Pest Prediction in Rice using IoT and Feed Forward Neural Network

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Abstract

Rice is a fundamental staple food commodity all around the world. Globally, it is grown over 167 million hectares and occupies almost 1/5th of total cultivated land under cereals. With a total production of 782 million metric tons in 2018. In Pakistan, it is the 2nd largest crop being produced and 3rd largest food commodity after sugarcane and rice. The stem borers a type of pest in rice and other crops, *Scirpophaga incertulas* or the yellow stem borer is very serious pest and a major cause of yield loss, more than 90% damage is recorded in Pakistan on rice crop. Yellow stem borer population of rice could be stimulated with various environmental factors which includes relative humidity, light, and environmental temperature. Focus of this study is to find the environmental factors changes i.e., temperature, relative humidity and rainfall that can lead to cause outbreaks of yellow stem borers. this study helps to find out the hot spots of insect pest in rice field with a control of farmer's palm. Proposed system uses temperature, relative humidity, and rain sensor along with artificial neural network to predict yellow stem borer attack and generate warning to take necessary precautions. result shows 85.6% accuracy and accuracy gradually increased after repeating several training rounds. This system can be good IoT based solution for pest attack prediction which is cost effective and accurate.

Keywords: Internet of things (IoT), Stem Borer Pest Prediction, Artificial Neural Network

1. Introduction

Rice is a species of Oryza sativa, a cereal grain, basic food and commodity of about 4 billion population of world [5, 6]. It is grown on almost 167 million hectares globally [7], and distributed throughout the world from Amur river banks (53°N) on the border between China and Russia to North and South America, Australia and across Asia, making it more widely cultivated cereal than any other grain crops.

In Pakistan, 2nd most important cereal grain crop after wheat is rice [8], while worldwide it is the 3rd largest food commodity after sugarcane and maize [9]. Rice is a type of grass from the Poaceae family which is leading cereal crops group around the world and in Pakistan. It is a vital food crop in Pakistan and its production directly relate to the economic prosperity of small as well as large growers in rural areas of Pakistan [10]. Rice is relatively cheapest source of protein among other cereals, almost 1/3rd of the world population fulfills their protein and calories requirement from it [11]. In Pakistan, it is the 2nd largest crop after wheat in terms of quantity and consumption.

Pakistan is 10th largest producer of rice making 8% of rice trade in world [7]. Rice is 3rd major yield of Pakistan in cultivation area, after wheat and cotton [12, 13]. It is sown in Kharif cropping season. Sindh and Punjab are two main rice-producing provinces in Pakistan, which accounts for almost 90% of total rice producing area. Rice plays a major role in fulfilling diversified food requirement of rural and urban population of Pakistan. Due to its fertile soil and best agro-climatic conditions, Punjab produced more that 90% of Basmati rice [14]. There are around 100 species of insect pests in the world, which attack rice crop [15-17]. It is a species of moths from Crambidae family. In Pakistan more than 70 types of insects are known which feeds specifically on rice crop. In which 24 species have been commonly observed in rice paddock of Punjab and Sindh [15, 18]. Among these insects, major insect pest of paddy which causes major yield loss in term of rain crop and for big economic crop losses in terms of national average yield are stem borers [19, 20].Globally, *Scirpophaga incertulas* causes major yield losses of around 10 million tones and damage on rice crop was more than 90% from *Scirpophaga incertulas* in Pakistan [21].

Globally, above 20 types of stem borers are recognized to attack on rice crop and about nine types are known which attacks on rice in Pakistan [21, 22]. Stem borers are crucial pest of rice crop throughout tropical and subtropical regions of South and Southeast Asia including Bangladesh, India, Pakistan, Nepal, Thailand, Vietnam, Myanmar, Singapore, Java, Philippines, China, Japan, and Taiwan [17, 23, 24].

Probability estimation or to get an answer from new data by analyzing historical data is called prediction [25]. There are two major types of prediction, classification, and regression. Classification is the prediction of discrete values [26], while regression is the prediction of continuous real-value such as integers or floating point numbers [27]. Various machine learning algorithms have been proposed for prediction like logistic regression [27], decision tree [28], random forest [29], Support vector machine SVM [30], Adaptive boosting [31]. Some of them can be used only for regression or classification and some can be used for both regression and classification.

Artificial Neural Networks (ANNs) are network of neurons. These neurons are simple processing elements like the human brain [32]. ANNs are widely used for number of applications. The main advantage of using neural network is its capability of processing huge data. Feed Forward Neural Network (FFNN) consists of a number of simple neurons organized in layers [33]. Every layer is connected with all the units of previous layers. FFNN are trained with back-propagation learning algorithms. They are very robust and need no assistance form the user for learning [33].

Internet of things (IoT) is referred to the objects having interconnection between them in a universal and intelligent way [34]. IoT is changing the internet by integrating every object for interaction which results in a distributed network of devices communicating with other devices and humans. The term IoT was first used in the supply chain management system in 1999 by Kevin Ashton [35]. After that this concept is widely used in many applications i.e., agriculture, healthcare, transport [36]. IoT is possible with the help of sensors and actuators. A sensor is a device that converts one form of signal to an electrical domain [37]. Broadly sensors are divided into two groups active and passive. Active sensors require power to operate while passive sensors need no power to generate output [37].

A wireless sensor network (WSN) is a network of sensors that monitors and collects data to a central location [38]. WSN may consist of different types of sensors such as thermal, light, acoustics, and magnetic. They can monitor many conditions that include temperature, humidity, noise, light condition, pressure, motion, etc. Sensor nodes can be used to capture data on the occurrence of any event or can continuously monitors data.

Adults of yellow stem borer are attracted to light conditions, which triggers the initiation and movement of offspring to a specific location. Along with light, some other influential factors for the exponential growth of yellow stem borer are relative humidity and rainfall [39]. However, the development and growth of the yellow stem borer and its life cycle is mainly influenced and derived by temperature [40]. Day length changes and cooler daytime temperatures induce temporary arrest or diapause in the growth and development of mature larvae.

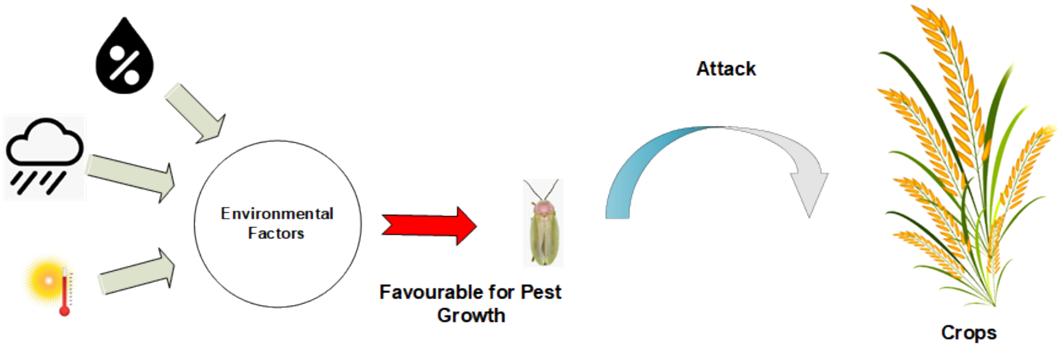

Fig. 1. Environment factors effecting insect growth

The **Fig. 1** shows about external environment factors making favorable conditions for insect pest growth which ultimately attacks on rice plant. The challenge for rice stem borer control is to accurately and timely identification of population hotspot in the field [41]. Sometime, farmer's pest scouting may lead to wrong estimate of population, delayed hotspot information which may leads to rapid increase in population. The adult of yellow stem borer is difficult to control and may cause drastic yield decline. Yellow stem borer population of rice could be affected with various environmental factors which includes relative humidity, light penetration, unfavorable climatic conditions, fertilizer application, nutrient status of the soil, water management and farming practices [42, 43]. It is also to note manual identification of pest population detection is time-consuming with less accuracy [44]. It may lead to wrong information, misleading diagnosis, and in-accurate pesticide application.

