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Sustainable Water Management in Precision Agriculture

Sharad Jagtap
ECE
Bharath Institute of Higher Education and Research, Chennai, India
Anantrao Pawar College of Engineering and Research,
Pune, India
sharadjagtap0710@gmail.com

G. Sudhagar
ECE
Bharath Institute of Higher Education and Research
Chennai, India
sudhagar.ece@bharathuniv.ac.in

Rahul Jadhav
ECE
Bharath Institute of Higher Education and Research, Chennai, India
AISSMS Institute of Information Technology,
Pune, India
rnjdrive@gmail.com

***Abstract*: This paper uses machine learning models to optimize the utilization of water in precision agriculture. The main objective is to create a dependable system that can forecast the ideal irrigation conditions, increasing sustainability and efficiency. The process entails the thoughtful placement of sensors, the creation of a wireless network of sensors (WSN), as well as the examination of a carefully selected dataset that includes vital variables like humidity, temperature, precipitation, wind speed, along with soil moisture. The dataset's integrity is guaranteed by further data pre-processing, which includes operations like cleaning, feature significance analysis, and refining. The 105,217-entry dataset provides the basis for training and assessing machine learning models, including Random Forest, the Decision Tree, and Support Vector Machines (SVM), along with Neural Network. The findings show that the Random Forest model performs better than the other models, with an astounding accuracy of 92.68%. At 91.83% accuracy, the model based on Decision Trees comes a close second. With accuracy levels of 90.78% & 90.21%, respectively, SVM as well as Neural Network models perform competitively. The Random Forest model's accuracy in forecasting ideal irrigation conditions is further supported by the precision along with F1-Score measures. This paper provides a strong foundation for environmentally friendly water use and offers insightful information about using machine learning techniques for precision agriculture.**

Keywords: SVM, Random Forest, Decision Tree, Support, WSN, Agriculture Efficiency.

I. INTRODUCTION

Agriculture is now the primary source of food for civilization, as it has been for millennia, with agricultural areas providing more than 74% of the daily intake of people. More than 70% of the fresh water in the world is used in agriculture, making it not only one of the world's most water-intensive industries but also essential to human survival. Furthermore, Water shortage is a worldwide issue, and with more people using water, thirty percent of the water is wasted or utilized improperly for several reasons, including poor management, which is unacceptable. To overcome these problems, technological usage in agriculture and sustainability have emerged as key subjects.

As technology has developed and our daily lives have become more information-driven, anyone can now access any type of information from anywhere at any time using a basic computer or smartphone. Additionally, devices and technology are being used in previously unheard-of activities. The proliferation of low-cost, compact gadgets that can gather vital data and are linked to the Internet has made this transformation feasible. The Internet of Things (IoT) may be created by combining various technologies via these devices. Precision farming, which can be used in conjunction with IoT to offer users a variety of benefits and solutions, including the ability to connect multiple IoT devices, send data, and manage data via web pages or mobile applications, was a major factor in the growth and achievement of IoT solutions. In order to ensure the health and quality of the fields, agriculture requires the proper management of water in order to produce a profitable crop. Since people are still managing the water resources, mostly via trial and error, the process produces complicated and imprecise outcomes. Utilizing sensors and real-time data enable efficient use of water, protecting an increasingly finite natural resource while also fostering a more sustainable farming method with improved agricultural conditions and lower farmer expenses. Given this, the technology described in this study has the potential to improve irrigation's sustainability and efficacy in agricultural areas. The system adapts automatically to the unique requirements of the region by using artificial intelligence and learning algorithms.

It is feasible to enhance the watering system and provide the proprietor with one that necessary data, for example, ideal period of day to water, by instantly gathering updated data from the field in real-time. By using this strategy, farmers may learn more about their fields and save money on maintenance and water. The highlights of the advancements that have previously been documented in the literature are provided after this introduction. These include the use of machines for learning and water conservation in agriculture, as well as our previous studies. The architecture of the system, which comprises every piece of gear, program, and educational system components, is then thoroughly explained. There will be a presentation of an investigation of machine learning methods, including the instruction procedure along with a detailed examination of various irrigation methods. A description of an actual case implementation situation is given, together with the findings and a discussion. Lastly, the outcomes of the implementation, the machine learning research, and the system architecture are shown. The world's freshwater supplies are being rapidly depleted as a result of rising global population, climate change, and increased industry. Remarkably, scientists project that 9.7 billion people, or 52% of the world's population, would live in areas with little or no access to water in 2050. In this context, the development and application of sustainable water management strategies is required due to health, environmental, and social considerations.

