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A Decomposition-Driven Deep Learning Model for Intelligent Irrigation Decision-Making

Rajesh Kumar [a,*], Anil Garg [a]

[a] Department of Electronics & Communication Engineering, Maharishi Markandeshwar Engineering College, Maharishi Markandeshwar (Deemed to be University), Mullana-Ambala, Haryana, 133207, India

* Corresponding Author Email: Kr.tejasv1981@gmail.com

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Abstract: Traditional farming methods still used in many regions contribute to lower crop yields despite the availability of ample arable land. Integrating emerging technologies such as Machine Learning (ML) and the Internet of Things (IoT) into agriculture can enable intelligent irrigation and smart farming. These technologies support real-time monitoring of environmental parameters and help optimize irrigation schedules using soil moisture, temperature, and humidity data. IoT devices and ML algorithms can predict irrigation needs, reduce water wastage, and enhance crop yields. Therefore, this study proposes a hybrid model that combines a Convolutional Neural Network (CNN) with Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) for irrigation classification and water conservation in agricultural fields. CEEMDAN decomposes the input features into multiple frequency components, which are then fed to the CNN to improve learning performance. To evaluate the proposed approach, the study developed six models, including standalone and hybrid models. The proposed model achieved the highest accuracy (98%), precision (0.95), recall (1), and F1-score (0.97) compared with the benchmark models. Furthermore, the confusion matrix reveals minimal misclassification, while the ROC curve, with an area under the curve (AUC) of 0.995, confirms excellent discriminative capability. These findings demonstrate the effectiveness and robustness of the proposed model for improving irrigation decision-making and promoting sustainable water management in agriculture.

Keywords: Agriculture, Internet of Things, Machine Learning, Water Management.

1. Introduction

By 2050, the global population is expected to reach 9.1 billion [1]. To meet this growth, food production must increase by 70%. About 40% of the world's food is produced on irrigated land, although such land accounts for only 17% of total cropland [2]. To satisfy rising food demand, groundwater is being used extensively in agriculture, causing significant depletion of water resources. In India, the population is projected to exceed 1.69 billion by 2050 [3], while current food supply is already insufficient to meet the needs of the population. Traditional farming practices, which are still prevalent in many regions, continue to contribute to lower crop yields despite the availability of ample arable land. Therefore, integrating emerging technologies into agriculture is essential for intelligent farming. Agriculture accounts for about 70% of global water withdrawals, with the majority used for irrigation [4]. As pressure on limited water resources increases and the need to reduce the environmental impacts of irrigation becomes more urgent, intelligent irrigation has emerged as a viable solution [5].

Over the past decade, sensors, wireless communications, and data platforms have advanced significantly while becoming more affordable. Low-cost, energy-efficient wireless sensor networks are essential for automated irrigation solutions [6]. Such networks can monitor temperature, humidity, soil moisture, the amount of irrigation water, and its electrical conductivity for different agricultural applications [7]. The Internet of Things (IoT) can interconnect sensors, control components such as microcontrollers, and data-handling units to provide real-time information for effective decision-making [8]. Using these data, smart irrigation systems can improve water management and schedule irrigation accordingly [9, 10]. Irrigation strategy is critical in farming. Inadequate irrigation reduces crop quality and yield, whereas over-irrigation increases nutrient demand, water loss, disease susceptibility, pumping costs, and pollution caused by nutrient leaching [11].

Water is the most critical resource in farming, and substantial effort has therefore been devoted to using it efficiently. Agriculture consumes a large share of global water resources—nearly 70% of river water and groundwater used for irrigation—making it the world's largest water-consuming sector [12]. Almost half of the available freshwater (4000 km³) is lost through crop transpiration and evaporation, while the remainder replenishes groundwater reserves [13]. Although much agricultural water comes from rainfall, irrigation is the only viable option in drought-prone regions. Numerous methods have been proposed to estimate crop irrigation requirements [14, 15]. Common irrigation methods include drip, sprinkler, furrow, and manual irrigation, with drip irrigation being the most efficient. A well-designed drip irrigation system can achieve nearly 100% water-use efficiency. An optimum irrigation schedule that delivers the right amount of water at the right time can be generated automatically by the control software of a smart irrigation system [16]. IoT devices collect real-time data through sensors and transmit them to the cloud. Additional analytical capabilities are then required to interpret these data and support intelligent decisions.

The integration of machine learning (ML) with IoT has introduced a new approach to efficient water management by enabling precise control and automation, thereby reducing human intervention and minimizing water wastage. ML plays a key role in analysing the data collected by IoT sensors. In [17], the authors employed a sensor-based network to monitor temperature, humidity, soil moisture, and light levels in real time. An ESP32 microcontroller was used to send data to the cloud through MQTT, and SVM, CNN, and LSTM algorithms were implemented. Tests indicated that the ESP32- and ML-based system increased agricultural production by 15%, reduced water use by 30%, and improved energy efficiency compared with previous approaches.

A CNN-based model has also been designed as a decision-making tool for automated irrigation in orchard systems, particularly for precision agriculture in hilly areas. Over two growing seasons, soil moisture data and leaf RGB images were collected. The model was trained, tested, and validated to determine optimal irrigation timing. It achieved about 80% accuracy in identifying water-stress levels in persimmon trees. These results highlight the potential of CNN-based models as an important component of remote irrigation systems [18]. In this paper, a hybrid CEEMDAN-CNN model is proposed for water conservation in agricultural fields through irrigation classification. CEEMDAN decomposes the input feature data into multiple frequency-based components, which are then provided to the CNN for training. This decomposition helps the CNN capture hidden patterns in the data more effectively and improves overall performance. To evaluate the proposed approach, the study develops six models, including standalone and hybrid variants. Integrating CEEMDAN with CNN enhances feature extraction and classification performance, resulting in significantly better predictive accuracy than traditional standalone models.

2. Research Motivation and Contributions

The use of recent technologies such as IoT and ML to improve water savings has become increasingly important in the intelligent irrigation literature. Deep learning (DL)-based irrigation systems have also been developed to improve agricultural yield. Sensors such as DHT11 temperature and humidity sensors and soil-moisture sensors are commonly used to analyse irrigation data and automate water application. One reported solar-powered automatic irrigation system uses a microcontroller to collect data from a soil-moisture sensor and control the outlet valve of a water tank to regulate water flow to the field. This system aims to optimize water use [19]. In another study, Naïve Bayes, KNN, and SVM achieved accuracies of 76.4%, 70.8%, and 87.5%, respectively, with SVM outperforming the other two algorithms [20]. In a related work, Naïve Bayes and KNN-based irrigation systems achieved accuracies of 80% and 86%, respectively [21]. Another study used multispectral and thermal images, meteorological data, and soil information to predict soil moisture content, reference evapotranspiration, and sap flow using artificial neural networks, SVM, and gradient-boosted decision trees [22].

IoT and cloud platforms have also been used to predict the amount of freshwater required to grow crops, thereby conserving substantial quantities of water. Such automated irrigation approaches have strong potential to transform the agricultural sector. In one IoT-based intelligent irrigation study, a K-means–SVM hybrid classifier achieved 98.5% accuracy and outperformed standalone Random Forest and Naïve Bayes models, while also supporting freshwater-saving decisions [23]. Other authors used neural networks and regression models to forecast irrigation needs and soil moisture levels, reducing water consumption by 18% while maintaining optimal soil moisture [24]. In another work, a precision irrigation system based on IoT sensors and ML models optimized water distribution and produced a 15% increase in crop yield under controlled conditions [25]. Similarly, smart irrigation systems using IoT with LR, DT, and SVM have been reported to improve water-use efficiency by considering multiple environmental parameters [26]. Additional studies have combined IoT-based environmental monitoring with ML algorithms for water distribution and multilinear regression for precise fertilizer recommendations [27].

In another work, an IoT-based intelligent irrigation system was proposed to minimize water use. The system measures soil moisture values from the field and makes irrigation decisions based on threshold values for three crops: beans, chili, and potato [28]. Another study reported a real-time data prediction system for agricultural irrigation that used the KNN algorithm to forecast irrigation schedules [29]. In a separate study, a Random Forest (RF) classifier was used for optimal irrigation scheduling and plant-species recommendation using field-parameter data, and the results showed improved crop productivity through efficient irrigation use [30]. Similarly, several ML techniques have been applied to optimal irrigation scheduling using IoT sensor data for soil moisture, temperature, and humidity, leading to better decision-making, cost savings, and increased yield [31]. Recent crop-yield research has shown that hybrid feature-selection strategies combining filter methods with Recursive Feature Elimination (RFE) can reduce redundant or less informative variables and improve the predictive performance of multiple ML models [32]. Another study addressed crop recommendation by using ML techniques to select fruit crops based on soil macronutrients, including nitrogen, potassium, and phosphorus, as well as temperature, rainfall, and soil pH. It compared DT, RF, KNN, NB, and SVM on the basis of classification accuracy [33].

