

An IoT Driven HTM Based Predictive Model for Early Detection of Sheath Blight Disease in Paddy Crops

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Abstract: - *Rhizoctonia solani* is a highly destructive fungal disease which can cause as much as 50% paddy loss. Timely and timely prevention and early prediction of these crop diseases are crucial to reduce losses and to foster sustainable agriculture. This study presents a new Internet of Things (IoT) based predictive model of sheath blight appearance using Hierarchical Temporal Memory (HTM), which mimics the human neocortex function to predict the probability of sheath blight occurrence in advance of the appearance of visible symptoms. Using IoT sensors, time-series information of the environment, such as temperature, humidity and rainfall in paddy fields were collected continuously. The HTM model was used to learn temporal patterns to predict disease occurrence using these parameters as input. The model was applied and tested with the data collected from the Cuddalore district of India from 2019 to 2023. The proposed HTM-IoT framework resulted in a consistent increase of the prediction accuracy as indicated, reaching the highest accuracy of 94% in 2023. Using correlation analysis, it was noted that there was a strong correlation between the environmental variables and the severity of the disease, such as humidity (0.86), rainfall (0.83) and temperature (0.79). The resulting model can be used to detect sheath blight outbreaks early, helping farmers to take timely actions to control it, minimize the use of pesticides, and move towards precision agriculture to ensure sustainable crop production.

Keywords: - Hierarchical Temporal Memory, Human Neocortex, Sheath Blight Disease, Plant Disease Prediction.

1. Introduction

The agricultural sector faces major difficulties because crop diseases, which affect plant growth, will decrease farm output and hinder sustainable agricultural development. Early disease detection allows farmers to implement preventive measures, which will decrease their losses while promoting environmentally friendly farming practices [1]. Climate change will lead to increased disease spread, which particularly impacts paddy plants through its effects on their growth [2]. Among rice diseases, sheath blight (*Rhizoctonia solani*) is one of the most destructive disease, because of its capability to reduce the rice yield to about 50% under ideal growing conditions which leads to great economic damage to farmers [3]. Paddy thrives under high humidity, continuous sunlight, and adequate water, with optimal temperatures between 21-37°C. The symptom begins with water-soaked lesions on the leaf sheaths that later expand into larger lesions, if relative humidity and temperature are high, particularly on soil high in nitrogen, where plants are densely planted [4]. A good knowledge on the relation between disease incidence and the environmental factors like temperature, humidity and rainfall is needed in order to estimate crop damage level at an early stage.

Existing plant disease detection methods such as image-based methods via CNNs, Random Forest and Support Vector Machines and spectral methods [5]. The model is effective, however requires large amount of labeled data and the data must be entirely processed and system re-trained with the change of environment conditions. The research work clearly showed the effectiveness of the data collecting by IoT based monitor system on a continuous stream of environment parameters on indicating the outbreak risk for achieving real time monitoring of the early outbreak warning in order to effectively control [6].

Human neocortex inspired structure of the HTM system, with the benefits of continuing learning through its noise resilience and temporal pattern recognition, can be widely used in agricultural IoT-based system monitoring [7].



HTM had already applied on anomaly detection in various fields such as cluster activities, traffic models, critical signals of human, electric power grid and computer hardware, however, combination of HTM on IoT based environmental monitoring for early detection of paddy sheath blight have never explored despite many research work on machine learning on plant disease detection [8]. In this HTM system model, both of the functionalities are used, that are temporal dynamics modeling and noisy data processing to predict disease outbreak that occurring under the condition changing of environment [9]. We developed an HTM-IoT system framework, which predicts the occurrence of sheath blight of rice paddy at the stage before symptoms appear. The framework gives the monitoring of environment with real-time operations, which allows agricultural disease control with sustainable cultivation for crop loss mitigation [10], [11].

Contribution of the Study

The study presents a new HTM-IoT framework for timely detection of Sheath Blight in rice and real-time monitoring of the environment. This approach predicts disease before showing any visible signs. It uses online learning in the sense of a constantly running system to incrementally increase its accuracy across seasons without any explicit system update. This approach is demonstrated through the field test performed from 2019 to 2023, where accuracy increases every testing phase. It allows for simple decision support for farmers in order for them to be aware, apply control measures at an appropriate time with minimum usage of pesticide.

2. Related Works

Farber et al. study the various types of spectroscopy tools to detect the plant disease (reflectance, infrared and Raman). The advantages and disadvantages of each method are discussed [12]. Liu Z et al. proposed using the Random Forest Machine learning method to predict mango plant diseases based on weather conditions. The proposed method is amazingly precise to forecast mango plant disease [14]. For identifying rice damage diseases, Chen et al. [17] suggested the Internet of Things and machine learning-based approach. The hyperspectral estimates of the rice field images are processed to create a machine-learning model to predict rice blast disease.

Real-time monitoring of plant characteristics for a plant health detection system was suggested by Lin F et al. [15]. Anna O et al. proposed real-time monitoring for IoT-based detection of plant diseases [16]. The shortcomings of the current disease detection techniques were reviewed by A. Bamaqa et al. A two-stage neural network architecture for real-time detection of plant diseases with an accuracy of 93.67% was proposed by this work [18]. A. Almeahadi et al. investigated various Convolutional Neural Network (CNN) techniques for plant disease detection and assessed their performance [19]. B. B. Bastaki et al. [20] compared the detection of plant resistance genes and the classification of plant diseases with machine learning methods. A. Barua et al. reviewed and analysed different deep learning approaches for plant disease detection [21]. S. Faezi et al. suggested a CNN-based approach for disease identification of apple and tomato leaf images [22]. An integrated approach for managing data, devices and algorithms for strawberry disease predictions known as FAAS (Farm as a Service) was presented by S. Ahmad et al. [23]. The suggested integrated agriculture specialised FaaS system makes it easier to implement the system.