II. RELATED WORK

This article describes the SWAMP construction, system rollouts and platforms with a focus on the platform's replicability. It also does an evaluation of the efficiency of the platform-integrated software components scalability is a crucial component for Internet of Things applications. The findings show that it can perform well for the SWAMP prototypes; nevertheless, to obtain more scalability with less computing resources, certain components need to be re-engineered and specifically designed configurations need to be implemented [1].

The authors of this article conduct a comprehensive systematic review of machine learning (ML) implementations within the domain of agriculture. The primary areas of emphasis include the forecasting of soil parameters, including moisture content and organic carbon, the identification of species, the forecasting of agricultural production, and the finding of pests and illnesses in crops. For the purpose of crop productivity additionally assess quality, research is conducted on the arrangement of a distinct collection of cropped pictures using computer vision and machine learning approaches. By utilizing collar sensor data to inform ML models that predict fertility patterns, diagnose feeding disorders, and analyse cattle behaviour, among other things, this strategy can be implemented to increase livestock production. Intelligent irrigation techniques, such as trickle irrigation and intelligent harvesting methods, which significantly reduce human labour, are also examined. This article illustrates the potential of knowledge-based agriculture to enhance both the quality and sustainability of agricultural products [2].

This paper examines the broad use of artificial intelligence techniques in sensor data analytics for agriculture. A case study of an Internet of Things (IoT) intelligent farm prototype that combines water, energy, and food systems is also presented [3].

This study proposes a survey on precision agricultural monitoring strategies using drones with multispectral, thermal, and visible cameras. Key limits and flight criteria are outlined for each application [4].

This research examines the significance of sensors in precision agriculture (PA) and the role of wireless sensor network (WSN) technology in remote monitoring across different applications in the agricultural industry [5].

This research offers helpful advice on the technical features of UAVs that are often used in the public administration sector. This document facilitates the selection of the most appropriate Unmanned Aerial Vehicles (UAVs) Featuring on-board sensors for a range of farming duties while considering all possible constraints. More than one hundred research articles were examined atop the use precision agriculture using UAVs (PA) and one that real-world challenges associated with mapping and monitoring field crops. In conclusion, we offered recommendations and proposed future strategies to address the difficulties in enhancing operational efficiency [6].

Precision livestock farming (PLF) uses automated monitoring of individual animals to optimize animal development, milk production, illness diagnosis, and monitoring of animal behaviour and physical surroundings, among other applications. The aim in order to present a

brief summary of the latest scientific and technical advancements in precision agriculture (PA) and their application to crop and animal production. It serves as a valuable research tool for both researchers and farmers looking to incorporate technology into their agricultural practices. Further investigation is required to ensure the accuracy and feasibility of the created systems for commercial implementation in PA applications, which involves several procedures and approaches [7].

III. METHODOLOGY

A. System Architecture:

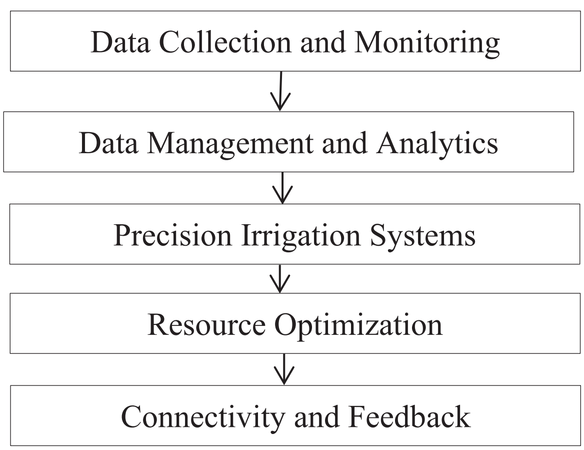

Fig. 1. Architecture of water management system

To facilitate the transmission of information, it was imperative to establish many nodes, each dedicated to a certain duty, so forming a Wireless Sensor Network (WSN) with a star topology. This configuration enables seamless sharing of essential data among the nodes. The system needs an aggregate node for network administration and server connectivity, multiple data-gathering sensor nodes gathering, and a point of actuator for irrigation system Turn it on or off control.

