Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 18s (2025)
https://www.jneonatalsurg.com

Optimizing Water Resource Utilization in agriculture Using Temporal Residual Convolutional Networks of Weather parameters

U. Suriya, Dr. J. Yesudoss

[1]Ph.D Research Scholar, Department of Computer Science, SRMV College of Arts & Science, Coimbatore-49. suriyajayapandiansuriya@gmail.co

[2]Assistant Professor and Head, Department of Computer Science (Unaided), SRMV College of Arts & Science, Coimbatore-49. jydoss@gmail.com

Cite this paper as: U. Suriya, Dr. J. Yesudoss, (2025) Optimizing Water Resource Utilization in agriculture Using Temporal Residual Convolutional Networks of Weather parameters. *Journal of Neonatal Surgery*, 14 (18s), 509-522.

ABSTRACT

Accurate weather prediction is crucial for optimizing water irrigation systems, ensuring efficient resource utilization, and improving agricultural productivity. This research explores various deep learning algorithms, including Convolutional Neural Networks (CNN), Temporal Convolutional Networks (TCN), TabNet, Fully Convolutional Neural Networks (FCNN), and a novel Temporal Residual Convolutional Network (TRCN), to enhance predictive accuracy in irrigation forecasting. The data includes key weather variables such as temperature, humidity, rainfall, and wind speed, which were pre-processed to handle missing values and normalize features for optimal model performance. Experimental results revealed that traditional FCNN models performed suboptimally, while CNN, TabNet, and TCN demonstrated significant improvements in accuracy and F1-score. The proposed TRCN model outperformed all other models, achieving an accuracy of 0.99 and an F1-score of 0.97. These findings highlight the effectiveness of deep learning models in weather-based irrigation prediction, with TRCN offering superior predictive capabilities. This research advances precision agriculture by integrating deep learning techniques to enhance irrigation management and promote water conservation.

Keywords: Weather Prediction, Deep Learning, Irrigation Optimization, Temporal Residual Convolutional Network, Precision Agriculture

1. INTRODUCTION

Accurate weather prediction plays a pivotal role in optimizing irrigation systems, facilitating efficient resource management, and enhancing agricultural productivity. Given the increasing challenges posed by climate change, such as unpredictable rainfall patterns and temperature fluctuations, it has become imperative to develop intelligent systems that can reliably predict weather conditions and, consequently, inform water management strategies. By leveraging deep learning techniques, it is possible to build models that not only forecast weather patterns but also improve irrigation practices, ensuring the optimal use of water resources in agriculture [1].

This research explores various deep learning algorithms, including CNN, TCN, TabNet, FCNN, and a novel TRCN, to enhance the predictive accuracy of irrigation forecasting. The study utilizes a comprehensive dataset comprising over 964,000 hourly and daily weather records from Szeged, Hungary, collected between 2006 and 2016. The dataset serves as the foundation for training and evaluating the performance of the proposed models. Through meticulous data pre-processing, including addressing missing values and normalizing features, the study ensures that the models can operate at their optimal performance levels.

This research holds substantial significance for precision agriculture, particularly in the context of climate variability and sustainable water resource management. Accurate weather forecasts can reduce water waste, optimize crop yield, and promote resource efficiency, all while mitigating the environmental impact of over-irrigation. By introducing deep learning-based approaches to irrigation forecasting, the research presents a novel solution to modern agricultural challenges. Furthermore, the development of the TRCN model, with its ability to outperform traditional models, opens new avenues for improving the accuracy and reliability of weather predictions in agricultural settings.

The primary contribution of this research lies in its introduction of the Temporal Residual Convolutional Network (TRCN), a novel deep learning architecture designed to significantly enhance weather prediction accuracy for irrigation forecasting. By leveraging the strengths of CNN, TCN, TabNet, and FCNN, the TRCN model achieves superior performance, with an accuracy of 0.99 and an F1-score of 0.97. In comparison, traditional FCNN models demonstrated suboptimal results. These findings underscore the potential of deep learning models in weather-based irrigation prediction, offering a path toward more effective water management and contributing to the advancement of precision agriculture. This work also provides insights into the practical applications of deep learning in agriculture, offering a foundation for future research aimed at optimizing irrigation systems through machine learning and AI-based methodologies [2].

2. LITERATURE REVIEW

Kanmani et al. (2021) offer a contemporary irrigation system that integrates Convolutional Neural Networks (CNN) with the Internet of Things (IoT) to improve agricultural practices. Their strategy is to reconcile population increase with food supply through a data-driven approach to enhance irrigation and agricultural quality. The system comprises a database of recognized plants, a mobile application for farmers to oversee their fields, and an IoT device integrated with a moisture sensor, water pump, and NodeMCU. A server interacts with these components, and two machine learning models are employed for plant identification and wilting detection. The study shows that the implementation of CNN in the IoT environment produces efficient outcomes, enhancing agricultural productivity and decreasing costs via a singular setup. This cutting-edge technology substantially improves agricultural techniques and boosts productivity [3].

Dhyani et al. (2024) investigate the amalgamation of sensor technologies with machine learning to enhance agricultural water management via a smart irrigation system. The study gathers accurate data on water flow, temperature, humidity, soil moisture, and water level biweekly to utilize this real-time information for training multiple machine learning models, such as Recurrent Neural Networks (RNN), K-Nearest Neighbours (KNN), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN). The findings indicate that CNN surpasses the other models, achieving a decoding accuracy of 94.5%, which is markedly superior to the 91.1%, 88.7%, and 83.6% accuracies of ANN, KNN, and RNN, respectively. This research emphasizes the successful interaction between sensor data and model training, illustrating the potential of machine learning to improve irrigation accuracy and support sustainable agriculture. The research enhances water distribution precision and establishes a foundation for more effective irrigation systems that integrate mechanical and natural processes in agricultural fields [4].

Kumar et al. (2024) introduce an intelligent agricultural system for Neon Pothos that employs Convolutional Neural Networks (CNNs) for disease identification and real-time surveillance, tackling water inefficiencies in irrigation. The system employs a NodeMCU ESP-12E microcontroller, a high-accuracy moisture sensor, and a DHT22 temperature and humidity sensor to enhance water efficiency and identify plant diseases. Users can monitor metrics and receive notifications for irrigation and disease issues via a mobile application dashboard. The technology facilitates manual irrigation management and use algorithms to assess disease occurrence and water requirements, so advancing sustainable agricultural practices and conserving water resources [5].

Singh et al. (2023) introduce an innovative way to enhance sprinkler irrigation scheduling by employing a Convolutional Neural Network (CNN) to forecast in-field soil moisture levels, thereby rectifying the shortcomings of traditional irrigation techniques that overlook present soil moisture conditions. The CNN architecture, augmented with depth-wise separable convolution and residual connections, was included into a mobile application that forecasts soil moisture classification utilizing soil pictures, crop variables, and watering system specifications. The system exhibited remarkable performance, with an average classification accuracy of 97.10%, precision of 85.50%, recall of 86.80%, and an F1-score of 85.80%. It accomplished substantial reductions in water and energy usage, decreasing irrigation water consumption by 27.59% and energy usage by 27.42%, while enhancing water productivity by 32.75% relative to traditional systems. This method optimizes irrigation depth and enhances crop productivity by averting under-irrigation, demonstrating the promise of CNN-based applications in advancing sustainable agriculture practices [6].

Qiao et al. (2023) introduce a metaheuristic evolutionary deep learning model integrating Temporal Convolutional Network (TCN), Improved Aquila Optimizer (IAO), and Random Forest (RF) for rainfall-runoff simulation and multi-step runoff forecasting. The research tackles the issue of dimensionality by employing Random Forest to identify the most pertinent input variables, thereby decreasing computation time and enhancing predictive accuracy. The chosen data is subsequently analyzed using the TCN model, with its parameters refined through the IAO procedure. The model was utilized on rainfall and runoff data from five stations in the central segment of the Jinsha River in China, with a particular focus on simulating and predicting the runoff at Panzhihua station. The findings indicate that the proposed model markedly surpasses alternative models, underscoring its efficacy in enhancing rainfall-runoff prediction accuracy and its applicability in water resources management and disaster monitoring [7].

