WATER STRESS DIAGNOSIS IN MAIZE CROP USING ENHANCED EXTREME LEARNING MACHINE MODEL FOR PRECISION IRRIGATION SYSTEMS

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Abstract:

Water stress is a significant component that limits crop productivity globally, particularly affecting maize yields. The adverse effects of water stress on maize necessitate an efficient method for rapid and accurate monitoring. An intelligent crop water stress identification model is an important component of the development of a decision support system for smart irrigation. The present study proposes an intelligent kernel extreme learning machine model (CS-KELM) to recognize water stress in maize crops. To optimize the model's performance, the meta-heuristic cuckoo search algorithm is integrated to fine-tune the model. The proposed approach has demonstrated an accuracy of 94.20% and an F1-score of 94.39%. Integrating the cuckoo search algorithm into the extreme learning machine (ELM) model has enhanced the model performance, resulting in an improvement of 4.27% in accuracy and a 4.32% increase in F1 score compared to the ELM model. The improved model performance underscores its potential effectiveness in deploying the model into a decision support system for IoT-based irrigation solutions, enabling efficient and precise water delivery based on real-time stress detection.

1 Introduction

Maize (*Zea mays L.*) is one of the one of the most vital cereal crops cultivated worldwide under a wide range of environmental conditions [1]. Climate change, marked by increasing amounts of carbon dioxide in the atmosphere and the subsequent rise in temperatures, has the potential to negatively affect the process of photosynthesis, the rates of crop growth, and the efficiency of water usage in crops, directly impacting productivity. Being sensitive to water shortages, maize plants exposed to water deficit conditions during the tasselling stage experience substantial yield loss [2], [3]. Maize is particularly affected with global yield losses of around 15% due to drought stress [4], [5]. Water is a crucial factor in determining the quality and quantity of crop yields, and when its availability decreases, plants undergo a physiological response known as water stress [6], [7]. Climate change, changed precipitation patterns and increased evaporative demand make water stress in agriculture inescapable and intensifying [8]. Under these challenging conditions, a crucial aspect of sustainable agriculture is the early detection of crop water stress by closely monitoring key indicators. In regions with water scarcity, precise planning of irrigation is also a vital factor for ensuring sustainable production [9]. Advancements in agricultural techniques have enabled the optimization of irrigation management. This includes the implementation of drip irrigation systems and the application of regulated deficit irrigation strategies, which are capable of maintaining crop yields while utilizing reduced irrigation volumes [10], [11]. In the context of climate change, successfully modelling the relationships between maize, soil, and meteorological conditions is crucial for sustainable water management and agricultural production. To reduce crop loss and effectively manage irrigation scheduling, it is crucial to determine whether the crop is

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under water stress or not. Traditional water use management practices in maize farming often lead to inefficiencies, including over-irrigation or under-irrigation, which can negatively impact crop yields and waste valuable water resources.

In the past, crop water status variations were measured using traditional methods like visual assessments or in situ measurements by trained experts [12]. However, these techniques are labour-intensive, costly, and relatively time-consuming, making them analyse data and process it in real-time. Hence, these traditional approaches are generally impractical for continuous and efficient monitoring. Advances in ICT have led to significant advancements across various domains, particularly in enhancing the efficiency of water resource management and irrigation practices through intelligent decision-making capabilities [13]. By utilising machine learning (ML) techniques, manual models can be replaced and experienced agronomists can be supported, resulting in the creation of an automatic irrigation decision support system. Machine learning offers a panacea for the abovementioned challenges by providing intelligent, human-like solutions for efficient water use management and supporting smart irrigation systems [14]. Essentially, ML involves improving future performance by learning from past experiences. This field of study empowers computers to operate and generate decisions autonomously without the need for explicit programming [15]. ML models can analyse massive soil, meteorological, and crop health data to generate accurate predictions and recommendations for water requirements of the crops. These models, integrated with decision support systems and IoT, ensure that crop water demand is met and that crop losses due to water stress are reduced. The present study focuses on developing an intelligent ML based on a kernel extreme learning machine to identify crop stress in maize. Additionally, the performance of the model is enhanced by integrating the meta-heuristic cuckoo search (CS) algorithm.

2 Related work

Technology integration in agriculture has transformed traditional farming into a more precise and efficient practice [16], [17], [18]. At the core of modern agricultural decision-making is data-driven analytics, which provides comprehensive insights by utilizing vast data from sources like weather patterns, soil sensors, and historical crop information [19]. Through predictive and prescriptive analytics, farmers can forecast outcomes and refine strategies with remarkable precision, supporting smarter and more efficient farming [20]. Crop stress detection, leveraging similar approaches, helps identify early signs of stress caused by multiple factors. Machine learning models can excel at representing crop water stress, but optimizing them is vital for maximizing their effectiveness. Tuning these models adequately to navigate the complexities of agricultural data ensures more reliable prediction and informed decision-making. This section provides a brief review of recent studies on machine learning models for crop water stress detection and optimization techniques in agriculture.

2.1 Machine learning models for crop water stress detection

Several studies have highlighted the potential of machine learning models in identifying crop water stress using multiple modalities. Rajwade et al. [21] employed RGB and thermal imaging for the assessment of water stress in maize crops under rainfed conditions. In this investigation, the pre-trained deep learning model 'DarkNet53' was trained to detect water stress and the model achieved above 90% accuracy on both datasets. Among the two approaches, thermal image-based detection was observed to be more accurate than RGB-based stress identification. Pradawet et al. [22] also utilized thermal imaging to accurately detect water stress for preventing the yield losses maize. In their study, the canopy temperature, growth parameters, and soil moisture data were collected at an interval of 5 days. Additionally, the study proposed a new wet/dry technique using sponge cloth for obtaining more reliable crop water stress index (CWSI) values. At tasselling, the CWSI at 55 days after sowing (DAS), showed a significant linear correlation with the yield. Loggenberg et al. [23] coupled hyperspectral remote sensing with ML models for identifying the water stress in vineyards. The two ensemble learners Random forest (RF) and Extreme Gradient Boosting (XGB) were employed for the classification. Further, Savitzky-Golay filter were also evaluated for smoothing the spectral data. RF was found to be superior in identifying crop stress with a test accuracy of 83.3%. In another study, Tunca et al. [24] also used XGB and RF along with SVM for ML-based crop water modeling. In their investigation, the crop water content was estimated using regression models using hyperspectral data.