N. Spruston recommended environmental monitoring through IoT for estimating disease populations to tackle the problem of climate change impacts on crops [24]. Nehru et al. suggested an Internet of Things-based disease warning system which is able to observe the field directly and use machine learning to build an early warning system [25]. Truong et al. proposed the use of IoT and machine learning skills for fungal disease recognition. IoT is used to directly observe the wheat field.

This study looks at Otsu's and K-means clustering methods to segment and extract features from images to classify diseases. Anna O et al. proposed a system called SENet to detect tomato leaf diseases and a few defects using CNNs. A hybrid CNN approach is proposed for tomato leaf disease detection, SENet. The proposed method aims to detect plant diseases with the efficient utilisation of computational resources.

W.L. Chen et al [13] suggested the detection of rice sheath blight using hyperspectral remote sensing. This showed improved accuracy with a decision tree classifier and asserted that the results laid the foundation for a special sensor to detect the disease. A.O. Conrad suggested a machine learning model and infrared spectroscopy for identifying rice sheath blight. It revealed that a testing accuracy of 86.1% was achieved and the model can be applied in disease diagnosis and management. The classification and detection of sheath blight disease using image processing and machine learning approaches were proposed in Liu Z et al. [14]. It was found that the approach has 90% testing accuracy in identifying the infected leaf images of the sheath blight disease.

Despite the proliferation of statistical, machine learning and deep learning techniques for disease detection in plants, particularly paddy, to our knowledge, there are no solutions based on a hierarchical temporal memory (HTM) model. But the spatial and temporal aspects of the HTM model approaches make them suitable for cross-domain problems that apply to plant disease detection, such as the sheath blight disease.

The effectiveness of hierarchical temporal memory (HTM) model in anomaly detection is addressed in Nehru.P et al. [25]. It demonstrates the effectiveness of the HTM model in anomaly detection compared to other machine learning models. Besides, HTMs also show good efficacy in detecting anomalies in cluster activities, traffic models, human crucial signals, electric power grids, and computer hardware.

Image-based plant disease detection and classification have been done successfully with conventional machine learning and deep learning models, including Convolutional Neural Networks (CNN), Random Forests, and Support Vector Machines. Nevertheless, these models can be very demanding in terms of data size, preprocessing, and retraining in case new data are available. Conversely, the Hierarchical Temporal Memory (HTM) model, which is based on the structure and functionality of the human neocortex, provides continuous learning and real-time flexibility to new patterns without complete retraining. The HTM models are very robust to noise and can identify temporal relationships in the streaming environmental data, and are therefore very appropriate in the case of IoT-based agricultural monitoring. The sparse distributed representation (SDR) of the model allows the effective processing of missing or varying data, which is a frequent occurrence in the actual agricultural setting. Such properties place HTM as a potential alternative to conventional AI models of dynamic and data-driven agricultural tasks like early disease detection.

Although many studies have been carried out on image processing, statistical and deep learning methods of detecting plant diseases, few studies have investigated the combination of HTM and IoT-generated real-time environmental data to early predict sheath blight in paddy crops. The temporal learning and noise-resistant characteristics of HTM are unique, and, therefore, it is especially appropriate to model changing environmental conditions that affect disease outbreaks. The research fills this gap by offering an HTM-IoT framework that is specially tailored to predict the occurrence of sheath blight in paddy fields before it manifests itself.

Several methods were introduced to detect disease using the computer vision approach after the symptoms of the disease and their outward characteristics on plants. These techniques can be applied after the disease has occurred and the crop has lost a substantial yield. A method is needed to predict the occurrence of the disease for preventive action. Disease life is closely related to the environment. It is proposed to predict the incidence of crop diseases based on temperature, humidity and rainfall, which has not been undertaken earlier. The uniqueness of the proposed solution is its ability to predict the probability of an outbreak of paddy (sheath blight) disease and any other disease having a high correlation with environmental factors.

Paddy is a staple food in India. In the 1980 fiscal year, India's paddy production was 53.6 million tons, which increased to an incredible 135 million tons in fiscal year 2023 (2022). We take the Tamil Nadu district of Cuddalore as our case study to apply the proposed system for estimating the incidence of the disease. The IoT-based system is developed to gather environmental data from the field. The architecture of the system, along with the DHT (Digital Temperature and Humidity) and rain sensor, is used to gather temperature, relative humidity and rainfall from the farm. The environmental data are transmitted to the server to be processed according to the proposed approach.

The proposed solution extracts the temperature, humidity and rainfall from the server and then it uses the current temperature, humidity and rainfall information, to determine how likely paddy plants are to be infected with sheath blight. The mean monthly temperature and humidity are determined using the daily temperature and humidity. The highest rainfall for the month is found by adding all the days' highest rainfall. The percentage of growth of a sheath blight in paddy plants is determined using the mean monthly temperature, humidity and maximum rainfall. The model forecasts are validated by field measurements. The threshold value of the sheath blight disease on paddy is reached when the field studies indicate that the disease has spread to more than 20% of the paddy plants. The model is confirmed by comparing the forecasts with the measurements. The verification of the forecasts is sent as feedback to the Hierarchical Temporal Memory model in order to improve its accuracy.