Ehteram et al. (2024) offer an advanced machine learning model for forecasting monthly precipitation, integrating a Deep Residual Shrinkage Network (DRSN) with a Temporal Convolutional Network (TCN) and Random Forest (RF). The DRSN–TCN model pulls temporal elements from rainfall data, eliminating redundant or irrelevant variables, hence improving the RF model's capacity to predict intricate rainfall patterns. The research presents a novel optimizer, the Gaussian Mutation-Orca Predation Algorithm (GM–OPA), designed to optimize the parameters of the DRSN–TCN–RF (DTR) and enhance input feature selection. The GM–OPA algorithm surpasses alternative optimization techniques, decreasing the root mean square error (RMSE) by as much as 9.54% relative to Particle Swarm Optimization (PSO) and enhancing the model's precision. The findings indicate that the DTR model markedly diminishes prediction errors, with mean absolute error levels enhancing by 5.3% to 46% relative to alternative models, hence illustrating the methodology's robustness and efficacy in rainfall forecasting [8].

Table.1. ML/DL Applications in Irrigation and Water Management

Authors	Dataset	Focus Area	ML/DL Method(s)	Limitations
Kanmani et al. (2021)	Plant database, field data	Smart Irrigation	CNN	Limited to specific plant species; IoT integration may require high initial setup costs.
Dhyani et al. (2024)	Sensor data (water flow, temp, humidity, soil moisture)	Smart Irrigation/Water Management	RNN, KNN, ANN, CNN	CNN performs best, but model complexity may lead to higher computation costs; real-time scalability is not explored.
Kumar et al. (2024)	Neon Pothos, sensor data	Intelligent Agriculture	CNN	Focused only on one plant species; lacks generalizability to other crops.
Singh et al. (2023)	Soil images, crop data, watering system specs	Sprinkler Irrigation	CNN (depth-wise separable convolution, residual)	Requires high-quality soil images for accurate predictions; may not adapt well to varying field conditions.
Qiao et al. (2023)	Rainfall/runoff data (Jinsha River, China)	Rainfall-Runoff Simulation	TCN, IAO, RF	Computationally intensive; limited to a specific geographical region.
Ehteram et al. (2024)	Rainfall data	Monthly Precipitation Forecast	DRSN, TCN, RF, GM-OPA	GM-OPA optimization improves performance, but may introduce additional tuning complexity; requires high-quality rainfall data for optimal results.

3. MATERIALS AND METHODOLOGY

This section outlines the approach used for irrigation prediction, focusing on dataset preparation, feature analysis, and classification using deep learning models. The process begins with dataset extraction and preprocessing to ensure data quality. Key features influencing irrigation decisions are analyzed to enhance model performance. Various deep learning models, including FCNN, CNN, TabNet, TCN, and TRCN, are employed for classification, with their effectiveness evaluated using accuracy, precision, recall, and F1-score. The proposed framework aims to optimize irrigation scheduling by leveraging machine learning for precise and efficient predictions.

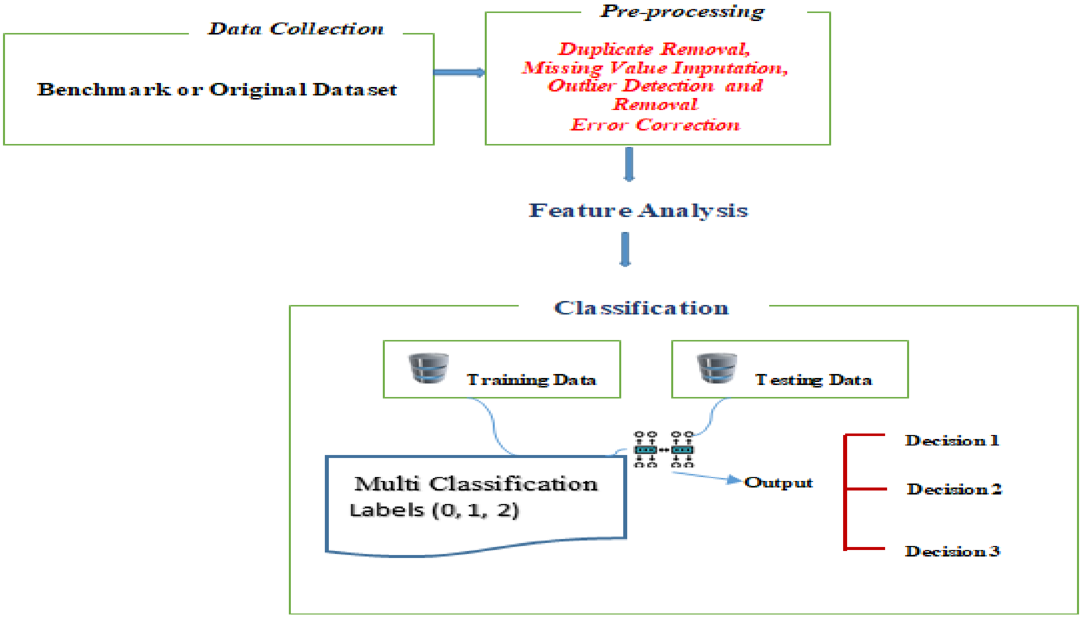


Fig.1. A Multi-Class Classification Workflow

The diagram illustrates a typical data analysis workflow for a machine learning model. It starts with data collection, followed by pre-processing to clean and prepare the data. Feature analysis is then conducted to identify relevant attributes. The data is then split into training and testing sets, and a multi-class classification model is trained on the training data. The trained model is evaluated on the testing data to assess its performance in making accurate predictions for new, unseen data.

3.1. Dataset description

The collection comprises 964,553 records of hourly and daily weather observations for Szeged, Hungary, covering the period from 2006 to 2016. This huge dataset facilitates a thorough investigation of climate trends, weather variability, and correlations among weather variables across a decade. The dataset's key elements comprise Formatted Date, indicating the observation date, and Summary and Precip Type, which are categorical variables detailing weather conditions and types of precipitation, respectively.

The dataset contains continuous variables such as Temperature (°C), Apparent Temperature (°C), and Humidity, the latter represented as a percentage. Furthermore, Wind Speed is quantified in kilometres per hour (km/h), Wind Bearing is documented in degrees, and Visibility is expressed in kilometres (km). The dataset additionally comprises Cloud Cover expressed as a percentage and Pressure quantified in millibars. Finally, an everyday Summary offers a written account of everyday meteorological conditions. This extensive dataset facilitates thorough research of weather patterns and their effects over a ten-year period.