In addition, Convolutional Neural Networks (CNNs) have been reported for intelligent irrigation systems, especially in the context of precision agriculture. A comprehensive literature review highlights the use of CNNs and other deep learning models to analyse information generated by IoT devices in agriculture, suggesting that CNNs can significantly improve irrigation scheduling and crop-health assessment [34]. CNNs can also accurately detect agricultural stress and disease from images. Early diagnosis enables timely adjustment of irrigation practices, thereby improving yield and resource management [35]. For CNN-based smart irrigation systems to function effectively, however, data security and privacy issues in cloud-IoT environments must also be addressed. Studies have emphasized secure data transmission and advanced protocols, and they show that integrating technologies such as blockchain and machine learning can strengthen data security in intelligent irrigation systems [36]. Remote sensing, IoT, and drones are also increasingly used for monitoring, estimation, and detection in precision irrigation. These technologies can collect large volumes of RGB and hyperspectral images at multiple wavelengths [37]. Recent research has further shown that combining signal-processing methods with ML models can improve performance.

For instance, Chen *et al*. presented an innovative approach to improve irrigation forecasting accuracy. Their hybrid VMD-ICNN model integrates Variational Mode Decomposition (VMD) with an Improved Convolutional Neural Network (ICNN). VMD decomposes complex and non-stationary irrigation-related time-series data into several Intrinsic Mode Functions (IMFs), enabling better feature separation and noise reduction. Each IMF is then processed by the ICNN, which is designed with optimized convolutional structures to extract spatial and temporal features effectively [38]. Likewise, Gulzar *et al.* proposed a seed classification model that used CNN to classify seeds based on characteristics such as colour, shape, and texture [39]. Other deep learning models have also been used to estimate soil temperature. For example, a smart irrigation scheduling system based on Bidirectional Long Short-Term Memory (Bi-LSTM) was developed to improve soil electrical conductivity (SEC) and soil moisture (SM) prediction. The Bi-LSTM achieved better results than multilayer neural networks (MLNN) in terms of RMSE, coefficient of determination, and MAE [40].

In another work, a Bi-LSTM model was developed to forecast field soil temperature. Using data from 30 sites and five depths, the study reported better accuracy than the comparison models [41]. Other authors demonstrated the use of an LSTM model for soil moisture estimation based on environmental variables such as temperature, humidity, and precipitation. Hybrid signal-processing and deep-learning approaches have also been explored in related domains. For example, an Empirical Fourier Decomposition (EFD)-Bi-LSTM model was proposed for photovoltaic power forecasting and was shown to outperform standalone Bi-LSTM and EMD-Bi-LSTM models across all seasons. It achieved the lowest RMSE, MAE, and MAPE, with RMSE reductions of 12.37%, 8.58%, 4.57%, and 7.89% in winter, spring, summer, and autumn, respectively, relative to the Bi-LSTM model [42]. Similar signal-processing techniques have also been applied successfully to wind and solar forecasting. For instance, solar irradiance has been predicted using iterative filtering combined with Bi-LSTM [43], and related work has likewise recommended hybrid models over standalone ones [44]. Collectively, these studies report significant improvements over single models in terms of forecasting error. A comparative summary of representative studies is presented in Table 1.

Based on the above studies, the following observations can be made: (a) ML models can effectively classify irrigation-related input features; (b) CNN and LSTM models generally provide improved accuracy; (c) signal-processing techniques can expose patterns that are useful for ML models; and (d) hybridizing signal-processing techniques with ML models can improve predictive performance. Motivated by these observations, the following contributions are made in this paper:

1) An insightful review of representative studies in the literature.
2) The application of different decomposition algorithms to key input features such as soil moisture, temperature, and humidity.
3) The integration of the IMFs produced in the previous step with ML models.

4) Implementation of the proposed CEEMDAN-CNN model along with comparison models: SVM, LSTM, CNN, EMD-CNN, and VMD-CNN.

5) Evaluation of the models using accuracy, precision, recall, and F1-score.

This work introduces an integrated CEEMDAN-CNN framework for irrigation classification. Unlike conventional approaches that use raw environmental measurements, the proposed framework leverages CEEMDAN-derived multiscale feature representations to capture hidden temporal and frequency-dependent characteristics of soil moisture, temperature, and humidity signals. The proposed approach is systematically evaluated against conventional ML, DL, and other decomposition-based frameworks, including SVM, CNN, LSTM, EMD-CNN, and VMD-CNN. In addition, ablation analysis and repeated cross-validation are used to investigate feature contributions and model robustness. Together, these methodological elements provide a comprehensive assessment of decomposition-based deep learning for irrigation classification.

2. Methodology

2.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) have emerged as a powerful class of deep learning models for feature extraction and pattern recognition. Unlike traditional Feedforward Neural Networks (FNNs), CNNs use convolutional filters in their initial layers to automatically learn spatial or temporal features from raw input data. This capability significantly improves the efficiency of pattern-recognition tasks, as demonstrated in various domains [50]. A simple CNN structure is shown in Figure 1.

Table 1. Representative studies reported in the literature

Ref.	Year	Author's	Target Parameter	ML/DL Models Used	Reported Model Performance	Application Area
[20]	2020	Bhanu *et al.*	Soil Moisture and environmental parameters	NB, KNN, SVM	Accuracy (%): 76.4, 70.8, 87.5	Smart irrigation decision support
[45]	2021	Bhoi *et al.*	Irrigation Recommendation System (IoT-IIRS)	NB, DT, SVM	Accuracy (%): 84.37, 86.15, 88.05	Water usage optimization
[46]	2022	Karthikeya *et al.*	Soil Moisture Classification	KNN	Accuracy (%): 63.63	Soil health monitoring
[26]	2023	Esmail *et al.*	Crop Water Requirement & Soil Monitoring	LR, DT, SVM	Accuracy (%): 85.14, 89.68, 84.15	Decision support in irrigation systems
[30]	2024	Tyagi *et al.*	Water Management Optimization	RF	Accuracy (%): 94.77	Smart agriculture for spider crop production
[47]	2024	Dolatsis *et al.*	Soil Moisture dynamics and water requirement for maize	Hybrid LSTM vs Standard LSTM & RF	Hybrid LSTM: R^2 0.95-0.97, Standard LSTM: R^2 0.90, RF: R^2 0.85	Maize crop irrigation scheduling
[48]	2025	Amudha *et al.*	Advance LSTM based DL model for fertilizer management	LSTM	Accuracy (%): 92 for nitrogen, 88 for phosphorous, 90 for potassium	Precision irrigation fertilizer management system
[49]	2025	Inyang *et al.*	Irrigation Classification for overhead, surface and precision irrigation	RF, SVM, XGBoost, KNN	Accuracy (%): RF 80, SVM 72, XGBoost 86	Irrigation techniques classification
[33]	2026	Umamaheswari *et al.*	Environmental and soil parameters	RF	Accuracy (%): 95.45	Highest fruit crop recommendation for different soil and climate zones

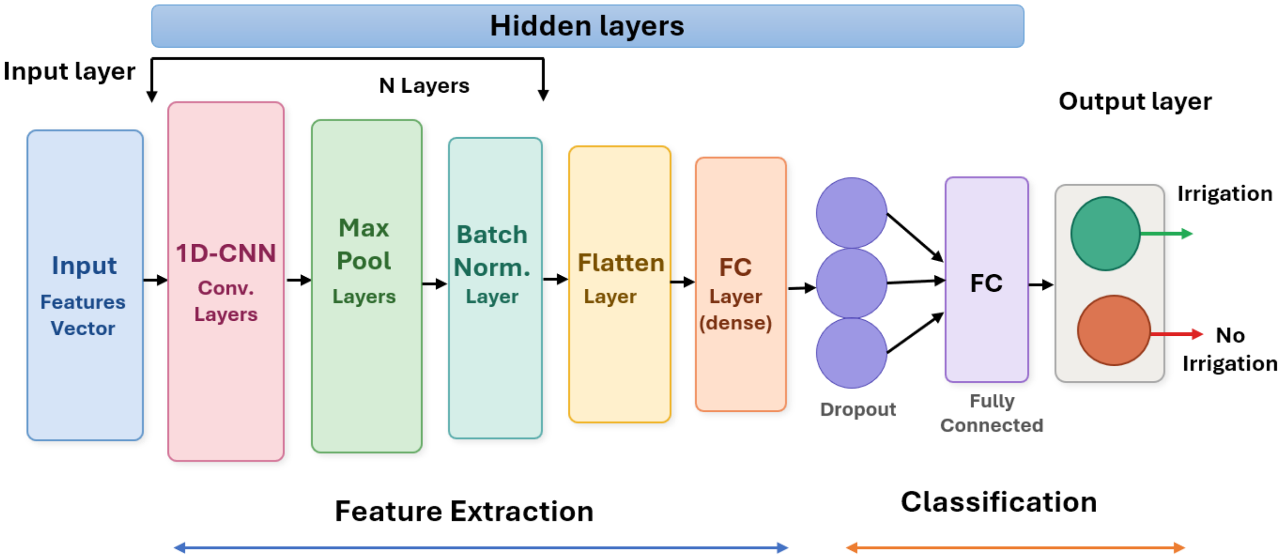


Figure 1. Structure of a CNN cell [45]