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2. Related Work

Datir and Wagh [45] have developed a remote sensor-based system to collect environmental data for farmers so they can take necessary actions before the occurrence of disease. AVR Board does remote construction using PCB software. After getting the data, farmers can spray fungicide from web application on time to minimize crop losses. This sensor-based system is specifically developed to prevent Downy Mildew at an early stage. The system is also implemented for monitoring and detection of pest and to control them remotely from any location in the world.

Azfar et al. [46] compiled a comprehensive information in a review article for monitoring of agriculture fields for insect pest prediction using wireless sensors network. The purpose of this research is to find the solution for complex situations in a biotic stressed environment and to gain best yield at low-cost application of insecticide. In this research, no of WSN applications are needed to increase on industrial scale.

IoT based smart agriculture system is proposed in this [47] study, S. S. Kalgapure et al. used various sensor and actuators to make irrigation efficient. They use temperature, soil moisture, rain and water level sensor to know whether crop need water or not if irrigation is required microcontroller board activates motor to start irrigation.

Ntihemuka and Inoue [48] did same kind of study and combined different sensors devices using wireless sensor network and using K-Nearest Neighbors (KNN) algorithm to monitor 8 different environmental factors to prevent pests and diseases caused by them. Different sensors are connected through breadboard jumper wiring on Arduino Board as microcontroller Data is collected through these planted sensors and sent to sink node using ZigBee wireless communication node. After classification of received data, predictions are made to increase the yield and improvement of farm performance.

In a recent research work done by Araby et al.[49], a censoring network is developed to collect field data of some crops including rice and is fed to machine learning algorithm (MLA) to receive a warning message through an interactive graphical user interface. The system developed is supposed to improve the detection of insect pest and diseases. It will also predict how diseases and insect pest population will spread in crop field.

Another research done by Lee et al. [50], in which a system is proposed that provides advance prediction information of diseases and insect pests so that farmers can promptly control them with minimum crop yield penalty, and helps them to make timely and rapidly decisions for control of attack.

Sakhare, et al.[51] developed a system for farmers to make better decisions about their crops by tracking their crops and searching about various diseases. This system is using a prototype that is made up of Raspberry Pi as a controller and hardware like moisture sensor and a motor that has an on/off switch. Farmers will be able to take better decisions about their crops and production would get better.

Shinde and Kulkarni [52] developed a system based on four modules, wireless sensor network, cloud storage, machine learning prediction algorithm and, notification system. In this system, different sensors are installed in a farm that takes temperature, humidity values and, sends data to the server and where prediction is made using machine learning algorithm which predicts the disease of crop using the training and already feed dataset. The last module contains a notification system that alerts the farmers through text messages.

Compared to various traditional image-based recognition system, i.e. scale-invariant features transform method [53] and histograms of oriented gradients (HOG) [54], deep learning and neural based detections methods have higher accuracy compared to human eye calculations [55] and have outperformed in detecting the crop pest population and diseases than traditional methods.

In another study, Yan, et al. [56] evaluates two different predictions models as per their advantages and disadvantages. Artificial neural network and multiple regression are different but mostly used models to predict pest populations and to quantify their risks in rice field. As per their result, ANN has high prediction accuracy for rice yellow stem borer compared to MR modelling. While MR have some advantages over ANN modeling for methodological calculations.

T. Wahyono et al. [57] studied effect of climate on pest prediction. They used Deep Long Short-Term Memory (LSTM) to predict possible pest attack in rice crop. They also focused on stem borer as pest and paddy as crop for their study.

Reji, et al.[58] developed pre-weather models to predict stem borer infestation zones in different part of country. The model based on geospatial interpolation information system showing risks maps of low, medium, and high-risk areas for stem borer and their damage to rice crop in the field. These system maps show correct data for devising management strategies for yellow stem borer in the region.

For insect identification, convolutional neural network (CNN) [59] and region based convolutional neural network systems (R-CNN) [60] are developed along with fast and faster-RCNN image based object detection systems [61, 62]. Among them, it is found that CNN proved to be most effective way of insect identification system in the field through crop image data processing system [63-65]. It uses convolutional system to extract image data for high level semantics fusion and deep features extraction for multi-layer networks [66]. Compared to Fast-RCNN and RCNN network, Faster-RCNN network using region based proposal network improves the insect detection accuracy [67].

Saleem et al. [1] developed an IoT based system which monitors rain, humidity, temperature and wind speed to find correlation with whitefly pest attack in cotton crop and also made prediction based on these features using deep neural networks. Parabhu et al. [2] in their study uses Back propagation Neural Network (BP-NN) and plant reflectance spectra data to detect borer attack on cashew trees. They collected reflectance spectra data about borer infected leaves and healthy leaves and train BP-NN model for detection of borer attack. Wahyono et al. [3] in investigated correlation between climate anomaly data and borer attack. They collected environmental data which is favorable for borer attack and calculated climate anomaly using LSTM model. Based on anomaly data they used to predict borer attack in rice crop. Markovic et al. [4] used IoT sensors with camera on insect trap to detect which type of insects are present in the field. Environmental data collected from sensors and insects detected from images is used to train machine learning algorithm and finally a prediction is achieved using captured data helping farmers to know possible pest attack and reduce efforts to physically visit farms.

Research shows strong relationship between pest population and environmental conditions. Temperature, light, humidity and air are most influencing factors in pest growth [68]. Various systems have been proposed which predicts different pests in differ crops. These environmental factors are associated with insect breeding as well as crop growth.

Table 1. Features of Previously Presented Work done on Pest Prediction

Work Year	Sensors/Techniques Used	Purpose
[69] 2014	AVR Board, Bluetooth Controller/Bayes Classifier Algorithm	Detection of Downy Mildew at Early Stages with Low Cost.
[70] 2018	Arduino Board, Zigbee, FM Transmitter,	To Control Pest Attack.
[48] 2018	Arduino Uno R3 Microcontroller Board, Raspberry Pi 3 Gateway	Yield Improvement and Farm Performance.

[49] 2019	Support vector Machine, Linear regression	Monitoring and Prediction of Pest Diseases at Low Cost.
[50] 2017	Android and web applications	Disease and Pest Prediction
[51] 2019	Raspberry Pi, KNN algorithm	Tracking Crops and Searching About Diseases.
[52] 2017	DHT22, Support vector regression and Adabost	Efficient crop disease prediction using IoT.
[71] 2019	CC3200, TMP007, HDC1010 camera, MT9D111 camera sensor SVM, Linear regression and decision tree.	Better Crop Yield Production with Good Quality and Crop Quantity.
[72] 2021	Navie Bayes, SVM, AdaBost, Random Forest	Early detection of pest infestation

Table 1 show various studies has been done in smart agriculture domain focusing on pest prediction or detections. Different machine learning algorithms, IoT devices, sensors are used to enhance results and accuracy.

