

Pest Prediction in Rice using IoT and Feed Forward Neural Network

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Abstract—Rice is a cereal grain, and in its domesticated form is the staple food for over half of the world's human population. Rice is the seed of the grass species *Oryza sativa* (Asian rice) or, much less commonly, *O. glaberrima* (African rice). It is cooked by boiling, or it can be ground into flour. It is eaten alone and in a great variety of soups, side dishes, and main dishes in Asian, Middle Eastern, and many other cuisines. Other products in which rice is used are breakfast cereals, noodles, and such alcoholic beverages as Japanese sake. Rice has become commonplace in many cultures worldwide; in 2021, 787 million tons were produced, placing it fourth after sugarcane, maize, and wheat. Stem borers are moths that attack rice crops. They feed upon tillers and causes deadhearts or drying of the central tiller, during vegetative stage and causes whiteheads at reproductive stage. Environmental factors such as relative humidity, rainfall, and temperature can influence the growth of stem borers in rice fields. This study aims to identify specific changes in environmental conditions, such as temperature, humidity, and rainfall, that may trigger outbreaks of stem borers. By pinpointing these factors, the study aids in identifying hotspots of insect pests in rice fields and provides insights for farmers. Our proposed system is a machine learning model which takes in data from temperature, humidity and rainfall sensors in fields and uses it to make predictions, whether pest attack will occur or not, so that necessary precautions can be taken.

Index Terms—deep learning, FNN, pest prediction, Field Plant

I. INTRODUCTION

Rice, cultivated as an annual grain, feeds over half of the world's population, particularly in Asia, Latin America, and Africa. The history of rice cultivation stretches back thousands of years. Evidence suggests rice was domesticated in the Yangtze River valley of China around 8,000 BC. From there, it spread throughout Asia and eventually across the globe. Rice comes in many varieties, differing in size, grain shape, and color. Traditionally, rice is grown in flooded paddies, though some varieties can thrive in upland conditions with regular rainfall. Rice is a water-loving crop, but proper water management is crucial for good yields. Six species of stem borer attack rice. These are the yellow stemborer, white stemborer,

striped stemborer, gold-fringed stemborer, dark-headed striped stemborer, and the pink stemborer.

Stem borers can destroy rice at any stage of the plant from seedling to maturity. The stem borer larvae bore at the base of the plants during the vegetative stage. On older plants, they bore through the upper nodes and feed toward the base. They feed upon tillers and causes deadhearts or drying of the central tiller, during vegetative stage; and causes whiteheads at reproductive stage. Eggs are laid in a cluster of about 200 white or brown eggs, similar in size to soybean seeds. These are laid on leaves and are covered with a yellow cottony layer, about 5 mm wide. Egg period is 5-8 days Larvae are pale yellow with dark brown head having prothoracic shield. Larval period is 28 to 30 days. Pupation takes place inside the rice stem, straw or stubble. Pupal period is 8 to 10 days. Symptom of Damage :Presence of brown coloured egg mass near the leaf tip. In the vegetative phase, the central shoot dies off turning yellow in colour (dead heart). In the ear bearing stage, the ear head appears completely chaffy and white in colour (white ear head). Both come out easily when pulled up and show indication of feeding injuries at the base.

Our proposed system has many advantages. Farmers rely on visual inspection to detect pests, often after damage has already occurred. This reactive approach means they can only address an infestation once it's established. By analyzing environmental data and historical trends, the system can predict potential outbreaks before they happen. This allows farmers to take preventive measures proactively, minimizing potential damage. By identifying hotspots, the system helps farmers target their pest control efforts to specific areas. This reduces reliance on broad-spectrum pesticides, promotes sustainable practices, and protects beneficial insects in other parts of the field. Machine learning algorithms used in the pest prediction system can analyze large volumes of data and identify patterns that may not be apparent to human observers. This can lead to more accurate and precise predictions of pest occurrences

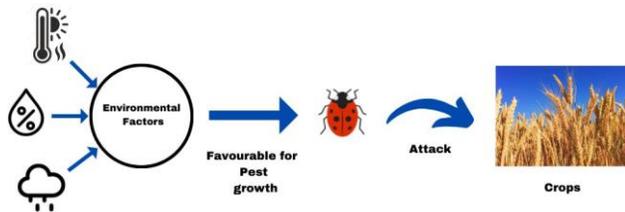


Fig. 1. Environment factors effecting pest growth

compared to subjective assessments made through manual inspection.

II. RELATED WORKS

Datir and Wagh 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, 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 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 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 ESP-32 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, 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, 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, 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 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 and histograms of oriented gradients (HOG), deep learning and neural based detections methods have higher accuracy compared to human eye calculations and have outperformed in detecting the crop pest population and diseases than traditional methods. In another study, Yan, et al. 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. 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. 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.

