Journal of Computer Science

Research Paper

Internet of Things and Human Neocortex Inspired Algorithms for the Plant Disease Prediction-Sheath Blight for Paddy Plant

Thangaraj E[1], K. Parthiban[2], Arockia Jayadhas S[3], Kalidoss Rajendran[4], M. S. Mohamed Mallick[1]

[1]*Department of Computer Science and Engineering, Vel Tech Rangarajan Dr.Sangunthala R&D Institute of Science and Technology, Chennai, India*
[2]*Department of Microbiology and Immunology, St. Joseph University College of Health and Allied Sciences, Tanzania*
[3]*Department of Electronics and Communication Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India*
[4]*Department of Microbiology, PSG College of Arts and Science, Coimbatore, India*

Article history
Received: 19 March 2025
Revised: 27 May 2025
Accepted: 5 June 2025

*Corresponding Author:
Thangaraj Ethliu
Department of Computer Science and Engineering, Vel Tech Rangarajan Dr.Sangunthala R&D Institute of Science and Technology, Chennai, India
Email: ethilthangaraj@yahoo.co.in

Abstract: Sheath blight disease (Rhizoctonia solani) poses a critical threat to paddy (Oryza sativa) production, causing up to 50% yield losses under conducive environmental conditions. Existing computer vision-based disease detection systems identify infections only after symptom manifestation, while conventional machine learning prediction models suffer from high computational demands, data preprocessing requirements, and noise sensitivity. This research proposes a novel Hierarchical Temporal Memory (HTM) framework for real-time, pre-symptomatic disease prediction using Internet of Things (IoT)-based environmental monitoring of agricultural fields. Inspired by human neocortex architecture, HTM exhibits inherent noise resistance and continuous learning capabilities without extensive retraining. The proposed system leverages three critical environmental parameters, temperature, humidity, and rainfall, collected via IoT sensors to predict disease onset before visible symptom development. Implementation and validation were conducted from 2019 to 2023 for sheath blight prediction in paddy cultivation, achieving 94% prediction accuracy in 2023. This pre-emptive prediction capability enables timely intervention, reduced pesticide application, and enhanced sustainable agricultural practices. The HTM-IoT integration represents a significant advancement in precision agriculture by transitioning from reactive disease detection to proactive disease forecasting, supporting both crop productivity and environmental sustainability objectives.

Keywords: Hierarchical Temporal Memory, Internet of Things, Precision Agriculture, Sheath Blight Disease, Disease Prediction, Environmental Monitoring, Sustainable Agriculture

Introduction

Crop disease outbreaks constitute a fundamental threat to global agricultural productivity and food security, necessitating proactive disease management strategies rather than reactive control measures. Early disease prediction systems enable timely interventions that minimize yield losses and reduce dependency on chemical pesticides, thereby supporting both economic viability and environmental sustainability in agricultural systems. Precision agriculture increasingly relies on advanced information and communication technologies to facilitate data-driven decision-making for disease management and resource optimization.

Climate change has intensified the frequency and severity of plant disease outbreaks through altered temperature regimes, precipitation patterns, and humidity levels (Tibpromma et al., 2021). Rice (*Oryza sativa*), which provides staple food for over half of the global population, demonstrates particular vulnerability to climate-induced disease pressure (Vishno et al., 2020). As a crop requiring extended photoperiods, high solar radiation, and elevated humidity, paddy cultivation creates inherently favorable conditions for fungal pathogen proliferation (Chaliha et al., 2020). Fungal diseases significantly compromise both grain yield and quality, with sheath blight (*Rhizoctonia solani*) representing the most economically damaging rice disease globally (Sen et al., 2020). Under severe infection conditions, sheath blight can reduce rice yields by up to 50%, threatening food security in rice-dependent regions (Chaliha et al., 2020).

Traditional disease management approaches rely primarily on calendar-based or reactive pesticide applications, contributing to environmental degradation, pesticide resistance development, and increased production costs (Raghavendra et al., 2014). Pre-emptive disease outbreak prediction enables targeted interventions, optimized pesticide timing, and reduced chemical inputs, aligning agricultural practices with sustainable development goals (Yang et al., 2016; Faber et al., 2019).

Limitations of Existing Disease Detection Approaches

Contemporary disease detection methodologies predominantly employ computer vision techniques for automated symptom identification through image analysis. While these approaches demonstrate high accuracy in disease classification, they fundamentally operate as reactive systems, identifying infections only after visible symptom manifestation. At this stage, crop damage is typically irreversible, and pathogen dissemination has already occurred, limiting the effectiveness of control measures. Furthermore, existing machine learning models for disease prediction face significant operational constraints including high computational requirements, extensive data preprocessing needs, sensitivity to environmental noise, and inability to adapt to evolving disease dynamics without complete model retraining.

The critical need exists for predictive systems capable of forecasting disease onset before symptom appearance, enabling truly proactive disease management. Given the well-established correlation between environmental conditions and disease development, environmental parameter monitoring provides a viable pathway for pre-symptomatic prediction.

Research Contribution

This study proposes a Hierarchical Temporal Memory (HTM) framework integrated with Internet of Things (IoT) sensor networks for real-time, pre-symptomatic prediction of sheath blight in paddy cultivation. HTM, inspired by mammalian neocortex architecture, offers distinctive advantages for agricultural disease prediction:

- Continuous Learning Capability: HTM systems learn incrementally from streaming data without requiring batch retraining, enabling adaptation to evolving environmental patterns and disease dynamics.
- Noise Robustness: The temporal pooling mechanisms inherent in HTM architecture provide natural resistance to sensor noise and environmental variability characteristic of field conditions.
- Temporal Pattern Recognition: HTM excels at identifying complex temporal sequences and patterns in time-series environmental data, capturing subtle pre-disease environmental signatures.

The proposed system monitors three critical environmental parameters, temperature, relative humidity, and precipitation, identified as primary drivers of sheath blight epidemiology. Real-time sensor data streams are processed through the HTM architecture to generate disease risk predictions before visible symptom onset, enabling timely preventive interventions.

Implementation and validation conducted from 2019 to 2023 in paddy cultivation systems demonstrated 94% prediction accuracy for sheath blight occurrence in 2023, validating the efficacy of the HTM-IoT approach for operational disease forecasting. This pre-emptive prediction capability supports optimized pesticide application, reduced environmental impact, and enhanced crop protection efficiency.

The remainder of this paper is organized as follows: Literature Review explores related work in disease prediction and HTM applications; Materials and Methods detail the proposed HTM-IoT architecture and implementation methodology; we also present experimental results and performance evaluation; discusses implications and limitations; and concludes with future research directions.

