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Proximal Weighted Correlative Sequential Extreme Learning Machine For Iot-Based Automatic Crop Prediction In Agriculture

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ABSTRACT

Agriculture is rehearsal of cultivating soil, rising crops, and hoisting animals for food, fiber, other products employed to maintain as well as improve human life. It is a key development in India's economy and social fabric, continuously evolving to meet the demands of a growing population and changing environmental conditions. Smart agriculture, also known as precision agriculture, leverages advanced technologies to enhance crop productivity by making farming practices more efficient, sustainable, and data-driven. Through utilizing tools namely IoT as well as information analytics, farmers observe and control their fields through unprecedented precision. Therefore, analyzing the soil and environmental parameters is crucial for optimizing crop forecast. Different ML methods have been designed for crop forecast, however the major challenging issues faced by existing techniques are accuracy levels, error, and complexity. In order to solve these existing issues, a novel proximal weighted correlative sequential extreme learning (PWCSEL) model is developed. Major aim of PWCSEL method is to improve accuracy of crop prediction with minimal error and complexity. The proposed PWCSEL model involves four major steps namely data acquisition, pre-processing, feature selection, classification. In data acquisition stage, IoT involves using interconnected tools as well as sensors to gather soil and environmental characteristics from the farming environment. These IoT-acquired data are stored in a dataset repository for further processing. Next, data pre-processing is carried out to handle missing data and outliers within the dataset. After pre-processing, the significant feature selection process is employed in PWCSEL model to reduce time and space complexity during the prediction process. This selection involves identifying the most pertinent features that contribute to the predictive accuracy using Spatially Uniform Rosenthal weighted Correlative Relief algorithm. With the selected pertinent features, classification is performed using the Hamann indexive sequential extreme learning model for accurate crop prediction with minimal error. The observed results reveal PWCSEL increases the prediction accuracy and substantial reduction in error rate and prediction time compared to conventional methods.

Keywords: *Agriculture, IoT, Crop Prediction, Spatially Uniform Rosenthal weighted Correlative Relief algorithm, Hamann indexive sequential extreme learning model*

1. INTRODUCTION

Agriculture plays a vital part in beneficial world's rising population. Through growing demand for food, farmers require to optimize their practices to maximize output as reducing losses. Predicting and analyzing crop development is significant aspect of contemporary agriculture. Smart farming is contemporary approach which uses advanced expertise to optimize crop prediction. Crop prediction is an essential aspect of modern agriculture, helping farmers and policymakers make informed decisions to enhance productivity and sustainability. Accurate crop prediction relies not only on historical data and plant but also significantly on soil and environmental characteristics. The aim of smart farming is to increase crop suitability prediction resulting it enhance the yield. Machine learning and advanced data analytics have become powerful methods for more precise crop prediction.

An IML-ASE was developed in [1] with the aim of improving the crop prediction accuracy by means of collecting the data connected to farming, and so on. However, IML-ASE model did not succeed in minimizing the time consumption of crop prediction. An IDCSO-WLSTM was developed in [2] to improve the crop predictions and recommendations based on significant features. But, it failed to accurately detect crop predictions when dealing with a large number of data samples. Different ML methods were designed [3] for accurate crop forecast with higher accuracy while analyzing agricultural data. However, these algorithms did not evaluate crop data using IoT data from different geographic regions. A multilayer perceptron rule-based classifier as well as decision table classifier were developed in [4] using IoT for identifying crop yield. However, the performance in minimizing the error rate for crop prediction faced significant challenges. A Random Forest classifier was developed in [5] for predicting crops based on agricultural environment characteristics through significant feature selection. However, time complexity of crop forecast was high. Tree-based ensemble learning method was developed [6] for predicting crop appropriateness and productivity through high accuracy and predictive performance. However, it failed to incorporate significant facet pertinent to crop enlargement as well as productivity. Additionally, it did not utilize advanced DL techniques to more improve prognostic accuracy. K-means clustering and the MapReduce framework were introduced in [7] to predict crops based on weather conditions using big data. However, this approach did not address the issue of imbalance between production and demand. Moreover, it failed to incorporate additional factors such as humidity and wind speed for all regions to enhance the accuracy of crop recommendations. An IoT-based soil nutrient classification method was developed in [8] for accurate crop recommendations and maximizing productivity. However, it does not consider the collection of datasets with a wide range of crop types for more comprehensive recommendations. ML and ensemble learning methods were developed in [9] to predict suitable crops as well as maximize yield efficiency and system accuracy. However, the algorithms did not utilize advanced algorithms such as neural networks, to enhance the detection of different types of crops. LSTM network was designed [10] for forecasting ideal crops based on weather patterns to improve the technical effectiveness as well as output of farmers. However, it failed to create scalable method for precision agriculture across different areas.The gradient boosting (GB) tree method was developed in [11] for an accurate crop forecasting system, achieving high accuracy and F1 scores. However, it failed to incorporate yield and fertilizer usage into the crop selection methodology. A ML-basis of crop selection model was developed [12]. But, it failed to incorporate sensors for gathering concurrent data on accurate weather states as well as soil parameters specific to region, which could enhance the model's efficiency.An ensemble machine learning approach was developed in [13] by integrating K-nearest Neighbors, RF, and Ridge Regression to efficiently forecast manufacture of key crops. However, it did not utilize deep learning methodologies to more accurately choose suitable crops for right land while minimizing time consumption. An adaptive bagging classifier model was developed in [14] for crop prediction. However, it was unable to predict crop cultivation within minimal time. A novel machine learning-based method was introduced in [15] for cropland suitability prediction to achieve healthy as well as computationally effective predictions across diversity of exact environmental conditions.