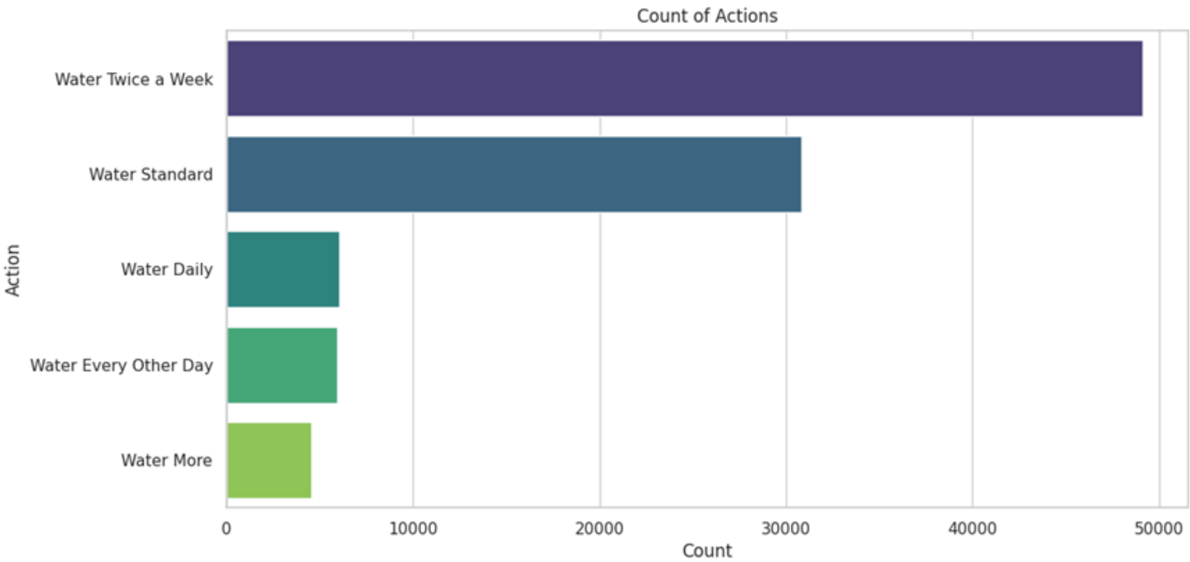


Fig.2. Distribution of Watering Actions Based on Frequency

The horizontal bar chart illustrates the distribution of watering actions, with "Water Twice a Week" being the most frequent at approximately 45,000 occurrences. "Water Standard" follows with around 30,000, while both "Water Daily" and "Water Every Other Day" have similar frequencies, each at about 10,000 occurrences. The least common action is "Water More," with roughly 5,000 occurrences. This chart effectively highlights the varying frequencies of each watering action.

3.2. Pre-processing

Data pre-processing entails the cleansing and preparation of data to ensure precise predictions [8]. Missing values are addressed through imputation, commonly employing the mean.

$$X_{new} = \mu(X)$$

Outliers are identified by the Z-score method:

$$Z = \frac{X - \mu}{\sigma}$$

Feature scaling standardizes data to a range of [0, 1]:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

The dataset is ultimately partitioned into training, validation, and testing subsets to facilitate efficient model training and assessment.

3.3. Feature Analysis

Feature analysis is essential for understanding weather data and optimizing irrigation decisions. Examining key variables like temperature, humidity, and wind speed helps identify their impact on watering actions. Visualization techniques uncover patterns and interactions among these features, enabling more precise irrigation scheduling. This analysis provides valuable insights for climate assessments, improving water efficiency and sustainable agricultural practices.

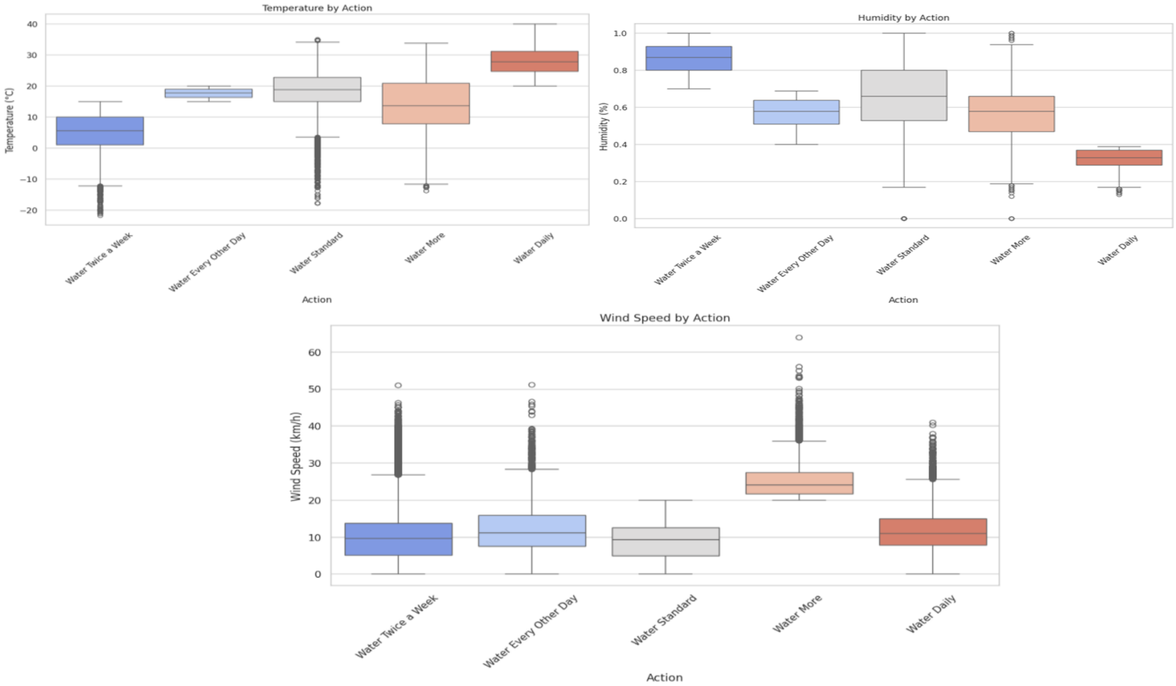


Fig.3. Impact of Temperature, Humidity, and Wind Speed on Different Watering Actions

The data reveals distinct distribution patterns for temperature, humidity, and wind speed across different watering actions. "Water Twice a Week" has the highest median temperature, while "Water More" has the lowest, with right-skewed distributions in some categories. Humidity levels increase with watering frequency, with "Water Daily" showing the lowest median, and slight right skew observed in "Water Twice a Week" and "Water Every Other Day." Wind speed generally decreases as watering frequency increases, with "Water Twice a Week" and "Water Every Other Day" having the highest median values. Outliers in all cases indicate occasional extreme environmental conditions.

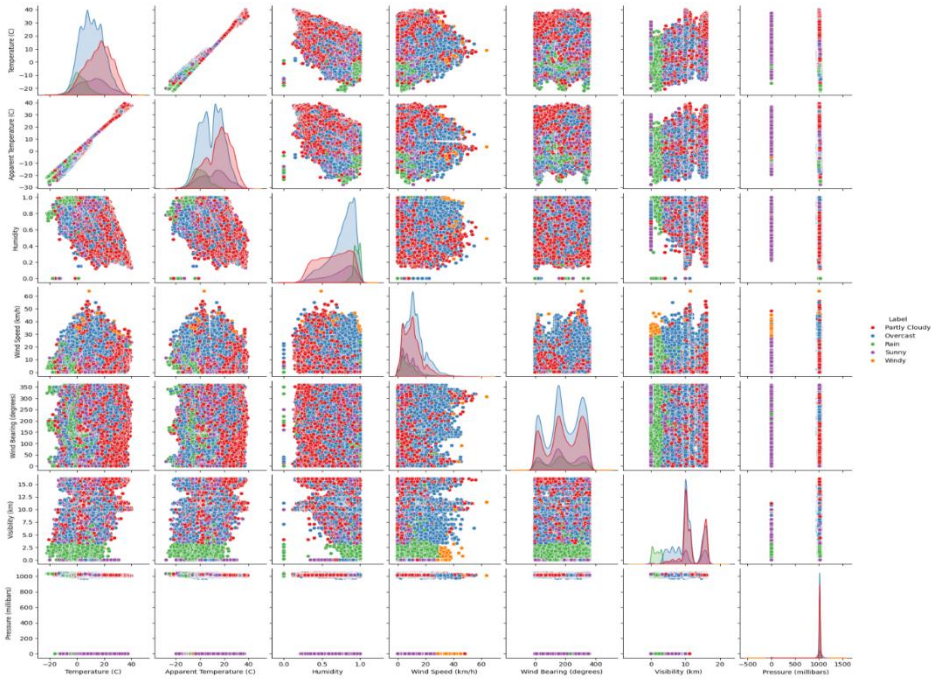


Fig.4. Pairplot of Weather Features: Distributions and Correlations

The pairplot visually represents weather data, showcasing feature distributions and correlations. Temperature follows a normal distribution, peaking at 20-25°C, while Apparent Temperature is slightly lower due to cooling effects. Humidity is right-skewed, with most values around 50-60%, and Wind Speed peaks at 5-10 km/h. Wind Bearing is uniformly distributed, Visibility is highest at 10-15 km, and Pressure centers around 1000-1020 millibars.