3. Materials and Methods

In this section describe about environmental data, about HTM model, how environmental data are acquired, flowchart for the prediction of disease on the crops, the research methodology has three steps in predicting crop diseases such as data collection (Environmental data) using IoT sensors, data processing (HTM model) and validation on the field. Proposed approach is that with present value of temperature, humidity and rainfall, calculate possibility of infection of sheath blight disease on paddy plants. Each days' humidity and temperature are averaged to give a median monthly humidity and average monthly temperature respectively. Summing the maximum rainfall of each days yields a monthly record rainfall. Using the average monthly temperature, average monthly humidity, and monthly maximum rainfall of a particular month the probability of occurrence of a sheath blight disease in paddy plants is worked out. Forecasts from the model are checked using field measurements. Sheath blight on paddy plants reaches the threshold limit when field investigations reveal that the disease affects more than 20% of the plants.

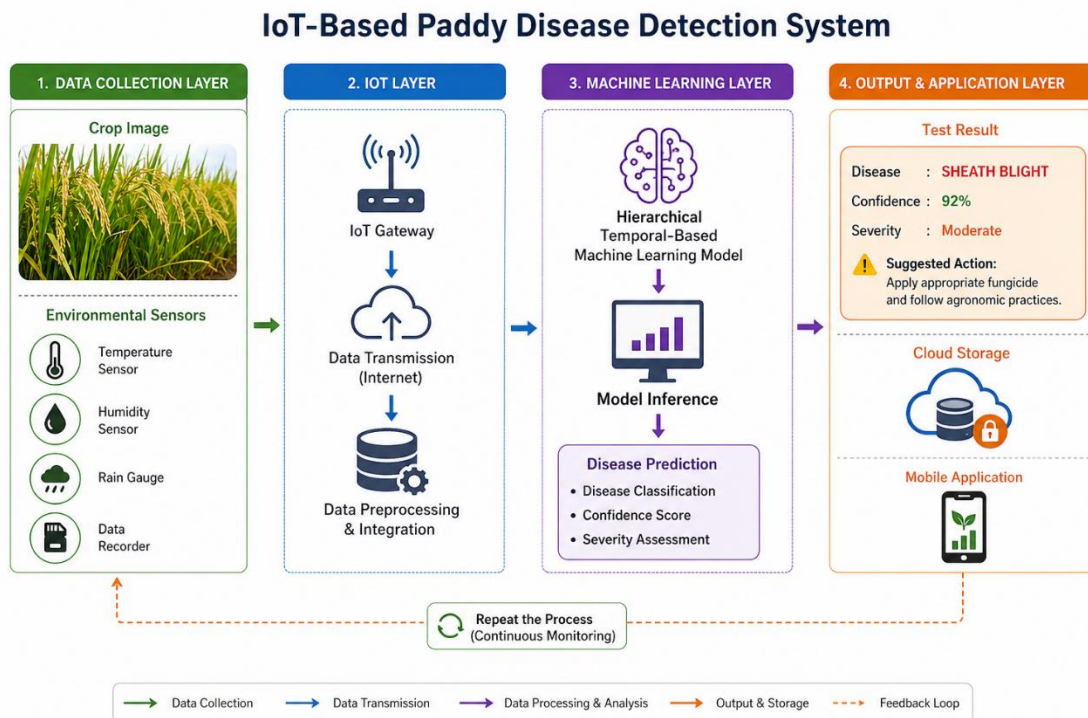


Figure 1: Proposed IoT Based Paddy Disease Detection Schematic Diagram

The predicted values are compared against the field measurements. The HTM model receives input from the confirmation of the estimations to increase its performance in the long run. Figure 1. Shows how data is processed in the proposed method.

3.1. Environmental Data Description

The environmental aspects relevant to infestation of paddy plants with the sheath blight disease are being discussed in this section. Attack of paddy plants by sheath blight disease is affected by amount of rainfall and relative humidity. During high humidity and moderate rain, the paddy plants are high infested with the sheath blight disease. Prediction algorithm involves with temperature because it reduce possibility of disease occurrence.

For generating monthly predictions, we have used (maximum monthly rainfall), (mean monthly humidity) and (mean monthly temperature). The environmental information can be directly observed from the farming field through the prototype described above. The environmental data, which had been collected, was divided into two portions, which included 70% for training and 30% for testing purposes. The entire process of preprocessing and optimization was executed using training data only, while test data remained completely hidden from the model training process to stop data leakage.

It is known that the diseases are correlated to the temperature. Equation 1 would be suitable for calculating mean monthly temperature (TE_{mean}) from the maximal daily temperature (TE_{maxday}). Take n , the number of days in a month, into account.

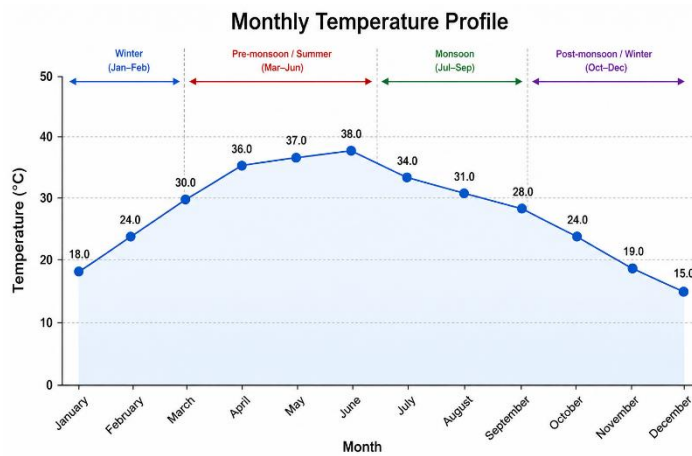
$$TE_{mean} = \frac{\sum_{Day=1}^n TE_{maxday}}{n} \quad (1)$$

Over the selected years, a selected location's temperatures are plotted month by month, from January to December. As shown in Figure 2 (a), the daily peak temperature (TE_{maxday}) and the monthly average temperature (TE_{mean}) are presented for the past five years. The paddy plantation season occurs at approximately high 30°C in which environment the disease likes to breed at. The percentage of wetness in air called humidity. Figure 2 (b) shows the monthly average humidity (HY_{mean}) and daily maximum humidity (HY_{maxday}) during last five years. Compared to the other months selected, June, July and August have a lower relative humidity that good to development of sheath blight attack on rice plant. The relative humidity range between 58% to 78% for chosen site from July to October. The mean relative humidity of a month was calculated by equation 2.