III. METHODOLOGY

A. Architecture of suggested Prediction Method

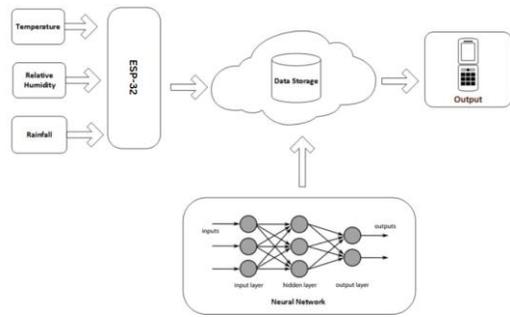


Fig. 2. Architecture of Pest Prediction

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 application.

The proposed system monitors the different environmental factor like temperature, humidity, and rainfall. Proposed system is divided into two modules i.e., External environment monitoring module for environmental data gathering and Prediction module for data examination. Detailed working of proposed system is consisting of following steps: 1. Data Collection consists of Temperature and Humidity sensor (DHT22) and Rainfall Sensor (FC-37) and ESP-32. 2. Recording of respective values in proposed system for analysis. 3. Data examination by FNN 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.

B. External Environment Monitoring and Prediction Module

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 other machine learning algorithms were not satisfactory. 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. 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. ANN is famous technique of machine learning, first developed in 1950s. It can produce and predict highly correct results and has the ability of

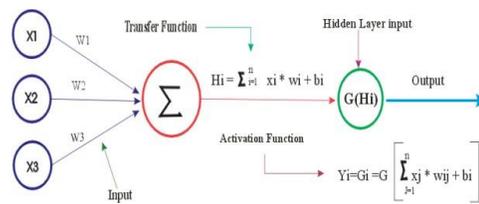


Fig. 4. Feed Forward Neural Network Model :

efficient and authentic decision-making like humans therefore 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. 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. ESP-32

C. Implementation

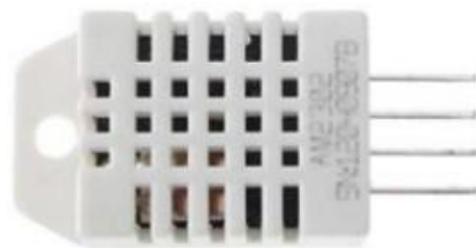


Fig. 5. Humidity and Temperature Sensor DHT22

To read data-values from environmental like temperature, humidity, and rainfall, we used following components. 1. Temperature and Humidity Sensor (DHT22) 2. Rain Sensor FC 37



Fig. 6. Rainfall sensor FC-37

The two sensors DHT-22 and FC-37 collect environmental data. ESP-32 processes the sensor data and transmits it wirelessly to a server. The server stores this data in a Firebase database. The machine learning model is deployed within a Flask application. A designated route within the Flask application accepts sensor data from the Firebase database via an API call. This route leverages the loaded model to generate a prediction, which is subsequently returned as a response through a separate API endpoint consumable by the mobile application.

D. Result Analysis

- The Fig.4 represents the environmental data humidity, rainfall, and temperature of 2020 from 1st June to 15 October. .

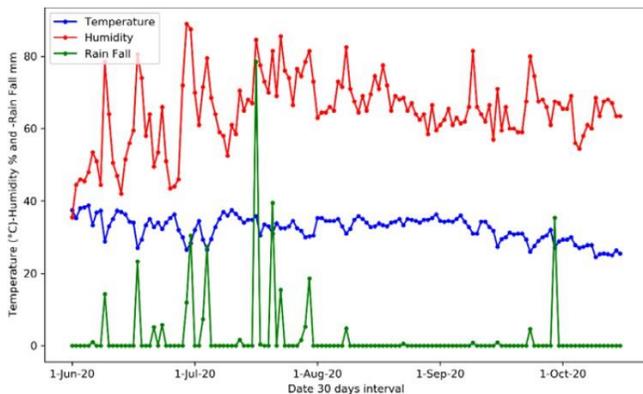


Fig. 7. Temperature, humidity, and rainfall data of 2020

- 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 our Feed Forward Neural network 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 predicted/Total predicted * 100

- Initially we collected 300 records from the sensors. 255 samples are used for training the model while 45 samples are used for validation purpose. 85 gradually increased after repeating several training rounds (epochs). The ANN algorithm binary classification designed in python language with keras and sklearn libraries.

