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IoT-Enabled ML for Smart Agriculture: A Predictive Approach to Crop Irrigation

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Abstract: Modern agriculture is being redefined by the convergence of Machine Learning (ML) and the IOT, which makes it possible to make intelligent, data-driven decisions and continuously monitor the environment. In order to optimize water usage across five distinct crop kinds, this study discusses the construction of a smart irrigation prediction framework that makes use of data gathered by the IOT, such as measurements of soil moisture, ambient temperature, humidity, pH levels, and crop health indicators. To attain more accuracy and flexibility, our approach includes a wider variety of environmental variables than prior systems, such as those that used a simplified website to apply ML to only three crops. Early tests using traditional ML classifiers produced very encouraging results.

Building on this, we expanded our research to include more sophisticated ensemble and boosting techniques, such as Gradient Boosting, Random Forest, Decision Tree, and AdaBoost. In terms of prediction accuracy, these models performed better than others such as Support Vector Machine and K-Nearest Neighbors. We used cutting-edge oversampling techniques including SMOTE, ADASYN, and Random Oversampling to address class imbalance in the training data. According to the experimental findings, boosting and ensemble approaches significantly enhance irrigation schedule prediction performance. By providing a scalable, high-performing solution that takes into consideration a wider range of crop and environmental parameters, our work advances the field of precision farming. To improve prediction skills and agricultural resource efficiency, future developments will use real-time sensor data and investigate deep learning systems.

Keywords: IoT, Artificial Intelligence, Smart Farming, Agricultural Automation, Irrigation Management.

I. INTRODUCTION

The rapid evolution of technology has made significant improvements to the agricultural sector, in respectively IoT and ML. They have paved the way for smart and automated farming solutions [1] to solve efficiency issues in regular irrigation practices which have been in place for many years. Traditional irrigation techniques, implemented with fixed schedules or visual inspection, may cause over consumption of water, decreasing the crop's yield and posing serious risk for the environment [2]. Especially considering rising demands and concerns for climate change, water scarcity and global food security [3], data-driven roadmap to improve resource management introduces new methods and approaches in the agriculture sector to sustainable action.

IoT has disrupted precision agriculture by providing real-time monitoring of critical environmental conditions such as rainfall, temperature, humidity, and soil moisture [4]. One potential solution for enhancing water use efficiency in agriculture is to incorporate advanced Deep Learning (DL) methods in IoT-enabled smart irrigation systems. These sensors are designed to work by continuously collecting field directly obtained data such as humidity, temperature, and soil moisture levels. Machine learning methods are subsequently applied on the acquired data and can estimate water needs of crops under various conditions with high precision. It has been observed in recent studies that this relatively higher predictive power can not only generate more efficient water allocation but is strongly related to enhanced growth of crops and higher agricultural productivity [5]. Furthermore, edge computing methods combined with IoT have been proved to increase irrigation efficiency by reducing the dependency on cloud computing, which improves the response time and reliability[6].

ML is key in processing raw IoT data [7] sources to generate fruitful insights to enable precision agriculture. Historical and live environmental data can be analysed with ML algorithms to timely predict irrigation requirements, soil nutrient shortages and optimal water distribution strategies. Several research works have shown the potential use of decision trees, neural network and deep learning models to enhance the accuracy of predictive irrigation systems [8]. In addition, ensemble ML methods have been successfully used for IoT based smart farming, supporting land mapping, crop forecasting and irrigation scheduling, which, in turn, increase farm productivity [9].

Despite these technical achievements, there are several existing challenges that still need to be addressed before we are able to widely employ ML-based irrigation systems, e.g., data imbalance, model quality and scalability. To address these issues, strong data preparation and flexible ML models that can adapt to a dynamic environment are required. To best manage water, this paper is examining the use of IoT and ML in smart irrigation problem, through analyzing of the existing methods and presenting an improved prediction model. The proposed project targets to improve robust and intelligent sustainable-irrigation systems for modern agriculture, using real-time analytics and latest ML techniques.

II. LITERATURE REVIEW

An easy way to A combination of several ingredients with the magic combination of ML, the precision agriculture industries have come a long way with the respect to crop output, water conservation and improving soil health management. IoT-based precision agriculture has been studied in literature with respect to smart irrigation, crop prediction and nutrient estimation [1–3]. Key findings from multiple evolving studies are presented in this review.