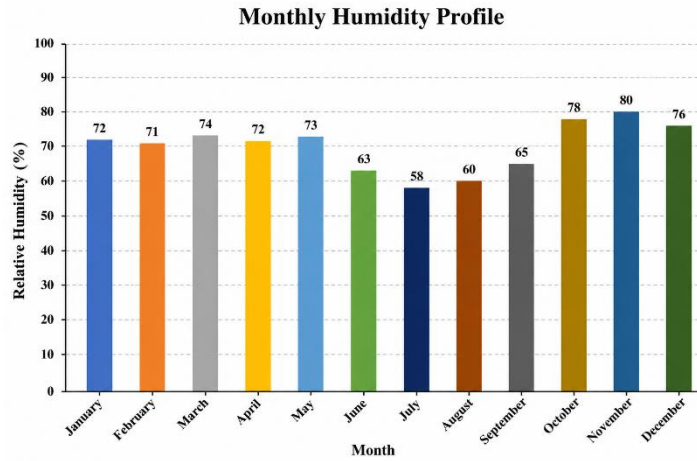
$$HY_{mean} = \frac{\sum_{Day=1}^n HY_{maxday}}{n} \quad (2)$$

Using Equation 3 we can calculate the highest amount of rainfall for a given month, this is the peak daily amount of rain for any given day in the month. The mean annual rainfall is shown in Figure 2 (c). The figure shows that relative to all of the months in a year the months from August to December show a higher proportion.

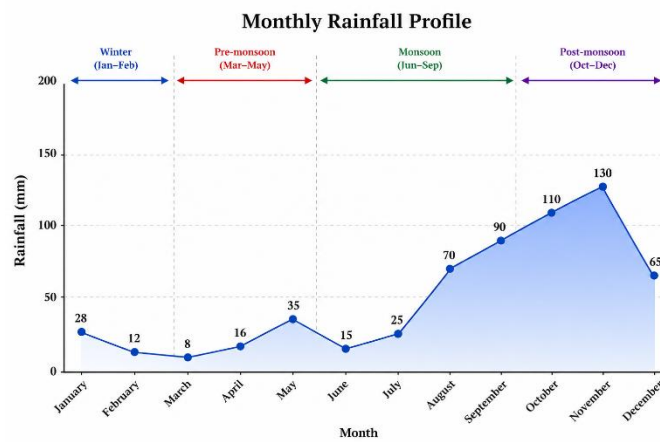
$$RF_{max} = RF_{maxday} \quad (3)$$



(a)



(b)



(c)

Figure 2. Average (a) Temperature, (b) Humidity, and (c) Rainfall profile in Cuddalore, India

3.2. HTM Model Description

In the human brain the learning cognition and perception of humans is determined by the neocortex. Each unit cell in the neocortex is called a neuron . In this paper, the authors develop a HTM neuron cell which is intended to perform the same operations of this biological cell. A model of this neuron cell is shown in Figure 3. There are 3 different kinds of dendritic branches: (i) distal dendritic branches connected with neurons from the above layer [24] and (ii) distal dendritic branches connected with lateral neurons, within the same layer, and (iii) proximal dendrite branches connected with neurons from the beneath layer. [24].

A layer in the HTM is composed of a stack of neurons in the shape of mini columns. Neurons are piled up to form mini columns. In our case, we add only one HTM layer. So in our neuron model we didn't take into account the back-propgations from the layer above. These lateral links in the distal dendrite enable the HTM to learn the timing of a sequence of inputs. That is what is crucial for the HTM in which we interact to detect and predict. An HTM neuron, similar to the biological neuron, can be in 3 different states, which are (i) not active (ii) predictive state, (iii) active state [25]. Beside, there is encoder, spatial pools, temporal pools and the HTM neuron cells shown in figure 3. For each time step the encoder produces high dimension binary vector for the input that has the SDR. SDR stands for sparse distributed representation, where the input are represented by few bits being activated. By means of the input data being spare represented this is usually set to 2 percent for HTM which yields to a good accuracy. The spatial pooler computes activation of the mini columns (i.e. Collections of HTM neurons) using another SDR about the same size of the input SDR. A part of the input SDR bits is connected to each micro column of an HTM by synaptic connections called sections of the proximal dendrite.