1.1 Key Contributions

- To enhance crop prediction accuracy in agriculture domain, a PWCSEL model has been developed, incorporating the pre-processing, feature selection as well as classification
- To minimize prediction time, PWCSEL model utilizes preprocessing and feature selection techniques. The Proximal Weighted Linear Regressive Interpolation method is employed for handling missing data, while Rosner's Normalized Deviation Test is used for outlier removal. Additionally, the Spatially Uniform Rosenthal weighted Correlative Relief algorithm is utilized to choose important aspect as of database, ensuring accurate crop prediction with minimal time consumption.
- To improve accuracy and minimize error rates, the Hamann Indexive Sequential Extreme Learning Model has been developed for precise crop prediction with minimal error. This model predicts various types of crops by simultaneously analyzing multiple training and testing datasets using the Hamann similarity function. As a result, it enhances the accuracy of predictions for multiple crops.

2. LITERATURE REVIEW

A graph NN method was designed [16] to evaluate crop appropriateness and achieve better results. However, the model failed to handle large volumes of data, which limited its performance in achieving optimal results. A decision support system was designed in [17] to provide quick and accurate crop recommendations using machine learning techniques. However, it failed to optimize and enhance performance when handling large datasets. A Random Forest algorithm was designed in [18] for forecasting soil-crop appropriateness patterns with better accuracy and the lowest classification error. A new cloud-based, machine learning-powered crop recommendation model was developed in [19]. In [20], ML techniques were developed to enhance performance of crop recommendations for cultivating appropriate crops. However, deep learning-based computer vision systems were not utilized to improve productivity in the smart farming sector. Microclimate modeling methods were designed [21] for forecasting prospect crop appropriateness at elevated spatial solution for current as well as potential climate scenarios. A method-assisted framework was introduced in [22] to forecast the suitability of target crops. However, it did not incorporate ML methods to enhance accuracy of crop forecast. In [23], Bayesian multiple linear regression and RF regression methods were designed for accurate forecasting of crop suitability with minimal error. But, these methods were not able to effectively predict crop suitability in minimal time. An IoT-based Smart Irrigation and Fertilization Framework was developed in [24] for precision agriculture to enhance crop prediction. A holistic approach called Agri-PAD was designed in [25] with the aim of incorporating crop selection into a more efficient and intelligent agricultural ecosystem using big data analytics.An IoT-based K-Nearest Neighbour and SVM learning methods were developed [26] for smart farming to accurately predict the water requirements of fields and to identify pests automatically. However, these algorithms did not achieve the desired accuracy or improve decision-making effectively. An electronic agricultural record (EAR) was employed in [27] to store and manage agricultural big data for recommending optimal crops. An efficient neural network was implemented in [28] to forecast crops based on spatiotemporal data. However, the prediction accuracy was not significantly improved. An IoT-enabled precision agriculture system was developed in [29] for optimized crop management. However, it did not incorporate advanced technologies, namely ML algorithms, to enhance result as well as scalability in crop management. An innovative method which integrates XAI with machine learning models was developed in [30] for accurate crop recommendation systems. However, the issue of time consumption in crop recommendation remains unresolved.