3. Methodology

This portion explained the model and design of the suggested solution about stem borer pest prediction, methods, and algorithm.

3.1 Architecture of suggested Prediction Method

The proposed system monitors the different environmental factor like temperature, humidity, and rainfall. Proposed system is divided into two modules i.e., sensor base module for environmental data gathering and Neural Network module for data examination.
Detailed working of proposed system is consisting of following steps:

1. Data Collection from environmental observing system consists of Temperature and Humidity sensor (DHT22) and Rainfall Sensor (FC-37) and Arduino device.
2. Recording of respective values in proposed system for analysis.
3. Data examination by NN model.
4. Demonstrating the generated results of planted sensors on mobile.
5. Informing farmers about the current environmental situation of their crop to take necessary steps.

3.2 External Environment Monitoring and Prediction Module

In proposed approach, data is collected using sensors and a hardware device Arduino as a microcontroller.

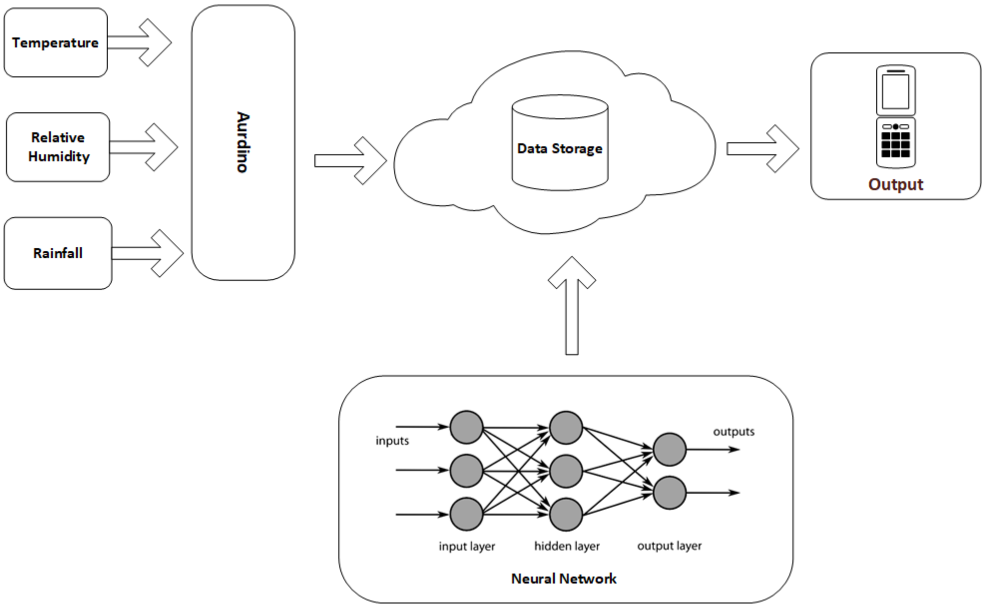

Fig. 2. Architecture of Pest Prediction

Fig. 2 elaborates details of working system containing Temperature, Humidity and Rainfall sensors, collected data is stored in cloud storage and processed using custom designed FFNN and after analysis output is generated as alert on mobile device.

In this study FFNN is proposed for classifying existing environmental situation to build effective pest prediction modeling system. Although there are several machine learning algorithms that can perform this type of classification, the results obtained from machine learning algorithms are not so much satisfying. That's why most researchers prefer neural network. Among many reasons of using NN some of them are:

- Neural Network has ability to manage large dataset without getting overfit [73]. Training data-size may vary in our projected scenario and in future if any factor like temperature, humidity and rainfall are deliberated for better results of proposed modeling system.
- NN can be customized by changing the training and testing data size. We preferred over other popular machine learning methods, which would eventually affect our output and no additional parameter would be required if any change occur in future.
- Another main reason of choosing ANN is that its output performance continues to increase by increasing its training data set [74].

ANN is famous technique of machine learning, first developed in 1950s. It can produce and predict highly correct results and has the ability of efficient and authentic decision-making like humans therefor appropriate to use in various decision-making applications such as, detection, prediction system and pattern recognition. Most well-known applications in agriculture are plant Image examination, climate change, population growth, and food security concerns [75]. Neural Network can discourse the problems of different supervised learning i.e., training dataset with all type of data with labels is provided. ANN can get patterns from this input training dataset which can be used to predict from unlabeled and uncategorized data.

Fig. 3 Shows proposed FFNN which is consist of three layers, Input, Output and Hidden.

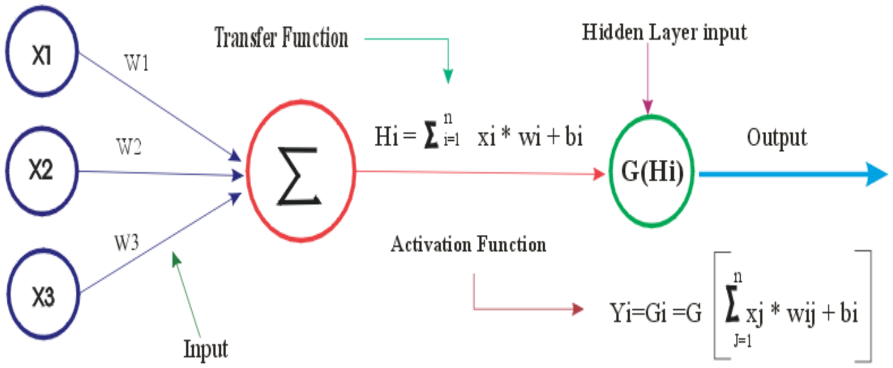

Fig. 3. Feed Forward Neural Network Model

One input layer X = environmental data obtained from sensors as input dataset containing values of temperature, humidity, and rainfall.
One output-layer Y of problem defined.
Y= 0 to denote probability of pest attack
Y= 1 denote favorable condition for rice crop.
For this study, we selected 10 hidden neurons, according to the formula given in (1).

$$N_h = \frac{N_t}{(\alpha * (N_i + N_o))} \tag{1}$$

Where
'N_h' = Number of hidden layers in NN
'N_t' = Number of total objects in training data-set
'N_i' = Number of total input neurons
'N_o' = Number of total output neurons
'α' = a scaling factor that usually lies between 2-10
'X_j'= is complete form of all inputs (temperature, humidity, and rainfall)

3.3 Transfer Function Used in ANN

In our proposed Neural Network model, we have three input neurons as nodes, eight hidden neurons (nodes) and one output node. To complete neural network we need mapping function which maps input layer to middle layers and middle layers to output layer [76]. For this purpose, we used common transfer function.

$$\sum_{i=1}^{n} X_i * W_i + b_i \tag{2}$$

Where
H_i = hidden layer input
X_i = all input values
W_i = all weights assigned by NN
b_i = biased value selected by NN
In our developed Neural Network Model, we took X_j= X_1, X_2, X_3
Where X_2= humidity, X_1= temperature, and X_3=rainfall
Used Transfer function in developed NN system for hidden layer node 1:
X_1*W_{11}+X_2* W_{12}+X_3* W_{13}+b_1