Background

Paddy is regarded as an essential crop when the security point of view of the world's food supply is considered. The cultivation of rice is recognized as the most important crop for the sustainable environment, the agricultural economy, and human feed. It is best suited to areas with lots of humidity, continuous sunlight, and a reliable supply of water. The average temperature needed for the crop to survive is noted to be between 21 and 37℃ (World Bank Group, 2022; Dean et al., 2012; Bevitori & Ghini, 2014). A conventional paddy garden is depicted in Fig. 1, whereas the extent of rice output throughout several global nations is displayed in Fig. 2.

Fig. 1. Paddy Plantation

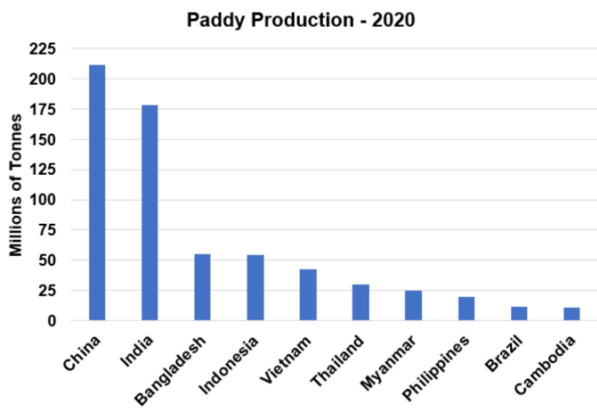

Fig. 2. Global Paddy production at 2020

Over ten prevalent paddy diseases, such as rice blast, sheath blight, rice brown spot, false smut, sheath rot, and tungro diseases, are often investigated globally. It is noted that rice sheath blight is one of the common prevalent diseases with the greatest global economic impact. Grain production and quality are significantly reduced by this disease. In the most favorable conditions, yield losses of up to 50% have been documented. Sheath blight, a soilborne disease, is caused by *Rhizoctonia solani* AG1-IA, a fungus (Li *et al*., 2014). The fungus is classified as a member of the family Ceratobasidiaceae and phylum Basidiomycota.

(a) Sheath Blight

(b) Leaf Blight

(c) Hispa

Fig. 3. Common Paddy Diseases

Early symptoms are repeatedly observed as greenish-gray, round, oval, or ellipsoid, water-soaked patches on the leaf sheaths at or slightly above the water line. The symptoms appeared as bigger lesions with irregular borders ranging from tan to dark brown around grayish-white centers as the condition worsened. Leaf blades may also be infected, resulting in irregular lesions surrounded by dark green, brown, or yellow-orange edges and symptoms are presented in Fig. 3. During wet seasons, the spread of disease is faster. Sheath blight infection is favored by high temperatures, high relative humidity, and high nitrogen fertilization, as well as closer distances to adjacent plants (Rajput *et al*., 2017).

Early prediction can be extremely beneficial in initiating proactive control measures and controlling the disease successfully for improved control. Ahead of time, farmers need to know how likely it is that a disease will strike in order to properly control illness. Strong correlations exist between plant disease outbreaks and environmental conditions. The growth of the paddy plant infection sheath blight is encouraged by moderate rainfall combined with high humidity. Humid environments during the summer are thrived upon by *Rhizoctonia solani*. The advancement of the disease is favoured by high humidity combined with rainfall (Tibpromma *et al*., 2021). It is possible for the emergence of a disease to be accurately anticipated in advance of its occurrence by using the association connecting environmental factors and the life cycle of the disease. The infection or disease outbreak can be combated more successfully by farmers if they are alerted to its impending arrival. Numerous machine learning-based methods are employed to identify and forecast the incidence of the illness.

Literature Review

Tanjore in Tamil Nadu is the granary of paddy cultivation presented in Fig. 4. The temperature, humidity and rainfall that are conducive for the maximum yield in Tanjore are presented in Fig. 5, Fig. 6, and Fig. 7. Various spectroscopic methods for identifying plant diseases, including reflectance, infrared, and Raman, are examined by Farber et al. The benefits and drawbacks of each of these methods are covered (Faber *et al*., 2019). The Random Forest machine learning method is suggested by Jawade et al. to forecast mango plant diseases depending on weather. When it comes to predicting mango sickness, a high level of accuracy is reported for the suggested method (Jawade *et al*., 2020). Paddy damage is assisted by machine learning in the context of the Internet of Things. Disease diagnosis was proposed by Chen et al. (2020). For the purpose of developing a machine learning model to forecast rice blast illness, the hyperspectral data from the rice field images is transformed.

A plant health detection system utilizing real-time plant characteristic monitoring was proposed by Yakkundimath *et al*. (2018). Real-time monitoring for IoT-based plant disease detection was suggested by Ramesh & Vydeki (2018). The limits of the current illness detection methods were examined by Arsenovic et al. With an accuracy rate of 93.67%, the study suggested a two-stage neural network design for real-time plant disease detection (Arsenovic *et al*., 2019). Various Convolutional Neural Network (CNN) methods for identifying plant diseases were examined by Nagaraju and Chawla, and their efficiency was compared (Nagaraju & Chawla, 2020). Plant resistance gene identification and plant disease categorization using machine learning techniques were evaluated by Yang & Guo (2019). Various deep learning methods for identifying plant diseases were examined and analyzed by Liu & Wang (2021). A CNN-based method for the disease identification of apple and tomato leaf pictures was proposed by Francis & Deisy (2019). An integrated strategy to manage data, equipment, and algorithms for strawberry disease prediction called FAAS (Farm as a Service) was suggested by Kim *et al*. (2018). The easy execution of the system is ensured by the integrated agriculture specialized FaaS system that was suggested. The diagram for the blight disease detection is presented in Fig. 8.

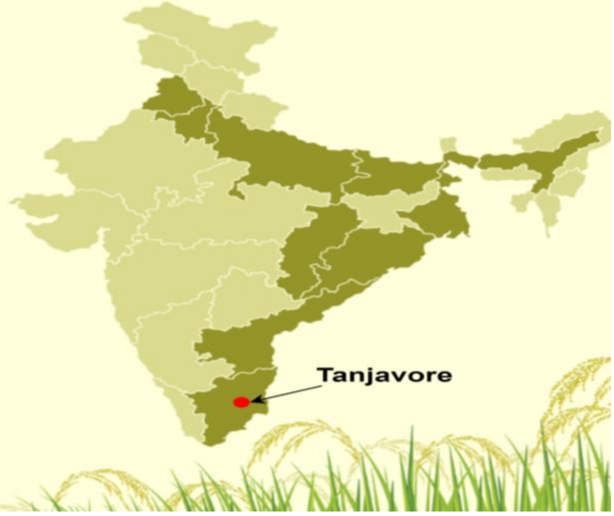

Fig. 4. Paddy producing regions in India.