3. PROPOSAL METHODOLOGY

Crop prediction based on weather and soil conditions involves a detailed analysis to identify mainly appropriate crops for given area. This procedure begins with evaluating weather patterns such as temperature, precipitation, and humidity, which directly influence crop growth and health. Soil characteristics also play a crucial role influencing which crops grow successfully. Machine learning-based crop prediction uses algorithms to analyze large datasets of weather, soil, and historical crop performance to forecast optimal crop yields and varieties. These models identify patterns and correlations that improving accuracy and adaptability. In this section, a novel method called PWCSEL is developed for predicting the suitable crops for a given region to achieve the better yield particularly in the agriculture. Precision agriculture within the land of IoT involves collecting large volumes of information as of several sensors organized on farm. These information provide spatial and temporal characteristics that are used for various types of crop prediction. By integrating sequential extreme learning, the model analyzes different factors namely soil type, climate conditions, water availability, historical data to compute most appropriate crops for exact region. This helps to provide farmers to maximize productivity and mitigate risks.

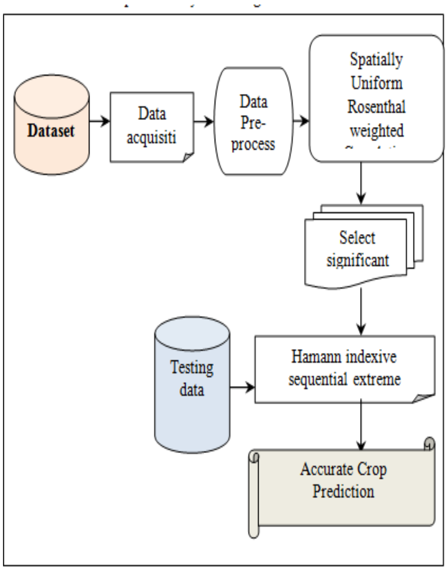

Figure 1 Structural design diagram of PWCSEL model

Figure 1 above shows architecture diagram of proposed PWCSEL model for accurate crop prediction in agriculture. The PWCSEL model involves different fundamental processes. These different fundamental steps of the proposed PWCSEL model are explained in detail as below.

3.1 Data Acquisition

In PWCSEL model, it is a fundamental step to ensure the model has access to accurate and relevant information for crop predictions. Data acquisition is systematic procedure of collecting information as of different sources, converting it to suitable format, preparing it for crop prediction. It involves gathering of information as of smart farming by ML dataset https://www.kaggle.com/code/talhanazir168/smart-farming-using-machine-learning/input. It is utilized for predicting crop depend on various soil as well as environmental characteristics. It comprises of 9 features or attributes and 2200 instances.

Table 1 Feature information

S.No	Features or attributes	Description
1	N	Nitrogen content in soil
2	P	Phosphorous content in soil
3	K	Potassium content in soil
4	temperature	Temperature in degree Celsius
5	humidity	moisture content in the Soil
6	ph	ph value of the soil
7	rainfall	rainfall in mm
8	label	13 types of crop maize, sugarcane, wheat, cotton, rice pulses, millets, mungbean, blackgram, lentil, banana, mango, grapes
9	district	50 districts

3.2 Data Pre-Processing

It is second step of PWCSEL method for preparing dataset for analysis crop prediction. In PWCSEL mode, data pre-processing is carried out to handle missing data and outliers within dataset.

3.2.1 Proximal Linear Regressive Interpolation Based Missing Data

Missing data is a common issue in datasets refers to the absence of data points or values in a dataset. Missing data is common problem in data investigation and poses important demands since it helps for maintaining accuracy of predictive method. So, PWCSEL method utilizes the proximal linear regressive interpolation to handle missing data effectively. The Proximal weighted linear regressive interpolation is an advanced technique used to estimate missing values in a dataset by utilizing the proximity of known data points.

Let us consider the input database 'DB' arranged in form of matrix as follows.

$$I = \begin{bmatrix} A_1 & A_2 & \dots & A_m \\ SD_{11} & SD_{12} & \dots & SD_{1n} \\ SD_{21} & SD_{22} & \dots & SD_{2n} \\ \vdots & \vdots & \dots & \vdots \\ SD_{m1} & SD_{m2} & \dots & SD_{mn} \end{bmatrix} \quad (1)$$

Where, I denotes an input matrix, 'm' denotes a column which indicates a features or attributes $A_1, A_2, A_3, \dots A_m$ present through entire 'n' sample instances of $SD_1, SD_2, SD_3, \dots SD_n$ are organized in row respectively. Linear Regression is statistical technique employed to method relationship among dependent variable (missing data) as well as one or more independent variables (already known information points).

$$M(SD) = \omega_0 + \omega_1 SD_1 + \omega_2 SD_2 + \dots \omega_n SD_n + \varepsilon \quad (2)$$

