Enhancing Crop Irrigation Prediction with Transformers Model in Smart Agriculture

MSc Research Project
Msc in Data Analytics

Venkata Krishna Reddy Modem
Student ID: X23379278

School of Computing
National College of Ireland

Supervisor: Dr. Christian Horn

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name:	Venkata Krishna Reddy Modem
Student ID:	X23379278
Programme:	Msc in Data Analytics **Year:** 2025 - 2026
Module:	Research Practicum Part-2
Supervisor:	Dr.Christian Horn
Submission Due Date:	28-01-2026
Project Title:	Enhancing Crop Irrigation Prediction with Transformers Model in Smart Agriculture
Word Count:	**8455** **Page Count:** **21**

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.
ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature: M.V.K.Reddy

Date: 28-01-2026

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST

Attach a completed copy of this sheet to each project (including multiple copies)	□
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	□
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	□

Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Enhancing Crop Irrigation Prediction with Transformers Model in Smart Agriculture

Venkata Krishna Reddy Modem
Student ID: x23379278
X23379278@student.ncirl.ie

Abstract

Agriculture increasingly relies on intelligent technologies to overcome challenges such as water scarcity, climate variability, and inefficient manual irrigation practices. Accurate irrigation prediction is essential for optimizing crop growth, conserving water, and improving productivity in modern smart farming environments. However, existing machine learning and deep learning models often struggle to capture complex nonlinear feature interactions, depend on manual feature engineering, and lack robustness against noisy or inconsistent IoT sensor data, limiting their generalizability across diverse agricultural conditions. This study presents an intelligent irrigation prediction framework that integrates Machine Learning, Deep Neural Networks, and the Feature-Attentive Transformer (FT-Transformer), a transformer-based architecture tailored for tabular agricultural data. Using the CRISP-DM methodology, the research encompasses data preprocessing, exploratory analysis, feature encoding, model training, and comprehensive evaluation. The FT-Transformer employs feature tokenization and multi-head self-attention to learn relationships among key variables such as soil type, crop stage, moisture index, temperature, and humidity, offering a more adaptive modelling approach than conventional ML and DL methods. Experimental results show that while baseline ML and DL models deliver strong performance, the FT-Transformer consistently outperforms them across all metrics. Achieving an 0.9819 accuracy, precision, recall, and F1-score of 0.9819, it demonstrates exceptional predictive reliability and balanced classification. The findings confirm the FT-Transformer's ability to capture intricate agricultural feature interactions and maintain robustness against data variability and sensor noise. Overall, the study establishes the FT-Transformer as a highly accurate, scalable, and effective solution for intelligent irrigation prediction in precision agriculture.

1 Introduction

Agriculture plays a very vital role in food security in the world despite the fact that the traditional irrigation practices are very inefficient due to the manual decision-making process, climatic variations, and lack of proper management of water resources. Farmers cannot normally supply the right amount of water at the right time because the crop water requirement is dynamically adjusted based on the soil properties, moisture content and weather conditions. The increasing environmental needs, insufficiency of resources, and the need to seek sustainable agricultural technologies are also a powerful compound of this issue. The intelligent and predictive irrigation systems are significant under such circumstances to utilize the water optimally and to make sure that the crops grow healthy and in good condition to bring forth the maximum potential of the yield.

The increased use of data-driven technologies in agriculture is an indicator of a high demand of automated irrigation forecasting systems capable of responding reliably to changing field conditions. IoT sensors have made it possible to monitor soil moisture, temperature, and humidity continuously, whereas machine learning models help farmers interpret the received data and make sound irrigation choices. Nevertheless, the need to develop higher AI models is driven by the weaknesses of the existing systems, which in most cases do not generalize in various crops, soil types and climatic conditions. An effective and smart irrigation system can greatly minimize the wastage of resources, reduce the agricultural expenses, and contribute to the sustainability of the farming industry, as well as assist farmers with raising their productivity with minimum manual efforts.

The literature in smart irrigation has utilized various machine learning and deep learning methods and has shown a high degree of improvement, but also has its weaknesses. Research works like Tace et al. (2022) and Puspaningrum et al. (2022) indicate that ML models like KNN, SVM, and Decision Trees are also successful in irrigation forecasting but tend to fail in capturing complex nonlinear interactions. Equally, LSTM-based models that Sami et al. (2022) and Nitya et al. (2025) suggest yield better temporal predictions but demand lots of data and considerable computing power. The studies conducted by Sangeetha et al. (2025) and Okayama et al. (2025) emphasize that CNNs can be used to make soil moisture and leaf-based irrigation decisions, but they are still not able to process heterogeneous tabular data. Moreover, IoT-based solutions like those by Munaganuri et al. (2025) improve real-time monitoring but have issues with sensor noise, scalability, and generalization. All these studies highlight the importance of having a more adaptive and feature-oriented model that can be used to process complex agricultural data.

Research Question:

How can a transformer-based model such as the FT-Transformer improve the accuracy and reliability of irrigation prediction agricultural data?

The rationale behind this question is that the traditional ML/DL models are limited by their inability to represent high-dimensional feature interactions, their inability to be robust to noisy IoT data, and their high reliance on manual feature engineering. The transformer-based model, along with its attention mechanism and tokenization of features, offers a good avenue to address these shortcomings.

This study has fourfold contributions. To begin with, it develops an end-to-end smart irrigation prediction pipeline based on machine learning, deep learning, and transformer-based systems. Second, it presents the FT-Transformer to agricultural tabular data, and proves its capacity to represent intricate relationships between soil, weather, and crop parameters within the framework of a more effective model than the current models do. Third, it offers a comparison of performance of several model families based on standardized evaluation measures to indicate the high reliability of transformer-based learning. Lastly, the research confirms a predictive and scalable model that can be used to achieve sustainable water management, real-time decision making, and advancement in precision agriculture in the future.

2 Literature review

There is a significant shift in agriculture due to the incorporation of sophisticated computing methods, which allow more accurate, data-oriented and sustainable methods. Intelligent irrigation, crop prediction and efficient resource management by use of machine learning, deep learning and IoT-based systems has become an effective tool to optimize irrigation. Nevertheless, regardless of these developments, current methods have limitations, and new directions allow new models to fill current gaps in research, including the Feature-Attentive Transformer.