Even though each node is unique, they all need a few basic parts to operate, such as the communication module and microcontroller that enable communication within the outdoors network. As a result, each node has a common base comprised of an RFM95W LoRa transceiver, an ESP32, Express if dual-core microcontroller, and other components. The LoRa protocol has been used for the communication module to facilitate interaction among all network nodes. Based on the benefits of the protocol, including its extended range, low power consumption, cheap device cost, as well as support for bi-directional communications, this decision was made. With a power consumption ratio as low as 70 mA, the RFM95W module allows for long-range communication at a distance of up to 2 km.

Understanding the fundamental structure of this system and its requirements, the following subsections provide a description of each of the constructed nodes, including their composition, duties, and characteristics.

Aggregation Node:

The Aggregate Node oversees enabling data interchange inside the network between the server and the other two types of nodes. The node's main components consist of an ESP32 and an RFM95W LoRa module, which provide message exchange across network nodes. Additionally, MQTT was used to establish communication with the server. MQTT requires a connection to the internet to function, additionally in this case, a protein-based remedy proved to be one that most practical choice. Due of the growing coverage in Portugal, NB-IoT technology was used for this case. This technology was specifically designed to facilitate the transmission of little data packets across a mobile network, enabling internet connectivity for small devices worldwide. The SIM7000E modules was connected to the aggregate node in order to provide NB-IoT Internet connectivity. This module has the capability to operate via either internet of things (IoT) or 2G cellular networks. The use of 2G technology in this module offers benefits due to the limited network coverage often seen in agricultural regions.

Sensor Node:

In other words, sensor nodes imply, are connected to which interfaces between sensors and are in charge of gathering field data. These nodes must contain sensors to gather information; a LoRa radio module for transfer sent the gathered information to the Aggregation Node, a control panel, and an electrical source. This microcontroller, the ESP32, like the Aggregation Node, is used to manage every of each unit. Unlike the Node for Aggregation, which must constantly be listening, this node may utilize an ESP32 power-saving mode features to conserve power, as the timed value collection allows the node to enter a deep sleep state. while waiting between collections. As previously described, an RFM95W radio is utilized to relay the gathered data to an Aggregation Node via LoRa.

- A temperature sensor (SI7021) and humidity monitor that may collecting humidity and temperature measurements to a high degree accuracy (±3%RH, ±0.4 C), in a temperature range of 40 C to 125 C and humidity values of 0 to 100%.
- Capacity in Analogue Ground Water Level is an impermeable sensor for humidity capable of collecting data with high accuracy. Capacitive sensing was used to create this collection.

A collection is conducted every 10 minutes to maintain the data of the field under investigation up to date. To preserve the power source for the node between collections, the electrical circuit is put When in Deep Sleep mode, the amount of energy used is lowered up to 100 µA.

Actuator Node:

The responsibility of acting was with the Actuator Node. based on the information acquired via the Sensor Node. This link is made up about a microcontroller, an A LoRa radio module called ESP32, an RFM95W, a pumps for irrigation and a meteorological station. As previously stated, The RFM95W is anticipated to in charge of swapping communications interconnected nodes as well as receiving instructions for irrigation at the Aggregation Node, and transmitting this present condition in every pump.

The microcontroller is going to get irrigation revisions and processing of messages to regulate a system of pumps throughout one that required period in all cases area. In addition, linked towards a meteorological station, the SEN 0186, which will be is able to gather data on wind speed, heading of the wind and the likelihood of precipitation. There is a lack of linked reaching a sensor node because they must continually gather data and are unable to function with batteries.

B. Data Collection

1) Deployment of Sensors and Network Creation:

In the first step of our technique, we methodically place sensors and construct a Wireless Sensor Network (WSN) to collect critical data for sustainable water management in precision agriculture. This entails identifying and deploying sensors capable of detecting crucial elements such as soil and air conditions, precipitation, wind direction and speed. The careful deployment of these sensors around the agricultural site, taking into consideration topographical peculiarities and crop distribution, enables full coverage. Simultaneously, a strong WSN is constructed to permit smooth communication between the installed sensors, enabling real-time data collecting and adding to the efficacy of precision agricultural operations.