Where, $M(SD)$ denotes a missing data samples, $\omega_0, \omega_1, \omega_2, \dots \omega_n$ are the coefficient of the independent variables, $SD_1, SD_2, SD_3, \dots SD_n$ are the data samples available in the dataset, The error term 'ε' is dissimilarity among observed value as well as missing value predicted by linear regression model. Missing value undergoes a proximity evaluation to determine how close it is to neighbouring data samples available in the dataset. The Manhattan distance is employed to measures distance among determined missing information points and already available data points in given dataset.

$$DIS = \sum_{j=1}^{m} \left| M(SD) - SD_j \right| \quad (3)$$

$$Q = \min[DIS] \quad (4)$$

Where, Q denotes an outcomes,min denotes a minimum function, DIS denotes a Manhattan distance measure between the determined missing data points $M(SD)$ and already available data points 'SD_j'. If the absolute distance value is minimal, then the determined missing data is more suitable for filling the particular column, resulting in minimized error. It suggests that the missing value is closest to the available data points, making it a used for imputation and it leading to improve the accuracy.

3.2.2 Outlier Data Detection

Outlier data points are information points which considerably vary as of mainstream of other information points at database. It may have high or low value compared to the rest of the data. The Rosner's normalized deviation test is employed to identify and manage outlier data points. This statistical test assesses the deviation of each data point from the mean of the dataset. Let us consider the number of data points $SD_1, SD_2, SD_3, \dots SD_n$ the Rosner's normalized deviation test is used to distinguish and categorize outliers from the dataset. The test is expressed as follows,

$$RT = \frac{|SD_i - \mu|}{\sigma} \quad (5)$$

Where, RT indicates a Rosner's test, SD_i indicates a data point in the particular cell, μ indicates mean, σ indicates a deviation between the data points and mean value. The statistical test provides the output ranged from 0 to 1.

$$z = \begin{cases} RT > Th \ ; \ Outlier \\ RT < Th \ ; \ normal \end{cases} \quad (6)$$

Where z denotes an outcome, if computed RTvalue is better than threshold 'Th', particular value is considered an outlier. If computed RT is lesser than or equal to threshold 'Th', the value is measured normal data. After detecting the outlier data, the particular data points are removed, and new values are imputed using missing data handling techniques. In this way, the PWCSEL model effectively manages both missing data and outlier data. The pre-processing algorithm is shown below.

// Algorithm 1: Data pre-processing
Input: Dataset 'DB', featuresA $= \{A_1, A_2, A_3, \dots A_m\}$ and data samples $SD_1, SD_2, SD_3, \dots SD_n$
Output: Pre-processed dataset
Begin **1.** **For each** Dataset 'DB' with Features 'A' **2.** Formulate input vector matrix 'I' as given in (1) **3.** **If** missing data **then** **4.** Measure linear regressionusing (2) **5.** **End if** **6.** Compute distance using (3) **7.** **If** (min [DIS]) **then** **8.** Fill the missing value to the respective column **9.** **End if** **10.** **for each** data point **11.** Measure the Rosner's normalized deviation test using (5) **12.** **End for** **13.** **if** ($RT > Th$)**then** **14.** Detected as outlier data **15.** **else** **16.** Detected as normal data **17.** **End if** **18.** **Remove** Duplicate data **19.** **Go to step** 3 **to** 9 **20.** **End for** **End**

Algorithm 1, as outlined above, illustrates the process of information pre-processing for crop prediction. Process begins with collecting the features and data from the dataset. Missing data is addressed by applying a linear regression function, with proximity evaluation used to identify suitable replacements for the missing values. Outlier data is detected using Rosner's normalized deviation test. After identifying outliers, the algorithm removes these data points and then proceeds with handling the missing data.

3.2 Spatially Uniform Rosenthal Weighted Correlative Relief Algorithm Based Feature Selection

The third process of the PWCSEL model is feature selection, which involves choosing subset of pertinent aspect to enhance method result with minimizing dimensionality of dataset. The feature selection process in the PWCSEL model is designed to minimize the time required for crop prediction. The spatially uniform Rosenthal Weighted correlative relief algorithm is employed for choosing subset of pertinent aspect as of database.

