERS

The study also compared different ML algorithms for their accuracy given in figure 16. According to the study the Deep Neural network model is more accurate in pest prediction as compared to the ML model. The accuracy of the proposed

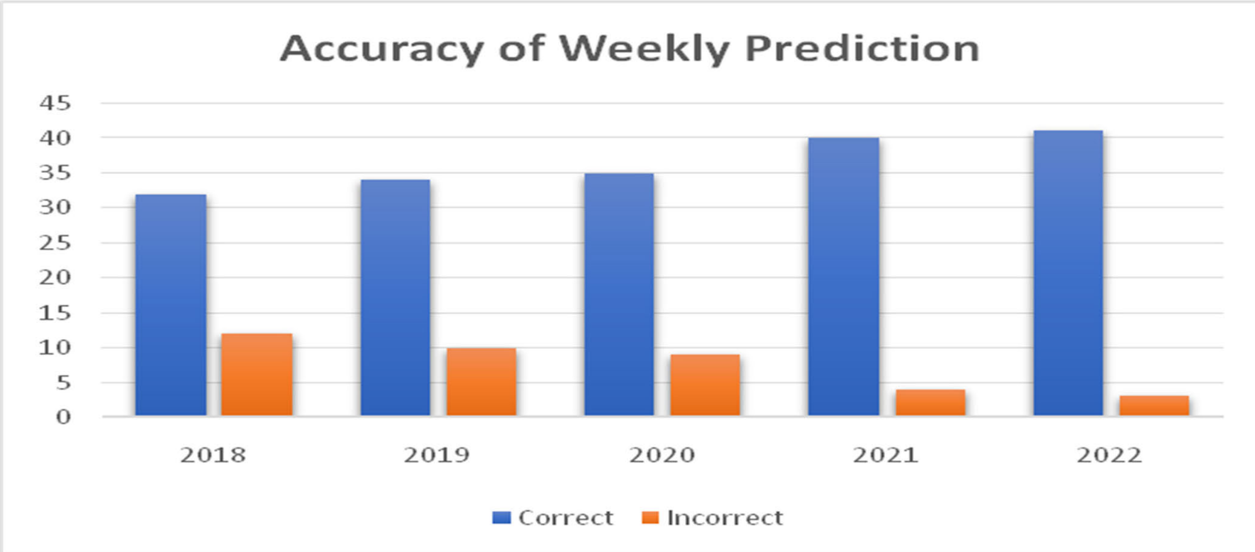

FIGURE 17. Population of whitefly may to nov.

solution with DL model is 94%, more than the existing approach.

C. FIELD EVALUATION OF PROPOSED MODEL

Correct and Incorrect Mean weekly prediction for all year is shown in Figure 17. Figure 17 shows the correct and incorrect weekly prediction in every year. It is observed that the correct predictions ratio increases with time due to better accuracy of Deep Learning. In 2022 only three incorrect predictions are made. In weekly predictions, the accuracy of the prediction gradually improves from 2018 to 2022 is shown in Figure 17. From the data analysis and discussions, the results demonstrate that the IoT and deep learning model accurately predicts the level of pest population.

VI. CONCLUSION

IoT and deep learning model is proposed, modeled, and implemented for pest prediction. The pest prediction model is implemented in the cotton crop for whitefly. Pest predictions are made based on temperature, humidity, sunshine, rainfall, and wind speed. This model which has been sketched is distinctive because it will ease the execution of lot for real-time crop field monitoring [50] as well as utilization of Deep learning abilities on the test dataset to determine the happening of whitefly strike on cotton crop. The execution of the model discloses that is expendable for other crops as well and it is precise to forecast the happening of whitefly pest strikes on whitefly crop. IoT architecture is proposed to assist the pest prediction on directly sensed data. The weekly predictions are generated from the last seven days of environmental conditions. Weekly predictions are useful for short term measures against pest attacks like the use of pesticides. The overall accuracy of the weekly predictions is 94% and high F-measure, Precision, Recall, Cohens kappa, and ROC AUC for making to optimize the prediction. This weekly prediction is based on test dataset. The accuracy of the pest prediction improves gradually with time. The deep learning model is evaluated for the test data set. The hypothesis of the study is that the proposed model of pest prediction can accurately predict the pest population is above or below the threshold level. The future direction regarding pest prediction model is implemented and evaluated in the cotton crop for whitefly. It can be easily extended to other types of pests for a variety of crops. The model of pest prediction needs to be evaluated for other types of pests on different other crops. The inclusion of other factors of pest predictions like the area of host crops available for the pest can significantly improve the accuracy of the pest prediction mode. Different other biotic and abiotic factors can improve the accuracy of the pest prediction model.

VII. LIMITATIONS

The proposed model is based on the abiotic factor only. Many other factors like the number of host plants, area of host plant cultivation, presence of predators, and pesticide usage affect the pest population. The factors are important but out of the scope of the study. Sensor faults may occur during monitoring.

CONFLICT OF INTEREST

None of the authors have conflict of interest related to the research and results presented in this paper.

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