2) Transmission and Aggregation of Data:

Once the sensors have been deployed, the collected data is transmitted and aggregated in order to form an all-encompassing dataset. This entails the deployment of streamlined data transmission protocols, such as MQTT or CoAP, in order to enable uninterrupted communication between the central data repository and the sensors. When aggregation techniques are utilized concurrently, data from numerous sensors are merged to produce a unified dataset. Through the integration of data from diverse sources, these methodologies furnish a comprehensive perspective of environmental circumstances, thereby facilitating a more intricate comprehension of the agricultural terrain.

3) Dataset Description

The dataset, which serves as a foundation for subsequent analyses, comprises 105,217 entries that have been carefully curated to include essential parameters that are fundamental to precision agriculture. The dataset is organized in a comprehensive framework that integrates temporal variables such as Year, Month, Day, and Hour. This configuration enables the documented observations to be situated within a temporal context. In addition to the aforementioned factors, the dataset is further enhanced by several different environmental variables, such as weather conditions (such as temperature, humidity, precipitation, wind speed, and direction), and soil moisture. This exhaustive compilation of parameters provides not only a temporal snapshot but also an all-encompassing analysis of the environmental factors that impact the precision agriculture domain. This dataset's temporal and environmental interactions serve as the foundation for a nuanced investigation and evaluation of elements that are vital for sustainable whereas precision farming makes effective use of water.

The data analysis in the context of improving irrigation efficacy via an IoT and WSN system entails pre-processing information obtained from deployed sensors. Cleaning and refining sensor data to handle outliers as well as missing values is part of this process. The investigation is centered on constructing and training a machine learning models that uses past sensor data to forecast the ideal watering hour. This model, which is linked into the irrigation management system, allows for exact water amount regulation in real time. Continuous feedback loops guarantee that the machine learning model is constantly refined, leading to a self-governing system that maximizes irrigation efficiency in agricultural regions.

4) Data Pre-Processing

The following phase consists of thorough data pre-processing in order to adequately prepare the sensor data for efficient analysis and model training:

- **Handling Missing Values:** To ensure a full dataset, identify and fill in any missing values in the sensor data using imputation methods like mean, median, or regression imputation.
- **Outlier Identification and Removal:** To identify and appropriately eliminate outliers in the sensor data and minimize their influence on further analysis, use statistical or visualization approaches.
- **Data Formatting and Consistency:** Make sure that all data formats are consistent, fixing any problems that may arise from mismatched data types, inconsistent date formats, or irregular formatting for a dataset that is standardized.
- **Duplicate Removal:** To avoid duplication and ensure that every data point is distinct, remove duplicate entries from the sensor data. This will increase the dataset's dependability.
- **Feature Engineering:** Utilize feature engineering to generate new features that might improve the machine learning model's accuracy and collect pertinent data.
- **Normalization/Scaling:** To avoid certain characteristics from predominating because of their scale, normalize or scale numerical features within the sensor data to a consistent range.
- **Temporal Alignment:** To preserve the temporal context necessary for irrigation forecasting, make sure the sensor data is temporally aligned while taking the chronological order of observations into account.

C. Train-Test Split

We seamlessly incorporate the crucial train-test split after completing the critical sensor data preparation procedures in our work on boosting irrigation effectiveness using an IoT and WSN system. The pre-processed dataset is broken down into multiple settings for training and testing in this split. We use the scikit-learn toolkit to train the machine learning model using 80% of the data, denoted by 'X_train' for features and 'y_train' for related target variables. The remaining 20%, labelled as 'X_test' and 'y_test,' is the unaltered testing set used to assess the model's performance. This intentional separation guarantees that the model is exposed to a varied collection of data during training while still retaining an independent sample for rigorous assessment. This split then serves as the foundation for choosing models, testing, validation, and training, all of which contribute to the construction of a robust and successful irrigation optimization system.

Following the completion of the train-test split, the next phases entail the creation as well as training for models that use machine learning using the training set.

D. Machine Learning model development/ Selection

1) Feature Selection: Before training the model, you may do further analysis on the training set to improve the feature set. The goal of feature selection is to improve the model's prediction skills by concentrating on the most important variables.