Spatially uniform Rosenthal Weighted correlative relief algorithm is popular feature selection technique to recognize and select relevant features from a dataset by considering the spatial uniformity of the features. In other words the spatial relationships between features are measured for accurate prediction or classification. The Rosenthal correlation function is used for measuring the spatial relationships between the features. Initialize a feature vector in the distributed in the dataset.

$$A = \{A_1, A_2, A_3, \ldots A_m\} \quad (7)$$

After the initialization, weight vector 'ϑ' is assigned for each features $A_1, A_2, \ldots A_m$ with zeros.

$$K = \vartheta\,[A_m] \quad (8)$$

For each iteration, randomly selects the features vector of the instances from the dataset and measure the correlation.

$$CR = \left[\frac{ST}{\sqrt{m}}\right] \quad (9)$$

$$ST = \frac{(A_i - A_j)^2}{V(A_i, A_j)} \quad (10)$$

Where,R denotes Rosenthal correlation among feature vector 'A_i' and A_j, ST denotes Standardized test statistics, m' indicates the number of featuresin the dataset. Based on correlation value, the nearest hit and miss value is computed as given blow,

$$CR = \begin{cases} 1, & Nhv \\ 0, & Nmv \end{cases} \quad (11)$$

The Rosenthal correlation 'CR' provides the output as 1 represents the nearest hit 'Nhv', coefficient provides the output as 0 represents the nearest miss 'Nmv'. After that, the initial weight vector of the each feature gets updated as given below,

$$\vartheta_n = \vartheta - (A_j - Nhv_j)^2 + (A_j - Nmv_j)^2 \quad (12)$$

Where, ϑ_n indicates an updated weight vector of the feature, ϑ represents the initialweight vector, A_j denotes a j^{th}feature vector, Nhv_j denotes a nearest hit value of the of the j^{th}feature vector, Nmv_j denotes a nearest miss value of the of the j^{th}feature vector. The above process gets repeated until reaches the iteration. The feature with the highest weight is selected while the features with less weightedare removed. Aspect which contain lower weights are considered less important. These features are detached as of database to reduce complexity. This process helps in refining model by focusing only on the most important features, leading to more efficient and effective crop prediction.

// Algorithm 2:Spatially Uniform Rosenthal weighted Correlative Relief algorithm

Input: Preprocessed dataset, features $A_1, A_2, \ldots A_m$
Output: Select significant features

Begin
1. **Initialize maximum iteration** 't_{mx}',weight vector '$\vartheta = 0$'
2. **Collect the** features $A_1, A_2, \ldots A_m$ and instances $SD_1, SD_2, SD_3, \ldots SD_n$
3. **While** ($t<t_{mx}$) **do**
4. **For** eachfeatures A_j
5. **Initialize** the weight vector 'ϑ' **using** (8)
6. **End for**
7. **For each** A_i
8. **For each** A_j
9. Measure the correlation 'CR using (9)
10. **End for**
11. **End for**
12. **if** ($CR = 1$) **then**
13. Features is said to be a nearest hit
14. **else**
15. Featuresis said to be a nearest miss
16. **End if**
17. Update weight (ϑ_n) using (12)
18. Increment t=t+1
19. Go to step 3
20. **End while**
21. Sort the weights in descending order
22. **Select** features with higher weight
23. **Remove** Features with lesser weight

End

Algorithm 2 describes a process for selecting relevant aspect as of database for crop forecast, with aim of minimizing time consumption. The pre-processed dataset is used as input to the feature selection algorithm. Initially, a weight value of zero is assigned to each feature in the dataset. Next, the correlation between feature vectors is measured. Based on this correlation, the nearest miss and hit are computed. The initial weights are then iteratively updated until maximum number of iterations is attained. Afterward, features are sorted in descending order according to their weight values. Finally, the features with the highest weights are selected for crop prediction, while the less weighted features are removed from the dataset.

3.3 Hamann Indexive Sequential Extreme Learning Model Based Crop Prediction

The final step of the PWCSEL model is a classification based crop suitability prediction with the selected significant features. The Hamann indexive sequential extreme learning model is employed for accurate classification of the data samples. ELM is kind of feed-forward NN that is extremely fast learning speed and good generalization performance than the conventional neural networks. Since it did not involves iteratively adjusting the weights of the network through back propagation. Extreme Learning Machine achieves rapid training by using a fixed, randomly assigned set of weights among input as well as hidden layers. This allows ELM to compute the output weights in a straightforward manner, resulting in a significantly faster learning and provide the better performance. The Hamann index function is used to enhance result of the extreme learning machine for accurate feature learning in hidden layer.