The pooling layer is a key component of CNN architecture because it reduces the dimensionality of feature maps while preserving important information. This reduction lowers computational complexity and helps control overfitting [51]. Although CNNs were originally developed for two-dimensional image processing tasks, recent advances have shown their effectiveness for one-dimensional time-series data through 1D-CNN architectures. In applications such as irrigation management, environmental monitoring, and agricultural forecasting, CNNs can effectively capture temporal dependencies and local patterns in sequential data. By arranging input parameters as a one-dimensional matrix, 1D-CNN models use convolutional kernels to extract meaningful features, enabling accurate classification and prediction [52]. Activation functions also play a crucial role in learning. The hyperbolic tangent (tanh) function is often used in early layers to normalize input signals within a bounded range, whereas the Rectified Linear Unit (ReLU) is widely used in hidden layers because of its computational efficiency and its ability to alleviate the vanishing-gradient problem. Recent studies in precision agriculture highlight the effectiveness of CNN-based models for irrigation decision-making. These models analyse time-series data such as soil moisture, temperature, and weather conditions to determine irrigation requirements with high accuracy. The adoption of 1D-CNN architectures in such applications has shown better performance than traditional ML approaches, making them well suited for intelligent irrigation systems [53].

2.2 Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN)

As an adaptive data-analysis tool, Empirical Mode Decomposition (EMD) has become one of the most widely used data decomposition methods since it was introduced by Huang et al. Its primary function is to decompose an input time series into several Intrinsic Mode Functions (IMFs). However, in real-world applications, EMD suffers from mode mixing. To address this issue, Zhang proposed Ensemble Empirical Mode Decomposition (EEMD), a noise-assisted technique [54]. The addition of white Gaussian noise effectively reduces mode mixing in EMD. With a finite number of repetitions, EEMD generates a set of high-frequency IMFs and low-frequency residuals. Although this process can be computationally expensive, increasing the number of ensembles generally reduces reconstruction error [55]. Pan *et al*. subsequently proposed CEEMDAN as a more efficient solution. By introducing adaptive white noise, CEEMDAN not only alleviates mode mixing but also reduces computation time [56].

The CEEMDAN algorithm proceeds as follows:

i) First, white noise is added to the original input time series. Let the input series, the white noise, and the noise standard deviation be defined as follows:

$$x^p(t) = x(t) + \beta_o \alpha^p(t),\ \ p = 1,2,\ldots\ldots,q \qquad (1)$$

Where q denotes the total number of realizations.

ii) Next, EMD is applied to the original signal to decompose it into several IMFs. The first IMF is obtained using the following equation:

$$\overline{Imf_1(t)} = \frac{1}{q}\sum_{p=1}^{q} Imf_1 x(t) \qquad (2)$$

The first residual is then obtained by

$$r_1(t) = x(t) - \overline{Imf_1(t)} \qquad (3)$$

iii) Next, the residual signal is decomposed using EMD to compute the second CEEMDAN mode:

$$\overline{Imf_2(t)} = \frac{1}{M}\sum_{i=1}^{M} EMD_1(R_1(t) + \beta_1 EMD(\alpha^p(t)) \quad (4)$$

Then, the residual is obtained as

Where the qth mode is calculated by EMD.

iv) Similarly, the qth residual and the (q+1)th component can be calculated as:

$$R_q(t) = R_{q-1}(t) - \overline{Imf_q(t)} \quad (5)$$

$$\overline{Imf_{q+1}(t)} = \frac{1}{q}\sum_{i=1}^{q} EMD_1(R_q(t) + \beta_q EMD_q(\alpha^p(t)) \quad (6)$$

After M decompositions, the final residual becomes:

$$R(t) = x^p(t) - \sum_{i=1}^{q} \overline{Imf_q(t)} \quad (7)$$

v) Finally, the decomposed input time-series signal is expressed as:

$$x^p(t) = \sum_{p=1}^{q} \overline{Imf_q(t)} + R(t) \quad (8)$$

3. Framework of the Hybrid Model (CEEMDAN-CNN)

This section describes the framework of the proposed hybrid CEEMDAN-CNN model for classifying irrigation requirements. Multiple crop types are considered in the study. The main objectives of the model are to: (a) improve the accuracy and precision reported in previous studies; (b) enhance learning capability by decomposing input features into several frequency components; and (c) support proper irrigation decisions for specific crops. The proposed model is shown in Figure 2.

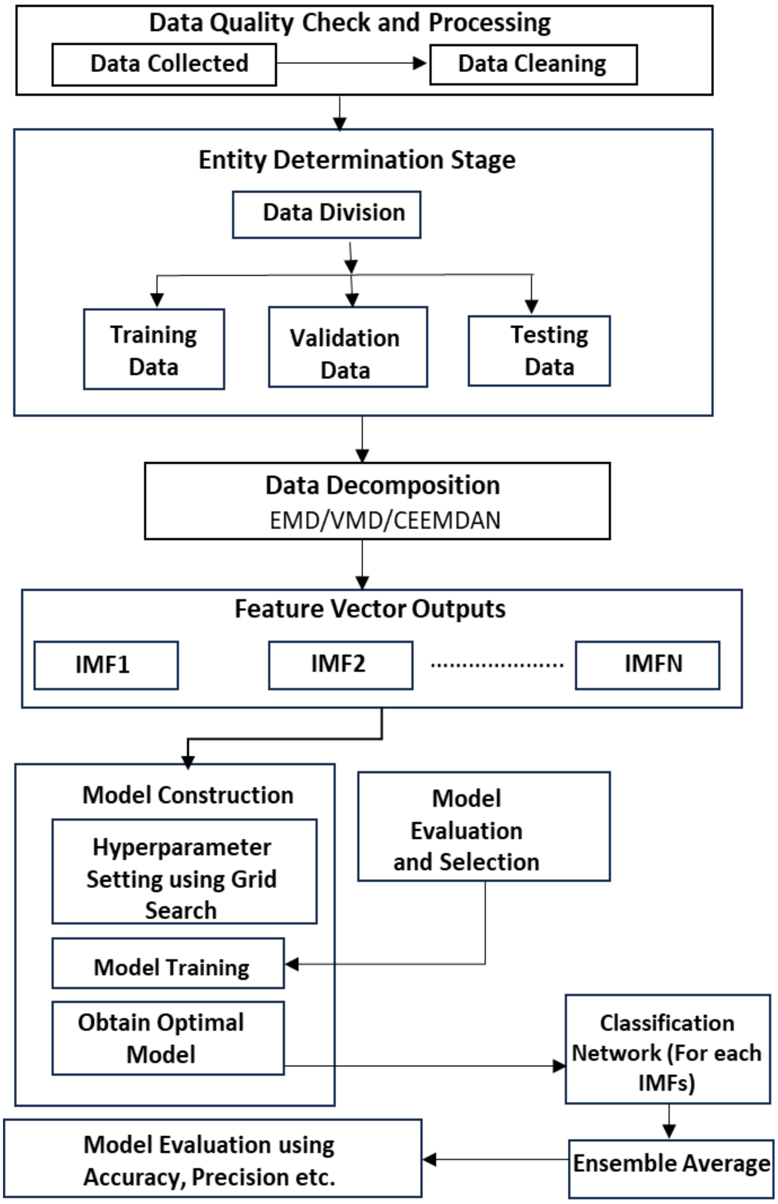


Figure 2. Framework of the proposed model

The role of each block in the decomposition-based CEEMDAN-CNN framework for intelligent irrigation is described below:

Data Collection: Raw environmental sensor data for intelligent irrigation, such as soil moisture (SM), temperature, and humidity, are collected using a YL-69 soil-moisture sensor and a DHT-11 temperature and humidity sensor.

Data Cleaning: This stage ensures high-quality input data. The data collected in the previous step may include missing values or erroneous entries caused by instrumentation error or falsification [57]. Therefore, such outliers and missing values are removed from the dataset.

Entity Determination Stage: This stage constructs the data used for model training and evaluation. The dataset is divided into 70% for training and 30% for testing [58]. The first subset is used to train the CNN model, while the second subset is used to assess its performance.