2.1 Machine Learning Models in Smart Agriculture

Machine learning (ML) is currently a pillar of precision agriculture, particularly in maximizing irrigation, crop forecasting, and harvest predicting. To a big degree, the conventional techniques are vulnerable to the change in climatic and soil conditions yet with the adoption of ML, pattern recognition could be achieved whenever large datasets are employed which improves decision-making. It has been found that such supervised ML algorithms as K-Nearest Neighbours (KNN), Logistic Regression, Support Vector Machines (SVM), Decision Trees, Random Forests, and Naive Bayes can be employed to provide effective solutions to the tasks such as soil moisture monitoring and irrigation scheduling. To give an example, Tace et al. (2022) demonstrated that KNN has low recognition rate and low RMSE, which is more advantageous than Logistic Regression, SVM, and Naive Bayes to predict irrigation demand, which reduces water consumption and increases crop growth efficiency.

Similarly, the ML algorithms have enhanced the crop prediction activities significantly. Comparing 15 algorithms with crop classification, Elbasi et al. (2023) found that the probabilistic models Bayes Net and Naive Bayes were used and showed excellent results in crop classification, which demonstrates that the two are efficient in agricultural decision-making. The issue of crop prediction with the help of ML does not only enhance the production rate, but also reduces the cost of efficient agricultural practice that is central to the problem of food supply worldwide. Having the capacity of ML to integrate the information received with the use of the IoT sensors with the real-time data on the state of farming in the country will allow the farmers to make reasonable decisions that will decrease the wastage and will result in more sustainability.

In addition to classification activities, the ML models are also widely applied to generate prediction and irrigation forecasting. Baio et al. (2022) compared the performance of the Random Forest, SVM, and other decision tree models in predicting the maize yields and found that the most effective model was the Random Forest that utilized irrigation management and spectral data. Similarly, Puspaningrum et al. (2022) compared SVM, KNN, Decision Trees, Random Forest, and Naive Bayes to predict irrigation, and the Decision Tree was more correct, remembered, and precise than other algorithms. Moreover, Ge et al. (2022) introduced the XGBoost regression to forecast the evapotranspiration in greenhouse tomatoes that demonstrated a higher accuracy rate compared to the conventional regression models, and it denotes that ensemble-based models are effective in regulating irrigation systems. In general, the results of this research point to the versatility and generalizability of traditional ML models to the optimization of water management and yield optimization in smart farming.

2.2 Deep Learning Models in Smart Agriculture

Deep learning (DL) techniques are also finding application in the agricultural field to overcome the limitations of traditional machine learning where large and complex data are used to provide a better prediction accuracy. Specifically, Long Short-Term Memories (LSTM) networks have gained significant popularity due to the fact that they allow modelling the time-dependent factors of time-series agricultural data. As an illustration, Sami et al. (2022) offered an LSTM-based neural sensor model, which substitutes the physical sensors in intelligent irrigation systems. They were also able to predict real time soil moisture, temperature, and humidity data which is highly accurate and which is very useful in making irrigation systems more dependable because it does not heavily rely on the physical sensors which may not be reliable. On the same note, Nitya et al. (2025) tested Vanilla, Stacked, and Bidirectional LSTM models on the management of rice crop irrigation with the use of the Internet of Things sensors, with the Bidirectional LSTM model performing the best, which proves its effectiveness in scheduling irrigation in dynamic mode.

The research has also been noted to be effective in the fields of soil moisture and crop monitoring through deep learning. Wong has created an IoT-based RNN-LSTM system to forecast soil moisture levels in the underground, which has been able to predict the accuracy and minimize the use of water. This shows the scalability of DL models to precision agriculture applications where it is needed to monitor continuously and in real-time. In a similar manner, Sangeetha et al. (2025) developed a deep CNN model that predicts soil moisture in various soil types based on sensor data and the temperature, to categorize the irrigation requirements. Their results affirmed that CNN-based soil moisture classification would be useful in making automated irrigation decisions, save water as well as enhance crop health. These findings indicate the flexibility of deep learning models when used to work with image and sensor-based agricultural data.

Moreover, CNN models have been investigated in making decisions in irrigation systems of orchards. In their study, Okayama et al. (2025) established a CNN with leaf RGB images and soil moisture data to identify water stress in persimmon orchards, with an accuracy of over 80%. This methodology points out the capability of deep learning in deriving useful patterns in unstructured data like plant images which cannot be effectively interpreted by conventional algorithms. The comparison of LSTM-based models with linear regression also demonstrated that the former is more effective in long-term forecasting of irrigation in the vineyard (Stojanova et al., 2025). All of the studies mentioned above suggest that deep learning models, especially LSTM and CNN, have a transformative role in smart agriculture, as it allows predicting irrigation correctly, monitoring the state of soil, and optimizing yield.

2.3 Hybrid and Ensemble Approaches for Enhanced Agricultural Intelligence

Recent developments in precision agriculture indicate that, the use of a single method of computation usually constrains performance in situations where there is a great deal of variability in the climate, soil and crop conditions. Consequently, there has been a lot of attention on hybrid and ensemble methods that integrate various machine learning, deep learning or optimization methods. These combined systems capitalise on the complementary nature of the various models to enhance robustness and predictive accuracy to various agricultural tasks. Indicatively, Abdallah et al. (2022) used the feature selection techniques, which were Random Forest, Recursive Feature Elimination (RFE), and SelectKBest, and stacked them with CART, Gradient Boost Regression, Random Forest, and XGBoost. Their approach recorded remarkably low values of MSE and high values of R 2, which demonstrates that hybrid feature selection and ensemble learning can perform better than individual algorithms in estimating irrigation and managing water resources. These models are more effective in solving multidimensional agricultural problems, through the elimination of redundant parameters and the increased interpretability and accuracy of predictive results.

In the case of dealing with complex multi-source types of data (satellite imagery, soil sensor streams, meteorological records) hybrid models can be useful to overcome the shortcomings of traditional ML and DL architectures. Geospatial and multispectral datasets demand models that can be used to extract long-term time variations as well as identify spatial heterogeneity. Ishaq et al. (2025) proposed a synergistic model that integrates crop growth simulation models with spectral indices and LSTM networks obtained based on satellite-derived data. The joint design made it easy to make more accurate predictions of yields with wheat as compared to the single models of LSTM or Random Forest which implies the strength of a combination of physical crop models with intelligence through data. Similarly, Munaganuri et al. (2025) developed a multi-layered architecture that integrates LSTM to predict the soil moisture, LoRaWAN to improve the efficiency of the communication system, blockchain to guarantee the integrity of data, and deep reinforcement learning (DRL) to develop the optimal irrigation timetable. The hybridization of these technologies led to the realization of high levels of irrigation efficiency and this demonstrates how the ensemble systems can simultaneously trade off accuracy and scalability with security and sustainability.