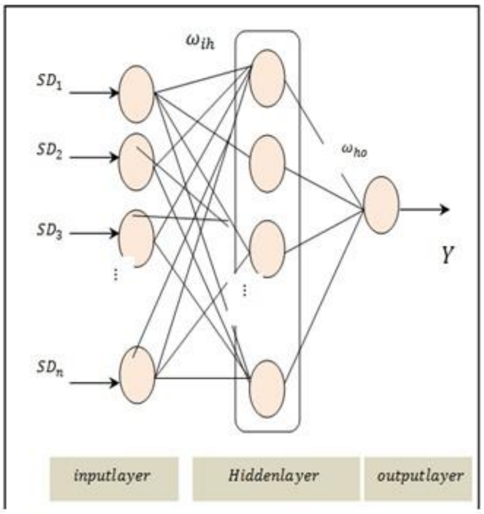

Figure 2 constructions of Hamann indexive sequential extreme learning model

Figure 2 demonstrates the constructions of extreme learning machines comprise input layer, hidden layer, and output layer. As exposed in figure 2, let us consider which training set $\{SD,\}$ where 'SD' indicates a training data samples $\{SD_1, SD_2, SD_3, \dots, SD_n\}$ and an output 'Y' representing output$Y_k \in Y_1, Y_2, Y_3, \dots Y_k$.

Each layer consists of neurons or nodes to transfer the input from one layer to another. Let us consider the number of features with data samples in input layer. Input is given to hidden layer

The hidden layer input is expressed as give below,

$$H = \sum_{i=1}^{n} F\ [SD_i . \omega_{ih}] + b_{ih} \quad (13)$$

Where, H indicates activity of neurons at hidden layer,D_i indicates training data samples, ω_{ih} indicates that the weight between input and hidden layer, b_{ih} denotes a bias function. Then the input is transferred from the input to hidden layers, F denotes a activation function,

In the hidden layer, Hamann index function statistical technique is used for estimating the similarity between the training and testing data samples.

$$S = 1 - \left[\frac{2\ |SD_i \Delta SD_t|}{n}\right] \quad (14)$$

Where, S indicates a Hamann similarity, SD_i denotes training data samples, SD_t denotes testing data samples, 'n denotes a number of data samples, $SD_i \Delta SD_t$ denotes a variation between the two data samples. The similarity 'S'returns a value from 0 to 1. Depend on similarity results, information samples are categorized to particular class.

Output of hidden layer is fed into the output layer, where softmax activation function is applied to provide multiple class classification results.

$$Y = F_s(\omega_{ho} * h_o) \quad (15)$$

Where 'Y' represents the final classification result of the output layer, F_s indicates a softmax activation function provides the multi class output, 'ω_{ho}' denotes the weight among hidden and output layer, h_o indicates output of hidden layer. In this way, accurate classification of multiple crops such as maize, sugarcane, wheat, cotton, rice pulses, millets, mungbean, blackgram, lentil, banana, mango, grapes is performed. Based on the selected outcome, the accurate crop prediction is performed with minimum time consumption . The algorithmic process Improved Extreme Learning Machine is given below,

// Algorithm 3: Hamann indexive sequential extreme learning model
Input: pre-processed Dataset, number of features $\{F_2, F_3 \ldots . F_n\}$ and data samples $\{SD_1, SD_2, SD_3, \ldots, SD_n\}$ **Output:** Crop prediction
Begin **1: Collect selected** features $\{A_1, A_2 \ldots . A\}$ with the data samples $\{SD_1, SD_2, SD_3, \ldots, SD_n\}$**--input layer** **2:For each data samples**SD **3:** Assign weight and bias using (8) **4: For each training data samples** SD_i **-- hidden layer** **5:For each testing data samples** SD_i 6. Measure the Hamann similarity using (14) **7:** Correctly classify the samples into different classes **8. End for** **9. End for** **10. End for** **11.return** (multi classifications labels)-- **output layer** **End**

Algorithm 3 describes the processes involved in accurate crop prediction using the Hamann-indexed Sequential Extreme Learning Machine. Initially, the algorithm collects relevant features, and the training information samples are fed into input layer. Input layer then transfers the data samples to hidden layer. In hidden layer, the Hamann index is applied to measure similarity among training as well as testing information samples. Depend on similarity measures and using a softmax activation function, multi label categorization outcomes are attained at output layer. Finally, accurate crop prediction is performed with minimal time consumption based on these classification results.

4. EXPERIMENTAL SCENARIO

Experimental evaluation of proposed PWCSEL model and existing IML-ASE [1], IDCSO-WLSTM [2], are implemented in Python using the Smart Farming using Machine learning dataset collected from https://www.kaggle.com/code/talhanazir168/smart-farming-using-machine-learning/input. This dataset is applied for accurately forecasting suitability of crop depend on soil as well as environmental conditions. It comprises 9 features and 2200 instances or data samples.