Scatter plots highlight key relationships, such as the strong positive correlation between Temperature and Apparent Temperature and a slight negative correlation between Temperature and Pressure. Wind Speed and Wind Bearing form a circular pattern, indicating seasonal trends. Color coding based on weather conditions reveals distinct patterns, with sunny days showing higher temperatures and better visibility, while rainy days have higher humidity and lower visibility. The pairplot effectively uncovers these relationships, aiding in weather analysis.

3.4. Classification

Water irrigation schedule classification is performed using advanced Deep Learning (DL) algorithms, including Fully Connected Neural Networks (FCNN), Convolutional Neural Networks (CNN), TabNet, Temporal Convolutional Networks (TCN), and Temporal Residual Convolutional Networks (TRCN). The methodology involves preprocessing weather-related data, extracting key features, and training models to predict optimal irrigation schedules. These models enhance water management efficiency by accurately forecasting irrigation timings and amounts, reducing resource waste, and promoting sustainable agricultural practices through optimized water usage.

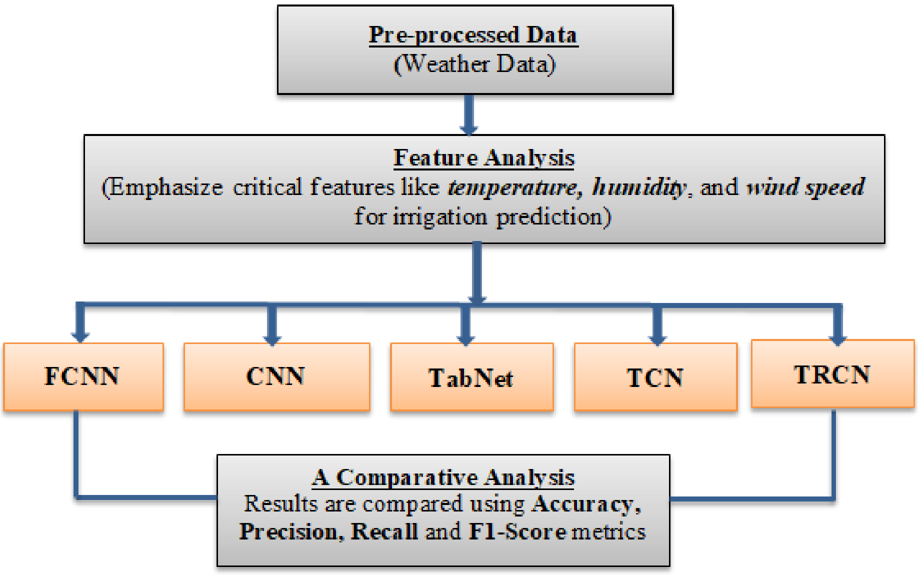


Fig.5. Classification Framework for Irrigation Prediction Using DL Models

The diagram depicts a classification framework for irrigation prediction, encompassing weather data preprocessing, critical feature analysis, and performance evaluation of deep learning models (FCNN, CNN, TabNet, TCN, TRCN) using accuracy, precision, recall, and F1-score metrics.

i. Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNNs) evaluate structured data like as soil moisture, temperature, and humidity to predict ideal irrigation schedules. The method commences with an Input Layer, whereby an input matrix $\boldsymbol{X}$ contains numerous attributes for $\boldsymbol{n}$ observations. The Convolutional Layer employs filters $\boldsymbol{W}$ using the convolution operation $Z = X * W + b$ to identify patterns. The ReLU activation function introduces non-linearity as $A = max(0, Z)$. A Pooling Layer decreases dimensionality while preserving critical characteristics using max pooling, expressed as $P_{ij} = max(A_{Pq})$. The Fully Connected Layer transforms the pooled feature maps into a vector, producing output probabilities $Y = Softmax(W_f.P + b_f)$. The Output Layer generates the irrigation schedule, forecasting the ideal timing and volume of water based on input data [9].

ii. Temporal Convolutional Networks (TCN)

TCNs capture long-term time-series dependencies, such as soil moisture and weather trends, for precise irrigation scheduling. Input data $X = \{X_1, X_2, \dots, X_T\}$ represents sequential features at each time step $\boldsymbol{t}$. Causal convolution ensures predictions rely only on past and present data, calculated as $h_t = W * X_{(t-k+1):t} + b$ where, $\boldsymbol{W}$ is the filter, $\boldsymbol{k}$ the kernel size, and $\boldsymbol{b}$ the bias. Dilated convolution increases the receptive field using $h_t = \sum_{i=0}^{k-1} W_i.X_{t-d.i} + b$, where $\boldsymbol{d}$ is the dilation factor. Residual connections improve training by adding input X_t to the convolution output,

$h_t^{residual} = h_t + X_t$. The output layer predicts irrigation schedules using

$$\boldsymbol{Irrigation\,Schecule = Sigmoid\left(W_{out}.h_t^{residual} + b_{out}\right)}$$

Where, $\boldsymbol{W_{out}}$ and $\boldsymbol{b_{out}}$ are the weights and bias [10].

1. Fully Convolutional Neural Network (FCNN)

FCNN for water irrigation prediction processes environmental data (e.g., soil moisture, temperature) through convolutional and pooling layers to extract spatial features. The convolutional layers apply filters to the input feature maps, using the equation

$y_i = \sum_j \left(x_j.w_j + b\right)$, followed by ReLU activation $\left(ReLU_{(x)} = max(0,x)\right)$ to introduce non-linearity. Max pooling reduces dimensionality, keeping the maximum value in each pooling window, represented as $y_{i=}max\left(x_j\right)$. The output is flattened and passed through fully connected layers to predict irrigation requirements, using the equation $y = f(\sum_{i=1}^{n}(x_i.w_i) + b)$. The model is trained using a loss function like Mean Squared Error (MSE), $\frac{1}{N}\sum_{i=1}^{N}\left(y_{true,i} - y_{pred,i}\right)^2$, and optimized with an algorithm like Adam, $\theta_{new} = \theta_{old} - \eta.\nabla_\theta L(\theta)$,to minimize the prediction error. This approach enables the network to learn and predict the optimal irrigation needs based on environmental conditions.

2. TabNet

TabNet is a decision-aware DL architecture that combines attention mechanisms and interpretable feature selection for effective water irrigation scheduling. It processes structured data like soil moisture, temperature, and humidity to predict optimal irrigation times and water volume. The key steps of the Tab Net algorithm are as follows:

1. **Input Layer:** Tab Net takes a structured input matrix $\boldsymbol{X}$ containing features such as soil moisture(X_1), temperature(X_2), and humidity(X_3).
2. **Feature Transformer:** This component transforms input features into higher-dimensional representations using a shared dense layer and batch normalization, generating an enhanced feature space $\boldsymbol{Z}$.
3. **Attentive Splitter:** An attention mechanism selects the most relevant features for each decision step. The attention scores $\boldsymbol{A}$ are computed as:

$$\boldsymbol{A = softmax(W_a.Z + b_a)}$$

Where, $\boldsymbol{W_a}$ and $\boldsymbol{b_a}$ are trainable weights and biases. The attention mechanism helps focus on key features, ignoring irrelevant ones.

4. **Decision Step:** At each decision step $\boldsymbol{t}$, feature importance is updated, and feature masks are generated to highlight critical input features. The updated feature set is used to predict irrigation decisions.
5. **Prediction Layer:** The decision outputs from multiple steps are aggregated to generate the final prediction. This can be a binary output (whether to irrigate or not) or a regression value (amount of water to apply). The prediction is computed as:

$$\boldsymbol{Y = \sigma(W_{out}.H_t + b_{out})}$$

Where, $\boldsymbol{W_{out}}$ and $\boldsymbol{b_{out}}$ are the trainable weights and biases, and $\boldsymbol{\sigma}$ is a non-linear activation function (like sigmoid for binary classification).