The problem of climate change impacts on crops was suggested to be addressed by Materne and Inoue using IoT-based environment monitoring for disease population estimates (Materne & Inoue, 2018). An Internet of Things-based disease warning system was suggested by Araby et al. (2019) through direct observations of the agricultural field and the utilization of machine learning to create an early warning system (Araby et al., 2019). The identification of fungal diseases was suggested to be aided by the use of IoT and machine learning skills by Truong et al. The environmental conditions of the wheat field are immediately observed via IoT. In order to segment and extract features from pictures for the purpose of classifying diseases, Otsu's and K-means clustering are examined by the study (Chaudhary et al., 2019). The identification of tomato leaf illness and flaws using a method called SENet was suggested by Pragya et al. A hybrid technique based on CNN for tomato leaf disease detection, called SENet, is suggested. The primary goal of the suggested method is to identify plant diseases while effective use of computational resources is made (Pragya et al., 2019).

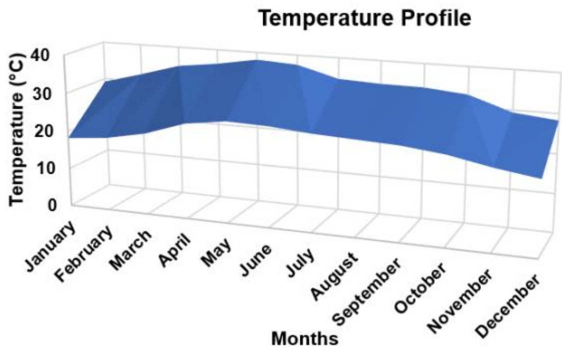

Fig. 5. Average Temperature Profile in Tanjore, India.

The detection of sheath blight disease in the paddy plant using hyperspectral remote sensing technology was proposed by Lin *et al*. (2020). Better accuracy was revealed through a decision tree classifier, and it was claimed that the results provided the basis for the development of a specific sensor for detecting this disease (Lin *et al*., 2020). A machine learning model with infrared spectroscopy for the detection of rice sheath blight was proposed by A.O. Conrad. It was shown that a testing accuracy of 86.1% was obtained and promise for application in disease diagnosis and management was suggested (Anna *et al*., 2020). Sheath blight disease detection and classification using image processing and machine learning were presented in Singh & Patel (2022). It was revealed that the method shows 90% accuracy in the testing phase in detecting the unhealthy leaf images that are affected by sheath blight disease.

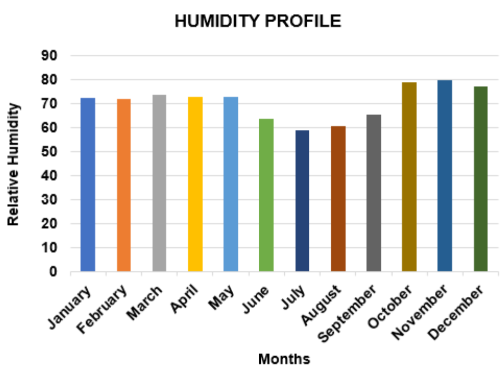

Fig. 6. Average Humidity Profile in Tanjore, India.

Despite the spread of statistical, machine learning, and deep learning approaches to disease detection in plants, especially paddy, it is known to us that no solutions based on hierarchical temporal memory (HTM) models have been proposed. However, the structural and temporal properties of HTM model approaches allow for excellence in cross-domain tasks that are applied to disease detection in plants, such as sheath blight disease.

The efficiency of the hierarchical temporal memory (HTM) model for anomaly detection in various applications is discussed in Ahmad *et al.* (2017). It is shown that better efficacy is provided by the HTM model compared to the other machine learning models in anomaly detection applications. In addition, efficiency in detecting anomalies in cluster activities (Bamaqa *et al*., 2020), traffic models (Almehmadi *et al*., 2020), human crucial signals (Bastaki *et al*., 2020), electric power grids (Barua *et al*., 2020), and computer hardware (Faezi *et al*., 2021) has also been proven by HTMs.

After the outward features of the sickness symptoms on plants have been observed, several techniques for disease detection utilizing the computer vision methodology have been presented in Fig 8. These methods can be used after the illness has established itself and large losses have been caused to the crop. A way to anticipate illness onset is required in order for preventative measures to be conducted. The life cycle of a disease is strongly correlated with its environmental factors. It is suggested that crop disease occurrence be anticipated based on temperature, humidity, and rainfall, which has not been done before. The distinctive quality of the suggested solution is its capacity to anticipate the likelihood of a paddy (sheath blight) disease assault and, in addition, any disease with a strong correlation with environmental conditions.

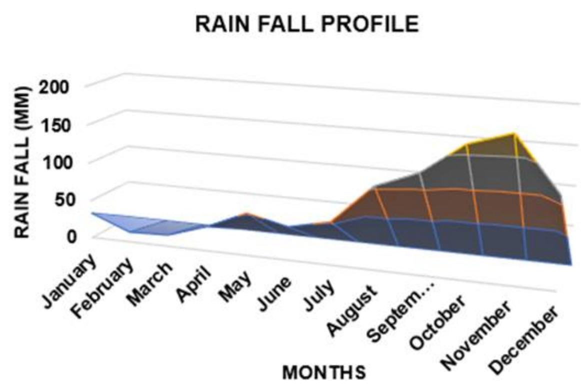

Fig. 7. Average Rainfall Profile in Tanjore, India.