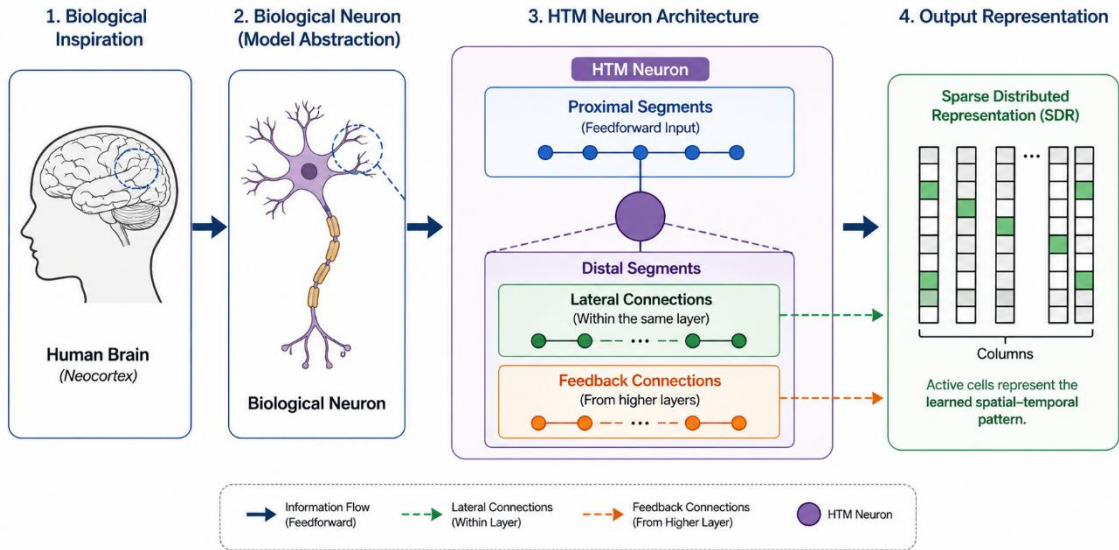


Figure 3. Architecture of the HTM Learning Method

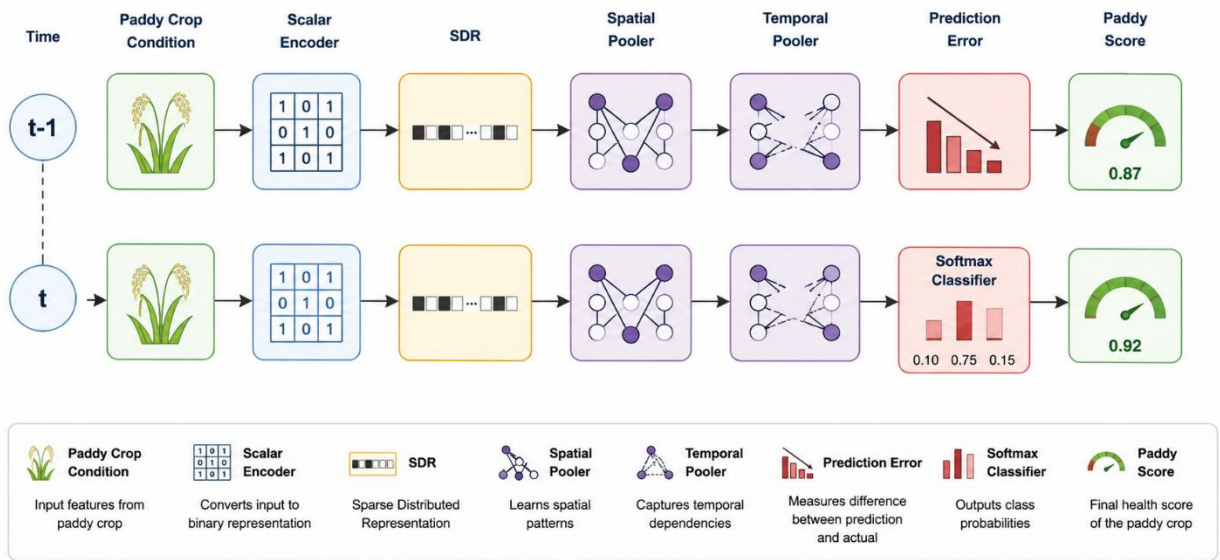


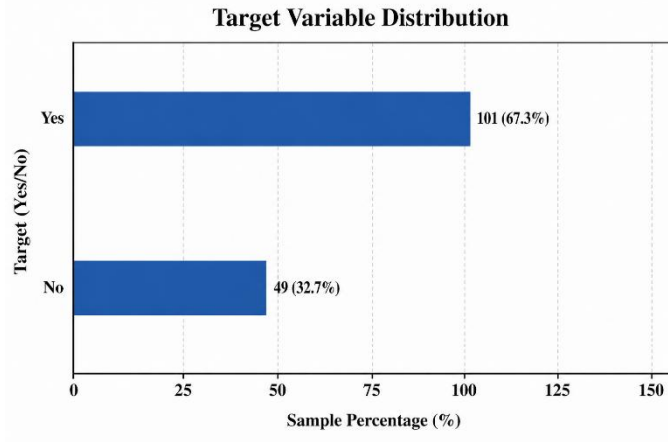
Figure 4. HTM Model for the detection and prediction of sheath blight disease

The output of the spatial pooler is the state of activation / trigger of the mini columns hence, it is an SDR.

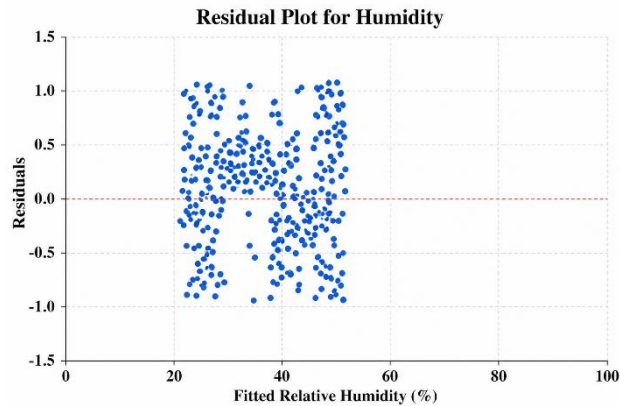
Multiple mini columns are composed with HTM neurons piled one above other in temporal pooler which contains them and multiple microcolumns stacked side by side forms a cortical column. The synaptic connections is the memory in an HTM, it encodes the temporal relationships. This connection between the two cells in different microcolumn in same layer and the activation implies that these two cells are temporally related. The cell, at the origin of the synapse, is alive, if the synapse is active. When the number of active synapse in a part of a dendrite is greater than a certain value, the cell become into predictive state. The predictive state of a cell gives the temporal context in the choice of its activation at the next time step.