Transfer functions for hidden layer node 2:
$X_1*W_{21}+X_2*W_{22}+X_3*W_{23}+b_2$

3.4 Activation Function

After computing input of hidden and middle layer nodes using transfer function, activation functions [76] used for output is described below.

$$Y = \text{Activation Function } (\textstyle\sum_{i=1}^{n} H_i) \quad (3)$$

Here
H_i = input for hidden layer nodes
Y= output
Activation functions like sigmoid, linear, logistic, step, tangent, gaussian and hyperbolic are generally used. In our Neural network model, we used sigmoid function because we want our prediction output as 1 or 0 (yes or no)
sigmoid function is specified as:

$$f(x) = \frac{L}{1+e^{-k(x-x_0)}} \quad (4)$$

Where
L –maximum value of Curve
k – Sharpness of the curve
x_0 – x midpoint value of Sigmoid
A standard logistic function is known as sigmoid function (k=1, x_0=0, L=1)

$$f(x) = \frac{1}{1+e^{-x}} \quad (5)$$

The sigmoid function gives an ‘S’ formed curve.
This S-Shaped curve has a finite limit of:
“0” as X approaches – finite limit
“1” as X approaches + infinite limit
The output of this sigmoid function when X =0 is 0.5
Thus, if the outcome is more than 0.5, we can categorize the output as 1 (or YES) and if it is less than 0.5, we can classify it as 0(or NO).
For example; If the output is 0.65, we can say in terms of probability as:
“There is a 65% chance that environment is not favorable for the rice crop and pest can attack”.
So, the outcome of the sigmoid function is used to categorize YES or NO.
can not only used to categorize YES or NO, it can also be used to decide the probability of YES or NO.

3.5 Error Function Used in NN

When Neural Network gives different output from expected output, then it is taken as an error [77]. The difference may change or vary. And to calculate this error, we used given equation:

$$E_{Rate} = Y_a - Y_p \quad (6)$$

Here
E_{Rate}= error rate
Y_a = Actual or desired Output
Y_p = Predicted Output by our neural network

4.5.1 Back Propagation

Backpropagation is important part in NN [78]. It is used to optimize weights of NN by using error rate of previous epoch. These optimized weights enable NN to reduce error rate and making it reliable model by increasing its simplification.

We used equation (6) for adjusting weights in Back propagation (BP) of our neural network to reduce the error rate:

$$\Sigma_{i=1}^{n} w_i = w_i - (\eta * b(err)/b(w_i)) \tag{7}$$

Here

W_i= weight; η = Learning rate; (error) / b(W_i) = difference in measurement of each weight that is contribution in total error rate.

4. Implementation

This section shows experimental settings, layout of experimental area, and prototype model deployment in an experimental area and Deep Neural Network implementation.

5.1 Equipment's used for collecting data

To read data-values from environmental like temperature, humidity, and rainfall, we used following components.

1. Arduino Uno
2. Temperature and Humidity Sensor (DHT22)
3. Rain Sensor FC 37

5.1.1 Arduino Uno

Arduino UNO which is an open source microcontroller board used in this system [79]. **Fig. 4** show Arduino UNO, it contains 14 analog input and 16 digital input pins which are used to interconnect with numerous expansion boards or devices. IDE (integrated development Environment) is used to program Arduino using serial bus cable.

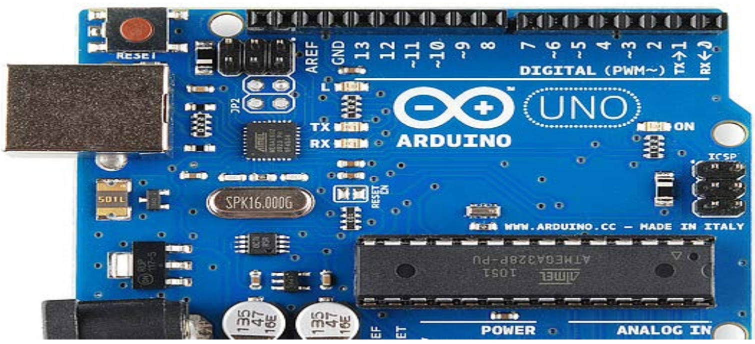

Fig. 4. Arduino UNO Microcontroller

5.1.2 Humidity and Temperature Sensor (DHT22)

We used DHT22 for our system to detect Humidity and temperature values of environment. DHT22 has humidity sensor and a thermistor which measures temperature and humidity of adjacent air [80]. It gives accurate results over the large range. **Fig. 5** shows temperature and humidity sensor DHT22.

Fig. 5. Humidity and Temprature Sensor DHT22

Technical details of DHT22 are given:
Voltages are 3.5V to 5.5V
Operating current: 0.3mA (measuring) 60 u A
Output = Serial data
Temperature Range is -40°C to 80°C
Humidity Range is 0% to 100%
Resolution: Temperature and humidity both are 16-bit
Accuracy: ±0.5°C and ±1%

5.1.3 Rainfall Sensor FC-37

The rain sensor used in our system is FC-37 to detect rain. FC-37 module is efficiently detects rain, this module can also be used for switching on raindrops on measuring board and to measures intensity of rain. **Fig. 6** shows rainfall sensor FC-37 used in our proposed system.

Fig. 6. Rainfall Sensor FC-37

5.2 Implementation of Proposed Neural Network

Data collected from sensors is sent to the server. Collected data is processed and analyzed using Feed-Forward Neural Network. This neural network can handle huge datasets with good accuracy we preferred it over other machine learning algorithms [73].

5.2.1 Implementation of Neural Network in Python

Neural network is designed in python using scikit-learn library [81] , which is well known to provide simple and efficient ways to non-experts for implementing machine learning algorithms on supervised or unsupervised problems.

5.3 Prototype Model and Deployment

The developed model is used to observe the yellow stem borer attack with the effect of environmental factors like temperature, humidity, and rainfall values. The hardware model is developed and deployed in the crop field as shown in **Fig. 7**.

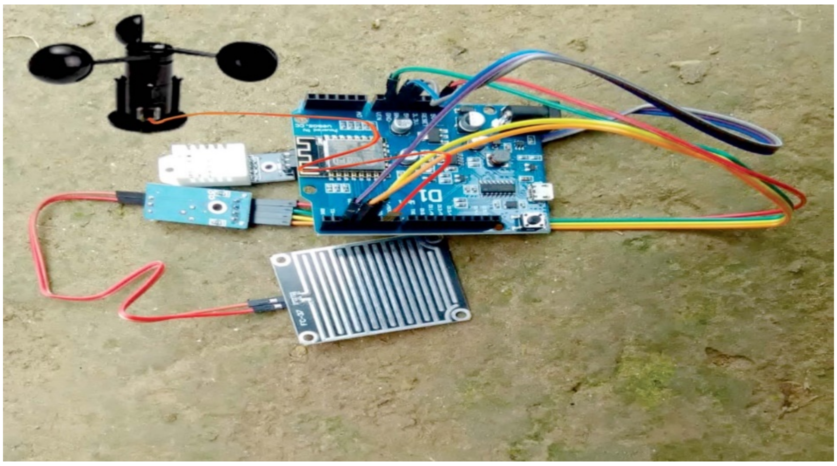

Fig. 7. Hardware Model

5.3.1 User Interface

An android application named "Pest Prediction" is developed which shows alert messages to farmer. **Fig. 8** shows developed application running on android v7.0 mobile device displaying alert message to farmer about potential pest attack.