The results showed that the XGBoost model obtained high accuracy, with an R^2 value of 0.96. In another study, Moshou et al. [25] utilized least squares SVM with sensor fusion to identify water-stressed winter wheat from healthy ones. The authors have achieved a classification performance of 99%. A multitude of studies have focused on employing machine learning models to evaluate water stress across several crops, highlighting the importance of this approach for optimizing water management and improving crop quality. For instance, research on wheat [26], rice [27], and maize [8] has demonstrated the effectiveness of these models. King and Shellie [28] developed and tested an IoT-based decision support system for precision irrigation by monitoring the weather parameters, crop, and soil parameters.

The modelling was performed using an artificial neural network and promising results were obtained. There were several other vineyard-based studies [29], [30] that emphasize the crucial requirement for precise water stress management to guarantee the health and productivity of grapevines, improve grape quality, and achieve sustainable viticulture practices. Edge computing approaches are found to be very effective in enabling timely interventions. Amogi et al. [31] developed an edge computing algorithm, coupling thermal-RGB images to estimate water stress in apple orchards. An edge compute and IoT-based ‘crop physiology sensing system (CPSS)’ was utilized for the data collection. Further, the CWSI estimation algorithm was developed and coupled with the CPSS node for efficient water stress monitoring. Recently, UAV-based data collection has been increasingly used for developing intelligent models for real-time monitoring and management of water stress in crops [32]. Sharma et al. [33] utilized UAV-based multi-spectral imaging for assessment of responses to water stress in maize and yield estimation. Multiple ML and DL regression models were employed in the investigation and the H2O-3 DL model outperformed the other models in performance. In a similar study, Yang et al. [34] also employed UAV-based multispectral imagery to assess the water stress. In their investigation, winter wheat was the focus, and different features were extracted from multispectral images. Ensemble models, including stacking and weighted stacking (WE-stacking), were developed to evaluate water stress.

2.2 Optimization techniques in agriculture

Optimization techniques have been increasingly applied in agriculture to enhance resource efficiency, refine crop management strategies, and strengthen decision-making processes [35], [36]. Coupling meta-heuristic optimization with ML models often yields improved predictive accuracy, efficient parameter tuning, and building robust models [37]. Meta-heuristic algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), grey wolf optimization (GWO), etc. are extensively used for solving complex optimization problems in agriculture. These techniques have been coupled with ML models and applied in real-world scenarios and case studies, including irrigation scheduling [38], crop yield prediction [39], pest and disease management, resource allocation [40], and other precision farming applications. Jia et al. [41] employed a hybrid PSO-LSTM model for predicting daily evapotranspiration and further scheduling irrigation precisely. Four climatic station data were used in the study for developing the model and results indicated that the predictive power of the LSTM model has significantly improved using PSO integration. In another study, Abuzanouneh et al. [42] designed an advanced smart irrigation system that integrates IoT sensors and a meta-heuristically optimized machine learning model.

The system utilizes data collected from IoT sensors monitoring soil moisture, humidity, temperature, and light levels in the field. For the classification process to determine irrigation requirements, the authors employed the artificial algae algorithm (AAA) to optimize a least squares SVM model. The proposed design demonstrated a high level of effectiveness, achieving an accuracy of 97.5%. Yuan et al. [43] coupled grey wolf optimization with an extreme learning machine model for predicting the soil plant analysis development (SPAD) value of cotton crops under verticillium wilt stress. The spectral reflectance of healthy and verticillium wilt-infected cotton leaves was analysed and GWO-ELM was found to be highly accurate in modelling. He et al. [44] estimated the soil moisture of maize using a hybrid SVM and chaotic whale optimization algorithm (WOA) for precision irrigation. The authors optimized the penalty parameter of the SVM and the kernel function's coefficient using the WOA to obtain the best results. Zanial et al. [45] developed a river flow prediction model using an enhanced machine learning approach that integrates Artificial Neural Network (ANN) with Cuckoo Search (CS) Optimization. The hybrid CS-ANN model demonstrated improved prediction performance, achieving an R^2 value of 0.935 during the testing phase, surpassing the performance of the standalone ANN model. Kiraga et al. [46] employed genetic algorithm to optimize state-of-the-art machine learning models for estimating the reference evapotranspiration. Multiple datasets were analysed at different timescales, revealing that the GA-optimized ELM model consistently outperformed other machine learning models. Several other studies have also demonstrated the improved predictive capabilities of machine learning by incorporating optimization techniques for modeling evapotranspiration, which is crucial for irrigation planning and water resource management [47], [48], [49].

3 Materials and Methods

The proposed framework involves the collection of crop and environmental parameters, followed by the development of a kernel-extreme learning machine model to identify water stress. The performance of the models was fine-tuned using the cuckoo search algorithm. This ensures that the optimal model is deployed in the decision support system for IoT-based solutions, enhancing the precision of water stress identification (Fig. 1). The implementation of the models was done using a Python environment, making it an easily deployable model. The following section covers the detailed approach used in the study.