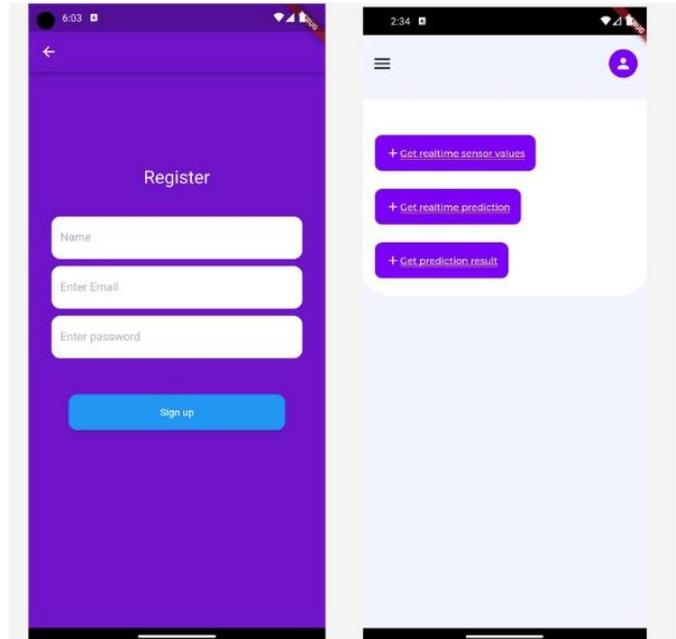


Fig. 8. Confusion Matrix

- 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.
- 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.
- In the mobile Application, farmers can first make an account and then login with their credentials.
- The app provides Farmers with three options.
- Get real time sensor values: Farmers can check climatic conditions which is being updated live
- Get real time prediction: the core functionality, getting predictions based on the sensor values.
- Get prediction result: here instead of using the values from the sensors, we can manually enter in values, and get predictions for those values. This is included so that, in the case that on field sensors stop working, we can measure the conditions our-self and manually enter it.

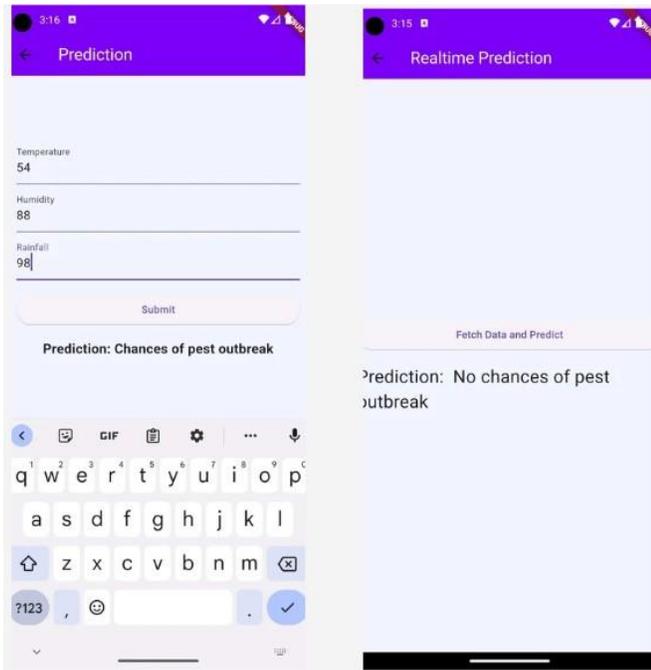


Fig. 9.

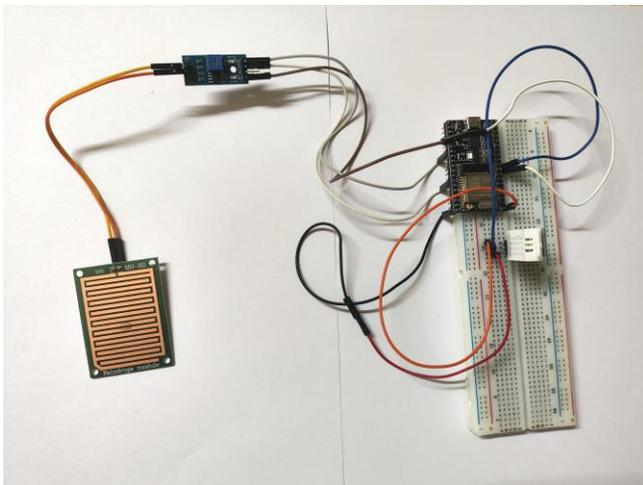


Fig. 10.

IV. CONCLUSION

This paper presented a pest prediction mobile app that uses machine learning to predict the presence of pests in crops. The app collects data from sensors and uses a machine learning model to make predictions. The app also provides a user interface that allows farmers to view the predictions and receive alerts if pests are detected. The app was tested on a real-world dataset and showed accurate predictions. It is designed to help farmers identify pests early on, which can lead to more effective pest control measures and reduced use of pesticides.

V. FUTURE WORK SCOPE

The system can be integrated with weather forecasting data to further refine predictions and account for potential changes in environmental conditions. By collecting data over time, the system can continuously learn and improve its accuracy in predicting pest outbreaks.

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] D. Markovic', D. Vujic'ic', S. Tanaskovic', B. orevic', S. Ranic', and Z. Stamenkovic', "Prediction of Pest Insect Appearance Using Sensors and Machine Learning," *Sensors*, vol. 21, no. 14, p. 4846, 2021
- [4] 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.
- [5] 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.
- [6] 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
- [7] 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.