Data Decomposition: This stage extracts relevant IMFs from complex environmental data. Signal-processing techniques such as EMD, VMD, and CEEMDAN are applied to obtain IMFs, which help reveal hidden trends and periodic components for classification or prediction.

Feature Vector Outputs: The IMFs serve as feature vectors for ML models. Each IMF emphasizes distinct frequency- and trend-based patterns, which are then fed independently to the classification network.

Model Construction: This stage builds the CNN-based ML model. Before training, the hyperparameters are tuned using a grid-search algorithm so that the best-performing configuration is used.

Model Evaluation and Selection: This stage validates model performance to avoid overfitting. The best model for each IMF is selected based on accuracy.

Classification Network: This stage learns patterns for intelligent irrigation decisions, namely whether irrigation is required or not. Different CNNs (or one CNN per IMF) can be used to classify the individual IMF-based inputs. Each model focuses on a distinct signal produced from an IMF.

Ensemble Average: This stage improves classification accuracy by combining the predictions from each IMF model. Ensemble averaging increases the robustness and reliability of the final decision.

Model Evaluation: In the final stage, the ensemble model is evaluated on test data using measures such as accuracy, precision, recall, and F1-score. This helps assess how effectively CNNs operating on decomposed signals can predict irrigation requirements and reduce water waste.

Pseudo-code of the proposed CEEMDAN-CNN model

```
1.  Clean dataset D and extract target y
2.  Define feature set F = {SM, Temp, Hum}
3.  Split dataset (D, y) → Training set T,
    Validation set V, Testing set S
4.  Initialize feature matrices XT, XV, XS = ∅
5.  for each feature f ∈ F do
6.      XT ← XT ∪ CEEMDAN(f in T)
7.      XV ← XV ∪ CEEMDAN(f in V)
8.      XS ← XS ∪ CEEMDAN(f in S)
9.  end for
10. best_acc ← 0
11. while hyperparameter set θ exists do
12.     Train CNN model Mθ on XT
13.     acc ← Validate Mθ on XV
14.     if acc > best_acc then
15.         best_model ← Mθ
16.         best_acc ← acc
17.     end if
18. end while
19. ŷ ← Predict best_model on XS
20. if multiple IMF outputs then
21.     ŷ ← Ensemble_Average(ŷ)
22. end if
23. Compute Accuracy, Precision, Recall, F1
24. Return final performance
```

4. Case Study

4.1 Data Description

The experiment was conducted using a dataset retrieved from the Kaggle repository (https://github.com/NitrrMCACommunity/Agriculture-Automation-/tree/master/Dataset). The dataset was generated by the Department of Computer Applications, NIT Raipur, India. It contains recorded values for crop type (encoded numerically), crop days (days after sowing), soil moisture (measured by a soil-moisture sensor), temperature, humidity (measured by a DHT11 sensor), and the target class (binary). Nine crop types are included and encoded as follows: 1 (Wheat), 2 (Ground Nuts), 3 (Garden Flowers), 4 (Maize), 5 (Paddy), 6 (Potato), 7 (Pulse), 8 (Sugar Cane), and 9 (Coffee). The target class is binary, where 1 indicates that irrigation is required and 0 indicates that it is not.

The dataset used in this study consists of 501 observations distributed across nine crop categories. Figure 3 illustrates the distribution of irrigation and non-irrigation samples. Of the total observations, 304 correspond to no-irrigation conditions (0), while 197 represent irrigation requirements (1), indicating a moderate class imbalance. This imbalance is similar to real farming situations, where irrigation is applied only when additional water is needed. The crop distribution is also uneven. Sugarcane has the highest number of samples, followed by wheat and potato, whereas pulse has comparatively fewer observations.

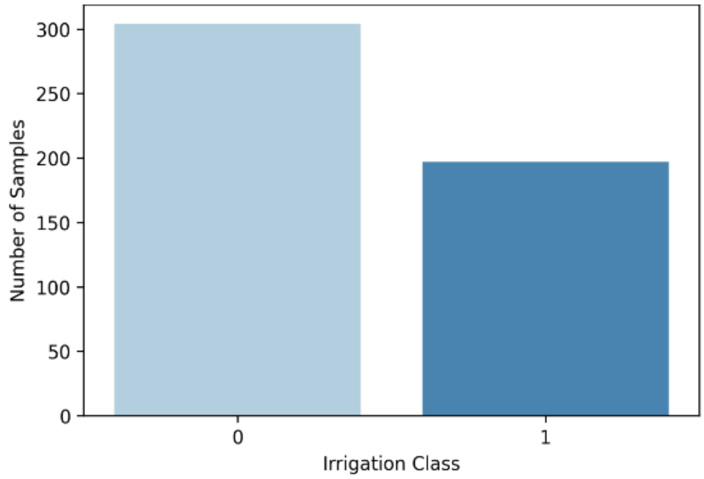
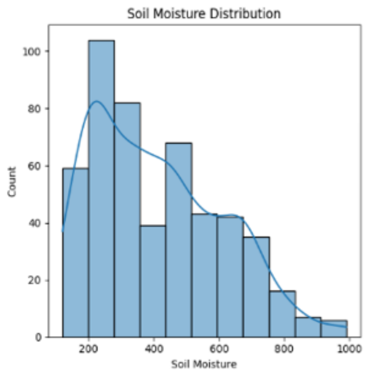
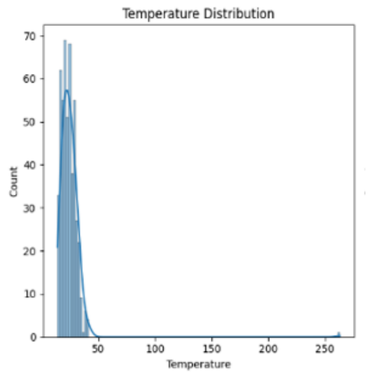


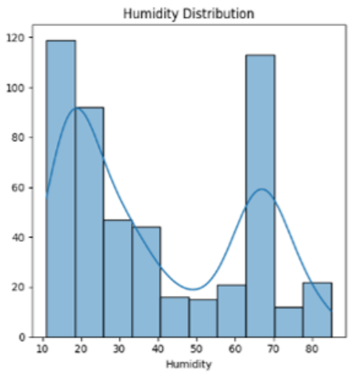
Figure 3. Distribution of samples (non-irrigation and irrigation)



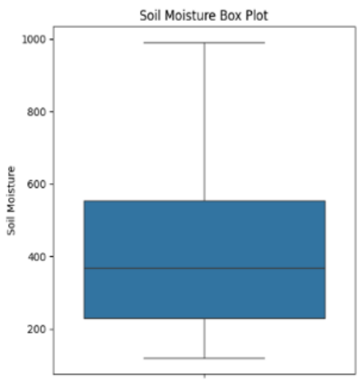
(a) Soil moisture distribution



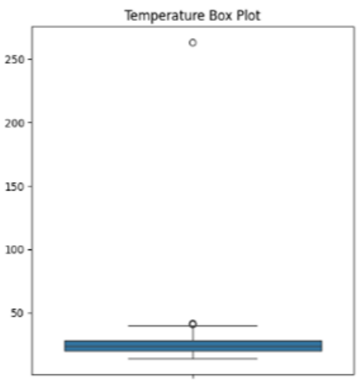
(b) Temperature distribution



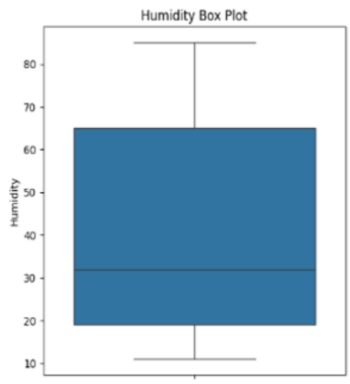
(c) Humidity distribution



(d) Soil moisture box plot



(e) Temperature box plot



(f) Humidity box plot

Figure 4. Kernel density estimation and box plots of the key input features

This diversity increases environmental variability in the dataset and may help the classification model generalize better. In addition, kernel density estimates and box plots of the key input features are shown in Figure 4. The soil-moisture data exhibit a wide range and a positively skewed distribution, indicating considerable variation over time. The broad interquartile range and long whiskers suggest substantial fluctuation in moisture levels, possibly due to unequal irrigation or changing environmental conditions. Likewise, the temperature data are concentrated in a relatively narrow range but show notable outliers in the box plot.

These outliers, together with the skewed distribution, suggest occasional abnormal or extreme events that alter otherwise typical temperature behavior. This contributes to data uncertainty and highlights the need to handle potential sensor errors or rare environmental conditions carefully.