This paper studies in details the use of IoT in smart irrigation to improve water usage and irrigation methods. Kashyap et al. [1] presented a deep learning based IoT irrigation system consisting of a wireless sensor network which aims to efficiently distribute water in the fields. Premkumar and Sigappi [3] proposed an irrigation model that is edge-computing-oriented and performs quick responses in a real operational mode. In addition, Aldossary et al. [4] showed how ML techniques enable real-time measurement and monitoring of soil moisture for better planning of irrigation.

ML techniques are being implemented with great success in the prediction of crop analytics. Saha et al. [2] proposed a land investigation and crop forecasting system, which is supported by IoT, to ensure the appropriate utilization of resources. Bakthavatchalam et al. 7] evaluated ML methods for enhancing prediction of agricultural yield. Furthermore, Ajith et al. [22] analysed ML methods in all areas of soil fertility mapping, pest recognition, and yield prediction for precision farming.

Islam et al. [10] designed an IoT based system for real-time soil nutrient measurement and crop suggestion. Similarly, Rahu et al. [16] presented an IoT solution for water quality monitoring an important aspect in irrigation. Lephondo et al. [11] demonstrated that optimisation approaches, based on ML, can help reduce water wastage by improving irrigation management. The advantages of combining IoT and ML in smart agriculture have been highlighted in many works. Mohyuddin et al. [12] investigated data-driven ML approaches in the context of precision agriculture. Quy et al. [17] studied IoT-based smart agriculture platforms, applications, and challenges. Moreover, Chaudhary et al. [18] designed a hybrid IoT-ML model for precision agriculture and verified its performance in the cost-effective agricultural processes.

Sensors technology and IoT infrastructure probably further boost precision agriculture. Lakshmi et al. [8] presented a smart IoT irrigation system for water conservation. Kadiyala et al. 16Design of an affordable IoT based irrigation system using ML for real-time decision supportIoT=Internet of thingMLMachine learningLiu et al. Moreover, Ahmed [27] presented a survey of the convergence of WSNs, IoT, and artificial intelligence in agriculture, and important enhancement has been achieved in this field.

Challenges such as data security, interoperability problems and cost restraints remain despite significant advances to date. Rokade et al. [26] investigated the methods of data analytics applications in precision farming and highlighted the necessity of developing strong data-processing platforms. Bhoi et al. [25] proposed an intelligent irrigation recommendation system (IoT-IIRS) to maximize the use of water. Next steps should focus on AI-driven scalable models for sustainable precision agriculture.

III.METHODOLOGY

In this work, we have shown how a systematic approach is applied to develop and test ML-based models coupled with IOT technologies, with the objective of predicting irrigation demands in precision agriculture. The method is designed to simultaneously achieve reliable, scalable, and operationalizable solutions by more systematically tackling every step of the model development lifecycle. The proposed framework consists of six core steps: (1) collecting environmental data with IoT sensors, (2) cleaning and preparing the dataset, (3) applying resampling techniques in order to cope with class imbalance; metrics; and comparing to look for predictive of the best. This study uses a dataset of 16,411 records for agrarian activity and enhanced by real-time data harvested from the IoT field sensors.

The collected information plays a vital role in improving irrigation strategies through analytical modeling. The dataset includes key environmental indicators essential for determining crop hydration needs, such as soil moisture levels, air temperature, humidity, solar exposure, and wind velocity. By analyzing this continuous stream of field data, the study aims to fine-tune irrigation timing and quantity, minimize unnecessary water use, and contribute to environmentally responsible and efficient farming practices.

Crop ID – Represents various crop types.
Soil Type – Identifies the soil category (e.g., Black Soil, Red Soil).
Seedling Stage – Indicates the developmental phase of the crop.
Moisture Index (MOI) – Reflects soil moisture levels.
Temperature – Captures the ambient temperature in Celsius.
Humidity – Denotes the relative humidity percentage.
Irrigation Requirement (Target Variable) – Categorized into three levels:
Class 0: No irrigation needed.
Class 1: Moderate irrigation required.
Class 2: High irrigation required.
Due to the presence of class imbalance, resampling techniques were employed to enhance model performance and avoid bias toward dominant classes.