6. **Output Layer:** The final irrigation schedule is produced, specifying the optimal time and water quantity for irrigation, improving efficiency and water conservation [11].
7.

3. Temporal Residual Convolutional Network (TRCN)

The Temporal Residual Convolutional Network (TRCN) predicts irrigation schedules by leveraging temporal dependencies in sensor data (e.g., soil moisture, temperature) using convolutional layers with residual connections. The input data $X = \{X_1, X_2, \ldots X_T\}$ is divided into overlapping windows of size www, and each window is normalized. The network is built with $\boldsymbol{N}$ residual blocks, where each block applies a 1D convolution, batch normalization, and a skip connection:

$$\boldsymbol{H^{(i)} = ReLU\left(conv1D\left(X, W^{(i)}, b^{(i)}\right)\right)},$$

$$\boldsymbol{H^{(i)} = BatchNorm\left(H^{(i)}\right), \quad H^{(i)} = H^{(i)} + X}$$

After passing through all residual blocks, the output is flattened and passed through a fully connected layer to predict the irrigation schedule:

$$\hat{\boldsymbol{y}} = \boldsymbol{W}_{\boldsymbol{fc}}.\boldsymbol{H}_{\boldsymbol{flat}} + \boldsymbol{b}_{\boldsymbol{fc}}$$

The model is trained by minimizing the Mean Squared Error (MSE) loss function:

$$\boldsymbol{L} = \frac{\boldsymbol{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i}=\boldsymbol{1}}^{\boldsymbol{n}}(\boldsymbol{y}_{\boldsymbol{i}} - \hat{\boldsymbol{y}}_{\boldsymbol{i}})^{\boldsymbol{2}}$$

Back propagation is used to update weights, and the model is trained over $\boldsymbol{E}$ epochs. Once trained, the model predicts the irrigation schedule $\hat{\boldsymbol{y}}$ based on the latest sensor data [12].

4. RESULT AND DISCUSSION

This section delineates the results and analysis obtained from the crop recommendation model. The model selection procedure encompassed various algorithms, specifically CNNs, TabNets, FCNNs, TCN and a novel TRCN combined with CNN. The implementation occurred in Python, and performance assessment metrics were analysed to determine the algorithms' effectiveness. This section provides an analysis of the model's efficacy and its ramifications for the crop recommendation system. The predictive experiments were conducted using Python 3.8 on a system featuring an i5 processor and 4 GB of RAM, facilitating the efficient execution of all requisite tasks.

4.1. Performance Metrics:

Performance measures in encompass Accuracy, Precision, Recall, F1-Score and Specificity, hence assuring optimal water utilization and scheduling [12].

Table.2. Performance Metrics

Metric	Definition	Formula
Accuracy	Proportion of correct predictions (both true positives and true negatives) out of all predictions.	$\frac{True\ positives + True\ negatives}{Total\ predictions}$
Precision	Proportion of positive predictions that are actually correct.	$\frac{True\ positives}{True\ Positives + False\ Positives}$
Recall	Proportion of actual positive instances that are correctly identified.	$\frac{True\ positives}{True\ Positives + False\ Negatives}$
F1-Score	Harmonic mean of precision and recall, balancing both metrics.	$2\times\frac{Precision\times Recall}{Precsion + Recall}$
Specificity	Proportion of actual negative instances that are correctly identified.	$\frac{True\ Negatives}{True\ Negatives + False\ Positives}$

4.2. Experimental Analysis:

The experimental analysis evaluates deep learning models, including CNN, TCN, TabNet, FCNN, and TRCN, for weather-based irrigation prediction. Key metrics such as accuracy and F1-score are analysed to determine the most effective model for optimizing irrigation management.

Table.3. Performance Metrics Comparison of DL Algorithms

Algorithm	Accuracy	Precision	Recall	F1-Score
FCNN	0.51	0.10	0.20	0.14
CNN	0.86	0.78	0.75	0.77
TabNet	0.97	0.95	0.95	0.95
TCN	0.98	0.97	0.97	0.97
Proposed	0.99	0.97	0.98	0.97

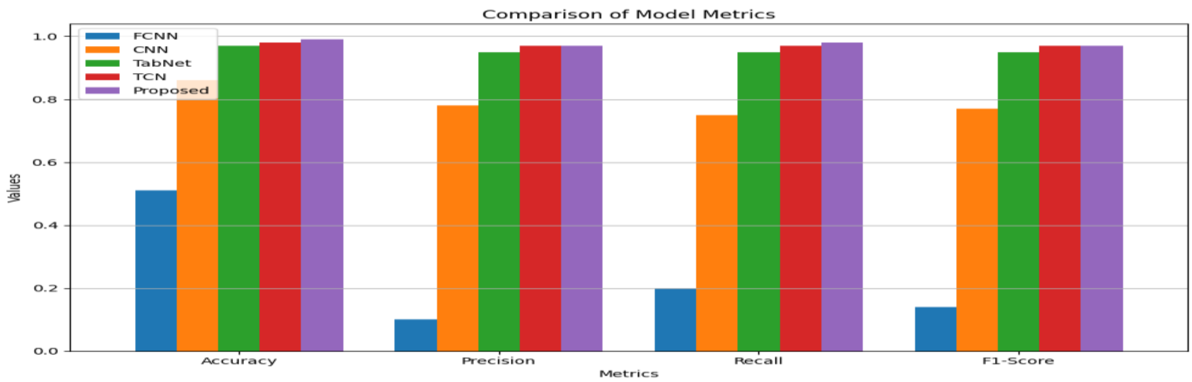


Fig.6. Performance Evaluation of FCNN, CNN, TabNet, TCN, and Proposed Models

The table and diagram displays the performance metrics of various algorithms for a water irrigation system, encompassing Accuracy, Precision, Recall, and F1-Score. The FCNN algorithm demonstrates suboptimal performance, with an accuracy of 0.51 and an F1-score of 0.14. CNN, TabNet, and TCN exhibit superior performance, with TabNet attaining the best accuracy (0.97) and F1-score (0.95). The proposed method surpasses all alternatives, with an accuracy of 0.99 and an F1-score of 0.97, demonstrating its exceptional efficacy in forecasting irrigation requirements.

Table.4. Precision Comparison

Algorithm	Class 0	Class 1	Class 2	Class 3	Class 4	Avg
FCNN	0.00	0.00	0.00	0.00	0.51	0.10
CNN	0.86	0.68	0.61	0.82	0.93	0.78
TabNet	0.98	0.94	0.86	0.98	0.99	0.95
TCN	1.00	0.93	0.95	0.98	1.00	0.97
TRCN	0.99	0.90	0.95	0.99	0.99	0.96