Besides, smart irrigation systems need hybrid models, which must be applicable and reliable in the real-life and dynamic agricultural environment. Older models are very difficult to adjust to noisy data, sensor errors or a rapid change in the environment. Researchers have thus started combining neural network structures with rule systems, fuzzy logic or optimization algorithms in order to develop robust decision-support systems. As an example, Saha et al. (2025) have integrated machine learning-based land and crop prediction with fuzzy logic-based irrigation control to attain substantial water savings and more adaptive irrigation control. On the same note, better optimization methods, including the upgraded LSTM optimizer suggested by Bhimavarapu et al. (2023), deal with issues such as underfitting and instability in predictive tasks. Such hybrid solutions achieve not only better computational performance but also make agricultural systems resilient to uncertainty so that they can continue operating in the future, and are a part of the future development of scalable, next-generation smart farming solutions.

2.4 Research Gaps

Despite the fact that machine learning and deep learning models have contributed to improving smart irrigation and crop prediction greatly, the current research has a number of limitations. Most of the models, including KNN, SVM, Random Forest, and even LSTM, are largely dependent on manual feature engineering, and may not always learn complex nonlinear interactions between environmental, soil, and crop parameters (Baio et al., 2022; Puspaningrum et al., 2022). Additionally, although CNN and LSTM methods also have potential, they typically need big labelled datasets and a substantial amount of computing power, which is hard to implement in real-time in small farms (Sami et al., 2022; Okayama et al., 2025). The other weakness is that of generalizability models that are trained on certain soil or climatic conditions are not likely to fit new regions without significant retraining (Stojanova et al., 2025). Also, existing IoT-based solutions, despite their effectiveness in monitoring, continue to face the challenge of noisy sensor data, security, and scalability in the long term (Munaganuri et al., 2025; Saha et al., 2025). These problems underscore the necessity of more powerful, flexible and feature-oriented solutions.

To overcome these difficulties, new transformer-based architectures, namely, the Feature-Attentive Transformer, can be considered promising to the next-generation smart agriculture system. In contrast to conventional ML and sequential DL models, FT-Transformer is unique at the ability to model nonlinear interactions between features, process heterogeneous tabular data, and context-sensitive relationships between multiple sensor modalities. The model has an attention mechanism that enables it to dynamically determine the importance of significant environmental, soil, meteorological and crop characteristics overcoming the restrictions of fixed-weight or sequential dependency models. Also, parallel computation is inherent in transformer-based architectures, which can be trained and inferred significantly faster than recurrent models. This will allow them to be used in real-time irrigation prediction and resource management, even in large-scale IoT data streams. The problem of sensor-driven agricultural systems also comes up since FT-Transformer is resistant to missing or corrupted inputs.

Following FT-Transformer through smart irrigation systems, future studies can be able to make more precise and scalable predictions that respond to complex agricultural environments. The capability of the model to integrate multi- sensor information, soil characteristics and climatic variables facilitates a integrated learning system that has the capability of generalizing under different environmental settings. Moreover, FT-Transformer is able to substitute or supplement more conventional and deep learning models by producing more enriched patterns, becoming more resilient to changes in data, and eliminating the use of manual feature engineering. This flexibility makes FT-Transformer a strong tool to counter the limitations found in the literature to establish ways of creating highly intelligent, autonomous and sustainable irrigation systems to cater to the current challenges of farming.

3 Research Methodology

3.1 CRISP-DM Methodology

The Cross-Industry Standard Process of Data Mining (CRISP-DM) framework offers a streamlined and dependable process of creating predictive models of irrigation in smart farming. To conform to this study, the process will start with business understanding, which will consider the main aim of the process, that is, to solve the inefficiency within the current irrigation forecasting systems and enhance water management through FT-Transformer. It is then succeeded by data understanding, which implies processing an available, field-collected dataset used to read an IoT sensor, weather, soil condition and irrigation logs to find out the data quality, detect gaps in the data, and see season-specific changes (dataset). Such steps are essential in the agricultural setting where failure of sensors, changes in the environment, and unreliable data gathering are rife. With the implementation of CRISP-DM, the study will guarantee systematic movement of identifying the real-life agricultural issues to the realization of the nature and constraints of the data gathered in the field.

Data preparation, modelling and evaluation are the next steps that are tightly connected with the FT-Transformer model. Noise elimination, normalization, feature encoding, and alignment of the temporal values are part of the data preparation to make sure that the heterogeneous IoT and environmental inputs are prepared to learn. FT-Transformer is used in the modelling phase because it can model the interactions between features with complexities and process tabular agricultural data more efficiently than other conventional ML and sequential DL models. The evaluation step strictly evaluates the performance based on the measures of RMSE, MAE, R2, accuracy and F1-score to guarantee consistency and reliability in the evaluation of performance in various environment. Lastly, the deployment stage will involve the implementation of the trained model into a smart irrigation system with the potential to make real-time automated decisions. This study has an orderly, repeatable, and flexible approach that facilitates the sound development of an intelligent irrigation prediction system through the use of CRISP-DM.

3.2 Dataset Description

The data set which has been used in this study is the structured agricultural observations conducted on the wheat crops that were growing in black soil in the seedling or germination stage. The parameters that are being captured in the records include moisture index (MOI), temperatures, and humidity in the environment and the soil and a binary value indicating the necessity or not of the irrigation. The combination of the following attributes is the natural modifications in the soil moisture conditions and atmospheric conditions which determine the demand of water in crops at an early stage. The dataset is realistic in the field patterns it records due to the gradual attenuation of moisture levels and also the variation of temperature and humidity which enables the model to learn the underlying relationships upon which the irrigation decisions are made. This tabular data is organized well, namely, as the FT-Transformer model, which is highly efficient in the identification of complex, nonlinear connections between heterogeneous agricultural attributes. Although the sample concentrates on the data of a single crop and soil type, the method is also expandable to multi-crops, multi-soils and multi-stages data sets and can be utilized more broadly in precision agriculture.

3.3 Data Preprocessing

The first step in the process of preprocessing involved loading the dataset and conducting the first structural analysis to get a sense of what the dataset is composed of. The dataset was made up of several thousand records each with attributes of agricultural like type of crop, type of soil, stage of seedlings, moisture index, temperature, humidity and the irrigation requirement label. In this check, the data structure, number of entries, and types of variables were evaluated so as to check consistency and any other problems that may arise before proceeding with any more processing. This action verified that the dataset included a combination of both categorical and numerical variables and all the columns were not blank with any unspecified numbers.