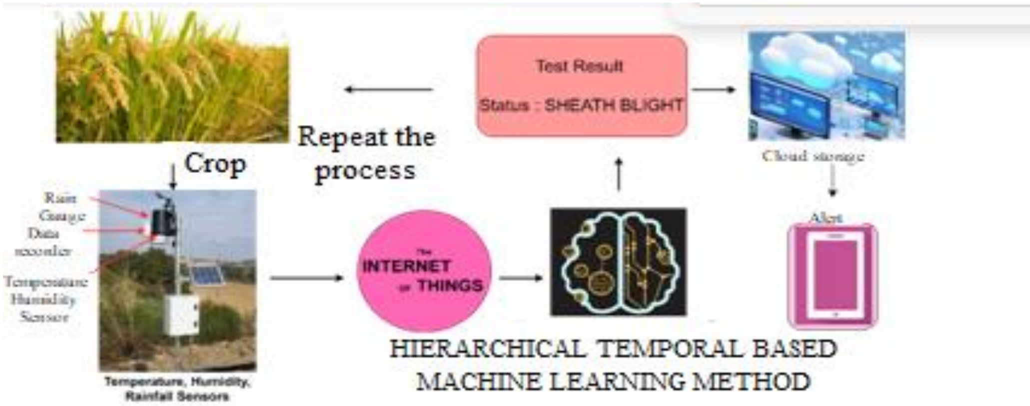

Fig. 8. Schematic Diagram for Proposed Paddy Plant Sheath Blight Disease Detection

Contribution of Society

Using the application of directly detected agricultural field environmental factors, a method for early plant disease prediction was proposed by the study. A hierarchical temporal memory model based on the human neocortex is devised and put into practice to forecast the incidence of sheath blight disease in India's rice plants. The suggested solution can also benefit any infection prognosis that has a significant association with environmental variables.

Materials and Methods

The environmental data, the Hierarchical Temporal Memory model, and the process of gathering environmental data and creating a flowchart for predicting crop diseases are described in this section.

Area of Study

Paddy is considered one of the world's leading agricultural products by India. In the 1980 fiscal year, 53.6 million tonnes of paddy were produced by India, and an astounding 135 million tonnes were produced in the 2022 fiscal year. The main paddy-producing locations of India are shown in Fig. 4. Tanjore district in Tamil Nadu has been chosen for this study in order to implement the proposed method of estimating the prevalence of the disease.

Environmental Data Sensing Test Kit

Environmental information from crop fields is collected using an IoT-built platform. The measurement of temperature, relative humidity, and rainfall is conducted by the DHT (Digital Temperature and Humidity) and rain sensor in collaboration with the system architecture directly from the agricultural field. The schematic diagram along with the required sensor is displayed in Figure 5. Information about the environment is received by the server and further processed in accordance with the proposed solution.

The Proposed Disease Prediction Flow Chart

The current temperature, humidity, and rainfall levels are used by the proposed approach to calculate the likelihood that sheath blight disease would be contracted by paddy plants. The median monthly temperature and mean monthly humidity are calculated using each day's temperature and humidity. The monthly record rainfall is determined by summing together all of the days' maximum rainfall. The chance of sheath blight disease spreading on paddy plants is calculated using the mean monthly temperature, humidity, and highest rainfall for the month. The forecasts produced by the model are verified by measurements in the field. The threshold limit of sheath blight on paddy plants is reached when it is revealed by field investigations that more than 20% of the plants are affected by the disease. The forecasts are verified by comparing them to the field measurements. Input from the confirmation of the estimations is received by the Hierarchical Temporal Memory model to enhance its performance in the long run. The data processing is shown in Fig. 5.

Environmental Conditions

The environmental factors that are critical for the growth of paddy plant sheath blight disease incidents are discussed in this section. An impact on paddy plant attacks by the sheath blight disease is made by rainfall and humidity together. In moderate rainfall and heavy humidity, paddy plants are attacked severely by the sheath blight disease. The prediction algorithm

DOI: 10.3844/jcssp.2025.2557.2569

includes temperature since the population of sickness is lowered by it.

Monthly projections are made using the highest monthly rainfall (RF_max), mean monthly humidity (HY_mean), and mean monthly temperature (TE_mean). The environmental data is immediately observed from the agricultural field using the prototype mentioned in the earlier part. The following part contains the environmental statistics.

Temperature

The development of diseases is closely correlated with temperature. The mean monthly temperature (TE_mean) could have been obtained from the maximum temperature for the day (TE_maxday) using Equation 1. It is considered that 'n' is the number of days in a month.

$$TE_{mean} = \frac{\sum_{Day=1}^{n} TE_{maxday}}{n} \tag{1}$$

For a chosen set of years, the temperature in the chosen location is monitored from January to December. The highest daily temperature (TE_maxday) and mean monthly temperature (TE_mean) for the last five years are displayed in Fig. 6. During the paddy plantation season, temperatures in the chosen location are often around the high 30s °C, which is supportive to the disease's growth.

Humidity

Humidity is referred to as the proportion of wetness in the air. The mean monthly humidity (HY_mean) and everyday maximum humidity (HY_maxday) for the last five years are displayed in Fig. 7. Compared to other chosen months, lower humidity levels are found in June, July, and August, which are conducive to the growth of sheath blight attacks on paddy plants. In the chosen location, humidity ranges from 58% to 78% from July to October. The mean monthly humidity is given by Equation 2.

$$HY_{mean} = \frac{\sum_{Day=1}^{n} HY_{maxday}}{n} \tag{2}$$

Rainfall

The maximum monthly rainfall is estimated by Equation 3, which is the highest amount of rain that falls on any one day in a given month. The average rainfall of the whole year is given in Fig. 8. It is shown that the months between August and December have high rainfall relative to the rest of the months in a year.

$$RF_{max} = RF_{maxday} \tag{3}$$

Disease Intensity Observations

The proposed approach is put into practice and verified through in-person field observations to determine the severity of the illness. If 20% of the paddy plants grown in an acre are infected, the disease attack is said to be above the economic threshold level (ETL). Ten acres of paddy plants are chosen for the crop.

The attack of sheath blight disease is dependent on high rainfall, and an important connection with the severity of the plant infection is held by temperature and humidity.

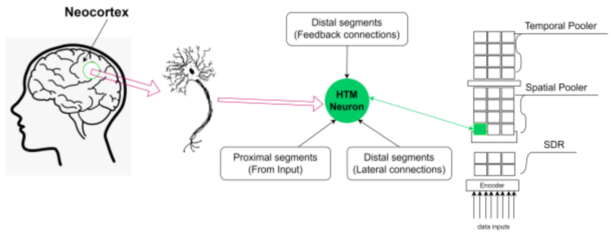

Fig. 9. Architecture of the HTM learning method.

Hierarchical Temporal Based Machine Learning Method

Human learning, cognition, and perception are all controlled by the neocortex in the human brain. The unit component of the neocortex is the neuron cell. In this paper, an HTM neuron cell is introduced that mimics the functionality of this biological neuron. The neuron model of the HTM is shown in Fig. 9. Three different types of dendritic segments are connected to a neuron: (i) proximal dendrite segments, from which inputs are obtained from neurons in the lower layer; (ii) distal dendrite segments, composed of synaptic relationships with neurons that are in the layer above; and (iii) distal dendrite segments, which are composed of lateral connections with same-layer cells (Spruston, 2008).