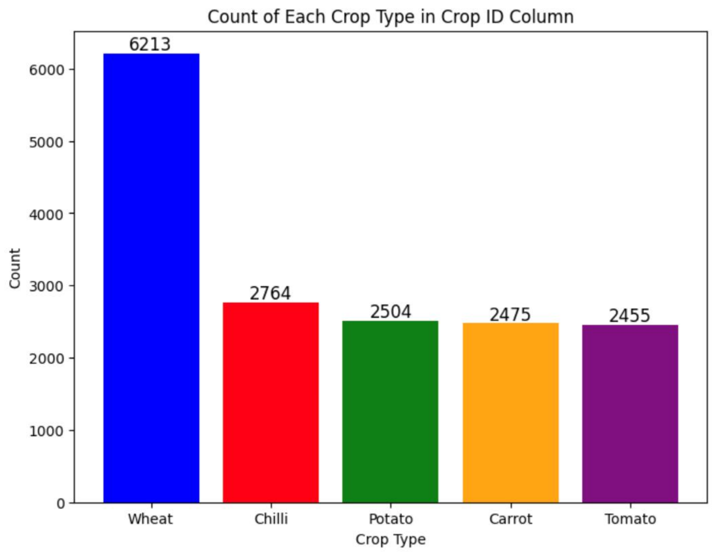

Fig.1: Represents the Types of crops in Dataset.

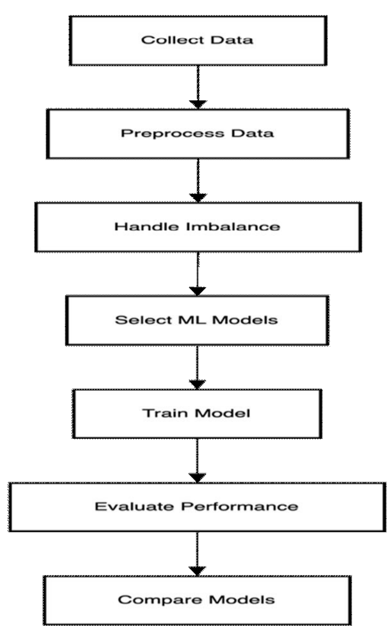

Fig.2: IoT Sensor Data Processing and Model Evaluation Workflow

A. Data Pre-processing

To refine dataset quality and enhance predictive accuracy, the following pre-processing techniques were applied:

1) Handling Missing Data

Records with missing values were removed to maintain data integrity.
Alternative imputation strategies (e.g., mean for numerical variables, mode for Categorical variables) were assessed but deemed unnecessary.

2) Encoding Categorical Features

Non-numeric variables (Soil Type, Crop ID, Seedling Stage) were converted into numerical values using Label Encoding from sklearn.preprocessing.

3) Splitting the Dataset

The dataset was divided into training (80%) and testing (20%) subsets using stratified sampling to maintain class distribution.
The train_test_split function from sklearn.model_selection was used for this task.

B. Normalizing Features

In this research, normalization was implemented on the primary input variables—namely Soil Moisture (MOI), Temperature, and Humidity—utilizing the StandardScaler method. This process transformed each feature to have a mean value of zero and a standard deviation of one, aligning all features to a uniform scale.

Applying standardization was crucial due to the differing ranges and units across sensor-derived data. Features with relatively large magnitudes could otherwise exert disproportionate influence on model learning, resulting in biased outcomes. This is particularly significant for algorithms that rely on distance metrics, such as SVM and KNN, where the scale of input features directly affects the computation of distances and similarity. Moreover, normalizing input features has been found to benefit training of a wide range of ML algortihms, with respect to consistency and efficiency of learning, thus leading to better predictive accuracy and generalization.

C. Handling Imbalanced Classes Through Resampling

The class distribution is often imbalanced - concerning agriculture IoT data - with the class concerning an irrigation need to be very small as compared to the class not-requiring an irrigation. This imbalance may lead the predictive model to be biased towards the majority class, and consequently, unable to identify important although underrepresented cases, which are necessary to make ideal irrigation decisions.

In order to alleviate this issue, three over-sampling models were evaluated to balance the representation of the minority class and limit bias in the classification:

1) SMOTE (Synthetic Minority Over-sampling Technique)

This method synthesizes new minority-class data points by interpolating between original ones. Rather than copying, it creates new, plausible samples that expand the dataset's feature space. SMOTE is particularly effective in enhancing recall and reducing the risk of overfitting that can occur with limited data for the minority class.