Since the data was in form of categorical variables, these textual data were converted to numbers so that they may be utilized in machine learning models. The categorical variables crop type, soil type and stage of seedling were integer coded whereby the first categories are the same as the coded ones. Such a change was needed, and the predictive model would be capable of understanding and managing such characteristics. The transformation of these fields into the numeric form rendered the data whole and in line with the subsequent learning stages.

The data was also taken through strict quality test to ensure consistency and reliability in the development of the models. Preliminary check was also conducted to make sure that the data did not have any missing or null value in any of the features, which meant that the data was complete and did not require imputation of any type. To avoid the inconveniences related to the models training, it was necessary to ensure that there are no missing entries in the data to ensure the correctness of the learned patterns. After this validation, the dataset was checked on the redundant observations and all the repeated entries were eliminated to avoid repetitive patterns that would potentially bias the learning process. The elimination of such duplicates enhanced integrity of the dataset so that the model would be trained on differing and distinct examples instead of being distorted by replications of the records.

The features and target labels were split to prepare the dataset to the model development, with the irrigation decision variable as the only output. This data was then split into training and testing sets with a part of the observations being used to evaluate the performance of the model. A random seed was set to be fixed to guarantee the ability to replicate the split, giving similar results when the split was executed repeatedly. This division formed a strong setup in which the model was able to learn using the training data and was objectively tested using independent testing data.

3.4 EDA (Exploratory Data Analysis)

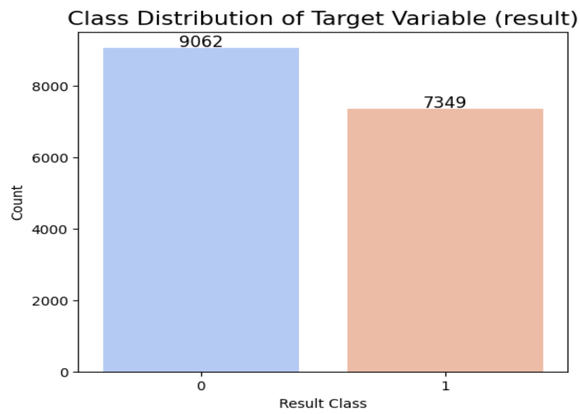

Figure 1. Target Class Distribution

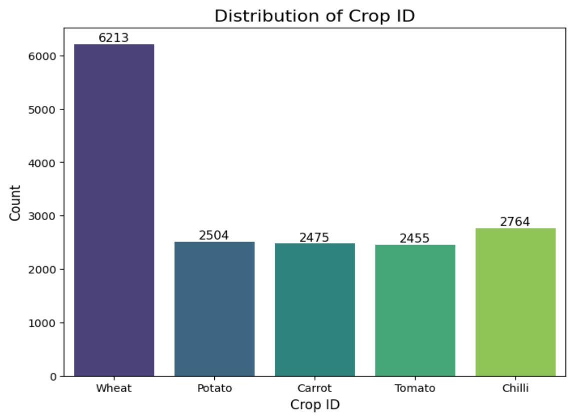

Figure 2. Crop ID Distribution

In figure 1 the plot has demonstrated the distribution of the classes of the target variable and both the classes are fairly balanced with the class which represents no irrigation required being slightly higher than the one which represents irrigation is required. Figure 2 shows the distribution of the types of the encoded crops in the plot, and it can be seen that there is a much greater number of times when one of the crop categories can be found than others. These plots collectively aid in determining the pattern of class balance and crop representation, which is valuable in determining the diversity of the data sets and training the model.

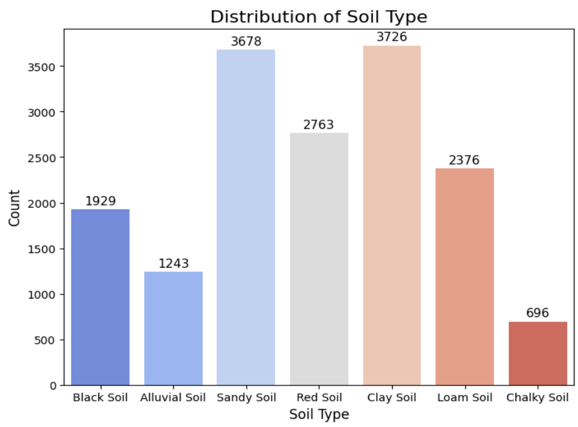

Figure 3. Soil Type Distribution

The figure 3 plot depicts the distribution of the encoded soil types with certain categories of soils being significantly represented than others, which implies an uneven representation in the dataset.

3.5 Leveraging FT-Transformer to Address Existing Drawbacks

To address the shortcomings of the literature, this research proposes to utilize the FT-Transformer model to address the shortcomings that are usually experienced by the conventional machine learning and deep learning models applied in smart agriculture. Previous research indicated that KNN, Random Forest, SVM, LSTM, and CNN models tend to be weak with high-dimensional agricultural data, sensor noise, missing data, and the inability to learn the complex correlations between soil, weather, crop and irrigation variables. FT-Transformer directly deals with these issues by providing the feature-attention mechanism that enables the model to automatically detect and rank the most important agricultural features that affect irrigation requirements. This both gets rid of the reliance on large manual feature engineering and allows the model to discover subtle interplay between heterogeneous sources of data that traditional models can often fail to capture. Also, FT-Transformer has an intrinsic ability to be resilient to incomplete or corrupted IoT sensor measurements, which means that it makes more accurate predictions even with uncertainties in the real field.

FT-Transformer offers a more adaptable and efficient learning procedure that may examine all features concurrently as opposed to sequential models that entirely rely on the sequence of data inputs. This strength allows the model to identify long-range relationships between the environmental and soil conditions more efficiently, leading to a high level of predictive performance. The fact that the model can process tabular agricultural data with a high level of accuracy also means that the chance of overfitting is minimized, unlike in earlier versions of the DL model where overfitting is highly prone to happen when small or medium-sized agricultural datasets are used to train the model. Moreover, FT-Transformer is scalable, which makes it appropriate to predict the irrigation activities in real-time and large scale and, hence, it can quickly adapt to the fluctuating environmental conditions. In general, the mentioned benefits precondition the FT-Transformer as a perfect model to build an even smarter, more precise, and more sustainable smart irrigation system that would exceed the abilities of the current ML and DL methods.

3.6 FT-Transformer Model Architecture

The FT-Transformer architecture is a tabular data specific architecture, so it is very well adapted to agricultural data as features constitute a combination of environmental measurements, soil properties, crop features, and sensor measurements. Unlike the conventional deep learning models which operate based on sequential structures, FT-Transformer operates on feature embeddings to translate each input variable into a learnable sequence of vectors. The result of these embeddings is then run through a sequence of attention layers enabling the model to model the more intricate interactions between the features, including moisture index, temperature, humidity, soil type, and seedling stage. This framework allows the FT-Transformer to more effectively interpret patterns that are not necessarily observable in traditional models, particularly when the decision-making process of many heterogeneous factors is involved in making irrigation choices.