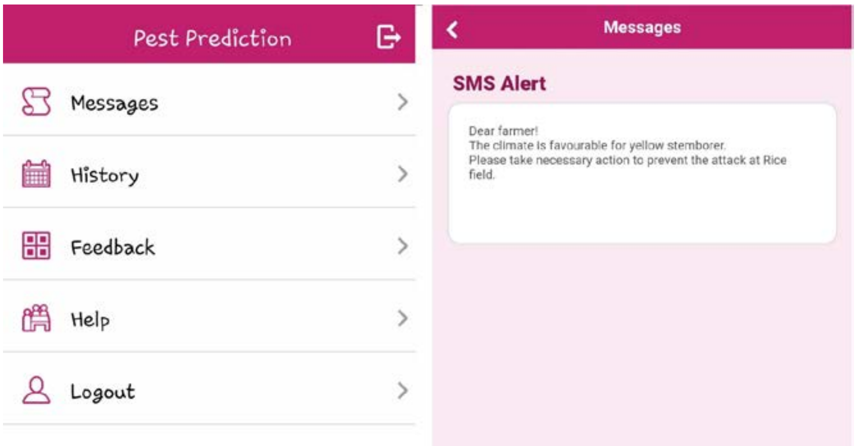

Fig. 8. Android Application showing Alert message to farmer.

5. Results and Discussion

The pest prediction approach of yellow stem borer is an effective approach capable of taking true decisions based on NN Model. Use of this approach for environment monitoring that is based on sensors using NN. The **Fig. 9** represents the environmental data temperature, humidity, and rainfall of 2019 from 1st June to 15 October.

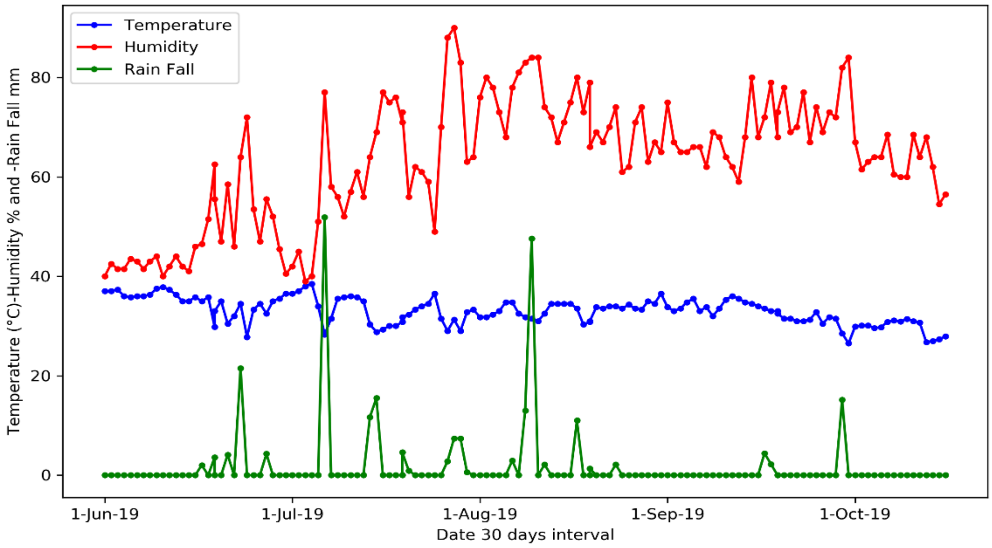

Fig. 9. Temperature, humidity, and rainfall data of 2019

The **Fig. 10** represents the environmental data humidity, rainfall, and temperature of 2020 from 1st June to 15 October.

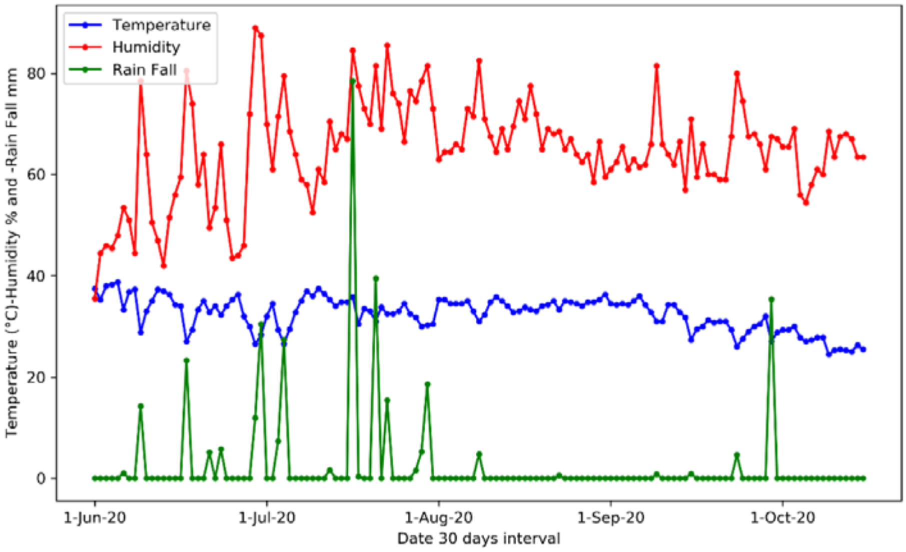

Fig. 10. Temperature, humidity, and rainfall data of 2020

We used NN (Neural Network) and binary classification model to predict environmental type. Neural Network has already implemented in many fields and research areas. We trained neural networks on the training dataset and then tested this trained neural network model by providing some unseen data taken from the fields. We evaluated attained output of our trained Neural Network with the formula given below:

$$Accuracy = Correctly \frac{Predicted}{TotalPredicted} * 100 \tag{8}$$

Initially we collected 340 records from the sensors. 285 samples are used for training the model while 55 samples are used for validation purpose. 85.6% accuracy achieved and accuracy gradually increased after repeating several training rounds (epochs). The ANN algorithm binary classification designed in python language with keras and sklearn libraries. The confusion matrix for describing the complete details of the proposed model evaluation is shown in **Fig. 11**.