2) Model Selection: Given the variety of models available to you, each with its own set of strengths and limitations, you'll need to carefully choose the best algorithm for your assignment. Each of the 4 models—Random Forest, the Decision Tree, SVM, & Neural Networks—brings something unique to the table.

- **Random Forest:** A tree-based algorithm known as Random Forest (RF) approach for classification and regression that combines numerous self-determining decision trees. It is possible to identify which is the best alternative by combining the many trees, with the primary goal being to achieve a single node in pure generated to just one category, bestowing onto it great forecast skills.
- **Decision Tree:** Decision Trees (DT) are based on trees. approaches wherein every route starts with a base node indicating a series of divisions in data and

progresses to a leaf node expressing a Boolean conclusion. These approaches may be used for categorization as well as regress. This method's ultimate objective in order to create one that is capable of anticipate the worth of the search for that particular circumstance via study basic principles for making a choice.

- **Support Vector Machines:** Support Vector Machines (SVMs) is a family of supervised neural networks algorithms created while dealing with outliers, regression, and classification identification. They are well recognized for their great effectiveness in large dimension spaces and their usage for training points in decision functions, as well as their memory efficiency.
- **Neural Networks:** One supervised learning approach is the Multi-Layer Perceptron (MLP) technique, which trains on a dataset to learn a function f(.): R m R o. was used for one that study of brain network algorithms, which are computer representations of the neurological system. Because of their versatility, these MLP networks adaptable, rather than linear. The intricacy of may be modified depending on the request made by adjusting how many levels alongside units in on every level.

E. *Model Training*

Training the model is a crucial part of the computer science model. The model is exposed to a labelled dataset throughout this phase, where it learns patterns and correlations between input attributes and related outputs. To minimize the discrepancy between its predictions and the actual labels in the training data, the algorithm repeatedly changes its internal parameters. This method allows the model to generalize its learning and generate accurate predictions on fresh, previously unknown data. The efficacy of the trained model is often evaluated using a different validation dataset to verify that it outperforms the data on which it was trained. Iterative training strives to improve the model's capacity to capture complicated patterns and make educated judgements in the environment for which it is created.

F. *Model Evaluation*

Following, the model is evaluated to determine its performance on fresh, previously unknown data. Metrics like as accuracy and precision are used in a different validation set to test its performance in real-world circumstances. Based on these findings, fine-tuning may be performed to optimize the model for a variety of applications.

1) *Accuracy:*

Accuracy is a straightforward measure that estimates how often a classifier produces correct predictions.[8] The statistic used to measure accuracy is the percentage of accurate forecasts relative to the overall forecasting capacity made by one that model.

$$Accuracy = \frac{TP + TN}{S} \tag{1}$$

2) *Precision:*

Accuracy is achieved by dividing accurately categorized occurrences with relation to the sum of all cases that have been classified [9].

$$\Pr ecision = \frac{TP}{TP + FP} \tag{2}$$

3) *F1-Score:*

The F1 indicator is computed by taking a harmonious average of the remember the details accuracy scores, which serves as the measure of variability[10].

$$F1 = \frac{2 * \Pr ecision * \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \quad .(3)$$

IV. RESULTS AND DISCUSSION

A. *Evaluation model*

The findings section offers a thorough analysis and assessment of the applied strategy for conserving water in precision agriculture, representing the pinnacle of the meticulous methodology used in this research. As per figure-2 the research attempts to find insights that help improve irrigation efficiency by using machine learning models, preparing the data, and collecting it all with great care. The results of algorithm for machine learning—decision tree, Random Forest models, Machines that Support Vectors, & Neural

Networks—will be shown and discussed in detail in this section. The main objective is to evaluate the predictive power, effectiveness, and overall efficacy of these algorithms in predicting the best time to water crops. The findings will clarify the applicability and effectiveness of the chosen machine learning approach in precision agriculture, with important ramifications for the development of self-sufficient and environmentally friendly irrigation techniques.