The dynamically assigning importance to input features is one of the key benefits of the FT-Transformer because the attention mechanism of this transformer is dynamic. When applied to smart irrigation, this will imply that the model will be able to figure out which variables have the greatest influence on the need of irrigation given different field conditions. Indicatively, the attention layers can be trained to the fact that moisture index is more dominant in the initial stages of seedling development, and temperature and humidity are more dominant as the environment changes. The model is also resilient to the absence of sensor readings and the presence of noisy data, which are typical issues in the real-world agricultural setting. This strength allows the predictive performance to be uniform, despite the failure of the IoT sensors, long-term drift, or environmental noise.

The FT-Transformer can be applied to the irrigation prediction problem by processing all features at once and learning dependencies between features globally, which is what it is best suited to do give that there are many interacting environmental factors that are non-linearly related to each other. The attention mechanism helps the model to concentrate on the conditions that are relevant and to disregard the irrelevant conditions and therefore the model makes a more precise and context sensitive irrigation recommendation. The FT-Transformer can outperform the conventional machine learning models, which rely on hard thresholds or decision boundaries. Lastly, the FT-Transformer is a tool with a high level of sophistication and adjustability and can be applied to automatize irrigation decisions, conserve water, reduce human involvement, and produce healthier crops in precision agriculture.

3.7 Evaluation Metrics

Accuracy, precision, recall and F1-score are the model tests to test its capacity to predict the irrigation requirements. It refers to the total accuracy of the predictions with accuracy whereas it refers to the number of the correct cases of the predicted irrigation requirements with precision. Recall is a measure that provides the ability of the model to detect all of the true conditions that require irrigation, and any significant cases are not omitted. F1-score is used in conjunction of precision and recall to provide a balanced evaluation of the performance, particularly when the classes are skewed. A combination of these metrics gives a clear picture of the extent to which the model is helpful in making sound irrigation decisions.

4 Design Specification

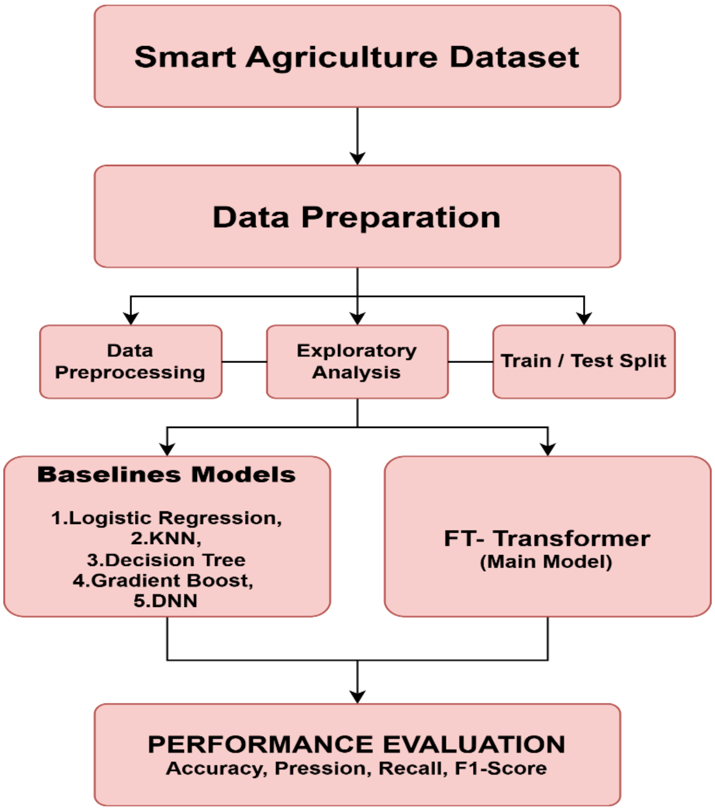

Figure 4.The Architecture Overview

The system architecture as illustrated in figure 5, the overall workflow of the leverage smart irrigation prediction model, and it starts with the smart agriculture data that is subjected to the data preparation procedures, which include preprocessing, exploratory data analysis, and train-test splitting. After the data has been ready, it enters into two modelling paths: the baseline machine learning models including Logistic Regression, KNN, Decision Tree, Gradient Boost, and Deep Neural Networks, and the base model, FT-Transformer, which uses feature attention to increase the accuracy of predictions. The two sets are then trained and tested on the processed dataset and their outputs are sent to the performance evaluation step where performance can be compared by the use of metrics like accuracy, precision, recall and F1-score. This architecture will guarantee an orderly flow of raw agricultural information to the model comparison with the final decision being the most dependable solution to irrigation decision-making.

The workflow pipeline and the smart irrigation prediction system are stipulated to be implemented on the basis of the modular architecture to ensure its flexibility, scalability, and the ability to give a clear separation of responsibilities on all processing points. The design specification is at the highest position, it is centred on a layered model in which every module data ingestion, preprocessing, modelling and evaluation are independent of one another but have some contribution to the overall system. The design begins with the merging of agricultural IoT and environmental data, which are rationally sent to the data preparation layer.

It has preprocessing functions such as cleaning inconsistencies, coding categorical attributes, missing values and data quality checks. The processed information is then sent to the exploratory analysis unit that helps in identifying the trends and distributions of the features that influence the irrigation decision. Once the data understanding phase has been completed, the pipeline will divide the dataset into training and testing data ready to be utilized by the downstream machine learning, deep learning, and transformer-based predictive modelling. This architectural system will ensure that all the single components of engineering features to prediction will enable healthy performance and will enable traceability in the system.

The data-processing workflow also describes the process of how the dataset changes at every transformation phase until it is trained on the model. Once the dataset has been loaded into the system, the system cleans the dataset by eliminating duplicates and checking the consistency of sensor-based parameters. Categorical data like crop type, soil type and seedling stage is coded to numerical labels whereas numerical feature is standardized or normalized based on the needs of the model. Machine learning models can take in the processed tabular form in its raw form, but deep learning models can transform the data into the form of a tensor, which can then be run on a sequential or dense architecture. Specifically, the FT-Transformer transforms every feature into a learnable embedding representation and uses feature tokenization to process the data to feed its attention mechanism. At the stage of the model training, structured features are trained with baseline ML algorithms, temporal and nonlinear dependencies trained with deep learning models, and the FT-Transformer multi-head attention captures the interactions among the complex features. Lastly, each of the models is measured by the same performance pipeline in terms of accuracy, precision, recall and F1-score, which allows a fair comparison of approaches and determines the most effective model to predict smart irrigation.