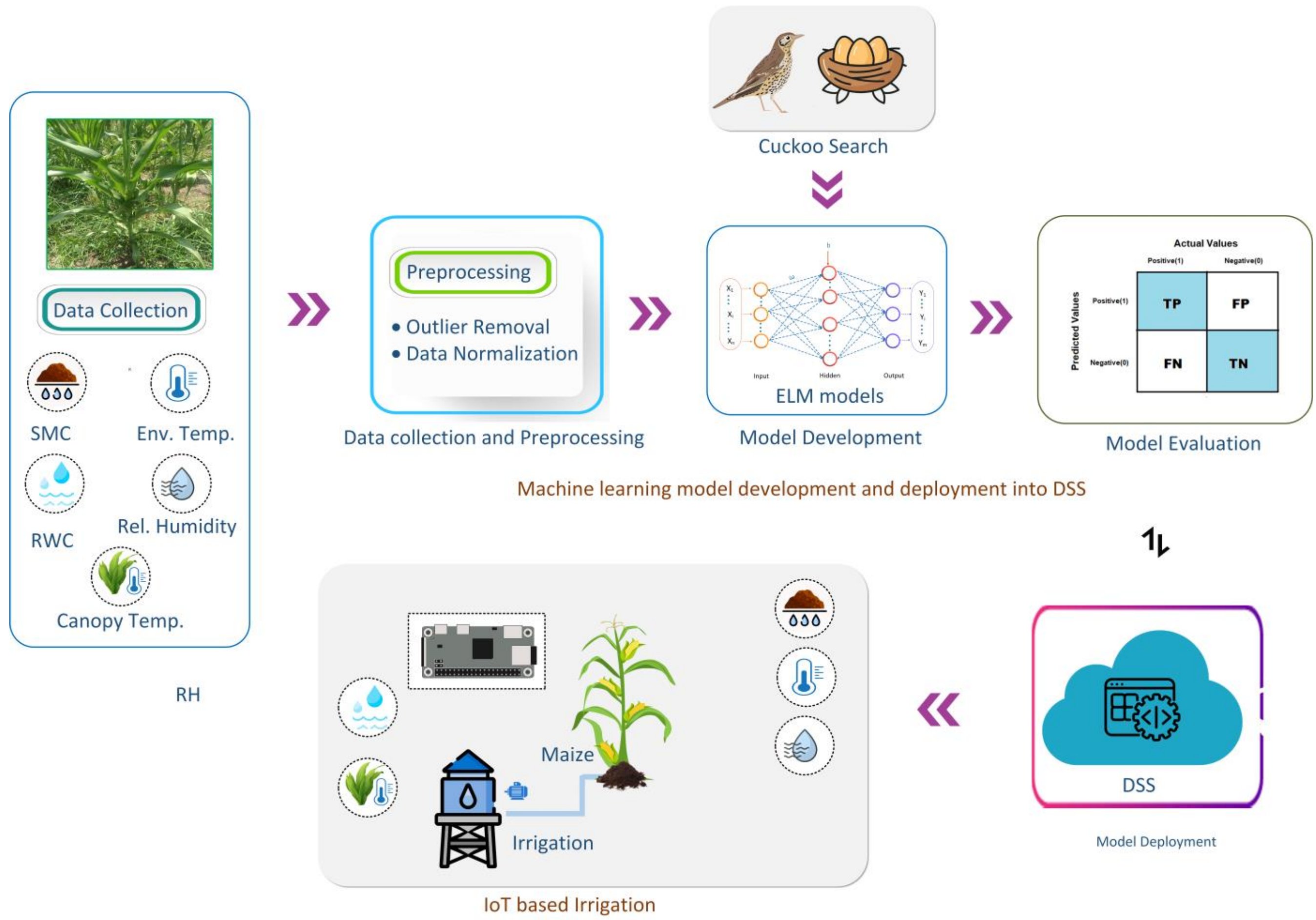

Figure 1. Overview of the key components of the stress detection framework using ELM.

3.1 Data set and Data pre-processing

Maize crops were grown at ICAR-Central Institute of Agricultural Engineering, Bhopal, India (77◦24′7.50′′ E, 23◦18′56.91′′N) between December and April during the years 2021-2023 to gather data. Environmental variables and soil parameters were recorded in real field conditions. The crop was grown in vertisols, with clay content exceeding 50%, moderate fertility, and low salinity. The collected variables included relative humidity, environmental temperature, average canopy temperature, relative water content, and soil moisture content to determine crop water stress. During two growing seasons, thermal imaging of the crop was conducted on selected days between 20 and 90 days after emergence (DAE), from 11 AM to 11 PM, under clear-sky conditions. The average canopy temperature is calculated from the thermal image data. Daily weather data were concurrently collected from a meteorological observatory during the same data collection period. The air temperature and relative humidity (RH) values were measured using a DHT22 sensor connected to an ESP32 microcontroller. A soil moisture meter equipped with a 200 mm sensing probe was utilized to monitor soil moisture content (SMC). Relative water content (RWC) was determined by measuring the fresh weight of fully expanded leaves immediately after sampling, oven-drying them at 70°C, and then calculating the RWC based on the fresh and dry weights. The dataset contained no missing values, so data imputation was not required during pre-processing. However, outliers were observed in the air temperature and relative humidity measurements, possibly due to occasional sensor fluctuations. Outliers were eliminated using the inter quartile range (IQR) method and normalization was performed to handle feature scaling issues. The dataset, consisting of 687 data points for these variables, was utilized for model development. The dataset is further divided into train and test sets with a ratio of 70:30 for the model training and testing. Further in the next stage, different ELM models (basic ELM, kernel ELM, CS-KELM) were developed and evaluated.