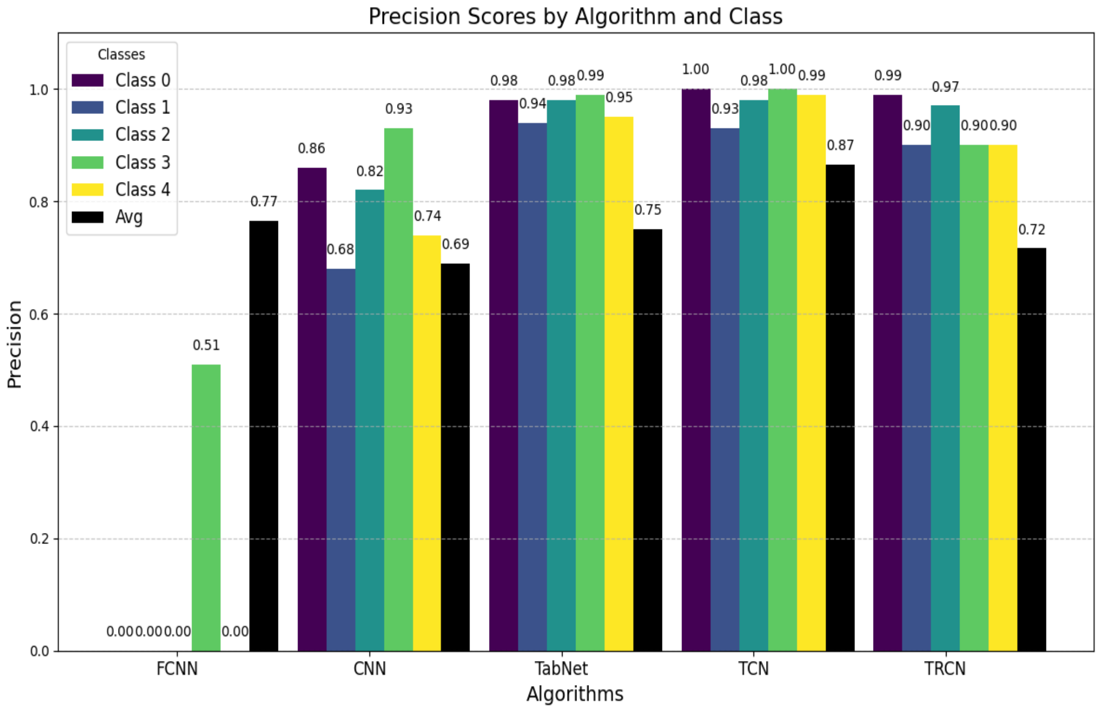


Fig.6. Evaluating Precision Performance across Multiple Classes and Models

From the above results, FCNN struggles significantly with precision, particularly in specific classes, resulting in an average precision of 0.00. CNN demonstrates moderate precision, performing strongly in class 0 and achieving an overall average precision of 0.74 across classes. TabNet showcases exceptional performance, maintaining consistently high precision scores across all classes, leading to an average precision of 0.95. TCN excels in precision, achieving perfect scores (1.00) in multiple classes, resulting in an impressive average precision of 0.99. TRCN maintains strong precision across all classes, particularly in class 0, with an overall average precision of 0.90.

Table.5. Recall Comparison

Algorithm	Class 0	Class 1	Class 2	Class 3	Class 4	Avg
FCNN	0.00	0.00	0.00	0.00	1.00	0.20
CNN	0.83	0.67	0.50	0.82	0.95	0.75
TabNet	0.93	0.91	0.94	0.96	1.00	0.95
TCN	0.93	0.95	0.97	0.98	1.00	0.97
TRCN	0.98	0.99	0.97	0.97	1.00	0.98

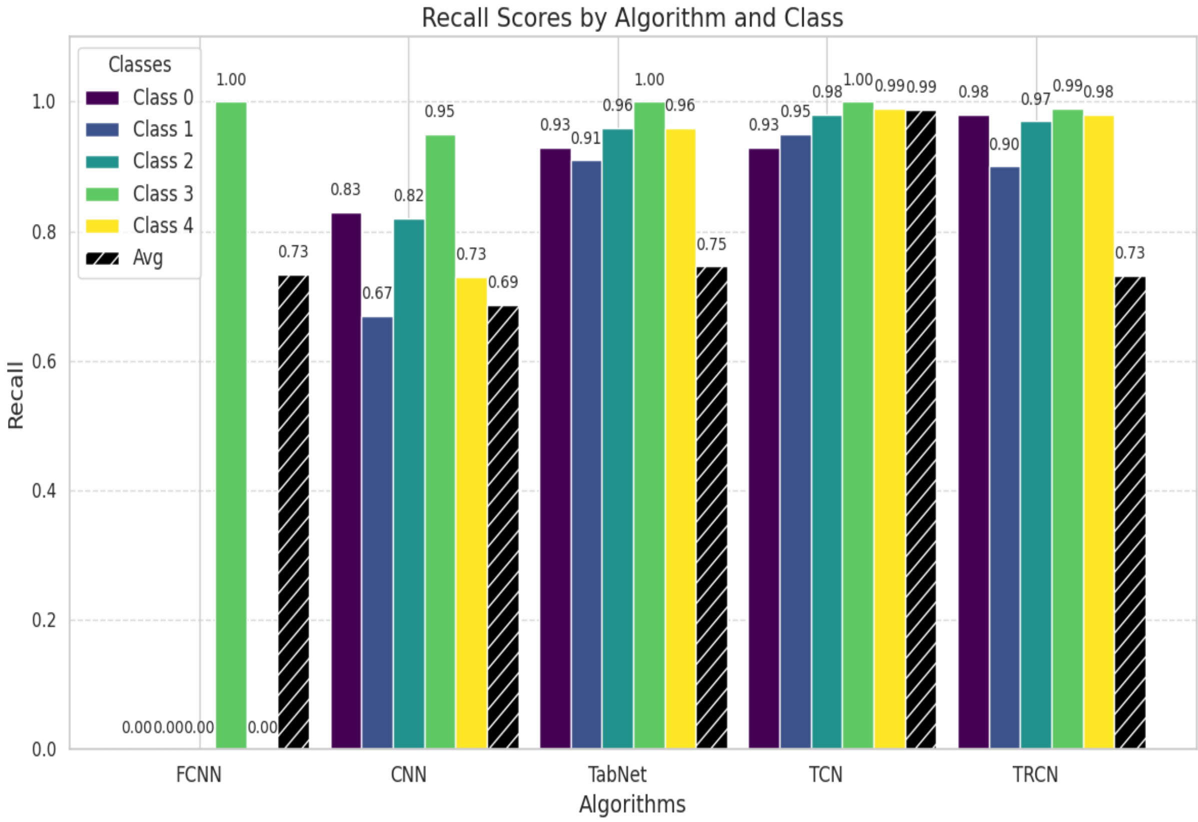


Fig.7. Evaluating **Recall** Performance across Multiple Classes and Models

FCNN demonstrates limited effectiveness, particularly in predicting weather events, with an average accuracy of 0.20. CNN provides moderate performance, maintaining an average accuracy of 0.80 and delivering consistent results across most weather conditions. TabNet excels in classification tasks, achieving a high average accuracy of 0.95, showcasing strong capabilities in handling weather data. TCN outperforms with an impressive 0.97 average accuracy, demonstrating its effectiveness in capturing temporal patterns. TRCN exhibits robust performance with an average accuracy of 0.96, highlighting its efficiency in processing weather-related data.

Table.6. **F1-Score Comparison**

Algorithm	Class 0	Class 1	Class 2	Class 3	Class 4	Avg
FCNN	0.00	0.00	0.00	0.00	0.68	0.14
CNN	0.84	0.68	0.55	0.82	0.94	0.77
TabNet	0.96	0.93	0.90	0.97	0.99	0.95
TCN	0.96	0.94	0.96	0.98	1.00	0.97
TRCN	0.99	0.95	0.96	0.98	1.00	0.98