5 Implementation

5.1 Machine Learning Models Implementation

5.1.1 Logistic Regression

The **Logistic Regression** model was optimized to consider various values of the regularization strength and two forms of penalty. Regularization parameter C was experimented with several values, namely 0.01, 0.1, 0.2, 0.3, 0.4, 0.5 and 0.6, and both L1 and L2 penalty. Both the best parameters C equal to 0.2 and the penalty L2 gave the model its optimal performance after cross-validation of all the combinations. This combination gave the most stable decision boundary and the highest accuracy of prediction of irrigation classification.

5.1.2 KNN model

With the **KNN** model, the tuning process considered a variety of values of the number of neighbours and the weighting strategy. The parameter search involved 30, 40, 50, 80, 100 as counts of neighbours and the weight setting was the same in all the experiments as indicated in figure 6. The model did not achieve the best results when the number of neighbours was reduced to 30 using uniform weighting, but this was the best result after experimenting with the different configurations. The best parameters helped the classifier to be dependent on a smaller, more pertinent neighbourhood of samples and this produced more precise irrigation forecasts.

5.1.2 Decision Tree classifier

The **Decision Tree classifier** was also optimized, in terms of the splitting criterion and minimum number of samples needed to split an internal node. The tuning process assumed entropy as the criterion of splitting and tested a variety of minimum split size 10, 20, 30, 50, and 70. The model provided the best result with the following parameters: criterion is entropy and min samples split is 10. This enabled the tree to make more refined splits on information gain but generalization was maintained.

5.1.4 Gradient Boosting model

In the case of Gradient Boosting model, the optimization process explored various values of boosting iterations and learning rate. The tested values of the number of estimators were 30, 40, 50, 70, 100, 150, and 200 and the learning rate. The most effective structure was obtained by utilizing 200 estimators and a learning rate. This enabled the model to be learned through numerous steps of boosting and to learn finer relationships of features and provide the best prediction in the irrigation model.

5.1.5 Deep Learning Models

Deep Neural Network (DNN) model was used to learn the intricate nonlinear relations among agricultural data, which provides a more expressive learning model than the traditional machine learning models. The deep neural model structure was composed of several fully connected layers where the first layer had 128 neurons, then 64 and 32 neurons, all of which were excited by the ReLU function so that the gradient could propagate effectively. An optimal use of dropout regularization between layers was used to prevent overfitting by randomly deactivating a fraction of neurons during training. The last output layer used a sigmoid activation to do binary classification to predict the need of irrigation. The training of the model was done by the Adam optimizer, with a controlled learning rate; the loss function was binary cross-entropy, which was applied to indicate the error in prediction. Early stopping was added to prevent additional training when the validation loss did not improve anymore to improve generalization. The model was trained on the processed dataset and then produced probability scores, which were transformed into binary predictions, and its performance was measured with the help of accuracy, F1-score, a classification report, and a confusion matrix. This application showed that the DNN can learn more significant interactions of features that are important in irrigation decision-making.

5.2 FT-Transformer Implementation

The FT-Transformer model was adopted so that the attention mechanisms of transformers could be used to exploit tabular agricultural data to teach the system complicated interactions among features, including soil type, moisture index, crop stage, temperature, and humidity. All the input features were made standard and a custom data format was developed to feed the data in the model effectively. Each feature was then turned into a learnable embedding vector with a numerical feature tokenizer that enables the transformer to treat each input variable as an independent token, which is supported by positional embeddings and layer normalization to learn it stably. Its architecture comprised of several transformer encoder blocks which comprised of multi-head self-attention and feed-forward layers, allowing the model to assign dynamically important features in the prediction of irrigation needs. Class weights were added to deal with imbalance, AdamW was the optimizer, the scheduling was cosine annealing, learning rate changed between epochs, gradient clipping avoided instability and label smoothing improved generalization. Training was done by continuous validation and early stopping and checkpointing to maintain the optimum model. The best model was tested and assessed based on accuracy, classification reports and confusion matrices and the results indicated that the FT-Transformer model is effective in being able to capture nonlinear relationships and provide sound predictions on irrigation.

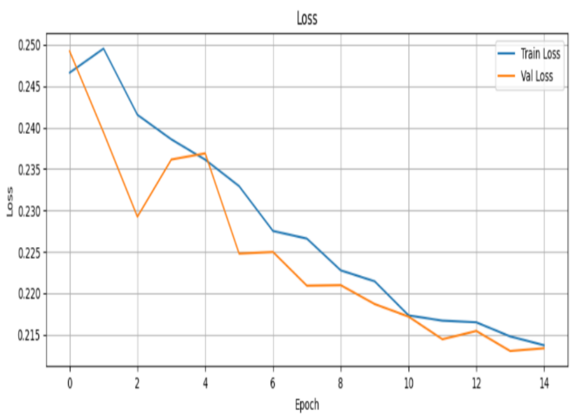

Figure 5. Training vs Validation Loss

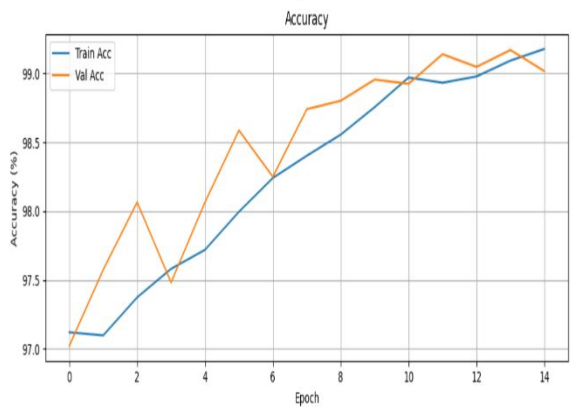

Figure 6. Train vs Val Accuracy

The plot of loss in figure 7 indicates a steady and gradual reduction in training and validation loss, which implies that the model is learning to improve its predictions with time. In figure8, the accuracy plot demonstrates that both the training and validation accuracy are increasing steadily, which means that the model is learning and is working well on unseen data.

5.3 Libraries Used

In this work, a number of Python packages were used in the implementation of the smart irrigation prediction system. The effective data processing and numerical processing were performed with Pandas and NumPy, whereas Scikit-learn allowed dealing with the label encoding, scaling, machine learning models, and evaluation metrics. The Deep neural Network was constructed and trained with the help of TensorFlow and Keras, which provides dense layers, optimization, and regularization options. The FT-Transformer was implemented and trained in PyTorch and is flexible in supporting custom tokenization and attention mechanisms with the help of a GPU. Moreover, Matplotlib and Seaborn allowed visual analysis with the help of plots and confusion matrices.