5. DISCUSSION

Performance results of proposed PWCSEL model and conventional IML-ASE [1], IDCSO-WLSTM [2], are explained with the dissimilar performance parameters.

Crop Prediction Accuracy

: Accuracy in crop prediction refers to a model forecasts kind of crops depend on different factors namely weather, soil conditions, other relevant variables. It is mathematically computed as follows,

$$CRPA = \left[\frac{tr_p + fl_p}{tr_p + fl_p + tr_n + fl_n}\right] * 100 \qquad (16)$$

Where, RPA denotes a crop prediction accuracy, tr_p indicates a true positive, fl_p denotes a false positive, tr_n indicates the true negative, fl_n indicates false negative. Accuracy is calculated in percentage (%).

Precision: it is a performance metric that calculates crop predictions based on proportion of true positive forecast out of every positive forecast made through method.

$$PCS = \left(\frac{tr_p}{tr_p + fl_p}\right) * 100 \quad (17)$$

Where, PCS represents a Precision, tr_p indicates true positive, fl_p denotes false positive. It is calculated in percentage (%).

Recall:it also known as Sensitivity is result parameter employed to estimate efficiency of classification method in recognizing positive instances. It computes proportion of actual positive cases which accurately recognized through method.

$$RLL = \left(\frac{tr_p}{tr_p + fl_n}\right) * 100 \quad (18)$$

Where 'RLL 'indicates a recall, tr_p represents true positive, fl_n symbolize false negative. It is calculated in percentage (%).

F1-score: F1-score is parameter employed to evaluate the performance of classification method with integrating both PCS and RLL into a single value. The formula for evaluating the F1-score is given below,

$$F1 - score = \left[2 * \frac{PCS * RLL}{PCS + RLL}\right] \quad (19)$$

Where F1-score is computed based on precision PCS and recall 'RLL. It is measured in percentage (%).

Error rate: it is parameter employed to estimate result of classification method through computing proportion of incorrect forecast out of total forecasts made. It is mathematically formulated as given below,

$$ER = \left[\frac{fl_p + fl_n}{tr_p + fl_p + tr_n + fl_n}\right] * 100 \qquad (20)$$

Where, R denotes a error rate, tr_p indicates a true positive, fl_p denotes a false positive, tr_n indicates the true negative, fl_n represents the false negative. The error rate is calculated in percentage (%).

Crop prediction time: It is referred as amount of time taken through method to forecast most appropriate crops based on the classification of the data samples. It is calculated as below,

$$CPT = \sum_{i=1}^{n} SD_i * t[CP] \quad (21)$$

Where, PT denotes a crop prediction time, SD indicates a number of data samples $[CP]$ denotes a time for crop prediction. It is calculated in milliseconds (ms). Table 2 illustrates performance results of accuracy versus the number of data samples. Average value of ten outcomes denotes PWCSEL model increases accuracy by 8% and 10% than the [1] , [2].

Table 2 comparison of crop prediction accuracy

Number of data samples	Crop prediction accuracy (%)		
	PWCSEL	IML-ASE	IDCSO-WLSTM
200	94.5	87.5	85
400	94.2	88.75	85.45
600	95	88.33	86.45
800	95.05	88.75	87.05
1000	95.32	87	85.45
1200	94.78	86.66	85.01
1400	95.11	87.14	85.44
1600	94.34	86.87	85.74
1800	95.25	87.22	86.45
2000	94.78	88.5	86.41

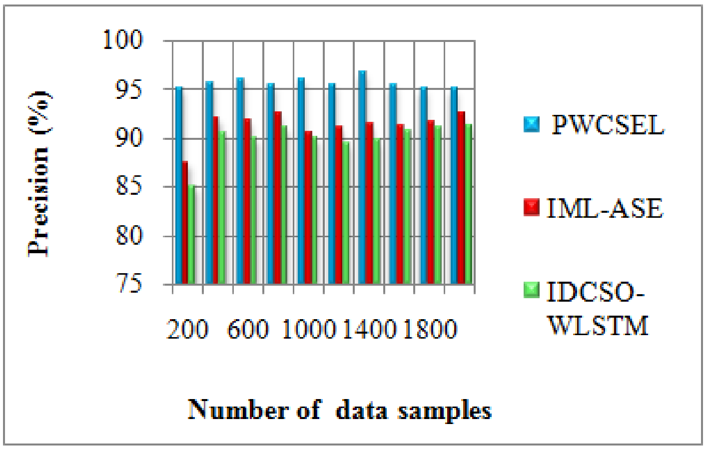

Figure 3 performance outcomes of *PCS*

Figure 3 illustrates overall result outcomes of *PCS* versus the number of data samples The average results indicate that the precision performance of PWCSEL model improved by 5% and 6% than [1], [2].