The humidity data show a bimodal distribution with a relatively balanced box plot, although the overall spread remains considerable. This suggests the presence of distinct atmospheric states, likely driven by natural cycles such as time of day or weather conditions. Rather than being purely random, this behavior reflects systematic variability that must be considered during modeling. Overall, the dataset contains both uncertainty and structured variability, making it suitable for analysis. To develop a precise model, the internal parameters were fine-tuned using a grid-search algorithm. For hyperparameter selection, the dataset was further divided into training (70%, 350 samples), validation (15%), and testing (15%) subsets. An initial search space was defined around the default values of the corresponding hyperparameters, with those defaults chosen based on previous literature. The optimum grid-searched hyperparameters are reported in Table 2.

4.2 Decomposition of Input Features

The study uses CEEMDAN to decompose the input features into multiple IMFs. Figure 5 presents the decomposed components of temperature, soil moisture, and humidity produced by CEEMDAN.

The decomposition is applied independently to the environmental variables, namely soil moisture, temperature, and humidity. For each variable, CEEMDAN generates multiple IMFs representing oscillatory components at different frequency scales. No IMF-elimination technique was used in order to avoid information loss. The final feature representation is created by horizontally concatenating the decomposed IMFs of the three environmental variables. As a result, the original environmental information, distributed across several frequency bands, is represented by a multi-component feature vector for each sample. This decomposition enriches the feature space and enables the learning model to capture hidden patterns that may not be evident in the raw data. The CNN then performs automatic feature extraction through successive convolution and pooling operations, after which the learned feature maps are flattened and passed to fully connected layers for irrigation classification. As shown in Figure 5, the input features are decomposed into several IMFs, each with its own statistical characteristics. Temperature and soil-moisture series are decomposed into seven IMFs, whereas humidity produces eight IMFs. In each variable, the first IMF has the highest frequency, while the last IMF corresponds to the lowest frequency. Higher-frequency components reflect more uncertain or rapidly varying patterns, whereas lower-frequency components capture more stable trends. Each decomposed series is then fed to the CNN for classification.

4.3 Performance Evaluation

Table 3 shows the formulas used for the performance evaluation of the models.

Here, TP, TN, FP, FN, TPR, and FPR denote true positive, true negative, false positive, false negative, true positive rate, and false positive rate, respectively.

5. Results and Discussion

To evaluate the robustness and reproducibility of the proposed model, repeated stratified 5-fold cross-validation with 10 repetitions was performed. This procedure generated 50 independent train-test evaluations while preserving the class distribution within each fold. For every run, Accuracy, Precision, Recall, F1-score, ROC-AUC, PR-AUC, Balanced Accuracy, and Matthews Correlation Coefficient (MCC) were computed. Final performance statistics are reported in terms of the mean, standard deviation, and 95% confidence interval. Figure 6 and Table 4 present the accuracy variation across repeated stratified cross-validation runs, together with the mean, standard deviation, and 95% confidence intervals for the evaluated metrics of the proposed model.

Table 4 shows that the proposed model achieved a mean accuracy of 97.83% with a standard deviation of 1.12% and a 95% confidence interval of 97.51–98.15%. Likewise, the mean precision, recall, and F1-score were 96.90%, 97.42%, and 97.16%, respectively. The model also achieved ROC-AUC, PR-AUC, balanced accuracy, and MCC values of 99.12%, 98.36%, 97.64%, and 95.27%, respectively. These results demonstrate strong and stable classification performance. Table 5 further presents the class-wise statistical results for the proposed and comparison models in deciding between irrigation and no irrigation.

Table 2. Hyperparameters selected using grid search

Model	Parameter	Optimum Value	Search Space
SVM	Kernel	RBF	Linear, RBF, Polynomial, Sigmoid
	C	10	0.1,1,10,100
	γ	0.1	1,0.1,0.01,0.001
CNN	Filter	64	16 -90
	Kernels	2	1-2
	Dropout	0.3	0.1-0.3
	Epoch	300	100-400
	Batch Size	16	Default
LSTM / GRU	Hidden Units	90	50-100
	LR	0.0001	0.01-0.0001
	Epoch	300	100-400

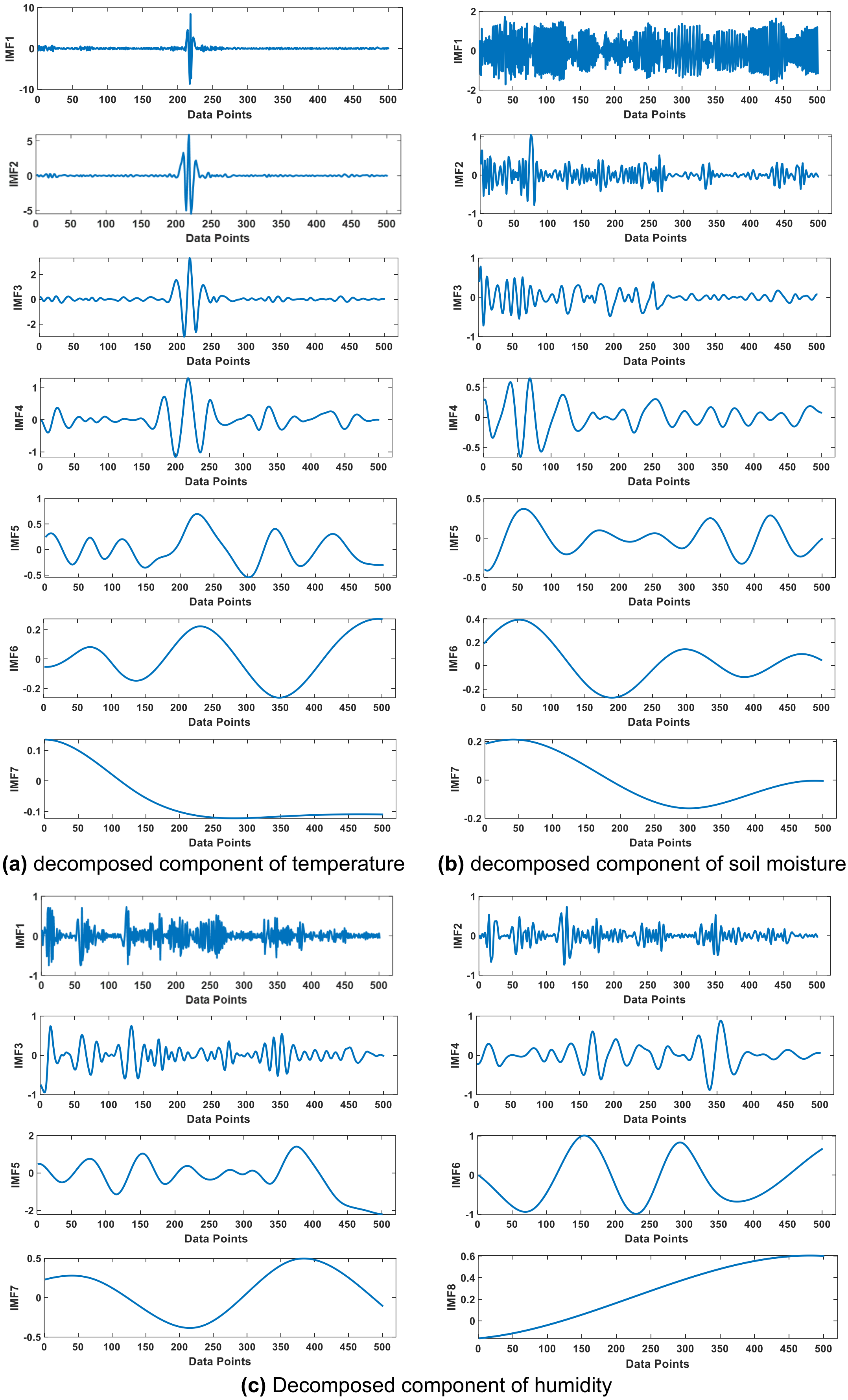


Figure 5. Decomposed components of temperature, soil moisture, and humidity

Table 3. Formulas and descriptions of the performance metrics

Metrics	Formula	Meaning
Precision [59]	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \times 100$	Percentage of all anticipated irrigation cases with accurate irrigation predictions.
Recall [59]	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \times 100$	The ratio of correctly predicted positive observations to all actual positive and negative observations is known as recall.
F1-score [59]	$2 \times \frac{\mathrm{Sensitivity} \times \mathrm{Precision}}{\mathrm{Sensitivity} + \mathrm{Precision}} \times 100$	It indicates robustness and resilience of a classifier.
Accuracy [59]	$\frac{\mathrm{TP+TN}}{\mathrm{TP+FP+TN+FN}} \times 100$	Percentage of overall accurate forecasts.
ROC-AUC [49]	$\mathrm{AUC_{ROC}} = \int_0^1 \mathrm{TPR\ (FPR)d(FPR)}$	Ability to distinguish between positive and negative classes across all classification thresholds.
PR-AUC [49]	$\mathrm{AUC_{PR}} = \int_0^1 \mathrm{Precision\ (Recall)d(Recall)}$	Trade-off between precision and recall over different thresholds.
Balanced Accuracy [60]	$\frac{\mathrm{Sensitivity} + \mathrm{Specificity}}{2} \times 100$	Provides an unbiased measure of performance when class distributions are imbalanced.
MCC [60]	$\frac{(\mathrm{TP} \times \mathrm{TN}) - (\mathrm{FP} \times \mathrm{FN})}{\sqrt{(\mathrm{TP}+\mathrm{FP})(\mathrm{TP}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})}}$	Matthews Correlation Coefficient evaluates the quality of binary classification by considering all elements of the confusion matrix.