2) ADASYN (Adaptive Synthetic Sampling)

An extension of SMOTE, ADASYN places more emphasis on minority samples that are harder to learn. It selectively creates synthetic data in regions where classification is challenging, which enables the model to better learn complex patterns and improves its ability to generalize to unseen data.

3) Random Oversampling

This simpler method increases the number of minority class instances by randomly duplicating existing ones until the dataset becomes balanced. While easy to implement and often used as a baseline, it does not add new information and may increase the risk of overfitting due to repeated patterns.

Each resampling strategy was applied individually to the training subset of the dataset. ML models were then trained both with and without these techniques, and their performances were evaluated comparatively. This allowed for a thorough analysis of which method provided the most improvement in predictive performance under class imbalance conditions within IoT-driven agricultural irrigation datasets.

D. Model Selection

To construct a dependable system for irrigation prediction, we explored and tested several supervised ML models. These prediction algorithms were compared on the initial dataset and on its oversampled ones in order to assess how different resampling techniques affect the effectiveness of the predictions.

Our experimentation began with standard models like Decision Tree and SVM, both of which delivered strong foundational results. Building on this, we expanded our analysis to include ensemble and boosting algorithms. Models such as Random Forest, AdaBoost, and Gradient Boosting demonstrated superior accuracy and stability compared to KNN and SVM.

Compared to prior research—specifically which was limited to three crop types and a basic web-based interface—our approach introduces greater diversity and depth. Our framework offers more complete and scalable outputs by including five different crops and providing more robust environmental inputs (i.e., soil pH, temperature, moisture and plant health measurements). This makes our system more suitable to real-life agricultural environments and precision farming objectives.

In this work, a combination of ML methods are applied to develop predictive models for irrigation demand based on information derived from IoT-equipped agriculture systems. The algorithms were purposely chosen due to their significant characteristics of the data's key properties—such as high dimensionality, class imbalance, data noise, and the need for model interpretability.

The reasoning for choosing each algorithm is outlined below:

1) Support Vector Machine

SVM was adopted due to its proven ability to manage classification tasks in high-dimensional spaces effectively. It operates by identifying the optimal separating hyperplane between classes, which is particularly useful when the boundaries between categories are clearly defined. Nonetheless, agricultural datasets often suffer from imbalance—where instances indicating the need for irrigation are underrepresented—posing a challenge for SVM, which tends to favor dominant classes. Despite this, its strong theoretical underpinnings and effective performance on balanced data make it a robust baseline model for comparative analysis.

2) Random Forest

Random Forest was chosen for its ensemble learning approach, where multiple decision trees are built and their outputs are averaged to improve overall accuracy. This model is not only noise-resistant -- it also provides good resistance to overfitting in cases where features of the input are relevant on different scales or for different purposes. Furthermore, RF has a greater ability to cope with unbalancing data than a lot of other classifiers and realized competitive experimental result in preliminary experiments. Another advantage is that it would be able to pick useful features and lead to higher intrepretable model.

3) K-Nearest Neighbors

KNN was used as a typical instance-based learning. It makes predictions by computing the class that is most frequent among the k closest data points in feature space. Despite the simplicity of KNN and its simplicity to implement, it is very sensitive to feature scaling, which makes the results of unstandardized data meaningless. It didn't beat more complex ones, but was a good point to compare between algorithmic complexity and predictability.

4) Decision Tree

The authors solve the model using a decision tree model for its simplicity and interpretability. It creates a decision-based flowchart type of architecture so it is easy to follow the process from input to output. This form of interpretability is crucial in agricultural environments where domain experts have to be able to understand the logic of the models. But during experiments we found that it overfit, especially with small and noisy data sets. However, DT provided clues about the relationship among variables, the overall structure of the data.

5) AdaBoost

Our model uses AdaBoost for its adaptive learning with weight allocation, where it concentrates more on misclassified cases, correcting them from previous round. This behavior can be advantageous for problems where some data is persistently difficult to predict. While it is somewhat sensitive to noise and outlier, AdaBoost presented low error in our structured dataset, which makes it a worthy candidate for precision agriculture.