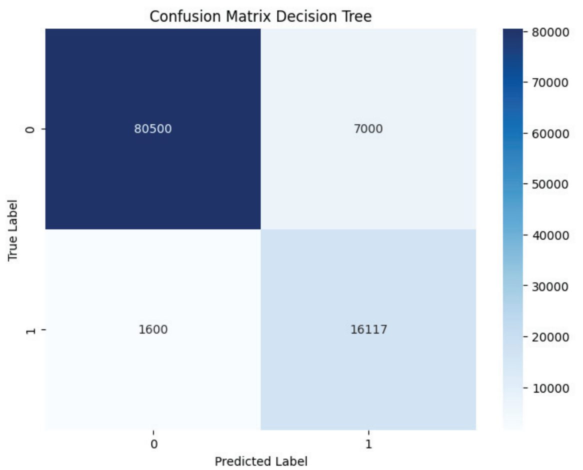

Fig. 2. Confusion matrix of Decision Tree

A thorough analysis about the Decision Tree model indicates an impressive precision of 91.83%. This precision indicates how well the algorithm can identify situations as either irrigation-friendly or unfavorable. In particular, the model obtains a True Positive (TP) count of 80,500, which means that it correctly identifies situations in which irrigation is beneficial. On the other hand, the model reports 7,000 False Positives (FP), or cases that are mistakenly classified as favorable. In addition, 1,600 False Negatives (FN) correspond to cases that were mistakenly classified as unfavorable. Positively, 16,117 cases are accurately identified by the model as non-favorable (True Negatives, TN). The present study offers a thorough examination of the TP, FP, FN, and TN values. The research sheds light on the Decision Tree model's strengths and possible areas for improvement in precision agricultural applications.