Table 4. Performance parameters across cross-validation runs for the proposed model

Metric	Mean	Std	95% CI
Accuracy	97.83	1.12	97.51-98.15
Precision	96.91	2.48	96.20-97.16
Recall	97.42	2.05	96.84-98.00
F1-Score	97.16	1.63	96.70-97.62
ROC-AUC	99.12	0.68	98.93-99.31
PR-AUC	98.36	1.12	98.04-98.68
Balanced Accuracy	97.64	1.08	97.33-97.95
MCC	95.27	2.14	94.66-95.88

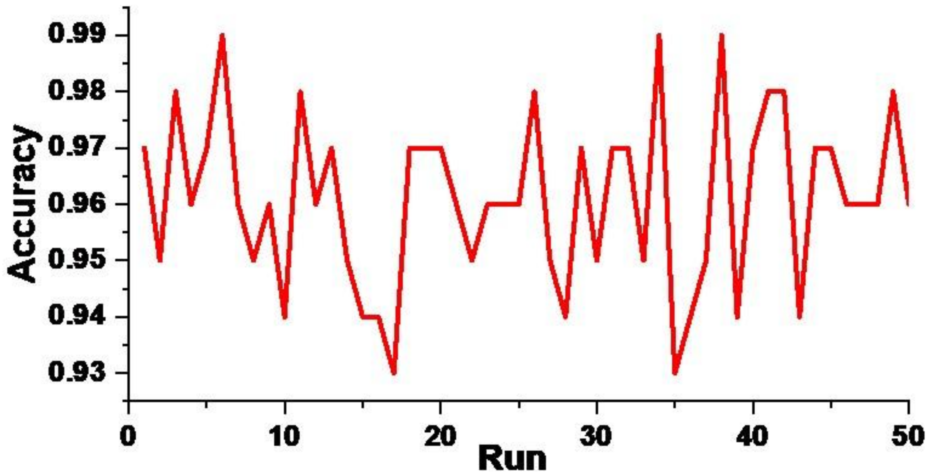


Figure 6. Accuracy across repeated cross-validation runs for the proposed model

Table 5. Statistical classification report of the proposed irrigation model

	Accuracy	Irrigation N/Y	Precision	Recall	F1-score
SVM	88.74	0	0.85	0.95	0.92
		1	0.88	0.72	0.83
LSTM	92.72	0	0.97	0.91	0.94
		1	0.87	0.95	0.91
CNN	92.05	0	0.95	0.93	0.94
		1	0.88	0.91	0.90
VMD-CNN	92.67	0	0.94	0.94	0.94
		1	0.90	0.91	0.90
EMD-CNN	94.7	0	0.99	0.93	0.96
		1	0.89	0.98	0.93
CEEMDAN-CNN	98	0	1	0.97	0.98
		1	0.95	1	0.97

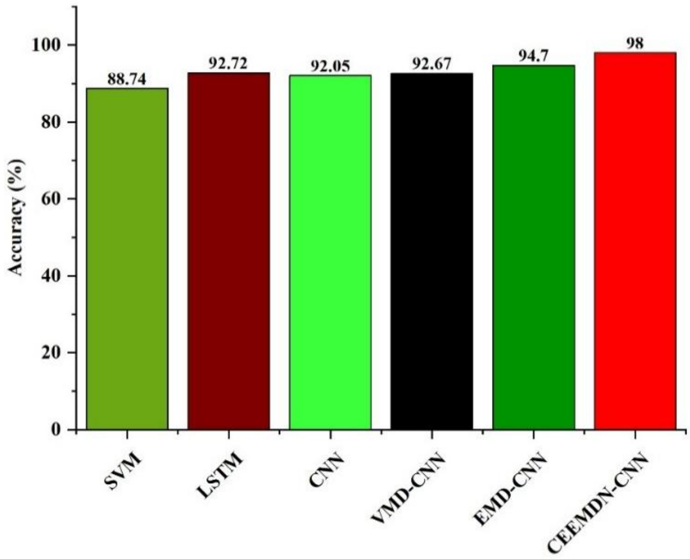


Figure 7. Accuracy analysis of different models

In Table 5, Irrigation = 0 denotes that no irrigation is required, whereas Irrigation = 1 denotes that irrigation is required. Among the hybrid models, CEEMDAN is used as the proposed decomposition technique and is compared with baseline decomposition methods (VMD and EMD). The results show that the proposed model achieved better accuracy, precision, recall, and F1-score than the other models for both classes. For example, the proposed model achieved an overall accuracy of 98%, which is higher than EMD-CNN (94.7%), VMD-CNN (92.67%), LSTM (92.72%), and SVM (88.74%). For the no-irrigation class (0), the proposed model also attained the highest precision (1.00), compared with EMD-CNN (0.99), VMD-CNN (0.95), LSTM (0.97), CNN (0.95), and SVM (0.85). Similar trends can be observed for the other evaluation metrics. These findings confirm that the proposed model provides better classification performance than the comparison models. In addition, Table 4 shows a mean PR-AUC of 98.36%, indicating a strong balance between precision and recall across decision thresholds. The balanced accuracy of 97.64% further demonstrates consistent performance across irrigation and non-irrigation classes, while the MCC value of 95.27% confirms the robustness of the proposed model. Therefore, the proposed model can support more reliable irrigation decisions. For deeper insight, visual comparisons of the metrics across models are presented in Figures.7–10.

The visual results clearly show that CEEMDAN improves the accuracy, precision, recall, and F1-score of the CNN model. As shown in Figure 8, the proposed CEEMDAN-CNN model achieves higher accuracy than the comparison models for both irrigation and non-irrigation classes. Similar observations can be made for recall and F1-score. The radar plot likewise indicates that the proposed model classifies irrigation requirements more effectively than the other models.

The confusion matrix shown in Figure 11 further analyses the performance of the proposed model.