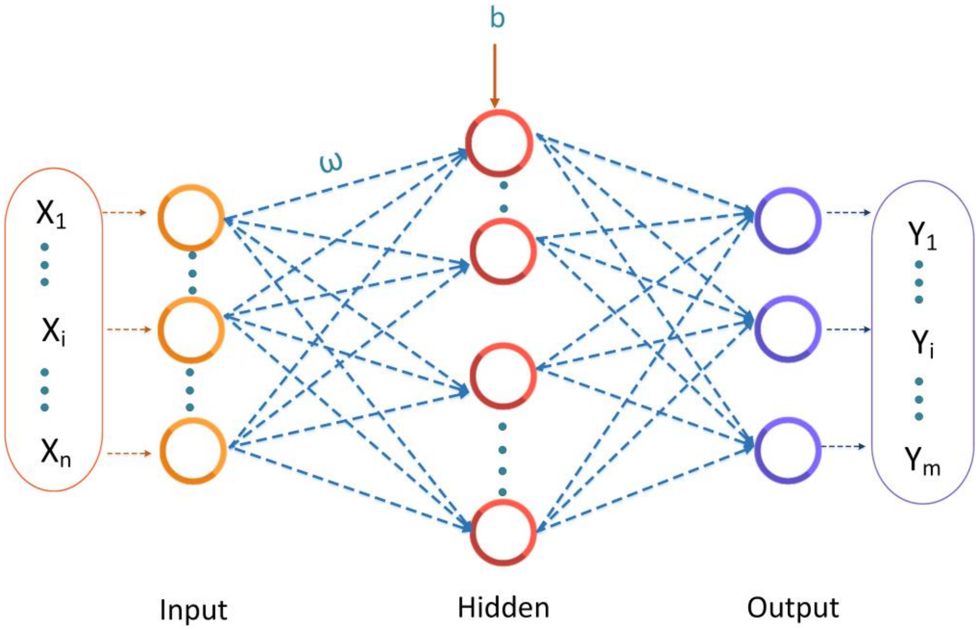

Figure 2. Schematic diagram of Extreme learning machine model.

3.2 Kernel extreme learning machine

ELM is a type of single-hidden-layer feedforward network consisting of three layers viz., an input, a hidden, and an output layer (Figure 2). A feedforward neural network employs gradient-based learning techniques to acquire knowledge from training data and iteratively modify parameters. This process leads to a reduced speed of learning, which can be a constraint for practical applications. On the other hand, ELM is characterized by only a single layer of hidden nodes and avoids the necessity for backpropagation. The output weights are determined using analytical methods in a single, straightforward calculation, without the need for iterative parameter adjustment. This strategy improves both the overall efficiency and speed of learning of the model [50]. The output of the hidden layer, shown as D, is computed by introducing the activation function f to the dot product of the input features and weights and then applying the bias term. This can be represented by the equation:

$$D = f(W.X + b) \tag{1}$$

The weights of the output layer in ELM are calculated by utilizing the Moore-Penrose inverse of the hidden layer output matrix. The weight matrix that is produced is represented by the symbol β. The output predictions denoted as (x) , are calculated by multiplying the output of the hidden layer D with the output weights β.

$$O(x) = D * \beta \tag{2}$$

ELM has the advantage of not requiring tuning because it randomly initializes the input weights and biases. However, this can compromise robustness. In order to enhance the ability of a model to generalize, the utilization of kernel approach can be integrated into the ELM. This study employs Gaussian kernel to the ELM model which is given by the Eq. (3).

$$K(u, v) = \exp(\gamma \, ||u - v||^2 \tag{3}$$

The kernel function acts as a hidden feature transformation, translating data from the original input space to a higher-dimensional feature space. Employing this kernel approach, KELM attains improved generalization capability than the traditional ELM [51]. The performance of KELM is significantly influenced by its hyperparameters, particularly the kernel parameter (γ) and the penalty parameter C. The value C controls the balance between model complexity and fitting errors, while γ represents a nonlinear mapping [52]. However, accurately determining the parameter intervals for KELM is challenging, as it often falls into local optima. To address this issue, the meta-heuristic cuckoo search algorithm is employed in this study. The integration involves initializing a population of candidate solutions representing different KELM parameter sets. The integration process is shown in Figure 3. CS iteratively updates these solutions by simulating the behavior of cuckoos laying eggs in the nests of host birds, combined with a Lévy flight mechanism for exploration. The objective function evaluates the accuracy or error of the KELM model for each parameter set. After several iterations, the best parameters are identified and used to retrain the KELM for improved performance.