6 Evaluation Results

In order to assess the performance of the various techniques in forecasting irrigation needs, a thorough comparison between the various machine learning and deep learning models was carried out. These models were evaluated by the standard performance metrics like accuracy, precision, recall and F1-score to have fair and equal assessment of all the methods. The findings give an idea of the strengths, limitations and capability of each of the models in capturing the multifaceted nature of agriculture and the environment. Here, the evaluation results are discussed with finer details and an analysis of the performance of each of the models is provided with respect to the prediction of irrigation task as in table 1.

Table 1. Comparison of All Models with 70% training size and 30% testing size Performance.

Model	Accuracy	Pression	Recall	F1-Score
Logistic Regression	0.8689	0.8410	0.8673	0.8539
KNN	0.9288	0.9235	0.9145	0.9190
Decision Tree	0.9414	0.9470	0.9187	0.9413
Gradient Boosting	0.9383	0.8903	0.9812	0.9336
DNN	0.9447	0.9112	0.9694	0.9394
FT-Transformer	**0.9819**	**0.9819**	**0.9819**	**0.9819**

6.1 Machine Learning Model Results

The Logistic Regression model yielded consistent yet average results in all measures of evaluation, which indicates that it is able to represent linear associations in the irrigation data. Its results were an accuracy of 0.8689, a precision of 0.8410, a recall of 0.8673, and an F1-score of 0.8539, which represents a balanced result in correctly identifying cases that need irrigation and avoiding false predictions. Although effective, the outcomes demonstrate that

Logistic Regression is restricted in the cases where the complex nonlinear patterns of the environmental and soil parameters are involved.

The K-Nearest Neighbours (KNN) model was much stronger and demonstrated its ability to depict local similarities of features in the dataset. It found a strong prediction capability and consistency as it had a high accuracy of 0.9288, precision of 0.9235, recall of 0.9145 with an F1-score of 0.9190. These results highlight the suitability of KNN in agricultural classification, especially where the irrigation decisions are made using the closely related environmental measurements.

The general behaviour of the Decision Tree model was good, as it was able to learn nonlinear boundaries and feature interactions, which are applied in irrigation demands. It achieved an accuracy of 0.9414, precision of 0.9470, recall of 0.9187, and an F1-score of 0.9413 which shows a good discriminative power. The results indicate that the tree-based model is effective in explaining the decision rules depending on the soil properties, moisture, temperature, and humidity and hence a high predictor of smart irrigation.

The Gradient Boosting model was also competitive in its ability to incorporate a series of weak learners to a strong ensemble predictor. The model also recalls a high rate (0.9812) with a precision of 0.8903 and F1-score of 0.9336, which is very high and demonstrates that the model was quite successful in identifying the cases that had to be irrigated. The ensemble-based learning enabled it to learn complex patterns and at the same time generalize.

6.2 Deep Learning Model Results

Deep Neural Network (DNN) was discovered to possess a high predictive capacity, and it can embody the complicated nonlinear interactions among soil, environmental, and crop-related variables, which can be employed to forecast the irrigation decision. The model was accurate with a value of 0.9447, precise with a value of 0.9112, recalled with a value of 0.9694 and F1-score of 0.9394 which means that it has a high generalization power and a high detection of cases that require irrigation. It has a high recall value, which means that the DNN was particularly effective at identifying the cases in which water was necessary, and the high F1-score means that it has an acceptable balance between the precision and the recall. These results indicate the capability of deep learning to learn the intricate interaction of features that machine learning models may fail to learn.

6.3 FT-Transformer Results

FT-Transformer model has indicated the greatest output of all the models that have been analysed with an excellent accuracy of 0.9819, precision of 0.9819, recall of 0.9819 and F1-score of 0.9819. The near-optimal and perfectly balanced results prove that the model can be used to determine the irrigation requirements with high degrees of reliability. Unlike the machine learning algorithms of the past which may not learn nonlinear relationships between variables in a complex agricultural dataset, the FT-Transformer learns the complex relationships between variables in a complex agricultural dataset, such as soil moisture, temperature, humidity, and crop stage, using feature tokenization and multi-head self-attention. This enables the model to dynamically give contextual meaning to every feature to make better informed and accurate predictions in a diverse environmental context.

Besides, the self-attention process enables the FT-Transformer to find both local and global interaction of the data as well as understand better how different factors can interact to influence the requirements in irrigation. The processing of all features can be done in parallel, hence it lacks the drawbacks of the sequential models and allows higher computational efficiency. It is also highly resistant to data imbalance and noise to a great extent that the model can be applied to real-life agricultural environments where sensor variability is also a frequent phenomenon. Overall, the fact that the FT-Transformer is highly performing indicates that the solution is a smart and stable tool that can be applied to carry out accurate irrigation, far superior to both classical machine learning models and deep learning models in the aspect of predictive accuracy and generalization.

6.4 Findings of the Study and Superiority of FT-Transformer

The results of the research show categorically that the FT-Transformer is much more effective than all other utilized models because it is capable of modelling nonlinear and complex relationships in agricultural data that cannot be effectively modelled by the conventional machine learning and deep learning models. Its high performance is based on the utilization of feature tokenization and multi-head self-attention that enable the model to consider each input variable as independent tokens and at the same time learn their interactions. This allows the FT-Transformer to find out dynamically the features that are most influential in irrigation decisions in varying conditions, which leads to very accurate and context-sensitive predictions. Moreover, the FT-Transformer learns global dependencies unlike sequential deep learning architectures because it processes all features concurrently instead of being constrained by the sequence of inputs. The high variability of features, data imbalance, and noise are further boosted by the fact that the model is able to deal with variability in features, imbalance in data and noise more effectively resulting in a strong consistency in accuracy, precision, recall and F1-score. All in all, the architectural strengths of the FT-Transformer predispose it to be a remarkably better fit to smart irrigation prediction, which makes it a highly reliable and intelligent tool to use in precision agriculture.