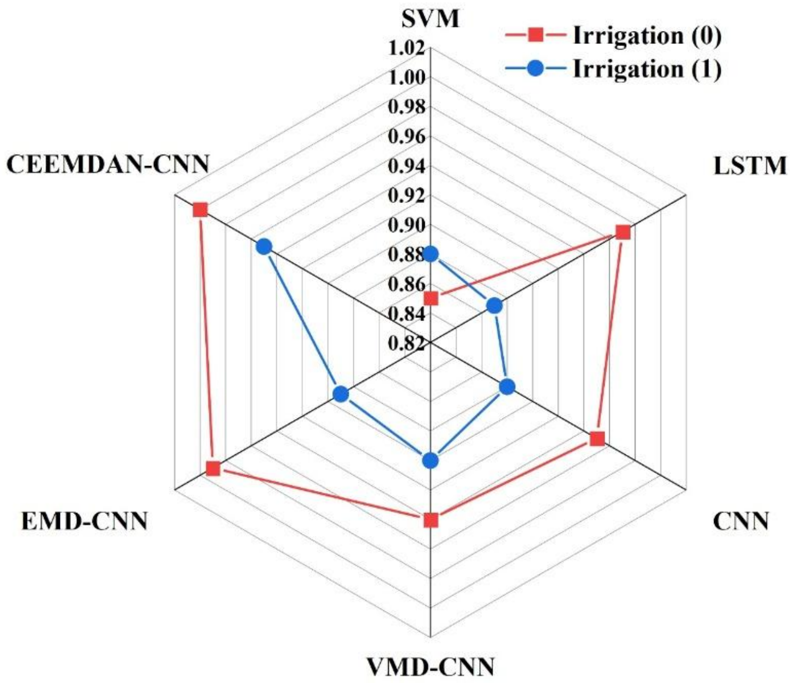


Figure 8. Precision analysis of the models

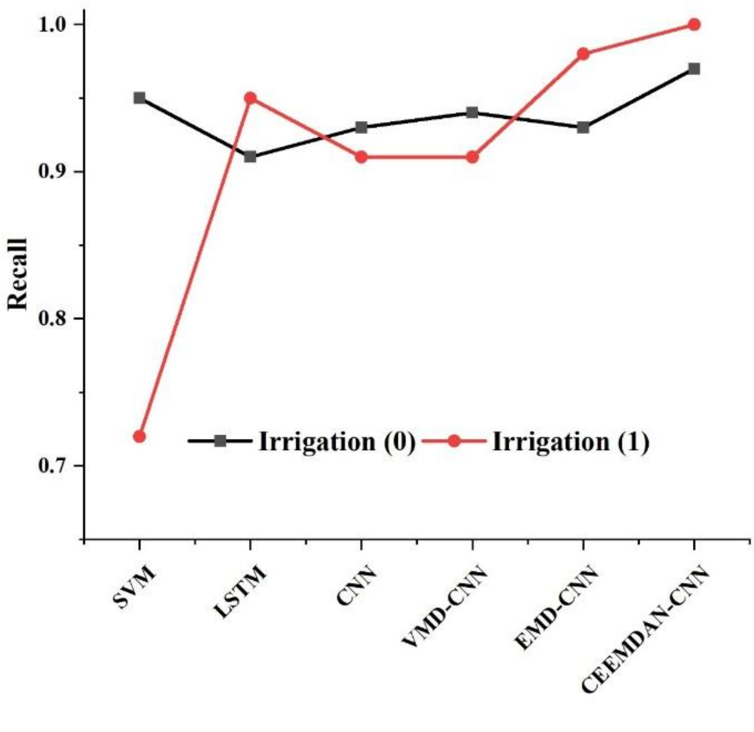


Figure 9. Recall analysis of the models

It indicates that the majority of non-irrigation samples are correctly classified, with only a small number misclassified as irrigation. Similarly, the model correctly identifies almost all irrigation cases. This behavior demonstrates high sensitivity to irrigation requirements and indicates that the proposed model effectively learns discriminative environmental patterns, resulting in reliable irrigation decision support. The confusion-matrix results are consistent with the high accuracy, precision, recall, and F1-score values reported in Table 5.

As shown by the confusion matrix, classification errors are limited to a small number of false-positive and false-negative predictions. These misclassifications are likely associated with samples whose environmental conditions lie close to the irrigation decision boundary, where soil moisture, temperature, and humidity characteristics overlap between irrigation and non-irrigation classes. Such borderline cases are inherently difficult to distinguish because similar environmental measurements may correspond to different irrigation requirements depending on crop growth stage and local conditions. Nevertheless, the small number of errors demonstrates the ability of the proposed model to learn discriminative patterns from decomposed environmental signals.

5.1 Training Behaviour and Model Convergence

The learning behaviour of the proposed model is illustrated through training and validation accuracy curves presented in Figure 12. From the visualization, it can be seen that training accuracy increases steadily and approaches convergence, while validation accuracy stabilizes around 96–98%. The small fluctuations in the validation curve are expected given the moderate dataset size. However, the close alignment between training and validation performance indicates stable learning behavior and no clear evidence of overfitting. Despite the dataset containing only 501 samples, the strong performance of the proposed model suggests that the learned convolutional representations capture meaningful irrigation-related patterns that are not fully exploited by conventional ML approaches. Because the CNN operates on decomposed feature representations containing both low-frequency and high-frequency information, it can automatically learn local interactions and hidden relationships associated with irrigation requirements.