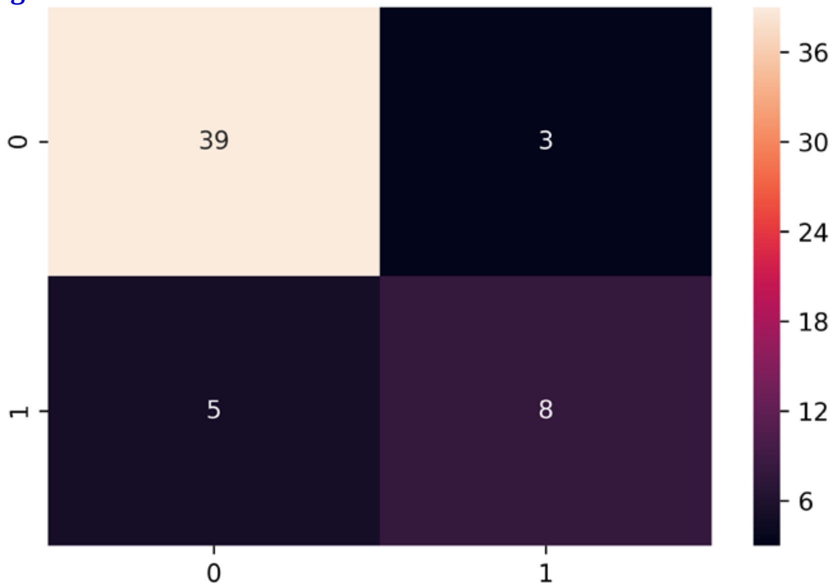

Fig. 11. Confusion Matrix

The f1 measure, Recall and precision the evaluation metrics for the prediction of stem borer is described in **Table 2**. The complete training and testing of the proposed model is shown in **Fig. 12**. Figure shows that model is smoothly trained and decrease the loss on every next epoch.

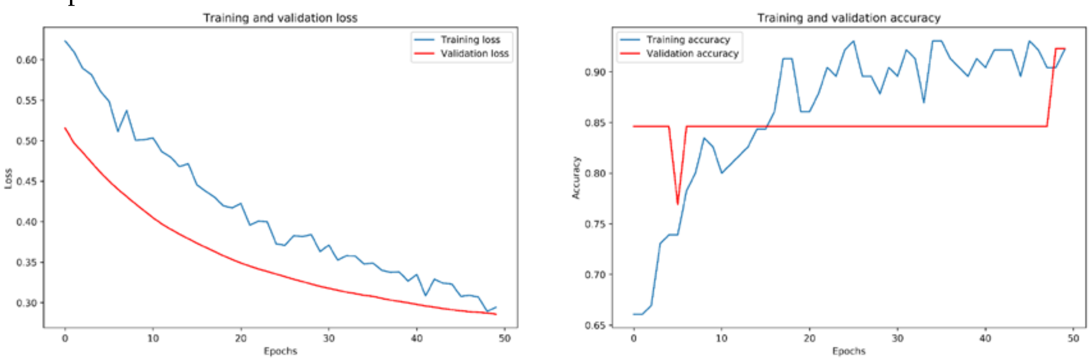

Fig. 12. Training and Testing of proposed model

In our experiment, we have set a parameter called ‘patience’ on the loss of the model to monitor. If the loss starts to increase gradually then after two epoch patience the model stops training automatically.

Table 2. Evaluation Metrics

Class	F1	Recall	Precision
0.0	0.71	0.63	0.79
1.0	0.84	0.85	0.84
Weighted Avg	0.77	0.74	0.81

Besides good accuracy, there are few limitations in the proposed system as the designed system is highly dependent on the network. If the network is unstable or our hardware gets disconnected then data collection may be affected. Moreover, sensors can be affected by extreme weather conditions like storms or floods making them give a false reading. Therefore, a good network is necessary and a good mounting position of hardware is also required to work properly.

6. Conclusions

In this research study, a prediction system is proposed that predicts the pest attack on rice crops using a neural network. It monitors and detects the intensity of different environmental factors i.e. environmental temperature, relative humidity, and rainfall. Our proposed system is divided into various modules i.e., sensor base module for environmental data collection for timely control application and Neural Network module for data analysis, pest prediction, and a notification system.

Data is collected using sensors. To do this, two sensors are used relative humidity and temperature sensor, and rainfall sensor. The proposed system collects the data of the current environment using sensor and a hardware device Arduino as a microcontroller.

In future, those factors that have the greatest influence on pests in climatic can be extracted to almost two using feature selection techniques to optimize the input and output results of the proposed model and improve the accuracy of prediction by ~5-10%. In accordance with the future directions, more sensors could be added to the existing system such as light sensor, soil moisture sensor and, air monitoring sensor to check more environmental properties to make predictions that are more accurate.

References

[1] R. M. Saleem, R. Kazmi, I. S. Bajwa, A. Ashraf, S. Ramzan, and W. Anwar, "IOT-Based Cotton Whitefly Prediction Using Deep Learning," *Scientific Programming*, vol. 2021, 2021. Article (CrossRef Link)

[2] Y. V. Prabhu, J. S. Parab, and G. Naik, "Back-Propagation Neural Network (BP-NN) model for the detection of borer pest attack," in *Proc. of Journal of Physics: Conference Series*, IOP Publishing, vol. 1921, no. 1, p. 012079, 2021. Article (CrossRef Link)

[3] T. Wahyono, Y. Heryadi, H. Soeparno, and B. S. Abbas, "Crop Pest Prediction Using Climate Anomaly Model Based On Deep-Lstm Method," *ICIC express letters. Part B, Applications: an international journal of research and surveys*, vol. 12, no. 4, pp. 395-401, 2021.

[4] D. Marković, D. Vujičić, S. Tanasković, B. Đorđević, S. Ranđić, and Z. Stamenković, "Prediction of Pest Insect Appearance Using Sensors and Machine Learning," *Sensors*, vol. 21, no. 14, p. 4846, 2021. Article (CrossRef Link)

[5] M. Kubo and M. Purevdorj, "The future of rice production and consumption," *Journal of Food Distribution Research*, vol. 35, no. 856-2016-57064, pp. 128-142, 2004.

[6] S. Tsunoda and N. Takahashi, *Biology of rice*, Elsevier, 2012.

[7] FAOSTAT, "Crops," Food and Agriculture Organization of the United Nations. [Online] http://www.fao.org/faostat/en/#data/QC/visualize (accessed 11 July, 2020).

[8] N. A. Memon, "Rice: Important cash crop of Pakistan," *Pak. Food J*, vol. 26, no. 7, pp. 21-23, 2013.

[9] U. Food and A. Organization, "Crops/Regions/World list/Production Quantity (pick lists), Rice (paddy), 2014," *Corporate Statistical Database (FAOSTAT)*, 2017.

[10] Pakissan, "Introduction to Rice,". [Online] https://www.pakissan.com/2017/01/15/introduction-to-rice/ (accessed August 5, 2020).

[11] M. Rizwan et al., "Measuring rice farmers' risk perceptions and attitude: Evidence from Pakistan," *Human and Ecological Risk Assessment: An International Journal*, pp. 1-16, 2019.

[12] S. Ahmad, M. Zia-Ul-Haq, M. Imran, S. Iqbal, J. Iqbal, and M. Ahmad, "Determination of residual contents of pesticides in rice (Oryza sativa L.) crop from different regions of Pakistan," *Pak. J. Bot*, vol. 40, no. 3, pp. 1253-1257, 2008.

[13] M. Irfan, M. Irfan, and M. Tahir, "Modeling the province wise yield of rice crop in Pakistan Using GARCH model," *International Journal of Science and Technology*, vol. 1, no. 6, pp. 224-228, 2011.

[14] G. Giraud, "Range and Limit of Geographical Indication Scheme: The case of Basmati rice from Punjab, Pakistan," *International Food and Agribusiness Management Review*, vol. 11, no. 1030-2016-82704, pp. 51-76, 2008.