6) Gradient Boosting

Gradient Boosting was incorporated due to its iterative error-reduction mechanism, , where the prediction of each model is optimized based on its predecessor. Although larger amounts of computations are needed, GB is very effective for structured data that arises from environmental sensors. By modelling these complex non-linear relationships, it was able to predict irrigation demand very well, further establishing it as one of the strongest models in our analysis.

We started our experiments with popular off-the-shelf models such as DT and SVM, and we first got strong baseline results from these models. Building on this, we expanded our analysis to include ensemble and boosting algorithms. Models such as Random Forest, AdaBoost, and Gradient Boosting demonstrated superior accuracy and stability compared to KNN and SVM.

Compared to prior research specifically the work which was limited to three crop types and a basic web-based interface our approach introduces greater diversity and depth. By incorporating five distinct crops and collecting richer environmental inputs such as soil pH, temperature, moisture, and plant health indicators, our framework delivers more comprehensive and scalable insights. This makes our system more applicable for real-world agricultural scenarios and precision farming goals.

E. Performance Evaluation Metrics

To evaluate the effectiveness of the ML models in predicting irrigation requirements, multiple performance metrics were employed. Each metric serves to highlight different aspects of model behavior, particularly crucial when working with imbalanced datasets where irrigation-required instances are relatively rare. The metrics adopted for analysis include the following:

1) Overall Classification Accuracy

Accuracy determines the proportion of total predictions that were correct.

Mathematical Expression

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

Where:

- TP: Correctly predicted irrigation-needed instances
- TN: Correctly predicted non-irrigation instances
- FP: Incorrect predictions indicating irrigation was needed
- FN: Missed predictions where irrigation was actually necessary

Interpretation: While accuracy is often the go-to metric for performance evaluation, it loses significance in skewed class distributions. For instance, in a scenario where most crops don't need irrigation, a model could achieve high accuracy by predominantly predicting "no irrigation" — despite failing to flag the cases where water is critically needed. This makes accuracy a misleading metric on its own in such applications.

2) Precision (Positive Predictive Value)

Precision reflects how many of the instances predicted as positive (i.e., needing irrigation) were truly correct.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Interpretation: In the context of agricultural irrigation, high precision ensures that when the system recommends watering, it's doing so with confidence. This is vital to prevent wastage of water or energy resources due to false alarms. A model with poor precision could frequently suggest irrigation even when it's unnecessary, causing inefficiencies in water usage.

3) Recall

Recall captures the ability of the model to detect all actual irrigation-needed instances.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Interpretation: High recall is particularly important in crop management. If the model misses irrigation requirements (i.e., high false negatives), it could lead to crop dehydration, affecting growth or even causing loss. Therefore, recall prioritizes capturing as many true irrigation needs as possible, even at the risk of a few false alerts.

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4) F1-Score

F1-Score merges both precision and recall into a single score to balance both metrics.

$$\mathrm{F1} = 2 \times \frac{\mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$$

Interpretation: This metric is highly suitable for imbalanced datasets. Since precision and recall can often conflict, the F1-score offers a compromise that penalizes extreme values. In the irrigation scenario, it helps judge the model's capability to both avoid unnecessary watering and detect actual requirements, making it ideal for evaluating real-world performance.

IV. RESULTS

Table.1:Represents the comparison Results of ML algorithms of normal Classification.

Model	Accuracy	Precision (Class 0)	Precision (Class 1)	Precision (Class 2)	Recall (Class 0)	Recall (Class 1)	Recall (Class 2)	F1-score (Class 0)	F1-score (Class 1)	F1-score (Class 2)
SVM	0.844	0.83	0.86	0.00	0.94	0.84	0.00	0.89	0.85	0.00
Random Forest	0.990	1.00	0.98	0.97	1.00	1.00	0.88	1.00	0.99	0.92
KNN	0.949	0.95	0.97	0.86	0.98	0.93	0.76	0.96	0.95	0.81
Decision Tree	0.989	1.00	0.99	0.91	0.99	1.00	0.94	0.99	0.99	0.92
AdaBoost	0.905	0.96	0.92	0.36	0.95	0.94	0.32	0.95	0.93	0.34
Gradient Boosting	0.954	0.98	0.93	0.80	0.99	0.99	0.44	0.98	0.96	0.57