A single layer of the HTM is created by a row of mini columns made up of stacked neurons. Mini columns are formed by the arrangement of the neurons one over the other. In this instance, one HTM layer is just included. As a result, the feedback connections from the layer above are excluded from our neuron model. The temporal relations in the data stream are enabled to be learned by the HTM through the lateral connections of the distal dendrites. This aspect of the HTM that is most essential for detection and prediction is influenced by us. Three possible states can be held by each HTM neuron, similar to a biological neuron, namely (i) inactive, (ii) predictive state, and (iii) active state (Barua et al., 2020; Hawkins & Ahmad, 2016).

In addition, Fig. 9 is composed of an encoder, spatial poolers, temporal poolers, and HTM neuron cells. The signal is transformed by the encoder into a high-dimensional binary representation at each time instant, which is a sparse distributed representation (SDR). Sparse representations are represented by SDRs, where a few active bits correspond to each input. With the incoming data of sparse representation, this is commonly set to 2 percent in HTM, and good accuracy is provided.

The activation state of the mini columns (i.e., grouped by HTM neurons), which is a second SDR of a similar size as the input SDR, is computed by the spatial pooler. Each microcolumn of an HTM is coupled to a subset of the input SDR bits through synaptic connections known as proximal dendrite sections. The activation/triggered state of the mini columns is produced as the output of the spatial pooler; as a result, the output of the spatial pooler is SDR.

A predetermined number of HTM neurons are layered one on top of the other in each mini column of the temporal pooler, which has many of them. A cortical column is created by stacking several microcolumns next to one another. The synaptic connections serve as an HTM's temporal memory and capture temporal relations. If two cells from distinct microcolumns in the same layer have an active synaptic connection, then there is a temporal relationship between those cells. A synaptic connection that is active indicates that the cell from which it was formed is also alive. The predictive state is entered by the cell if the total number of active synapses in any one of the dendritic sections goes beyond a specific threshold value. The predictive state of a cell also gives the temporal setting for the choice of activation in the following period. Active synaptic connections that successfully detected the predicted state are strengthened, while those that unsuccessfully or wrongly identified it are weakened. A higher-order temporal representation of the sequential data is learned by the HTM through a process known as Hebbian-type learning. This representation can be utilized for prediction and anomaly detection.

The structure of the HTM model for concurrent disease prediction and real-time disease detection is shown in Fig. 10.

The HTM implementation for disease detection, which consists of the following collection of blocks, is the subject of this section. The data x_t at each time step t-1 is transformed into an SDR by the scalar encoder. Each SDR (x_t-1) matrix is converted into a sparse binary vector representation SP (x_t-1) by the spatial pooler. P(x_t-1) is produced by the temporal pooler, which is the last block. The term P (x_t-1) is an SP forecast made using SP (x_t) based on SP (x_t-1) at t-1. The discrepancy between the middle of the anticipated value, P(x_t-1), computed at the previous time step, and the actual value, SP (x_t), is calculated by the last block. The usefulness of the HTM in detecting spatial as well as subtle temporal patterns present in disease data is established by using the dataset-formulated model.

Evaluations

Assessments are carried out using.

- The HTM model's effectiveness
- The precision of predictions based on field observations.

Effectiveness of the HTM model

In this part, various statistics are provided to put the framework for HTM into practice. The relationship between environmental factors and the onset of sheath blight disease is shown in Table 1. A strong positive correlation with the onset of sheath blight disease is held by rainfall, temperature, and humidity. Regression line models are utilized to be executed since a relationship exists between the predictor and response variable. The correlation coefficients are determined based on the relationship between the predictor variable (temperature, humidity, and rainfall) and sheath blight disease. It is estimated based on covariance and standard deviation.

The spectrum of "yes" and "no" probabilities within the data set is displayed in Figure 7. In the available data, the chances of predicting "Yes" and "No" exceeding the ETL are dispersed equally. The `Yes` and `No` probabilities are selected based on the ETL value. If 20% of the paddy plants grown in an acre are infected, then the disease attack is said to be above the ETL, marked as the probability being 'Yes.' Otherwise, the probability is considered to be 'No' (Fig. 11). The residual values for the humidity-based sheath blight disease prediction are likewise uniformly distributed about the standard deviation, as seen in Fig. 12. The residuals are estimated based on the predicted value and the actual value.

DOI: 10.3844/jcssp.2025.2557.2569

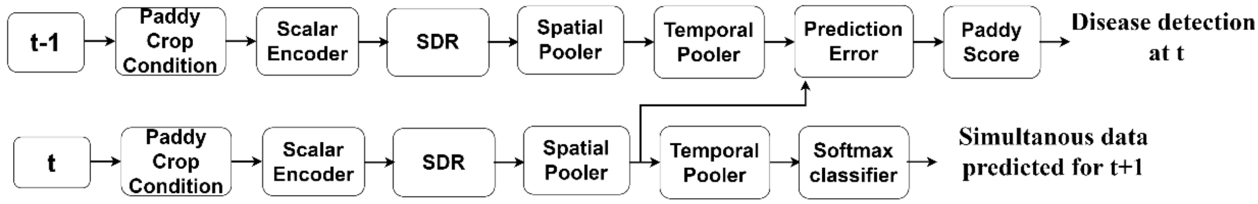

Fig. 10. HTM Model for sheath blight disease detection and prediction.

The residual values for the rainfall-based forecast of the paddy sheath blight disease are likewise seen to be uniformly spread around the average, as shown in Fig. 13. The temperature-based forecast of the paddy sheath blight disease is displayed in Fig. 14 and is observed to be uniformly distributed relative to the averages.