7 Conclusion and Future Work

7.1 Conclusion

The paper will introduce a smart irrigation prediction system employing the combination of Machine Learning, Deep Learning, and Transformer-based models to improve decision-making in precision agriculture. Based on the CRISP-DM approach, the work systematized data preprocessing, exploratory analysis, feature encoding, model training, and evaluation in a systemic pipeline by using the soil type, crop stage, moisture index, temperature, and humidity as the most important features. The results indicate that compared to the traditional ML and DL models, the FT-Transformer is much more accurate and its high predictive power is due to the use of feature tokenization and multi-head attention that allow the model to capture the complex interactions in agricultural data. Transformer architectures are shown to be appropriate in smart irrigation systems due to their capability to deal with nonlinear patterns, variability and noise. On the whole, the paper demonstrates the opportunities of improved AI-controlled solutions to ensure the sustainability of water management, diminish human interference and enhance crop yields, which is a solid basis to continue the further research in the domain of intelligent irrigation systems.

7.2 Future Work

The study can be further developed in the future by adding bigger and more diverse agricultural data with various types of crops, types of soil, and seasonal values to enhance the generalizability of the FT-Transformer model. Other sensor measurements like the speed of wind, the intensity of rainfall, evapotranspiration measures, and satellite-based vegetation indices are also possible to enhance predictive power. The implementation of real-time deployment with the help of IoT hardware, integration of models on the cloud, and mobile application interfaces would enable farmers to obtain real-time irrigation recommendations on the field. Future improvements may consider lightweight variants of the transformers to support edge computing, model explainability methods to understand attention weights better, and hybrid methods that combine reinforcement learning to support adaptive irrigation control. The extensions would assist in developing the system into a fully autonomous, scalable, and highly reliable smart irrigation system suitable in the actual agronomical setting.

References

Abdallah, E.B., Grati, R. and Boukadi, K., 2022, June. A machine learning-based approach for smart agriculture via stacking-based ensemble learning and feature selection methods. In 2022 18th *International Conference on Intelligent Environments (IE)* (pp. 1-8). IEEE. 10.1109/IE54923.2022.9826767

Baio, F.H.R., Santana, D.C., Teodoro, L.P.R., Oliveira, I.C.D., Gava, R., de Oliveira, J.L.G., Silva Junior, C.A.D., Teodoro, P.E. and Shiratsuchi, L.S., 2022. Maize yield prediction with machine learning, spectral variables and irrigation management. *Remote Sensing,* 15(1), p.79. doi: https://doi.org/10.3390/rs15010079

Bhimavarapu, U., Battineni, G. and Chintalapudi, N., 2023. Improved optimization algorithm in LSTM to predict crop yield. *Computers*, 12(1), p.10. https://doi.org/10.3390/computers12010010

Elbasi, E., Zaki, C., Topcu, A.E., Abdelbaki, W., Zreikat, A.I., Cina, E., Shdefat, A. and Saker, L., 2023. Crop prediction model using machine learning algorithms. *Applied Sciences*, 13(16), p.9288. https://doi.org/10.3390/computers12010010

Ge, J., Zhao, L., Yu, Z., Liu, H., Zhang, L., Gong, X. and Sun, H., 2022. Prediction of greenhouse tomato crop evapotranspiration using XGBoost machine learning model. *Plants*, 11(15), p.1923. https://doi.org/10.3390/plants11151923

Ishaq, R.A.F., Zhou, G., Jing, G., Shah, S.R.A., Ali, A., Imran, M. and Jiang, H., 2025. Geospatial Robust Wheat Yield Prediction Using Machine Learning and Integrated Crop Growth Model and Time-Series Satellite Data. *Remote Sensing*, 17(7), p.1140. https://doi.org/10.3390/rs17071140

Munaganuri, R.K., Yamarthi, N.R. and Bolem, S.C., 2025. Design of an improved graph-based model integrating LSTM, LoRaWAN, and blockchain for smart agriculture. *PeerJ Computer Science*, 11, p.e2896. https://doi.org/10.7717/peerj-cs.2896

Munaganuri, M.R.K., Gonnuri, P., Badiguntla, R., Kasukurthi, A., Sarma, S.L., Basha, S.M. and Yamarthi, N.R., 2025. Deep Learning-Based Crop Prediction Using LSTM And GRU For Sustainable Agriculture. International Journal of Environmental Sciences, 11(11s), pp.538-545. https://doi.org/10.7717/peerj-cs.2896

Nitya, E., Gangwar, S., Singh, J., Dandotiya, M., Saini, H. and Mishra, S., 2025, May. Predictive Irrigation Management Using Long Short-Term Memory Networks and IoT Data in Agriculture. In 2025 6th *International Conference for Emerging Technology (INCET)* (pp. 1-6). IEEE. https://doi.org/10.1109/INCET64471.2025.11140807

Okayama, A., Yamamoto, A., Kimura, M. and Matsuno, Y., 2025. Utilizing convolutional neural network (CNN) for orchard irrigation decision-making. Environmental Monitoring and Assessment, 197(2), p.168. https://doi.org/10.1007/s10661-024-13602-1

Puspaningrum, A., Sumarudin, A. and Putra, W.P., 2022, September. Irrigation prediction using machine learning in precision agriculture. In 2022 5th *International Conference of Computer and Informatics Engineering (IC2IE)* (pp. 204-208). IEEE. https://doi.org/10.1109/IC2IE56416.2022.9970092

Saha, G., Shahrin, F., Khan, F.H., Meshkat, M.M. and Azad, A.A.M., 2025. Smart IoT-driven precision agriculture: Land mapping, crop prediction, and irrigation system. PloS One, 20(3), p.e0319268. https://doi.org/10.1371/journal.pone.0319268

Sami, M., Khan, S.Q., Khurram, M., Farooq, M.U., Anjum, R., Aziz, S., Qureshi, R. and Sadak, F., 2022. A deep learning-based sensor modeling for smart irrigation system. *Agronomy*, 12(1), p.212. https://doi.org/10.3390/agronomy12010212

Sangeetha, S.K.B., Immanuel, R.R., Mathivanan, S.K., Jayagopal, P., Rajendran, S., Mallik, S. and Li, A., 2025. Smart Irrigation System Using Soil Moisture Prediction with Deep CNN for Various Soil Types. In *Artificial Intelligence and Applications* (Vol. 3, No. 2, pp. 200-210). https://doi.org/10.47852/bonviewAIA42021514

Stojanova, S., Volk, M., Balkovec, G., Kos, A. and Stojmenova Duh, E., 2025. The Future of Vineyard Irrigation: AI-Driven Insights from IoT Data. Sensors, 25(12), p.3658. https://doi.org/10.3390/s25123658

Tace, Y., Tabaa, M., Elfilali, S., Leghris, C., Bensag, H. and Renault, E., 2022. Smart irrigation system based on IoT and machine learning. *Energy Reports*, 8, pp.1025-1036. https://doi.org/10.1016/j.egyr.2022.07.088