[15] S. Karim and S. Riazuddin, "Rice insect pests of Pakistan and their control: a lesson from past for sustainable future integrated pest management," *Pakistan Journal of Biological Sciences (Pakistan)*, 2, 261-276, 1999. Article (CrossRef Link)

[16] M. Rahaman, K. Islam, M. Jahan, and M. Mamun, "Relative abundance of stem borer species and natural enemies in rice ecosystem at Madhupur, Tangail, Bangladesh," *Journal of the Bangladesh Agricultural University*, vol. 12, no. 2, pp. 267-272, 2014. Article (CrossRef Link)

[17] V. Amsagowri, N. Muthukrishnan, C. Muthiah, M. Mini, and S. Mohankumar, "Biochemical changes in rice yellow stem borer infested rice accessions," *Indian Journal of Entomology*, vol. 80, no. 3, pp. 926-934, 2018.Article (CrossRef Link)

[18] S. Nadeem, M. Hamed, and M. Shafique, "Feeding preference and developmental period of some storage insect species in rice products," *Pakistan Journal of Zoology*, vol. 43, no. 1, 2011.

[19] M. T. Rahman, M. Khalequzzaman, and M. A. R. Khan, "Assessment of infestation and yield loss by stem borers on variety of rice," *Journal of Asia-Pacific Entomology*, vol. 7, no. 1, pp. 89-95, 2004. Article (CrossRef Link)

[20] A. A. Khakwani et al., "Agronomic and morphological parameters of rice crop as affected by date of transplanting," *J. Agron*, vol. 5, no. 2, pp. 248-250, 2006. Article (CrossRef Link)

[21] M. Sarwar, "Management of rice stem borers (Lepidoptera: Pyralidae) through host plant resistance in early, medium and late plantings of rice (Oryza sativa L.)," *Journal of Cereals and Oilseeds*, vol. 3, no. 1, pp. 10-14, 2012. Article (CrossRef Link)

[22] R. A. Khan, J. A. Khan, F. Jamil, and M. Hamed, "Resistance of different basmati rice varieties to stem borers under different control tactics of IPM and evaluation of yield," *Pakistan Journal of Botany*, vol. 37, no. 2, p. 319, 2005.

[23] A. R. Dhuyo, "Integrated control of yellow rice stem borer Scirpophaga incertulas (Walker)(Lepidoptera: Pyralidae)," *University of Sindh*, Jamshoro, Pakistan, 2009.

[24] M. Savela, "Lepidoptera and some other life forms," *Retrieved February*, vol. 8, p. 2018, 2015.

[25] J. Aitchison and I. R. Dunsmore, *Statistical prediction analysis*, CUP Archive, 1980.

[26] S. B. Kotsiantis, I. Zaharakis, and P. Pintelas, "Supervised machine learning: A review of classification techniques," *Emerging artificial intelligence applications in computer engineering*, vol. 160, no. 1, pp. 3-24, 2007.
[27] W. Bergerud, "Introduction to logistic regression models with worked forestry examples: biometrics information handbook no. 7," *Res. Br., BC Min. For., Victoria, BC Work. Pap*, vol. 26, p. 1996, 1996.
[28] J. R. Quinlan, "Induction of decision trees," *Machine learning*, vol. 1, no. 1, pp. 81-106, 1986. Article (CrossRef Link)
[29] L. Breiman, "Random forests," *Machine learning*, vol. 45, no. 1, pp. 5-32, 2001. Article (CrossRef Link)
[30] V. Jakkula, "Tutorial on support vector machine (svm)," *School of EECS, Washington State University*, vol. 37, 2006.
[31] Y. Freund and R. Schapire, "A tutorial on boosting," 2013.
[32] W. S. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," *The bulletin of mathematical biophysics*, vol. 5, no. 4, pp. 115-133, 1943. Article (CrossRef Link)
[33] D. Svozil, V. Kvasnicka, and J. Pospichal, "Introduction to multi-layer feed-forward neural networks," *Chemometrics and intelligent laboratory systems*, vol. 39, no. 1, pp. 43-62, 1997. Article (CrossRef Link)
[34] F. Xia, L. T. Yang, L. Wang, and A. Vinel, "Internet of things," *International journal of communication systems*, vol. 25, no. 9, pp. 1101-1102, 2012. Article (CrossRef Link)
[35] K. Ashton, "That ‘internet of things’ thing," *RFID journal*, vol. 22, no. 7, pp. 97-114, 2009.
[36] H. Sundmaeker, P. Guillemin, P. Friess, and S. Woelfflé, "Vision and challenges for realising the Internet of Things," *Cluster of European research projects on the internet of things, European Commision*, vol. 3, no. 3, pp. 34-36, 2010.
[37] D. Sehrawat and N. S. Gill, "Smart sensors: Analysis of different types of IoT sensors," in *Proc. of 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, IEEE, pp. 523-528, 2019. Article (CrossRef Link)
[38] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Computer networks*, vol. 38, no. 4, pp. 393-422, 2002. Article (CrossRef Link)
[39] G. Guru-Pirasanna-Pandi et al., "Effect of weather parameters on rice yellow stem borer Scirpophagain certulas (walker) population dynamics under shallow low land ecology," *Journal of Agrometeorology*, vol. 22, no. 1, pp. 89-91, 2020.
[40] N. Manikandan, J. Kennedy, and V. Geethalakshmi, "Effect of elevated temperature on development time of rice yellow stem borer," *Indian Journal of Science and Technology*, vol. 6, no. 12, pp. 5563-5566, 2013. Article (CrossRef Link)
[41] M. S. Islam, S. Das, K. S. Islam, A. Rahman, M. N. Huda, and P. K. Dash, "Evaluation of different insecticides and botanical extracts against yellow stem borer, Scirpophaga incertulas in rice field," *International journal of biosciences*, vol. 3, no. 10, pp. 117-125, 2013. Article (CrossRef Link)
[42] A. Kakde and K. Patel, "Seasonal Incidence of rice yellow stem borer (Scirpophaga incertulas Wlk.) in relation to conventional and sri methods of planting and its correlation with weather parameters," *Journal of Agriculture and Veterinary Science*, vol. 7, no. 6, pp. 05-10, 2014. Article (CrossRef Link)
[43] K. R. Sharma, S. Raju, D. R. Roshan, and D. K. Jaiswal, "Effect of abiotic factors on yellow stem borer, Scirpophaga incertulas (Walker) and rice leaf folder, Cnaphalocrocis medinalis (Guenee) population," *Journal of Experimental Zoology. India*, vol. 21, no. 1, pp. 233-236, 2018.
[44] D. Li et al., "A recognition method for rice plant diseases and pests video detection based on deep convolutional neural network," *Sensors*, vol. 20, no. 3, p. 578, Jan 21 2020. Article (CrossRef Link)