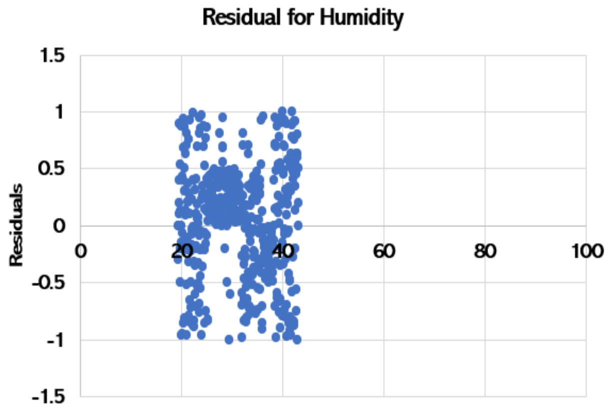

Fig. 12. Humidity Residual Graph

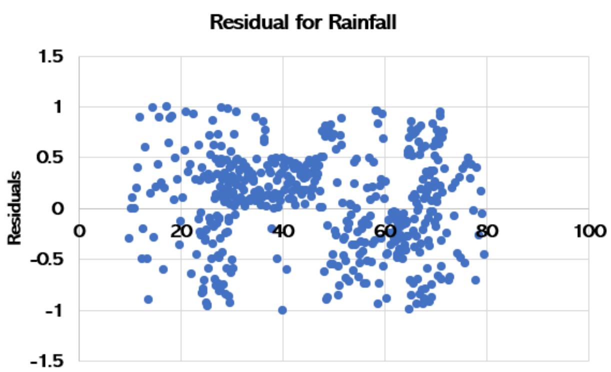

Fig. 13. Rainfall Residual Graph

The rate of occurrence of the disease is the factor that is dependent, while the following variables are independent: humidity, rainfall, and temperature. To create the humidity-based forecast, the best-fitted regression line for the humidity variable is displayed in Fig. 15. To create a rainfall-based forecast, Fig. 16 is used, which displays the best-fitted regression line for the rainfall variable. The best-fitted line of regression for the variables related to temperature, which is used to create the temperature-based forecast, is displayed in Fig. 17. Regression line methods are employed to forecast the likelihood of illness.

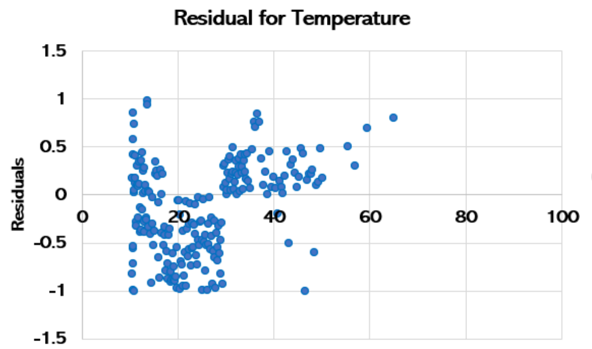

Fig. 14. Temperature Residual Graph

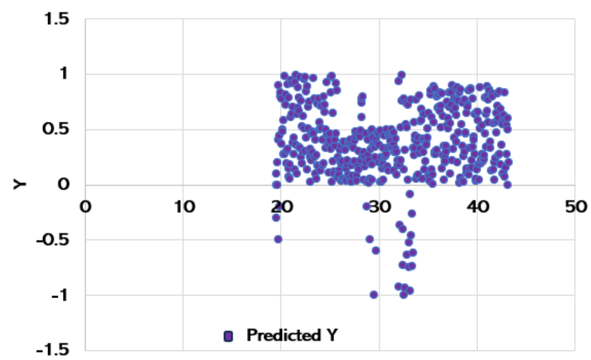

Fig. 15. Humidity Regression line for sheath blight prediction

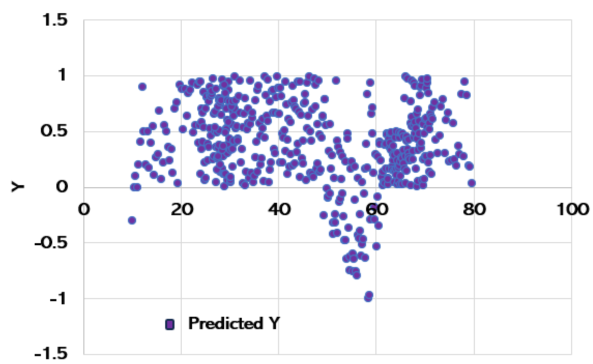

Fig. 16. Rainfall Regression line for sheath blight prediction

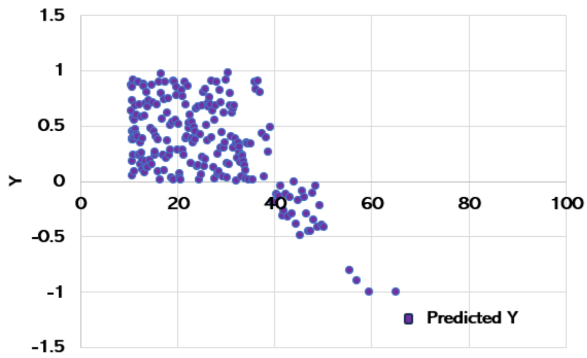

Fig. 17. Temperature Regression line for sheath blight prediction

The regression results for each variable are displayed in Table 2. The values for multiple R, R square, corrected R square, standard error, and total number of observations are provided by Table 2. With 1820 assessments, the multiple regression value is noted to be 0.66, the R-squared is reported as 0.44, the corrected R-squared is recorded as 0.44, and the standard error is indicated to be 0.32. It was demonstrated by these findings how well the likelihood of the illness was predicted by the HTM model given a specific combination of environmental factors. The test statistics for the various failures are displayed in Table 3. Prediction mistakes are noted to be quite rare. As a result, the forecast is fitted by the model.

Table 1. Disease intensity and environmental factors correlation

	Humidity	Rainfall	Temperature
Intensity of the Sheath Blight Disease in Paddy	0.86	0.83	0.79

Table 2. Analysis of Regression

Regression Statistics	
Observation Samples	1860
Multiple R	0.66
R Square	0.44
corrected R Square	0.44
Standard Error	0.32

Table 3. Standard Errors

	Coefficient	Standard Error	P-Value
Intercept	-0.426	0.086	7.83e-9
X Variable 1	0.026	0.0015	4.86e-6
X Variable 2	0.0016	0.00075	0.183659
X Variable 3	0.001	0.001	1.658e-12

Table 4. Accuracy of the disease prediction through Years

Year	Correct Prediction	Probability
2019	7	69 %
2020	9	77 %
2021	9	85.6 %
2022	10	87 %
2023	11	94 %

Field Validations

The predictions made by the HTM model are verified by field findings. The correct forecasts from 2019 to 2023 are summarized in Table 4. Because fresh data sets are used to train HTM and recursive feedback is received, an increase in prediction accuracy is observed over time. It is illustrated how accuracy steadily increases between 2019 and 2023. The accuracy is estimated based on the prediction result from the HTM model and validation from the field observations. Predictions are considered accurate in 69% of cases in 2019, 77% of cases in 2020, 85.6% of cases in 2021, 87% of cases in 2022, and 94% of cases in 2023. The forecast accuracy across the chosen years is displayed in Fig. 18, from which it is clear that better performance of the recommended strategy is exhibited with time.