The active synaptic connections which predicted state correctly are reinforced whereas the active synaptic connections which did not predict the state correctly are pruned. This higher order representation of sequence data is acquired by HTM via Hebbian type learning.

This can be used for both prediction and anomaly detection. HTM model architecture for predicting diseases simultaneously and real time disease detection is given in the figure 4. Only the HTM implementation for disease detection will be discussed here; it is a combination of blocks as follows: Each element x_{t-1} at each time t-1 is encoded into an SDR by the scalar encoder. The spatial pooler takes each SDR x_{t-1} matrix into a sparse binary representation vector SP (x_{t-1}) The temporal pooler outputs x_{t-1} which is the SP prediction of SP (x_{t-1}) In this block, we compute the difference between the predicted value, $P(x_{t-1})$ generated in the previous time step, and the real value SP(x_t). We show that HTM can correctly identify both spatial and low-level temporal features in the disease data with the formulated model based on the dataset.



(a)



(b)

Figure 5. (a) Probability Distribution and (b) Humidity Residual Graph

1.3 Field Observation and Validation

The proposed method has been applied and field tested to estimate the degree of severity of disease attack, At this stage the attack was determined to have reached ETL (Economic threshold level) when it is infecting up to 20% of paddy plants within an acre. Ten acres of paddy plants are selected and cropped to be. The proposed HTM-IoT framework enables early prediction of sheath blight disease in paddy crops through continuous environmental monitoring. IoT-based sensors collect key environmental parameters such as temperature, humidity, and rainfall, which are recorded and transmitted to cloud storage. The stored data is then fed into an HTM-based machine learning algorithm that identifies temporal trends associated with sheath blight probability. This result-whether the disease is

likely to occur or not-is presented to the farmer via an attached mobile or web-based interface to facilitate an immediate decision. After the test, the entire cycle is repeated continually. Through online learning the model gets updated in increments with each cycle to improve its prediction performance over time.

4. Results and Discussion

This part demonstrates the outcome and discussion of developed HTM - IoT for sheath blight prediction. Previous studies have considered purely image-based methods or time-invariant models; while this study employs temporal environmental learning for prediction. The measures are done based on the accuracy of the HTM model in classifying and predicting based on ground observations. The analysis indicated that humidity had the strongest correlation ($r = 0.86$) with disease intensity, while precipitation was second ($r = 0.83$) and temperature was next ($r = 0.79$). In general, over the model years, the accuracy improved steadily from 69 % in 2019 to 94 % in 2023, showing the adaptive learning capability of the HTM algorithm.

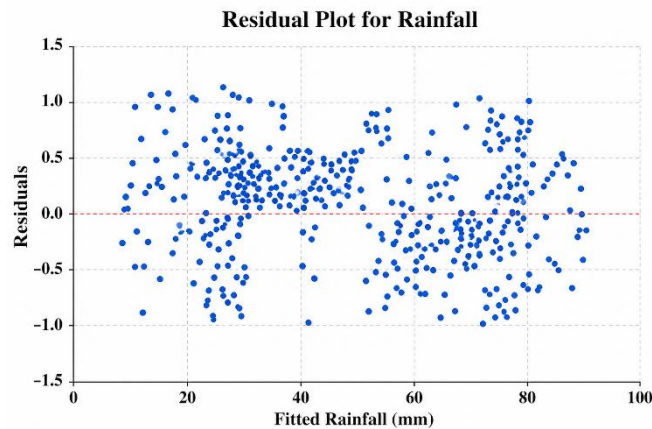
1.4 Effectiveness of the HTM model

In this section some of the statistics are suggested to implement the structure of HTM. Table 1 show the relation between environmental attributes with disease intensity. Correlation between rainfall, temperature and humidity with outbreak of sheath blight disease has a significant positive association. Relationship is present between predictor and response variable, we use regression line model to forecast. The coefficients of correlation are based on the relationship between the predictor variable (temperature, humidity, and rainfall) and the disease sheath blight. It is calculated using the covariance and the standard deviation.

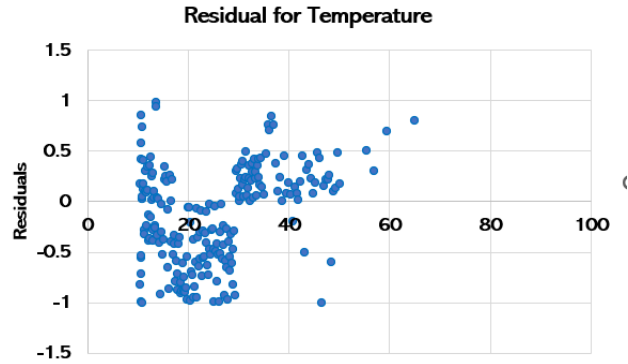
Table 1. Correlation of Environmental attributes with Disease Intensity

	Humidity	Rainfall	Temperature
Intensity of the Sheath Blight Disease in Paddy	0.87	0.81	0.78

The distribution of probabilities of Yes and No in the provided dataset is shown in Figure 5. In the existing data, the probabilities predicted Yes and No over ETL are uniformly distributed. The probability Yes and No is selected in relation to value of ETL. If disease infected plants in one acre are 20 % if the attack of disease is more then ETL it is marked as 'Yes' probability and otherwise it is marked as 'No' probability (Figure 5). The residuals of humidity based prediction on sheath blight also showed normally distributed spread around std dev, similar to Figure 5. The residual values are calculated using both predicted value and actual value. Also, the residual values on the rainfall based forecast of paddy sheath blight disease have evenly distributed about the mean, shown in figure 6. They are uniformly distributed relative to the averages.