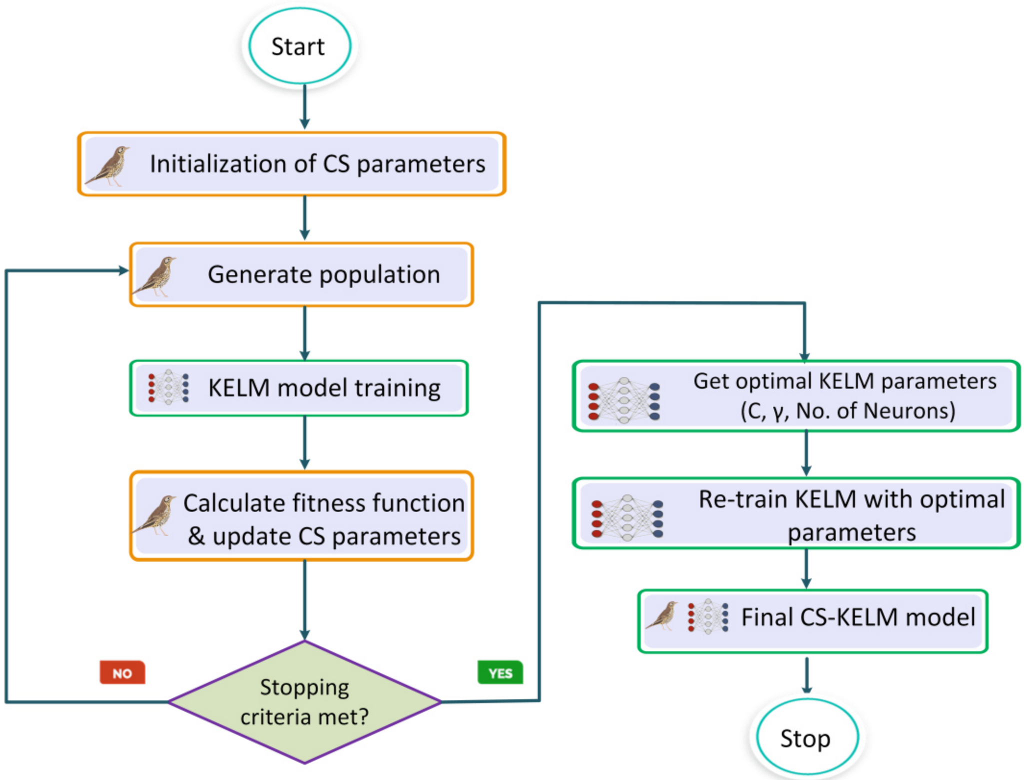

Figure 3. Flowchart of CS-KELM integration.

3.3 Cuckoo search (CSA)

The CSA is a swarm intelligence optimization algorithm that was initially introduced by Yang et al. [53] in 2009. The Cuckoo Search Algorithm (CSA) draws inspiration from the brood parasitism strategy of cuckoo birds. This strategy involves cuckoos laying their eggs in the nests of other birds, relying on the host birds to either raise the cuckoo chicks alongside their own or to reject the foreign eggs (Figure 4). The primary goal for cuckoos is to ensure the survival of their offspring by exploiting the natural reproductive behaviours of host birds. In CSA, each cuckoo symbolizes a potential solution to an optimization problem, while the eggs represent candidate solutions. The host birds act as the objective function, evaluating the quality of these solutions [54], [55]. The flowchart of CSA is shown in Figure 5. The algorithm begins by initializing a population of cuckoos with randomly generated solutions. These solutions are iteratively refined using a blend of local and global search methods.

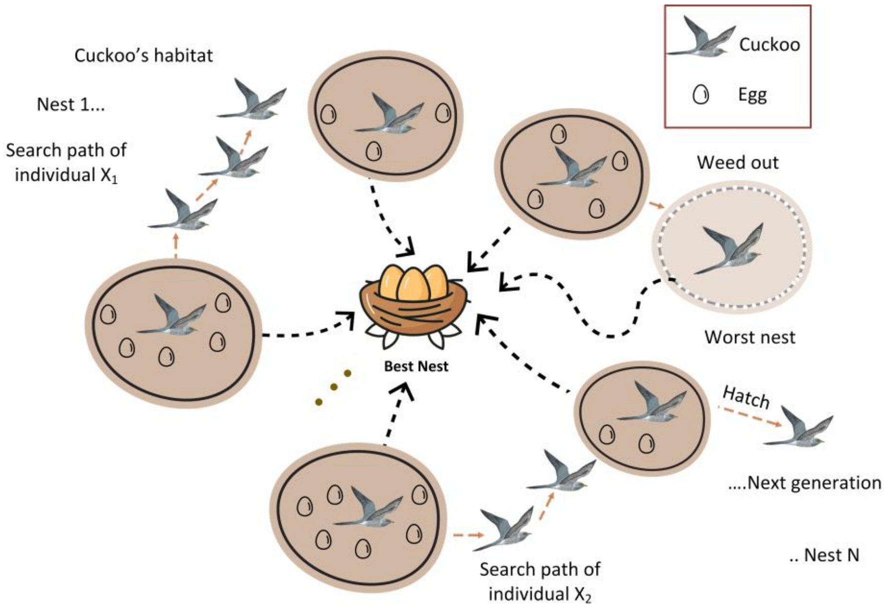

Figure 4. Schematic diagram of cuckoo search algorithm.

Initially, each cuckoo selects a random nest X^{t-1}_m and then chooses the nest X^t_n using a Levy flight. The nests are evaluated by the function G. The cuckoo replaces X^{t-1}_m with X^t_n if $G(X^t_n) > G(X^{t-1}_m)$ and places egg in the nest X^t_n. Subsequently, it identifies the best nest in generation t by sorting the nest list. Meanwhile, some of the less suitable nests are abandoned with probability $P_d \in [0,1]$, and new nests are constructed.

A new nest (or solution) X^{t+1}_m is determined using Levy flight as shown in Eq. (4)

$$X_n^{t+1} = X_n^t + \beta \times flight\_length \tag{4}$$

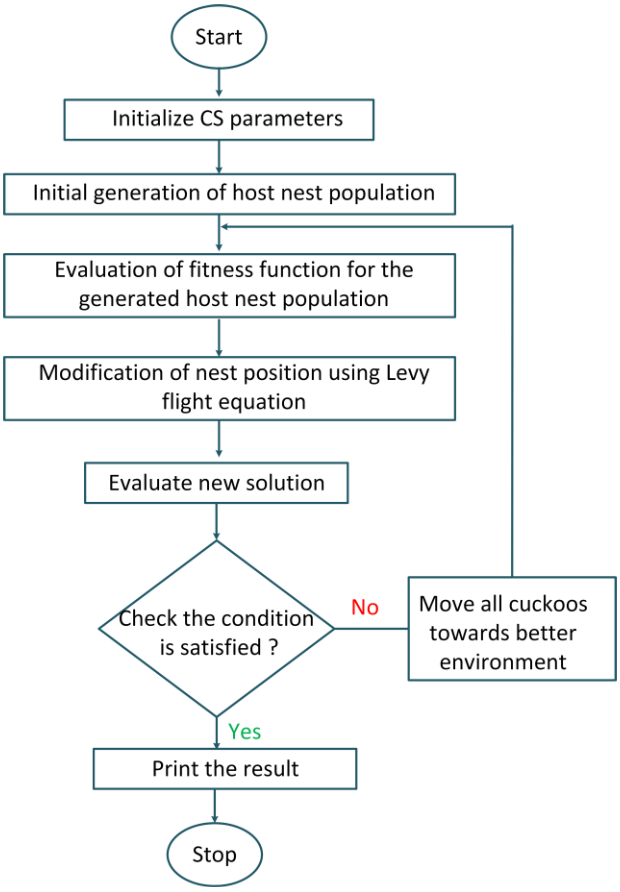

Figure 5. Flowchart of cuckoo search algorithm.