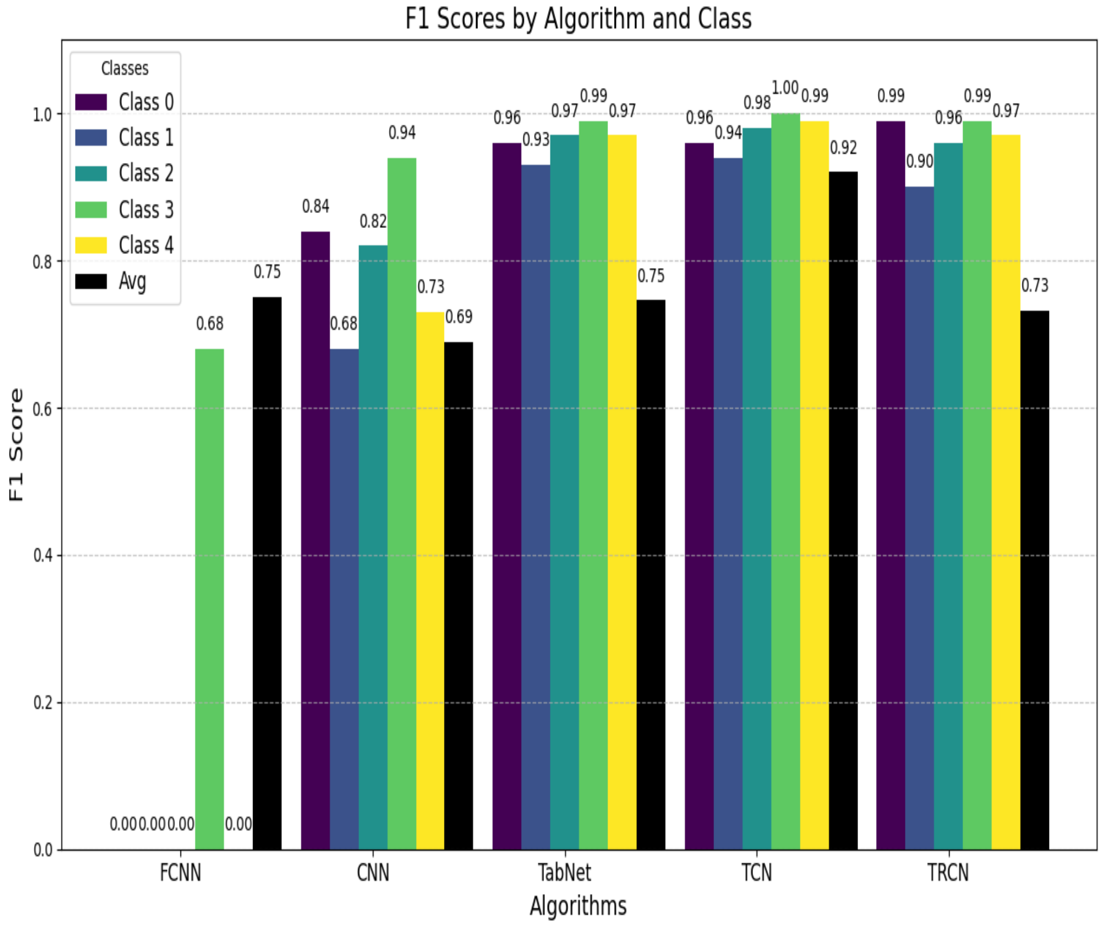


Fig.7.

Evaluating F1-Score **Performance across Multiple Classes and Models**

FCNN performs poorly, with F1 scores close to 0 across most classes, except for class 3, where it achieves a moderate score of 0.68. CNN delivers consistent performance, maintaining F1 scores between 0.73 and 0.94, reflecting balanced precision and recall across classes, particularly strong in class 3. TabNet demonstrates robust classification capabilities with high F1 scores across all classes, averaging around 0.97. TCN excels with near-perfect F1 scores ranging from 0.98 to 1.00, highlighting its superior ability in weather classification tasks. TRCN maintains excellent performance, with F1 scores ranging from 0.90 to 0.99, ensuring high accuracy and reliability across all classes.

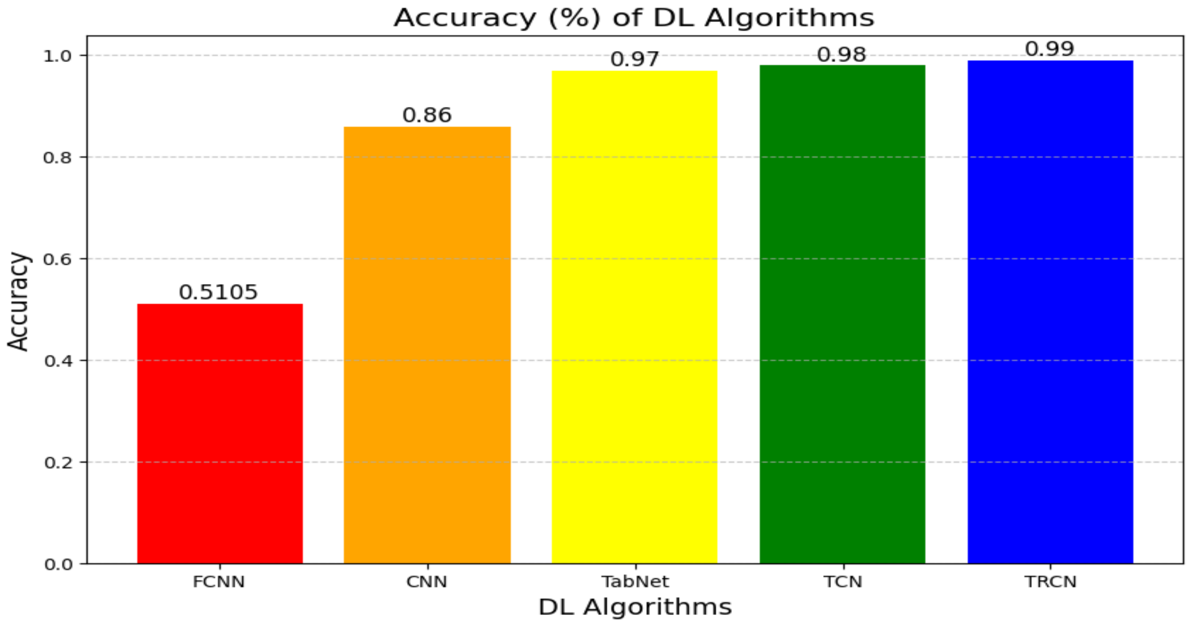
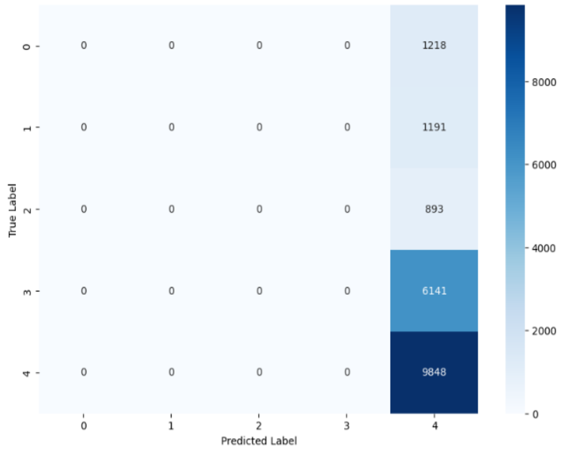


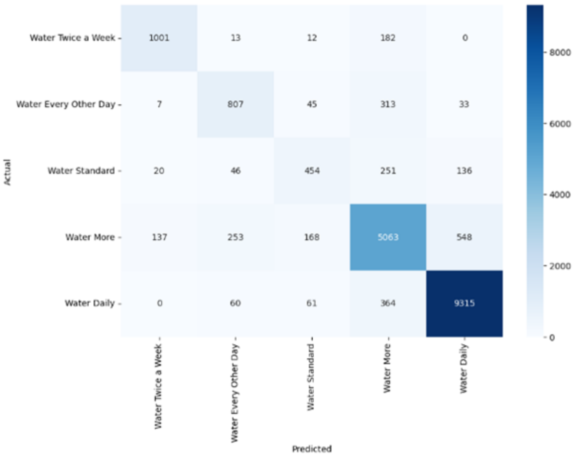
Fig.8.

Confusion matrixes of DL Models

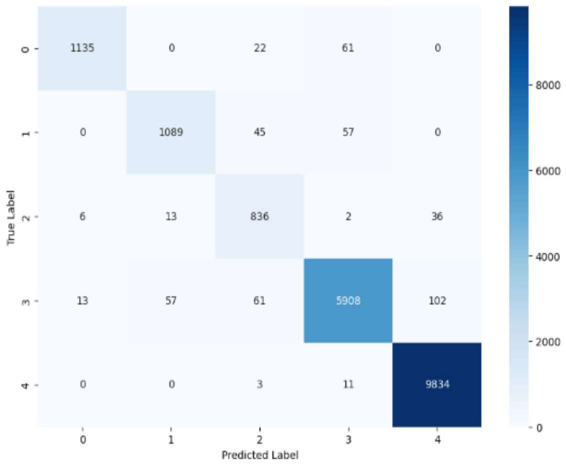
The bar plot presents a visual comparison of the accuracy of five deep learning algorithms: FCNN, CNN, TabNet, TCN, and TRCN. TRCN achieves the highest accuracy at 99%, followed closely by TCN at 98% and TabNet at 97%. CNN demonstrates moderate performance with an accuracy of 86%, while FCNN records the lowest accuracy at 51%. The plot effectively emphasizes the superior performance of temporal convolutional and residual convolution networks in handling the dataset.