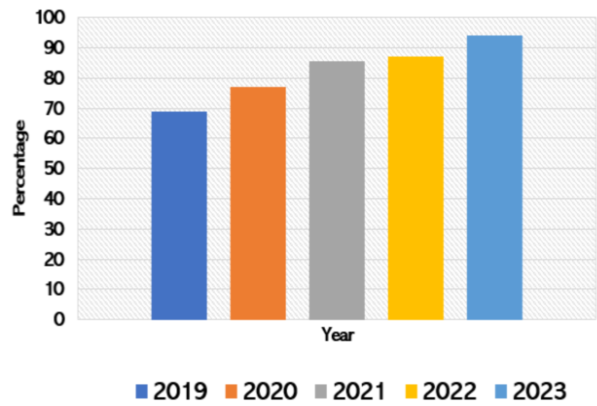

Fig. 18. Accuracy of the disease prediction graph through years

The likelihood of paddy sheath blight disease incidence is precisely forecasted by the recommended solution before the outbreak of the disease. The method works better than image processing methods for identifying diseases, which are only beneficial after an illness attack has already taken place. In comparison with the decision tree, it was seen that HTM architecture had captured temporal dependencies. This is often overlooked by decision trees. It was found that the decision tree shows the non-linear relationships within the complex data sets.

Similarly, SVM (Support Vector Machine) has been found to struggle with the integration of temporal data. While the HTM can integrate process temporal relationships directly from environmental data and predict disease outbreak temporal components.

Based on the CNN (convolutional neural networks), it was found that their application had limitations with visual data applications and lacked temporal dynamics. HTM requires less computational power and data sets. In comparison, the random forest ensemble method performs well with large data sets and lacks temporal dynamics, which is essential in agricultural disease prediction, while HTM performs well for agricultural environments. The result of this comparison suggests that the HTM model outperforms other models.

Conclusion

Utilizing precise environmental sensing of agricultural fields, a model based on Hierarchical Temporal Memory has been proposed for the forecasting of sheath blight disease in paddy plants. The correlation between the environmental factors and the disease's rate of growth is determined by creating regression line models. Temperature, humidity, and rainfall from the agricultural field are immediately collected using the Internet of Things (IoT). The proposed approach is trained, tested, and validated with crop-related environmental data from 2019 to 2023. When evaluated against the test data set, good prediction accuracy is demonstrated by the model based on Hierarchical Temporal Memory. Predictions generated by the suggested approach are also evaluated using personal observation from the field data. To enhance the performance of the recommended model, the observation is additionally included in the model every year as a training set of data. Annual increases in forecast accuracy have been noted. Sustainable agricultural growth is recommended to be promoted by using pesticides sparingly and by managing the disease outbreak well.

Acknowledgement

The authors are grateful to the publisher for their constant support in the publication of this manuscript. The author, Dr. Kalidoss Rajendran, expresses his deep sense of gratitude to the PSG CAS Management for their constant encouragement that enabled him to work on this research, and all authors are thankful to everyone who contributed to the successful publication of this research paper.

Funding Information

This study was not supported by any funding agencies. The funders had no role in study design, decision to publish or preparation of the manuscript.

Author Contributions

Dr. Thangaraj drafted the manuscript, compiled information from the literature. Dr. Parthiban K gathered information from the literature, and revised the manuscript. Dr. Arockia Jayadhass supervised the manuscript. Dr. Kalidoss Rajendran supervised and the manuscript and designed the figures and tables and Dr. Mohammed Malick reviewed the manuscript.

Ethics

This article does not contain any studies with human participants or animals performed by any of the authors.

References

Ahammad, M., *et al.* (2024). Advanced model based machine learning technique for early stage prediction of ankylosing spondylitis under timely analysis with featured textures. *Multimedia Tools and Applications, 83*(26), 68393–68413. https://doi.org/10.1007/s11042-024-18765-0

Ahmad, S., Lavin, A., Purdy, S., & Agha, Z. (2017). Unsupervised real-time anomaly detection for streaming data. *Neurocomputing, 262*, 134–147. https://doi.org/10.1016/j.neucom.2017.04.070

Almehmadi, A., Bosakowski, T., Sedky, M., & Bastaki, B. B. (2020, August). HTM based anomaly detecting model for traffic congestion. In *Proceedings of the 4th International Conference on Cloud and Big Data Computing* (pp. 97–101).

Araby, A. A., Abd Elhameed, M. M., Magdy, N. M., Said, L. A. A., Abdelaal, N., Abd Allah, Y. T., & Mostafa, H. (2019, May). Smart IoT monitoring system for agriculture with predictive analysis. In *2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST)* (pp. 1–4). IEEE. https://doi.org/10.1109/MOCAST.2019.8741923

Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A., & Stefanovic, D. (2019). Solving current limitations of deep learning based approaches for plant disease detection. *Symmetry, 11*(7), 939. https://doi.org/10.3390/sym11070939

Bamaqa, A., Sedky, M., Bosakowski, T., & Bastaki, B. B. (2020, August). Anomaly detection using hierarchical temporal memory (HTM) in crowd management. In *Proceedings of the 4th International Conference on Cloud and Big Data Computing* (pp. 37–42).

Barua, A., Muthirayan, D., Khargonekar, P. P., & Al Faruque, M. A. (2020). Hierarchical temporal memory-based one-pass learning for real-time anomaly detection and simultaneous data prediction in smart grids. *IEEE Transactions on Dependable and Secure Computing, 19*(3), 1770–1782. https://doi.org/10.1109/TDSC.2020.3018727

Bastaki, B. B. (2019). *Application of hierarchical temporal memory to anomaly detection of vital signs for ambient assisted living* (Doctoral dissertation, Staffordshire University).

Bevitori, R., & Ghini, R. (2014). Rice blast disease in climate change times.

Chaliha, C., & Kalita, E. (2020). Blister blight disease of tea: An enigma. In *Diagnostics of plant diseases*. IntechOpen. https://doi.org/10.5772/intechopen.92760

Chaudhary, S., Kumar, U., & Pandey, A. (2019). A review: Crop plant disease detection using image processing. *International Journal of Innovative Technology and Exploring Engineering, 8*(1), 472–477.