Here, flight_length is the step length of the Levy flight, which follows a Levy distribution, and β is the scaling parameter for the step length [56]. In this study, the Cuckoo Search Algorithm is employed to optimize the hyperparameters of the Kernel Extreme Learning Machine, with the aim of achieving the optimal model configuration.

3.4 Performance evaluation of models

The performance of the models were evaluated using metrics derived from the confusion matrix for the binary clasification problem.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Sensitivity/Recall = \frac{TP}{TP + FN} \tag{7}$$

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{8}$$

Accuracy, precision, recall, and F1 score matrices are used for evaluating the model performance (Eq. 5-8). Here, TP denotes the True Positive, indicating the number/percentage of instances of stress accurately predicted by the model, FP denotes the Fall Positive/type I error.

4 Results and discussion

During the first step of the experiments, the crop stress data set is loaded and standardized to ensure uniform feature scaling. Exploratory data analysis is performed to understand the data distribution. The pairplot shown in Figure 6 provides a visual overview of the relationships and distributions among the input variables. The diagonal elements of the pair plot show histograms for each variable, providing insight into their distributions. Relative Humidity and environmental temperature appear to be evenly distributed across specific ranges, with noticeable peaks suggesting clustered values at certain points. The average canopy temperature shows a broader distribution, while both relative water content and soil moisture content exhibit a fairly uniform spread across their respective ranges, indicating variability in measurements. Off-diagonal plots display scatter plots depicting the relationships between each pair of variables. Notably, there seems to be a distinct pattern or correlation between average canopy temperature, relative water content, and soil moisture content, where clusters or trends are observable. These patterns could suggest underlying environmental interactions or dependencies, such as the effect of canopy temperature on soil moisture levels and water content. For the modelling, The KELM model is defined, and a parameter combination is specified, including the regularization parameter C ranging from 0.001 to 1000, the kernel parameter ranging from 0.00001 to 10, different kernel types (radial basis function, linear, polynomial, and sigmoid), and the hidden layer has a variable number of neurons ranging from 5 to 50.

The parameter grid includes 100 discrete values for both C and γ to provide a thorough search. The optimizer is then configured with a maximum of 1000 evaluations and a population size of 25. This setup executes 40 generations. The optimizer iteratively searches for the best combination of hyperparameters over these 40 generations. After fitting the model, the best parameters are extracted. The final optimal model parameter is shown in Table 1 and the final KELM model is evaluated using this configuration using the test dataset for accuracy. For all the models, the key performance metrics were closely monitored on both the training and test sets. There were no signs of overfitting observed, as the models maintained consistent performance metrics across different train-test splits. This uniformity suggests that the model's performance is stable and generalizes well across various subsets of the data, rather than being overly tailored to any single partition. The Figure 7 shows how the number of neurons in the KELM model affects testing and training accuracies when optimized with the cuckoo search algorithm. As the number of neurons increases, both testing and training accuracies improve initially, reaching their highest performance at 32 neurons with a testing accuracy of 95.21% and a training accuracy of 94.2%. Beyond 32 neurons, the testing accuracy fluctuates slightly but remains close to the peak, while training accuracy stabilizes around 93-94%. The results show that CS-KELM model exhibits superior performance with an accuracy of 94.20%, precision of 95.28%, recall of 93.52%, and an F1 score of 94.39%. These values suggest that the optimization process enhances the model's ability to correctly classify stress and non-stress instances, minimizing both false positives and false negatives. CS-KELM with 101 true positives and 94 true negatives, demonstrates its high capability in correctly identifying both stress and non-stress instances.

The model also shows fewer errors, with 5 false positives and 7 false negatives, indicating lower Type I and Type II errors, respectively (Figure 8). This superior performance is because of the dual benefits of kernel methods with the cuckoo search optimization algorithm, which effectively tunes the model's parameters to enhance the model's accuracy. The kernel function enables the transformation of the input space into a higher-dimensional space, where complex patterns become more linearly separable, thus improving the model's ability to distinguish between stress and non-stress instances. The cuckoo search optimization further refines this by exploring a wide parameter space to find the optimal hyperparameters, reducing both false positives and false negatives, resulting in its superior performance metrics.