(a)



(b)

Figure 6. (a) Rainfall Residual Graph and (b) Temperature Residual Graph

Multiple R, Adjusted R^2 , standard error, and number of observations is shown in table 2. With 1860 assessments, the multiple regression value is 0.66, the R^2 is 0.44, the corrected R^2 is 0.44, and the standard error is 0.32. These findings demonstrated how well the HTM model predicted the likelihood of the illness given a specific combination of environmental factors. Various failures test statistic can be found from Table 3. The prediction errors are small indicating a strong model fit and reliable forecasting performance.

Table 2. Regression Analysis

Regression Statistics	
Observation Samples	1870
Multiple R	0.63
R^2	0.44
corrected R^2	0.42
Standard Error	0.31

Table 3. Standard Errors

	Coefficient	Standard Error	P-Value
Intercept	-0.416	0.084	7.81e-8
X Variable 1	0.024	0.0013	4.85e-5
X Variable 2	0.0014	0.00073	0.183453
X Variable 3	0.001	0.001	1.654e-11

Independent variables are humidity, rainfall and temperature and the dependent variable is disease incidence. For the humidity-based forecast in Figure 7, regression line for the variable humidity is well fitted.

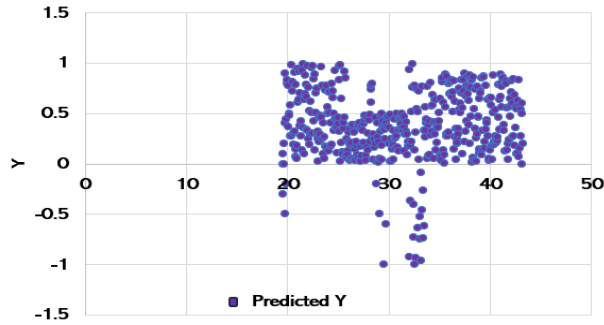


Figure 7. Humidity Regression Line for Sheath Blight Prediction

1.5 Field Validations

Field findings verify the predictions made by the HTM model. The actual values for 2019-2023, and the correct predictions are shown in Table 4. Because HTM is trained with fresh data sets and receives recursive feedback, prediction accuracy increases with time. Forecast accuracy over the years is illustrated in Figure 8, while rainfall- and temperature-based regression lines are shown in Figure 9. The accuracy rate is evaluated by using the predicted results by the HTM model and also based on verification by the field survey. The predicted results were correct by 69% in 2019, 77% in 2020, 85.6% in 2021, 87% in 2022 and 94% in 2023. The proposed scheme predicts exact probable occurrences of the paddy sheath blight disease prior to the disease epidemic. The proposed method outperforms image-based approaches, which are typically effective only after visible symptoms appear.

Table 4. Accuracy over the years in the Disease Prediction

Year	Correct Prediction	Probability
2019	8	70 %
2020	9	78 %
2021	10	86.7 %
2022	11	88 %
2023	12	94.2 %

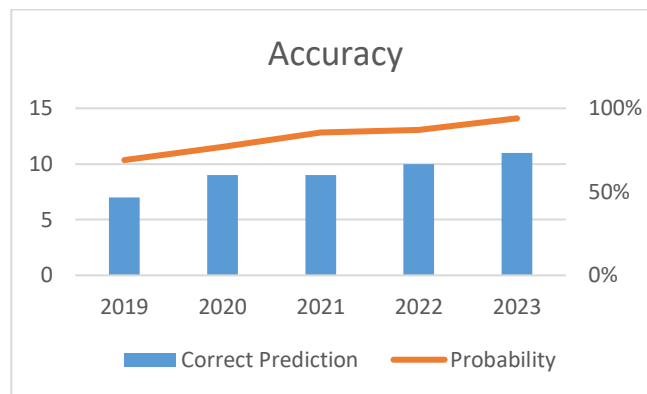


Figure 8: Accuracy over the years in the Disease Prediction Graph.

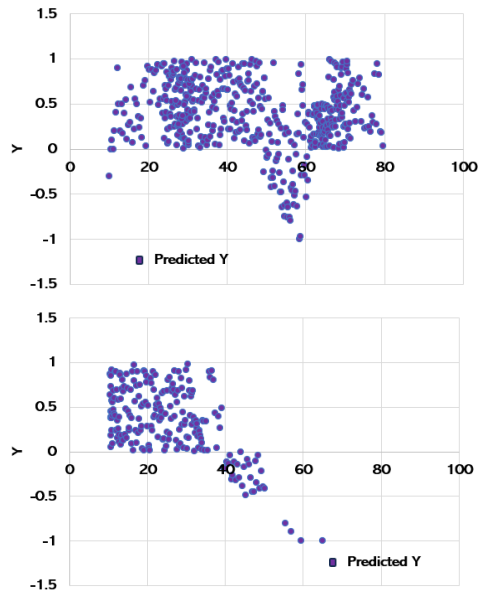


Figure 9. (a) Rainfall Regression Line and (b) Temperature Regression Line for Sheath Blight Prediction

Table 5 shows how the proposed HTM model has performed annually in the years 2019-2023 in the predicting sheath blight disease. This takes into account the different evaluation measures (accuracy, F1-score, area under the ROC and error bars for ROC) to track the classification reliability and consistency over years. A consistent year-on-year increase in the model performance is clearly observed as the model learned on different yearly data sets. The accuracy increases from 69% in the year 2019 to 94% in the year 2023, with similar increase in the F1-scores, which means better balanced precision and recall. The AUC values from 0.72 to 0.95 shows good discrimination ability in distinguishing disease and non-disease conditions and the errors bounds are narrow (from 1.8% to 3.1%), which represents stable predictions over the years and less variance on yearly datasets.