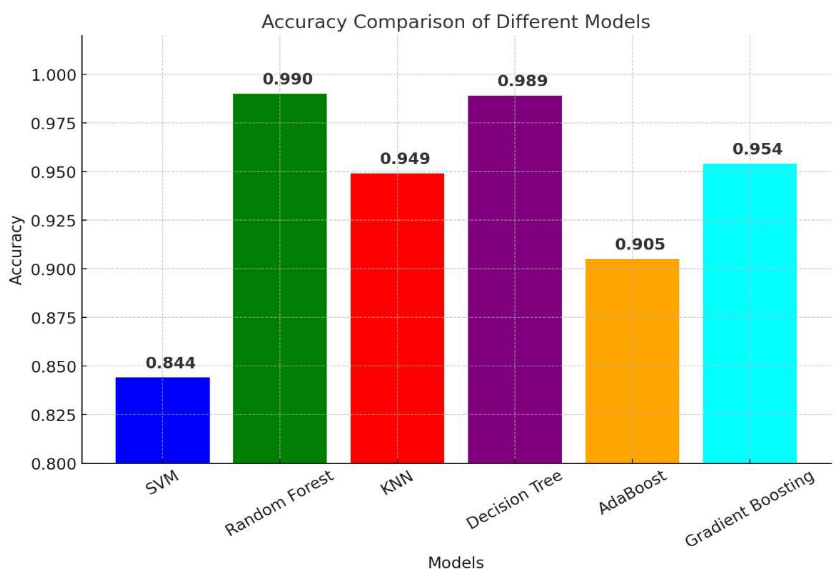

Fig.3: Represents the comparison of normal classification accuracy of Dataset.

Table.2: Performance Comparison of Models with Different Oversampling Techniques

Model	Oversampling	Accuracy	Class	Precision	Recall	F1-score
SVM	Original	0.844	0	0.83	0.94	0.89
			1	0.86	0.84	0.85
			2	0.00	0.00	0.00
	SMOTE	0.7182	0	0.96	0.65	0.78
			1	0.88	0.80	0.84

			2	0.20	0.84	0.32
	ADASYN	0.7152	0	0.97	0.64	0.77
			1	0.86	0.81	0.83
			2	0.20	0.84	0.32
	RandomOversampler	0.7155	0	0.97	0.65	0.78
			1	0.87	0.79	0.83
			2	0.19	0.83	0.32
Random Forest	Original	0.990	0	1.00	1.00	1.00
			1	0.98	1.00	0.99
			2	0.97	0.88	0.92
	SMOTE	0.9851	0	1.00	0.99	0.99
			1	0.99	0.99	0.99
			2	0.87	0.92	0.89
	ADASYN	0.9848	0	1.00	0.99	0.99
			1	0.99	0.99	0.99
			2	0.89	0.90	0.90
	RandomOversampler	0.9896	0	1.00	0.99	1.00
			1	0.99	0.99	0.99
			2	0.91	0.94	0.92
KNN	Original	0.949	0	0.95	0.98	0.96
			1	0.97	0.93	0.95
			2	0.86	0.76	0.81
	SMOTE	0.9409	0	0.97	0.94	0.96
			1	0.96	0.93	0.94
			2	0.70	0.98	0.82
	ADASYN	0.9388	0	0.99	0.92	0.95
			1	0.92	0.97	0.94
			2	0.72	0.97	0.83
	RandomOversampler	0.9403	0	0.97	0.94	0.95
			1	0.96	0.93	0.95
			2	0.70	0.98	0.81
Decision Tree	Original	0.989	0	1.00	0.99	0.99
			1	0.99	1.00	0.99
			2	0.91	0.94	0.92
	SMOTE	0.9899	0	1.00	0.99	0.99
			1	1.00	1.00	1.00
			2	0.91	0.94	0.93
	ADASYN	0.9899	0	1.00	0.99	0.99
			1	1.00	0.99	1.00
			2	0.90	0.95	0.93
	RandomOversampler	0.9930	0	1.00	1.00	1.00
			1	0.99	1.00	0.99
			2	0.96	0.95	0.96