Table 3 comparison of *RLL*

Number of data samples	*RLL* (%)		
	PWCSEL	IML-ASE	IDCSO-WLSTM
200	95.93	91.30	89.47
400	96.02	93.54	92.45
600	95.74	93.75	92
800	96.05	93.89	92.04
1000	96	93.90	92.1
1200	97.05	92.92	91.78
1400	96.78	93.04	92.45
1600	95.45	93.23	92.88
1800	96.05	93.37	92.04
2000	96	94.11	93.74

Table3depicts performance outcomes of recall versus number of data samples.Overall performance results of PWCSEL model indicate performance of recall is improved by 3% and 4% than the [1] ,[2].

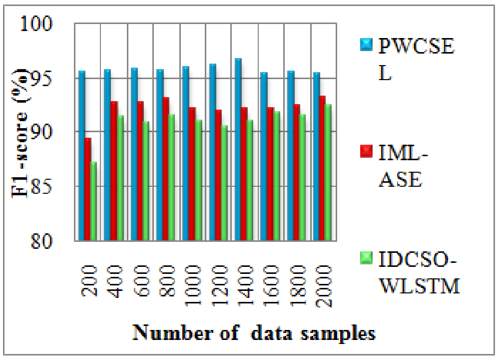

Figure 4 performance results of F1 score

Figure 4 illustrates the performance results of the F-score using three methods. Entire performance outcomes denote F1-score of the PWCSEL model is improved by 4% compared to [1] and by 5% compared to [2].

Table 4 comparison of error rate

Number of data samples	Error rate (%)		
	PWCSEL	IML-ASE	IDCSO-WLSTM
200	5.5	12.5	15
400	5.8	11.25	14.55
600	5	11.67	13.55
800	4.95	11.25	12.95
1000	4.68	13	14.55
1200	5.22	13.34	14.99
1400	4.89	12.86	14.56
1600	5.66	13.13	14.26
1800	4.75	12.78	13.55
2000	5.22	11.5	13.59

Table 4 demonstrates the overall performance results of error rate in the crop prediction versus the number of data samples, Comparing the PWCSEL model with the existing methods, the overall performance of error rate is considerably reduced by 58% and 63% for [1] and [2].

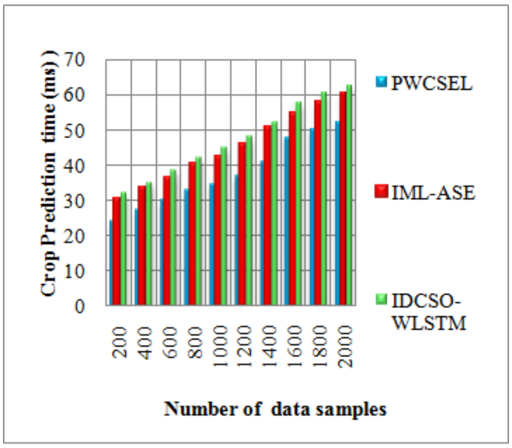

Figure 5performance outcomes of *CPT*

Figure 5 demonstrates graphical outcomes of *CPT*.Average of ten comparison results shows crop prediction time using PWCSEL model was reduced by 17% and 21% than the [1] and [2],.

6. CONCLUSION

Forecast of various crops is crucial feature of agricultural planning as well as management. Accurate crop prediction help farmers makes informed decisions about resource allocation, planting schedules, and potential yields, leading to improved agricultural productivity and sustainability. To achieve this, a novel PWCSEL model has been developed to improve crop prediction accuracy of various crops. During pre-processing, input data samples are organized to ensure quality and consistency. Following this, advanced algorithms, such as the Spatially Uniform Rosenthal Correlative Relief algorithm is employed to choose more important features as of database. By analyzing correlations between these features vectors, PWCSEL model accurately improving the prediction accuracy of crop prediction while minimizing time as well as error rate. An experimental analysis was conducted to estimate result of PWCSEL method as well as compare it through conventional methods using various parameters. The implementation and performance results demonstrate that proposed PWCSEL model significantly outperforms conventional methods.

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