Chen, W. L., Lin, Y. B., Ng, F. L., Liu, C. Y., & Lin, Y. W. (2019). RiceTalk: Rice blast detection using Internet of Things and artificial intelligence technologies. *IEEE Internet of Things Journal, 7*(2), 1001–1010. https://doi.org/10.1109/JIOT.2019.2949915

Conrad, A. O., Li, W., Lee, D. Y., Wang, G. L., Rodriguez-Saona, L., & Bonello, P. (2020). Machine learning-based presymptomatic detection of rice sheath blight using spectral profiles. *Plant Phenomics*, Article 5801024. https://doi.org/10.34133/2020/5801024

Dean, R., Van Kan, J. A., Pretorius, Z. A., Hammond-Kosack, K. E., Di Pietro, A., Spanu, P. D., & Foster, G. D. (2012). The top 10 fungal pathogens in molecular plant pathology. *Molecular Plant Pathology, 13*(4), 414–430. https://doi.org/10.1111/j.1364-3703.2011.00783.x

Faezi, S., Yasaei, R., Barua, A., & Al Faruque, M. A. (2021). Brain-inspired golden chip free hardware trojan detection. *IEEE Transactions on Information Forensics and Security, 16*, 2697–2708. https://doi.org/10.1109/TIFS.2021.3063280

Farber, C., Mahnke, M., Sanchez, L., & Kurouski, D. (2019). Advanced spectroscopic techniques for plant disease diagnostics: A review. *TrAC Trends in Analytical Chemistry, 118*, 43–49. https://doi.org/10.1016/j.trac.2019.05.020

Francis, M., & Deisy, C. (2019, March). Disease detection and classification in agricultural plants using convolutional neural networks-A visual understanding. In *2019 6th International Conference on Signal Processing and Integrated Networks (SPIN)* (pp. 1063–1068). IEEE. https://doi.org/10.1109/SPIN.2019.8711708

Grace, A. E., & Prabu, R. T. (2024). Comparative analysis of machine learning classifiers for differentially methylated gene classification in rheumatoid arthritis. In *International Conference on Machine Intelligence, Tools, and Applications* (pp. 177–188). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-58562-6_14

Hawkins, J., & Ahmad, S. (2016). Why neurons have thousands of synapses: A theory of sequence memory in neocortex. *Frontiers in Neural Circuits, 10*, 23. https://doi.org/10.3389/fncir.2016.00023

Jawade, P. B., Chaugule, D., Patil, D., & Shinde, H. (2019). Disease prediction of mango crop using machine learning and IoT. In *International Conference on E-Business and Telecommunications* (pp. 254–260). Springer. https://doi.org/10.1007/978-3-030-36178-5_21

Kim, S., Lee, M., & Shin, C. (2018). IoT-based strawberry disease prediction system for smart farming. *Sensors, 18*(11), 4051. https://doi.org/10.3390/s18114051

Lahari, R., *et al.* (2024). Sign language classification using deep learning convolution neural networks algorithm. *Journal of the Institution of Engineers (India): Series B, 105*(5), 1347–1355. https://doi.org/10.1007/s40031-024-00952-1

Lin, F., Guo, S., Tan, C., Zhou, X., & Zhang, D. (2020). Identification of rice sheath blight through spectral responses using hyperspectral images. *Sensors, 20*(21), 6243. https://doi.org/10.3390/s20216243

Materne, N., & Inoue, M. (2018). IoT monitoring system for early detection of agricultural pests and diseases. In *2018 12th South East Asian Technical University Consortium (SEATUC)* (pp. 1–5). IEEE. https://doi.org/10.1109/SEATUC.2018.8788956

Nagaraju, M., & Chawla, P. (2020). Systematic review of deep learning techniques in plant disease detection. *International Journal of System Assurance Engineering and Management, 11*(3), 547–560. https://doi.org/10.1007/s13198-020-00903-4

DOI: 10.3844/jcssp.2025.2557.2569

Pragya, P., Sharma, V., & Sharma, V. (2019). Senet CNN based tomato leaf disease detection. *International Journal of Innovative Technology and Exploring Engineering*, 773–777.

Raghavendra, K. V., Naik, D. B., Venkatramaphanikumar, S., Kumar, S. D., & Krishna, S. R. (2014). Weather based prediction of pests in cotton. In *2014 International Conference on Computational Intelligence and Communication Networks* (pp. 570–574). IEEE. https://doi.org/10.1109/CICN.2014.122

Ramesh, S., & Vydeki, D. (2018). Rice blast disease detection and classification using machine learning algorithm. In *2018 2nd International Conference on Micro-Electronics and Telecommunication Engineering (ICMETE)* (pp. 255–259). IEEE. https://doi.org/10.1109/ICMETE.2018.00061

Rajput, L. S., Sharma, T., Madhusudhan, P., & Sinha, P. (2017). Effect of temperature on growth and sporulation of rice leaf blast pathogen *Magnaporthe oryzae*. *International Journal of Current Microbiology and Applied Sciences, 6*(3), 394–401.

Sen, S., Rai, M., Das, D., Chandra, S., & Acharya, K. (2020). Blister blight: A threatened problem in tea industry-A review. *Journal of King Saud University – Science, 32*(8), 3265–3272. https://doi.org/10.1016/j.jksus.2020.07.017

Singh, S., & Patel, M. (2020). Sheath blight detection and classification using image processing and machine learning. *International Journal of Research Publication and Reviews, 3*(6), 673–678.

Spruston, N. (2008). Pyramidal neurons: Dendritic structure and synaptic integration. *Nature Reviews Neuroscience, 9*(3), 206–221. https://doi.org/10.1038/nrn2286

Tibpromma, S., Dong, Y., Ranjitkar, S., Schaefer, D. A., Karunarathna, S. C., Hyde, K. D., & Sheng, J. (2021). Climate–fungal pathogen modeling predicts loss of up to one-third of tea growing areas. *Frontiers in Cellular and Infection Microbiology, 11*, 610567. https://doi.org/10.3389/fcimb.2021.610567

Vishnoi, V. K., Kumar, K., & Kumar, B. (2021). Plant disease detection using computational intelligence and image processing. *Journal of Plant Diseases and Protection, 128*(1), 19–53. https://doi.org/10.1007/s41348-020-00359-9

World Bank Group. (2022, April 8). *Food security update*. https://www.worldbank.org/en/topic/agriculture/brief/food-securityupdate

Yakkundimath, R., Saunshi, G., & Kamatar, V. (2018). Plant disease detection using IoT. *Global Journal of Computer Science and Technology, 18*(9), 18902–18906.

Yang, X., & Guo, T. (2017). Machine learning in plant disease research. *European Journal of Biomedical Research, 3*(1), 6–9. https://doi.org/10.18088/ejbmr.3.1.2017.pp6-9

Yang, X., Zhang, J., Guo, D., Xiong, X., Chang, L., Niu, Q., & Huang, D. (2016). Measuring and evaluating anthocyanin in lettuce leaf based on color information. *IFAC-PapersOnLine, 49*(16), 96–99. https://doi.org/10.1016/j.ifacol.2016.10.018