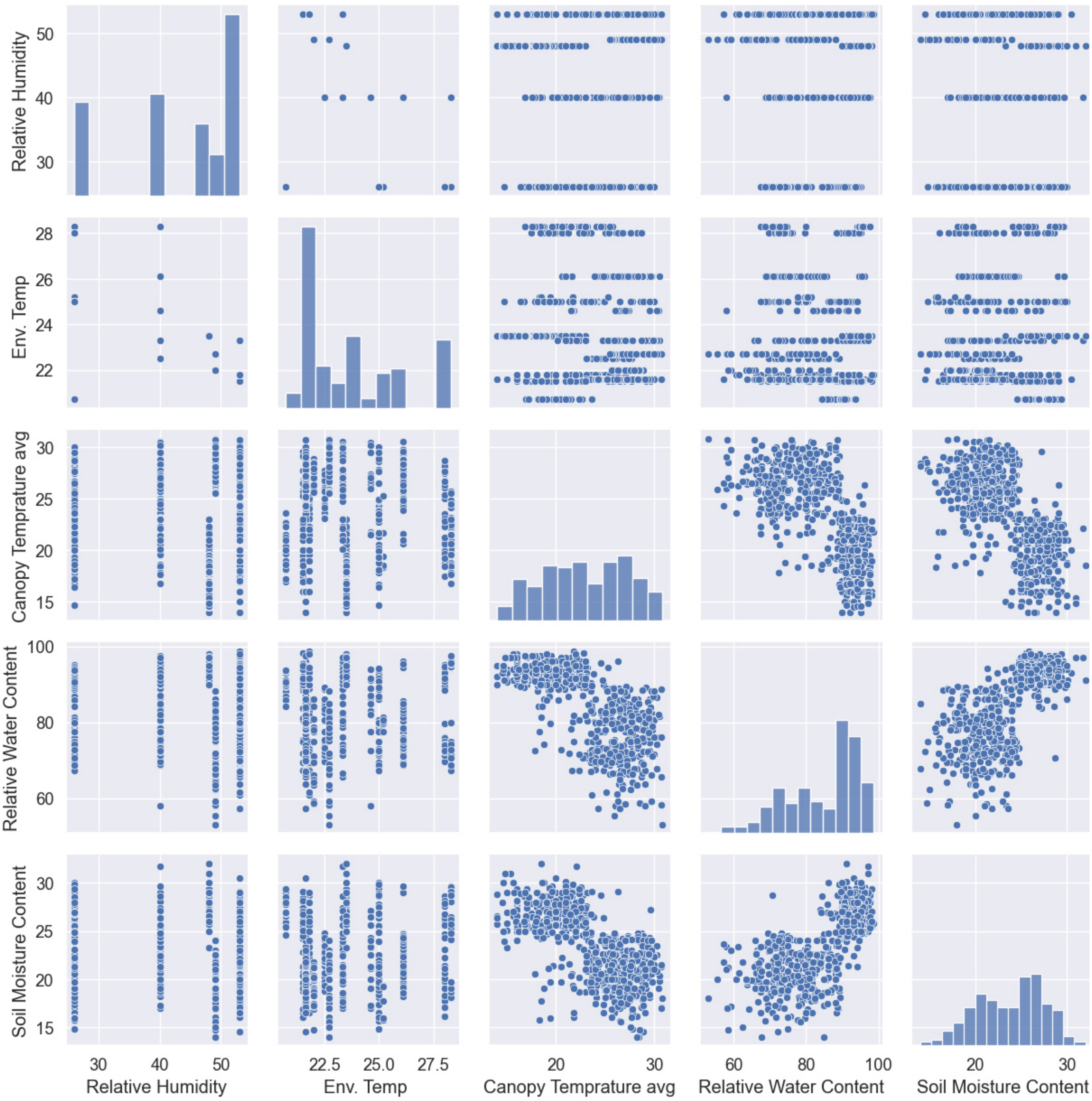

Figure 6. Pairplot of the dataset used in the study.

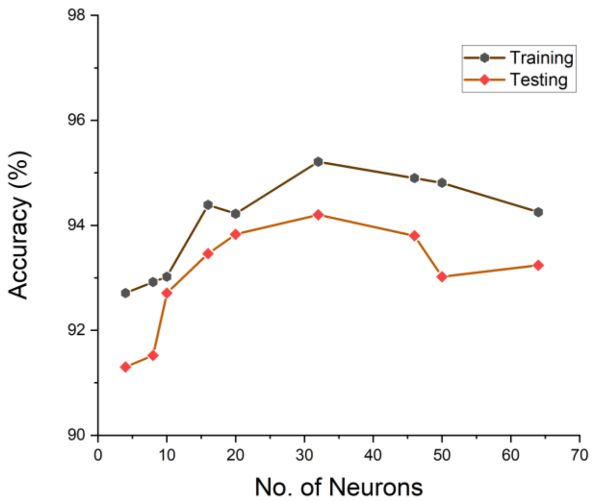

Figure 7. Accuracy of the KELM model with respect to number of neurons during CS optimization.

In contrast, the KELM model, without parameter optimization, shows slightly lower performance metrics with an accuracy of 92.75%, precision of 95.15%, recall of 90.74%, and an F1 score of 92.89% (Figure 9). The KELM model which achieves 98 true positives and 94 true negatives, falls slightly behind, showing an increase in false negatives (10) while maintaining the same number of false positives (5) as the CS-KELM (Table 2). This indicates a higher Type II error rate, suggesting it occasionally fails to identify stress instances.

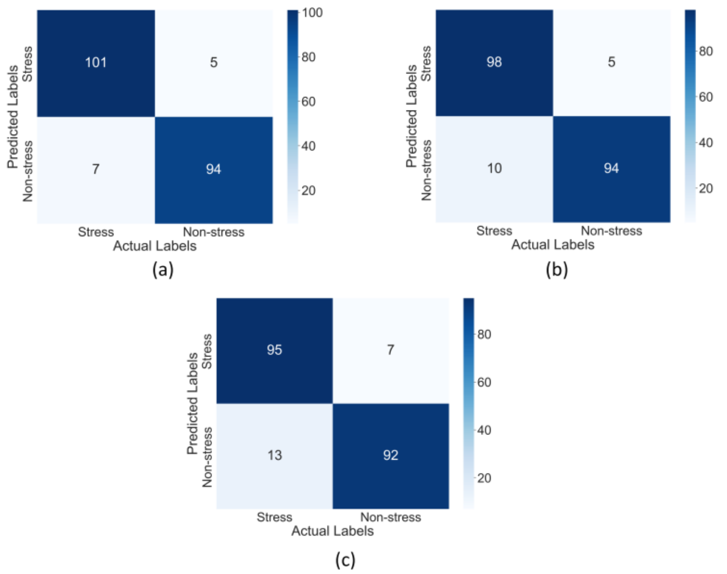

Figure 8. Confusion matrix of (a) Cuckoo search optimized KELM (b) KELM (c) ELM.

Table 1. Performance of ELM models.