Table 5. Performance Evaluation of the HTM Model (2019–2023)

Year	Accuracy (%)	F1- Score (%)	ROC	Error (
2019	69.0	67.1	0.72	3.1
2020	77.0	76.1	0.80	2.7
2021	85.6	85.1	0.88	2.4
2022	87.0	86.6	0.90	2.1
2023	94.0	93.7	0.95	1.8

Table 6 shows that HTM model got better accuracy in both prediction accuracy and stable prediction. In 2023, HTM prediction accuracy achieved was 94%, and the F1-score achieved was 93.7%, while the Random Forest score was 88% and 83%, the SVM score was 85% and 82%, and the CNN score was 86% and 83%. By continually learning, HTM can cope with the variations and noises present in the IoT data, which can't be done by traditional methods.

Table 6. Comparative Evaluation of HTM with Other Machine Learning Models

Model	Accuracy (%)	ROC (%)	F1-Score (%)
Random Forest (RF)	88.0	86.5	86.8
Support Vector Machine (SVM)	85.0	83.5	83.8

Convolutional Neural Network (CNN)	86.0	84.6	84.9
Proposed HTM Model	94.0	95.8	93.7

To further demonstrate the effectiveness of the presented HTM-IoT framework, the Rice Leaf Disease dataset available publicly was selected for testing (<https://www.kaggle.com/datasets/soni535/rice-leaf-bacterial-and-fungal-disease>). This dataset comprises of several paddy diseases including Sheath Blight, captured under various circumstances along with images and environmental details of the disease occurrence. To conform with the requirements of the framework, only the environmental features (Temperature, Humidity and Rain fall) that helped in prediction using HTM are taken into consideration for analysis. Comparing the results of HTM model on Rice leaf disease dataset with that of other machine learning models, the following is observed in Table 7.

Table 7. Comparative Evaluation of HTM on the Rice Leaf Disease Dataset with Existing Models

Model	Accuracy (%)	ROC (%)	F1-Score (%)
Random Forest (RF)	87.3	89.0	86.9
Support Vector Machine (SVM)	84.5	83.0	84.4
Convolutional Neural Network (CNN)	85.8	84.6	85.2
Proposed HTM Model	92.2	91.3	90.3

When the HTM model was evaluated on the Kaggle dataset it performed better compared to the traditional ML methods giving good accuracy, F1-score, ROC values. The validation of the HTM-IoT model used K-fold cross validation. The performance of the model was measured in different folds. In different folds of the cross validation it was measured by 3 performance metrics, which are accuracy, F1-score and precision. From the Table 8 we observe that in different partitions of data the model gave reliable results proving the consistency in different testing conditions. It was able to maintain its accuracy in all environments.

Table 8. Cross-Validation Analysis

Fold	Accuracy (%)	F1-score (%)	Precision (%)
Fold 1	91.8	91.2	90.9
Fold 2	92.6	92.0	91.7
Fold 3	93.4	93.0	92.6
Fold 4	94.1	93.8	93.2
Fold 5	93.7	93.3	92.9
Average	93.1	92.7	92.3

An ablation study was performed to ascertain the relative effect that each HTM component has on model performance. It can be observed from Table 9 that removing either the spatial pooler, the temporal pooler, or the encoder resulted in drastic reductions in the system's performance, since each of the components is vital for processing the environment information.

Table 9. Ablation Study of HTM Model Components for Sheath Blight Prediction

Model	Accuracy (%)	F1-score (%)	Precision (%)
Without Temporal Pooler	88.5	87.8	86.9
Without Spatial Pooler	85.2	84.7	83.8
Without Encoder	82.7	82.1	81.5
Full HTM	94.0	93.7	92.9

1.6 Discussion of Error Cases and Limitations

The presented HTM model performed well in predictions within the range but had troubles predicting during extreme climate conditions. The extreme climate conditions were; high rainfall, rapid change of temperature and extended drought period. The deviations from model training based on established conditions lead to false negatives reducing predictions for monsoon season 2021. Sensor data must be provided for the model with acceptable accuracy levels alongside known threshold definition standards of the disease. The future research will gather data from various geographic locations while investigating hybrid methodologies to improve reliability outcomes. The HTM-IoT model proved its predictive accuracy during three extreme weather tests, which included sudden heavy rain and rapid temperature increase, and prolonged dry periods, as shown in Table 10, while showing robust error resistance through its incremental learning process.

Table 10. HTM-IoT Model Attack Resistance Under Extreme Environmental Conditions

Environmental Challenges	Predicted Accuracy (%)	Observed Accuracy (%)
Sudden Rainfall	92	90
Rapid Temperature Increase	91	89
Extended Dry Weather	89	87

5. Conclusion

The HTM-IoT model makes accurate predictions for sheath blight in paddy crops through its use of current environmental data, which resulted in 94% accuracy during 2023. Regression analysis shows that temperature and humidity and rainfall show strong relationships with disease occurrence. The combination of yearly field data with existing data enhances prediction accuracy throughout the time period. Early detection enables reduced pesticide use which protects the environment while decreasing costs and promoting sustainable agricultural practices. The model shows capabilities to adapt and function in different agricultural environments. The upcoming research will test framework validation using extensive multi-regional data while evaluating system performance across different climate and soil conditions through mobile advisory application integration which delivers real-time decision support to enhance precision and sustainable agricultural methods.

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