[45] S. Datir and S. Wagh, "Monitoring and detection of agricultural disease using wireless sensor network," *International Journal of Computer Applications*, vol. 87, no. 4, 2014. Article (CrossRef Link)
[46] S. Azfar et al., "Monitoring, Detection and Control Techniques of Agriculture Pests and Diseases using Wireless Sensor Network: A Review," *Int. J. Adv. Comput. Sci. Appl*, vol. 9, pp. 424-433, 2018.Article (CrossRef Link)
[47] S. S. Kalgapure, P. V. Birajdar, R. C. Biradar, and M. G. Kadam, "Iot Based Monitoring System And Smart Agriculture Using Raspberry Pi," *International Journal*, vol. 5, no. 12, 2021.
[48] M. Ntihemuka and M. Inoue, "IoT Monitoring System for Early Detection of Agricultural Pests and Diseases," pp. 1-5, 2018.
[49] A. Araby et al., "Smart IoT Monitoring System for Agriculture with Predictive Analysis," in *Proc. of 2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST)*, pp. 1-4, 2019. Article (CrossRef Link)
[50] H. Lee, A. Moon, K. Moon, and Y. Lee, "Disease and pest prediction IoT system in orchard: A preliminary study," in *Proc. of 2017 Ninth International Conference on Ubiquitous and Future Networks (ICUFN)*, pp. 525-527, 2017. Article (CrossRef Link)
[51] A. Sakhare, T. Patil, P. Giri, and R. Gulame, "Crop Yield Prediction and Disease Detection Using IOT Approach," 2019.
[52] S. S. Shinde and M. Kulkarni, "Review paper on prediction of crop disease using IoT and machine learning," in *Proc. of 2017 International Conference on Transforming Engineering Education (ICTEE)*, IEEE, pp. 1-4, 2017. Article (CrossRef Link)
[53] D. G. Lowe, "Object recognition from local scale-invariant features," in *Proc. of he seventh IEEE international conference on computer vision*, vol. 2, pp. 1150-1157, 1999. Article (CrossRef Link)
[54] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *Proc. of 2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)*, vol. 1, pp. 886-893, 2005.
[55] D. Cireşan, U. Meier, J. Masci, and J. Schmidhuber, "A committee of neural networks for traffic sign classification," in *Proc. of The 2011 international joint conference on neural networks*, pp. 1918-1921, 2011. Article (CrossRef Link)
[56] Y. Yan, C.-C. Feng, M. P.-H. Wan, and K. T.-T. Chang, "Multiple regression and artificial neural network for the prediction of crop pest risks," in *Proc. of International conference on information systems for crisis response and management in Mediterranean countries*, Springer, pp. 73-84, 2015. Article (CrossRef Link)
[57] T. Wahyono, Y. Heryadi, H. Soeparno, and B. S. Abbas, "Crop Pest Prediction Using Climate Anomaly Model Based On Deep-Lstm Method," in *Proc. of ICIC express letters. Part B, Applications: an international journal of research and surveys*, vol.12, pp. 395-401, 2021. Article (CrossRef Link)
[58] G. Reji, S. Chander, and K. Kamble, "Predictive zoning of rice stem borer damage in southern India through spatial interpolation of weather-based models," *Journal of environmental biology*, vol. 35, no. 5, p. 923, 2014.
[59] Y. Le Cun et al., "Handwritten zip code recognition with multilayer networks," in *Proc. of 10th International Conference on Pattern Recognition*, vol. 2, pp. 35-40, 1990.
[60] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in *Proc. of the IEEE conference on computer vision and pattern recognition*, pp. 580-587, 2014. Article (CrossRef Link)
[61] R. Girshick, "Fast R-CNN object detection with Caffe," *Microsoft Research*, 2015. Article (CrossRef Link)
[62] S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards real-time object detection with region proposal networks," *arXiv 2015, arXiv preprint arXiv:1506.01497*.

[63] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems*, pp. 1097-1105, 2012.

[64] W. Ding and G. Taylor, "Automatic moth detection from trap images for pest management," *Computers and Electronics in Agriculture*, vol. 123, pp. 17-28, 2016. Article (CrossRef Link)

[65] M. M. Ghazi, B. Yanikoglu, and E. Aptoula, "Plant identification using deep neural networks via optimization of transfer learning parameters," *Neurocomputing*, vol. 235, pp. 228-235, 2017 .Article (CrossRef Link)

[66] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*, MIT press, 2016.

[67] C. Szegedy et al., "Going deeper with convolutions," in *Proc. of the IEEE conference on computer vision and pattern recognition*, pp. 1-9, 2015. Article (CrossRef Link)

[68] M. L. Margosian, K. A. Garrett, J. M. S. Hutchinson, and K. A. With, "Connectivity of the American Agricultural Landscape: Assessing the National Risk of Crop Pest and Disease Spread," *BioScience*, vol. 59, no. 2, pp. 141-151, 2009. Article (CrossRef Link)

[69] S. Wagh and S. Datir, "Monitoring and Detection of Agricultural Disease using Wireless Sensor Network," *International Journal of Computer Applications*, vol. 87, no. 4, pp. 1-5, 01/31 2014. Article (CrossRef Link)

[70] S. Azfar et al., "Monitoring, Detection and Control Techniques of Agriculture Pests and Diseases using Wireless Sensor Network: A Review," *International Journal of Advanced Computer Science and Applications*, vol. 9, pp. 424-434, 12/31 2018.Article (CrossRef Link)

[71] V. N. D. Prasanna and D. B. K. R., "<A Novel IOT Based Solution for Agriculture.pdf>," *Peer Reviewed Journal*, vol. 8, no. 1, p. 3, 2019.

[72] H. Kurdi, A. Al-Aldawsari, I. Al-Turaiki, and A. S. Aldawood, "Early Detection of Red Palm Weevil, Rhynchophorus ferrugineus (Olivier), Infestation Using Data Mining," *Plants*, vol. 10, no. 1, p. 95, 2021. Article (CrossRef Link)

[73] A. Laudani, G. M. Lozito, F. Riganti Fulginei, and A. Salvini, "On training efficiency and computational costs of a feed forward neural network: a review," *Computational intelligence and neuroscience*, vol. 2015, p. 818243, 2015. Article (CrossRef Link)

[74] H. Sug, "The effect of training set size for the performance of neural networks of classification," *WSEAS Trans Comput*, vol. 9, pp. 1297-306, 2010.

[75] A. K. Jain, J. Mao, and K. M. Mohiuddin, "Artificial neural networks: A tutorial," *Computer*, vol. 29, no. 3, pp. 31-44, 1996. Article (CrossRef Link)

[76] M. Rafiq, G. Bugmann, and D. Easterbrook, "Neural network design for engineering applications," *Computers & Structures*, vol. 79, no. 17, pp. 1541-1552, 2001. Article (CrossRef Link)

[77] S.-C. Wang, "Artificial neural network," in *Proc. of Interdisciplinary computing in java programming*, Springer, pp. 81-100, 2003. Article (CrossRef Link)

[78] R. Hecht-Nielsen, "Theory of the backpropagation neural network," *Neural networks for perception*, pp. 65-93, 1992. Article (CrossRef Link)

[79] I. Albatish, M. J. Mosa, and S. S. Abu-Naser, "ARDUINO Tutor: An Intelligent Tutoring System for Training on ARDUINO," 2018.

[80] Adafruit. DHT22 temperature-humidity sensor. [Online] Available: https://learn.adafruit.com/dht

[81] F. Pedregosa et al., "Scikit-learn: Machine learning in Python," *the Journal of machine Learning research*, vol. 12, pp. 2825-2830, 2011.

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