Model	Parameters	Training Accuracy	Testing Accuracy
CS-KELM	C = 0.007, γ = 75, K ='RBF', Neurons = 32	95.21%	94.20%
KELM	C = 1, γ = 'scale', K ='RBF', Neurons = 40	94.28%	92.75%
ELM	Neurons = 40	92.71%	90.34%

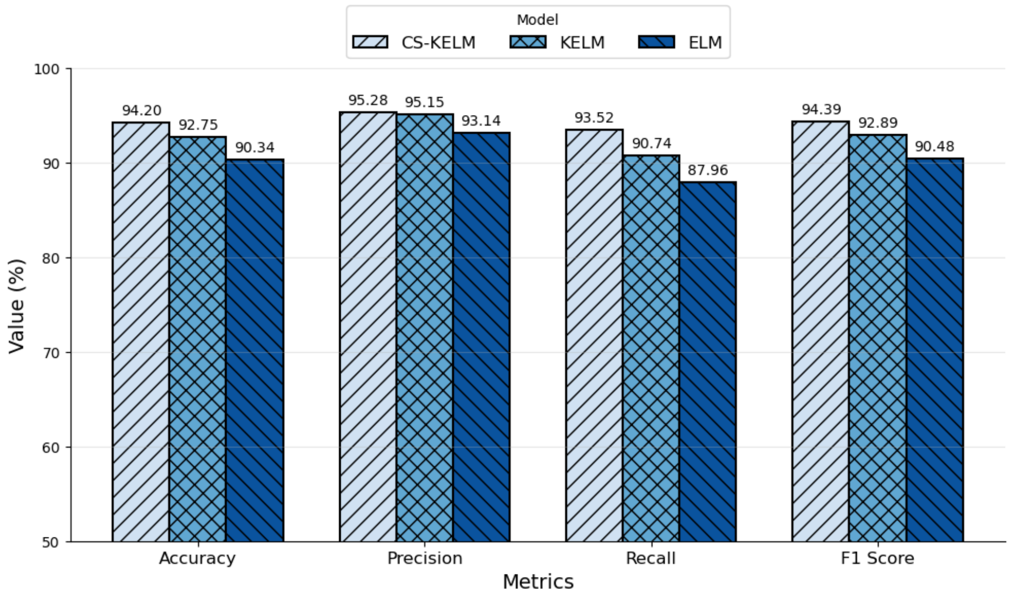

Figure 9. Performance comparison of (a) CS-KELM (b) KELM (c) ELM.

Table 2. Evaluation results of the models on the test dataset.

Model	TP	TN	FP	FN	Accuracy (%)
CS-KELM	101	94	5	7	94.20
KELM	98	94	5	10	92.75
ELM	95	92	7	13	90.34

This indicates that while the kernel method is effective, optimization further refines its accuracy and reliability. The ELM model, which does not incorporate kernel methods, demonstrates the lowest performance among the three, with an accuracy of 90.34%, precision of 93.14%, recall of 87.96%, and an F1 score of 90.48%, underscoring the impact of both kernel methods and optimization in improving model accuracy and robustness. The ELM model, with 95 true positives and 92 true negatives, exhibits the highest number of errors, with 7 false positives and 13 false negatives. The higher false negative count in the ELM model underscores its lower recall, reflecting its inferior sensitivity to detecting true stress instances compared to the CS-KELM and KELM models. The ELM model, which does not incorporate kernel methods, relies on a simpler architecture where the hidden layer weights are randomly assigned and fixed, and only the output weights are trained. This simplicity, while computationally efficient, limits the model's capacity to handle complex, non-linear relationships in the data. Consequently, the ELM model exhibits the lowest performance among the three, with significantly lower accuracy, precision, recall, and F1 score. The lack of both kernel transformation and parameter optimization results in a model that is less capable of accurately identifying between stress and non-stress states, highlighting the critical role of advanced optimization techniques in improving model performance. Overall, the CS-KELM model's superior performance in minimizing both types of errors makes it the most reliable for precise stress detection, crucial for effective IoT-based water management solutions. To deploy a Cuckoo-Optimized Extreme Learning Machine (CS-KELM) model from a Python environment to a cloud-based decision support system, accessible via mobile or computer, it is crucial to export the model in a suitable format for efficient utilization. Commonly, models are serialized using formats such as Joblib or Pickle. Joblib is particularly effective for handling large Numpy arrays and is frequently used with scikit-learn models due to its efficiency in serialization and deserialization. Alternatively, Pickle offers a general-purpose serialization format capable of storing various Python objects, though it may not be as efficient as Joblib for large models. For broader compatibility and framework interoperability, models can also be exported to ONNX (Open Neural Network Exchange), which is especially useful for models trained in diverse environments. After exporting the model in one of these formats, it can be easily loaded into a web service created with frameworks like Flask or FastAPI. This setup allows mobile applications to access the model via API calls, facilitating real-time predictions and integration into precision irrigation systems. By automating water delivery adjustments based on accurate predictions from the CS-KELM model, the system can enhance water efficiency and crop yield. Additionally, this cloud-based decision support system can automate irrigation schedules using edge devices such as Raspberry Pi and sensors deployed in the maize field.

5 Conclusion

This study has demonstrated the effectiveness of employing a Cuckoo Search algorithm coupled with kernel extreme learning machine (CS-KELM) for diagnosing water stress in maize crops for the development of an IoT-based precision irrigation framework. The integration of cuckoo Search with KELM was found to significantly enhance performance in comparison to the standard KELM and extreme Learning machine models. By leveraging the strengths of cuckoo search and KELM, this approach offers a robust solution for monitoring and management of water stress, ultimately contributing to more effective and sustainable agricultural methods. Integration of the models into the decision support system for smart irrigation can ensure efficient water usage and maximise productivity. Future research could further explore the scalability of this model and its applicability to other crops and environmental conditions, potentially expanding its impact on precision agriculture.

Conflicts of interest

The authors declare no conflict of interest.

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