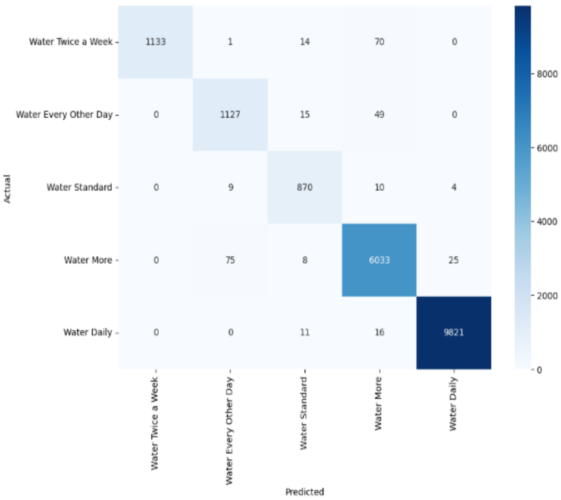
(a) CM for FCNN



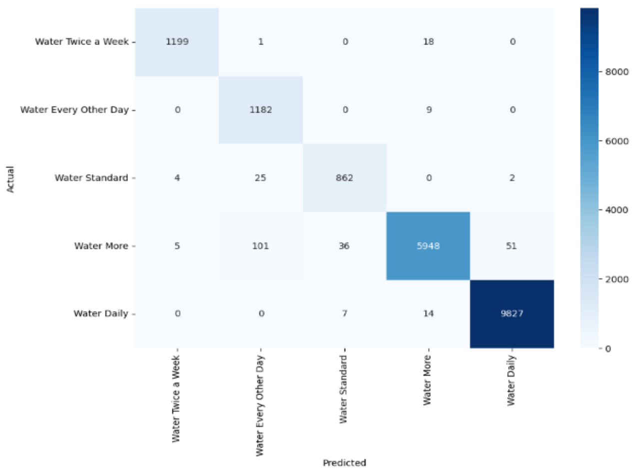
(b) CM for CNN



(c) CM for TabNet



(d) CM for TCN



(e) CM for TRCN

Fig.9. CMs for DL Models

The proposed TRCN model demonstrated the highest classification accuracy, correctly predicting 1,199 instances for Water Twice a Week, 1,182 for Water Every Other Day, 862 for Water Standard, 5,948 for Water More, and 9,827 for Water Daily, with minimal misclassifications. Compared to other models, FCNN failed to classify multiple classes due to severe class imbalance, while CNN and TCN showed moderate performance with notable misclassifications. TabNet performed well but had minor errors across multiple categories. The TRCN model outperformed all, effectively reducing misclassifications and enhancing predictive accuracy, making it the most reliable approach for optimal irrigation scheduling.

5. CONCLUSION

This study systematically analyzed the performance of multiple deep learning models for predicting irrigation requirements based on weather parameters. The evaluation of FCNN, CNN, TabNet, TCN, and the proposed TRCN model revealed significant performance variations, with FCNN demonstrating limited effectiveness. CNN, TabNet, and TCN exhibited promising results, but TRCN achieved the highest accuracy and F1-score, indicating its superiority in predicting irrigation needs. The results underscore the potential of deep learning in optimizing water management systems and improving agricultural sustainability. Future research should explore integrating additional meteorological and soil parameters to further enhance predictive accuracy and scalability. The findings highlight the practical implications of deep learning in precision agriculture, offering a viable approach for data-driven irrigation optimization and sustainable water resource management.

Reference

[1] Fitsum T. Teshome, Haimanote K. Bayabil, Bruce Schaffer, Yiannis Ampatzidis, Gerrit Hoogenboom, Improving soil moisture prediction with deep learning and machine learning models, Computers and Electronics in Agriculture, Volume 226, 2024, 109414, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2024.109414.

[2] Bouali Et-taibi, Mohamed Riduan Abid, El-Mahjoub Boufounas, Abdennabi Morchid, Safae Bourhnane, Tareq Abu Hamed, Driss Benhaddou, Enhancing water management in smart agriculture: A cloud and IoT-Based smart irrigation system, Results in Engineering, Volume 22, 2024, 102283, ISSN 2590-1230, https://doi.org/10.1016/j.rineng.2024.102283.

[3] R. Kanmani, S. Muthulakshmi, K. S. Subitcha, M. Sriranjani, R. Radhapoorani and N. Suagnya, "Modern Irrigation System using Convolutional Neural Network," 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2021, pp. 592-597, doi: 10.1109/ICACCS51430.2021.9441917.

[4] R. Dhyani, N. Manne, J. Garg, D. Motwani, A. K. Shrivastava and M. Sharma, "A Smart Irrigation System Powered by IoT and Machine Learning for Optimal Water Management," 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2024, pp. 1801-1805, doi: 10.1109/ICACITE60783.2024.10617429.

[5]

[6] A. Kumar, H. K. Upadhay and J. N. M. Iqubal, "SMART FARMING SYSTEM: Enhancing Water Efficiency, Automated Care, and Disease Detection Using IoT and CNN," 2024 Advances in Science and Engineering Technology International Conferences (ASET), Abu Dhabi, United Arab Emirates, 2024, pp. 1-7, doi: 10.1109/ASET60340.2024.10708639.

[7] Naseeb Singh, Kethavath Ajaykumar, L.K. Dhruw, B.U. Choudhury, Optimization of irrigation timing for sprinkler irrigation system using convolutional neural network-based mobile application for sustainable agriculture, Smart Agricultural Technology, Volume 5, 2023, 100305, ISSN 2772-3755, https://doi.org/10.1016/j.atech.2023.100305.

[8] Xiujie Qiao, Tian Peng, Na Sun, Chu Zhang, Qianlong Liu, Yue Zhang, Yuhan Wang, Muhammad Shahzad Nazir, Metaheuristic evolutionary deep learning model based on temporal convolutional network, improved aquila optimizer and random forest for rainfall-runoff simulation and multi-step runoff prediction, Expert Systems with Applications, Volume 229, Part B, 2023, 120616, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2023.120616.

[9] Ehteram, M., Afshari Nia, M., Panahi, F. et al. Gaussian mutation–orca predation algorithm–deep residual shrinkage network (DRSN)–temporal convolutional network (TCN)–random forest model: an advanced machine learning model for predicting monthly rainfall and filtering irrelevant data. Environ Sci Eur 36, 13 (2024). https://doi.org/10.1186/s12302-024-00841-9.

[10] Ye, Z., Yin, S., Cao, Y. et al. AI-driven optimization of agricultural water management for enhanced sustainability. Sci Rep 14, 25721 (2024). https://doi.org/10.1038/s41598-024-76915-8.

[11] Xiujie Qiao, Tian Peng, Na Sun, Chu Zhang, Qianlong Liu, Yue Zhang, Yuhan Wang, Muhammad Shahzad Nazir, Metaheuristic evolutionary deep learning model based on temporal convolutional network, improved aquila optimizer and random forest for rainfall-runoff simulation and multi-step runoff prediction, Expert Systems with Applications, Volume 229, Part B, 2023, 120616, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2023.120616.

[12] Shah, C.; Du, Q.; Xu, Y. Enhanced TabNet: Attentive Interpretable Tabular Learning for Hyperspectral Image Classification. Remote Sens. 2022, 14, 716.

[13] Taravat, A.; Wagner, M.P.; Bonifacio, R.; Petit, D. Advanced Fully Convolutional Networks for Agricultural Field Boundary Detection. Remote Sens. 2021, 13, 722.