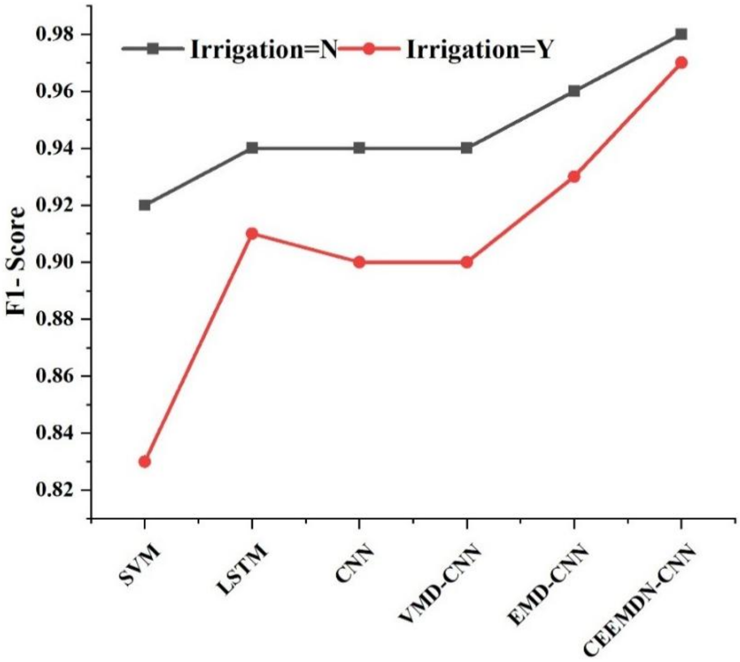


Figure 10. F1-score analysis of the models

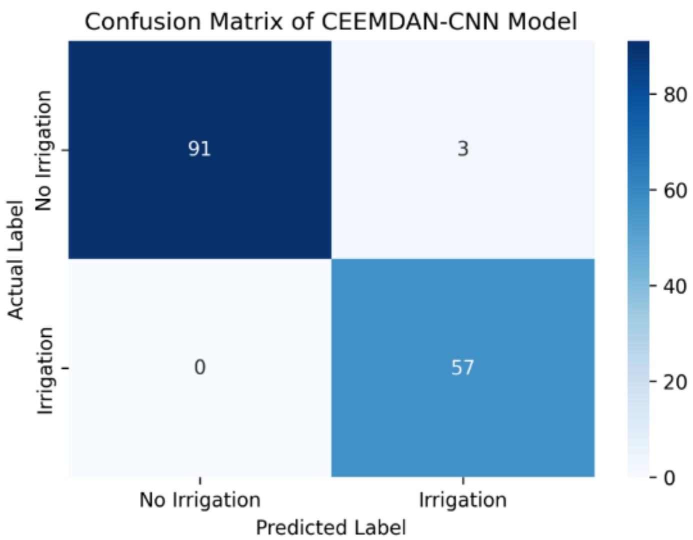


Figure 11. Confusion matrix of proposed model

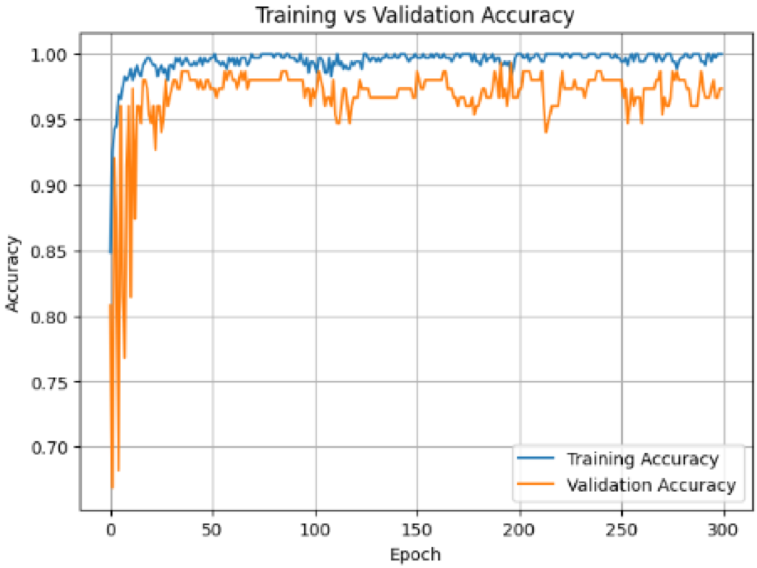


Figure 12. Training Vs validation accuracy

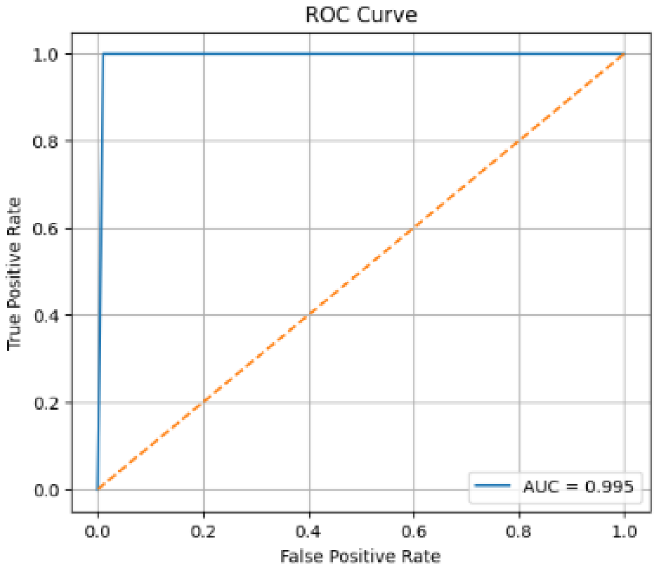


Figure 13. ROC curve

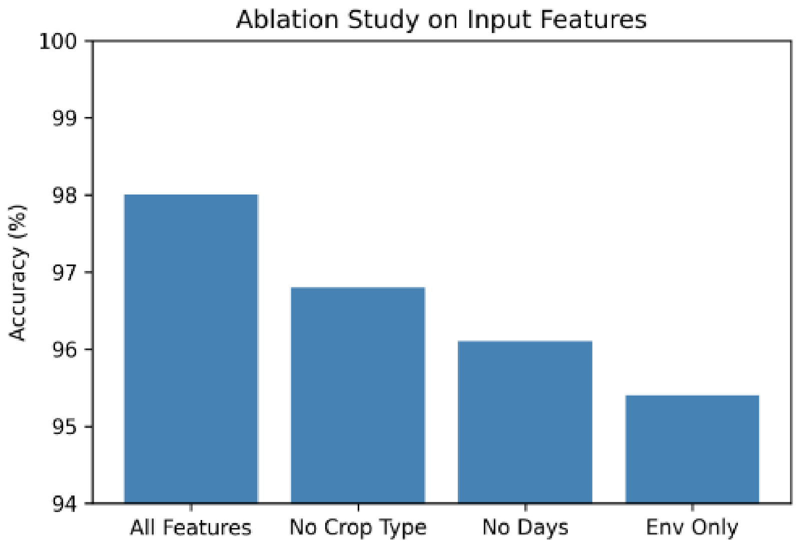


Figure 14. Ablation study on input features

Table 6. Comparative analysis of the proposed model with previous studies

Ref.	Publication Year	Author's	Target Parameter	Models Used	Performance
[62]	2023	Sarjerao et al.	Irrigation decision	ANN, LSTM, CNN	Accuracy (%): ANN-97.24, LSTM-95.68, CNN-93.39
[61]	2023	Singh et al.	Sprinkle irrigation	CNN	Accuracy (%): 97.10, Precision (%): 85.50
[64]	2024	Silaban et al.	Irrigation or Not Irrigation	ANN	Accuracy (%):91.33
[30]	2024	Tyagi et al.	Water Management Optimization	RF	Accuracy (%): 94.77
[18]	2025	Okayama et al.	Water management	CNN	Accuracy (%): 80
[63]	2025	Markose et al.	Irrigation or non-irrigation decision	1D-CNN with Attention	Accuracy (%): 97%
[49]	2025	Inyang et al.	Irrigation Classification for overhead, surface and precision irrigation	RF, SVM, XGBoost, KNN	Accuracy (%): RF 80, SVM 72, XGBoost 86
[33]	2026	Umamaheswari et al.	Environmental and soil parameters	RF	Accuracy (%): 95.45
	2026	Kumar et al.	Irrigation or Not Irrigation	CEEMDAN-CNN	Accuracy (%):98, Precision (%): 95

This advantage is reflected in the comparative results, where CNN-based models consistently outperform the conventional SVM baseline, and the proposed model achieves the highest classification accuracy.

5.2 Receiver Operating Characteristic Analysis

The Receiver Operating Characteristic (ROC) curve of the proposed model is shown in Figure 13. In this study, the classifier achieves an AUC value close to 0.995, demonstrating excellent discriminative capability between irrigation and non-irrigation conditions. The curve rapidly approaches the top-left corner, indicating high true-positive rates with very low false-positive rates.

5.3 Feature Relationship and Leakage Analysis

To investigate the influence of crop-related variables and to address potential information leakage concerns, an ablation study is also conducted by systematically modifying the input feature set. Figure 14 illustrates the classification accuracy obtained under different feature configurations.

The results show that the highest performance is obtained when all features are used. Removing crop type or crop days causes only a moderate reduction in classification accuracy, while the model continues to perform competitively when the environmental variables are retained. These findings indicate that crop-related variables provide useful contextual information but are not the dominant source of predictive power. From an agronomic perspective, irrigation decisions are largely driven by climatic and environmental factors such as soil moisture, temperature, and humidity. CEEMDAN further improves the process by identifying multiscale patterns and hidden variations in the environmental data, enabling the CNN to learn discriminative characteristics related to irrigation demand. Thus, the performance gains are primarily attributable to environmental sensing information and decomposition-based feature extraction, while crop type and crop age serve as supportive contextual factors. This behavior reduces the likelihood that model performance is driven mainly by crop identity or growth stage and suggests that the framework captures generalizable irrigation-related patterns across diverse crop groups. Overall, environmental conditions play the dominant role in irrigation decision-making, while crop-specific variables contribute complementary context. Therefore, the proposed model does not rely solely on crop identity or growth stage, thereby reducing the risk of information leakage.

5.4 Comparative Discussion with Existing Studies

Table 6 presents a comparative analysis of the proposed model against existing studies on irrigation management. The proposed model achieves a higher accuracy (98%) than most of the reported methods. For example, Sarjerao *et al.* [62] reported accuracies of 97.24%, 95.68%, and 93.39% using ANN, LSTM, and CNN models, respectively, while Markose *et al.* [63] achieved 97% accuracy using a 1D-CNN with an attention mechanism. Similarly, traditional ML models such as RF have reported accuracies ranging from 94.77% to 95.45% [30, 33, and 49]. The superior performance of the proposed model can be attributed to the integration of CEEMDAN with CNN. Unlike conventional CNN-based approaches, CEEMDAN decomposes soil moisture, temperature, and humidity data into multiple IMFs, enabling the CNN to learn hidden temporal patterns while reducing the influence of noise and non-stationary behavior in agricultural sensor data.

Furthermore, the proposed model achieved a precision of 95%, recall of 100%, and F1-score of 97%, indicating a strong ability to identify irrigation requirements while minimizing incorrect decisions. These results suggest that the proposed model can provide more reliable irrigation decision support than conventional ML and DL models. Therefore, the proposed CEEMDAN-CNN model offers an effective solution for intelligent irrigation management and sustainable water-resource utilization in precision agriculture.

6. Limitations and Future Scope

Although the proposed model shows excellent performance for irrigation classification, several limitations provide directions for future research. The current study uses a moderately sized dataset, and future work should focus on collecting large-scale, multi-season field data to improve model generalization and robustness under diverse climatic and soil conditions. More concrete future research directions include: (i) field deployment and validation of the proposed framework under real agricultural operating conditions; (ii) multi-season investigations covering different crop growth cycles to assess temporal robustness; (iii) evaluation using datasets collected from geographically diverse regions with varying climates, soil properties, irrigation practices, and crop types to improve generalizability; and (iv) investigation of deployment on resource-constrained edge devices using lightweight architectures, model compression, pruning, and quantization techniques to enable real-time irrigation decision support.

7. Conclusion

Traditional agricultural methods, still prevalent in many regions, often result in suboptimal yields despite the availability of fertile land. This study highlights how emerging technologies, particularly IoT and ML, can support smart farming and efficient irrigation management. By enabling real-time sensing of environmental factors such as soil moisture, temperature, and humidity, these technologies can optimize irrigation schedules, reduce water wastage, and improve crop yield. In this context, the work proposed a hybrid CEEMDAN-CNN model to classify irrigation requirements effectively. CEEMDAN decomposes the input feature data into individual frequency components, which are then processed by the CNN, leading to improved model performance. A total of six standalone and hybrid models were developed and evaluated. The results show that the proposed CEEMDAN-CNN model outperformed the comparison models. Specifically, it achieved the highest accuracy (98%), precision (0.95), recall (1), and F1-score (0.97) for the irrigation-required class. The proposed model also supports higher water-saving efficiency, reducing unnecessary water use by up to 9% compared with lower-performing models such as SVM, which makes it a promising solution for intelligent irrigation systems. In addition, the model shows strong generalization ability, minimal misclassification, and stable convergence behavior. These findings confirm the robustness and effectiveness of the proposed framework for accurately identifying irrigation requirements. Overall, the study advances intelligent irrigation research by offering a reliable and efficient approach to water conservation and sustainable agricultural practice, with strong potential for real-world deployment in precision agriculture.

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Authors Contribution Statement

Rajesh Kumar: Conceptualization, Methodology, Investigation, Writing – Original Draft, Data Curation, Software, Validation, Formal Analysis. Anil Garg: Supervision, Visualization, Writing – Review and Editing. Both authors have read and agreed to the published version of the manuscript.

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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