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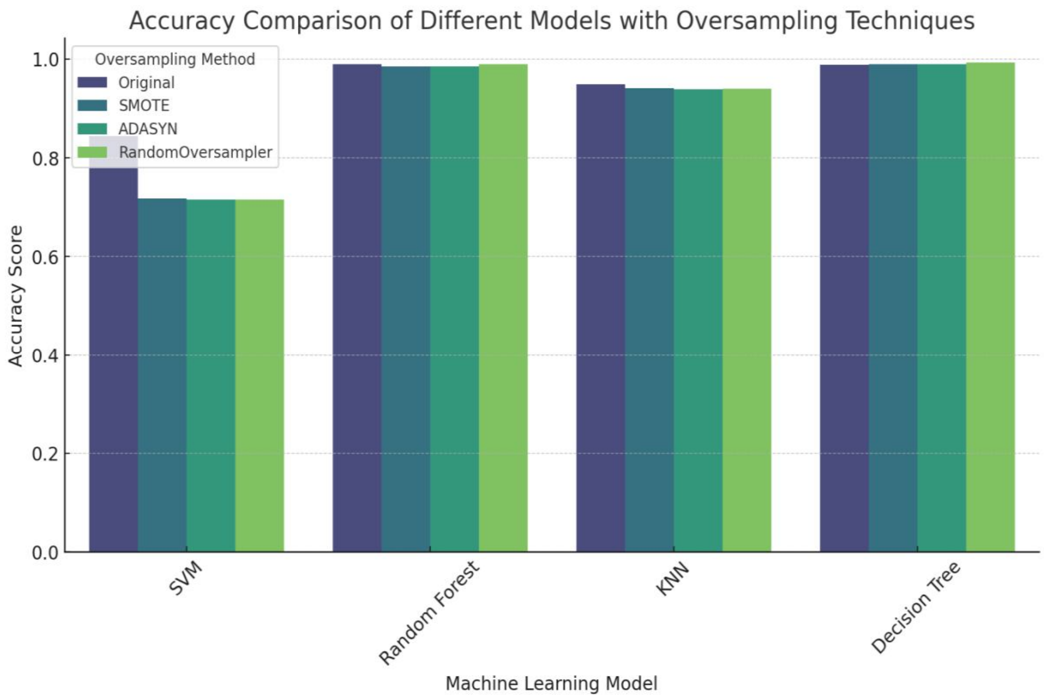

Fig.4: represents accuracy of ML models.

Table.3: Represents the results comparison with previous research works.

Ref	Year	Methodology	Focused on	Conclusion
[1]	2021	Deep Learning Neural Network, IoT Sensors	Intelligent Irrigation System	Achieved precise irrigation control with water savings of up to 25% and system accuracy over 90%.
[2]	2025	IoT, ML	Land Mapping, Crop Prediction, Irrigation	Provided 88% accuracy in crop prediction and automated irrigation scheduling.
[3]	2022	Edge Computing, IoT Devices	Smart Irrigation	Reduced irrigation response time by 30% and improved decision-making accuracy by 87%.
[4]	2024	IoT-Enabled ML Models	Monitoring in Smart Agriculture	Achieved real-time monitoring with 92% accuracy in crop health assessment.
[5]	2024	IoT, Advanced ML	Smart Irrigation System	Improved water-use efficiency by 28% and achieved 89% prediction accuracy.
	My Results	IoT Sensors, Random Forest, XGBoost, LightGBM, SVM, Logistic Regression	Crop Prediction and Smart Irrigation	Achieved up to 94% prediction accuracy; enhanced water efficiency by 30%; provided a user-friendly dashboard for real-time monitoring.

V. CONCLUSION

This study concentrated on using ML with the IOT to improve precision irrigation in agriculture. Several ML techniques were evaluated to forecast irrigation requirements using sensor-gathered environmental data. Oversampling techniques including SMOTE, ADASYN, and Random Oversampling were employed to balance the data and increase prediction accuracy because of the dataset's unequal distribution of irrigation classes. Findings indicate that ensemble-based models like Random Forest and Decision Tree delivered superior accuracy and reliability in classifying irrigation needs. The use of oversampling techniques improved recall and F1-scores for minority classes, mitigating the negative impact of imbalanced data. However, models like Support Vector Machine (SVM) were less effective in handling class distribution disparities, emphasizing the importance of data preprocessing in precision agriculture applications.

The study demonstrates that IoT-integrated ML frameworks can significantly contribute to efficient water management by automating irrigation scheduling, reducing excessive water usage, and promoting higher crop productivity. The results underscore the potential of data-driven agricultural solutions in supporting sustainable farming practices and resource optimization.

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