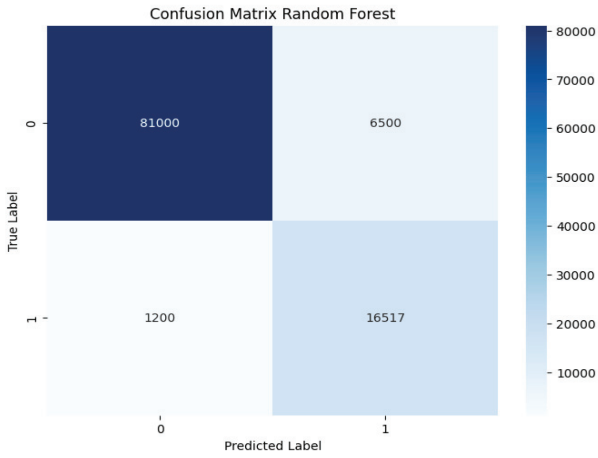

Fig. 3. Confusion matrix of Random Forest

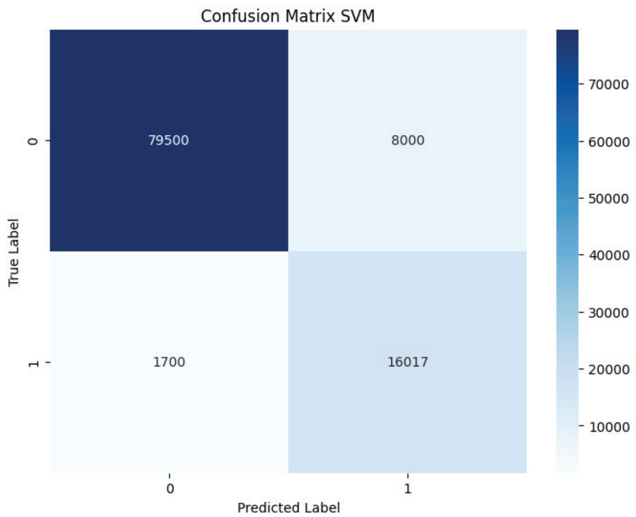

Fig. 4. Confusion matrix of SVM

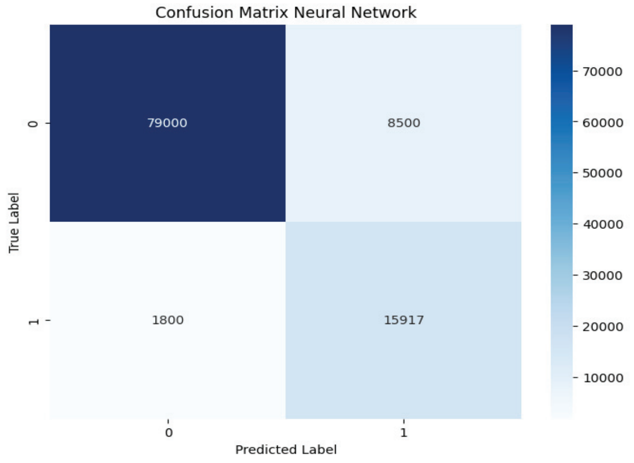

Fig. 5. Confusion matrix of Neural Network

In terms of irrigation favorability prediction, mentioned in figure-3 the model known as Random Forest performs well, with an astounding precision of 92.68%. A significant True Positive (TP) score of 81,000 in the detailed breakdown indicates accurate identification of situations when irrigation is beneficial. But the programmed also records 6,500 Irrespective Results (FS), which are instances when the errors occurred identified as favorable. There are also 1,200 Not True Results (FN), which are instances of cases it happened to be erroneously classified as unfavorable. Positively, 16,517 cases are accurately identified by the model as non-favorable (True Negatives, TN). In the context of precision agriculture, this detailed evaluation which takes into account TP, FP, FN, and TN values offers a thorough grasp of the advantages and shortcomings of the

Random Forest model and contributes to continuous attempts to maximize irrigation efficiency.

The Support Vector Machine or SVM model in figure-4 is able to predict irrigation favorability with a noteworthy accuracy of 90.78%. A true positive (TP) count of 79,500 is included in the comprehensive breakdown of performance measures, demonstrating precise identification of situations when irrigation is beneficial. 8,000 conflicting results, however, indicate that one that model has mistakenly forecasted 8,000 cases as favorable. 1,700 False Negatives (FN) are also included; these are cases when the prediction was incorrectly made that the outcome would be negative. Positively, 16,017 occurrences are accurately classified as non-favorable by the model (True Negatives, TN). This thorough study, which takes into account the values of TP, FP, FN, and TN, contributes to continuing efforts to maximize irrigation efficiency by illuminating the advantages and potential areas for development of the SVM model in precision agricultural applications.

As shown in figure-5 confusion matrix of neural network, performance is moderate as compare to SVM.

Performance Metrics:

TABLE I. PERFORMANCE METRIC

Models	Accuracy	Precision	F1-Score
Random forest	0.9268	0.9213	0.9239
Decision Tree	0.9183	0.9107	0.9145
SVM	0.9078	0.9086	0.9032
Neural Network	0.9021	0.9027	0.8973

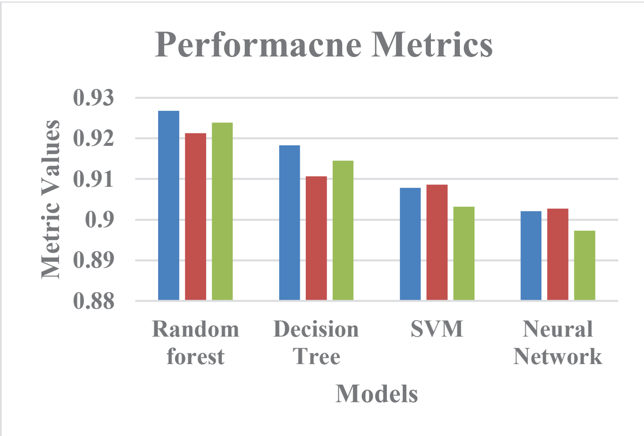

Fig. 6. Comparisons of Performance Metrics of the Models

The show metrics on the several predictive models in figure-6 for machines—Random Forest, the Decision Tree Model, SVM, and Neural Network—are compiled in the table. Interestingly, Random Forest is the most accurate at 92.68%, demonstrating its ability to forecast ideal irrigation conditions. As per table 1 Decision Tree comes in second with 91.83% accuracy. Further evaluation of these models is done in terms of accuracy and F1-Score, where Random Forest consistently performs better than the other models on all analyzed criteria. This brief summary makes it easier to determine each model's relative efficacy for precision agricultural applications in a hurry.

V. DISCUSSION

Important new information is revealed by the assessment of machine learning algorithms for precision agriculture's prediction of ideal irrigation conditions. With the maximum accuracy of 92.68%, the Random Forest model is the most reliable performer, demonstrating its efficacy in making precise predictions. With an accuracy rate of 91.83%, the Decision Tree approach closely trails, exhibiting good predictive power. Even while Machine Learning using Support Vector (also known as support vector machines (SVMs) and neural networks models perform admirably, their accuracies are a little bit lower at 90.78% & 90.21%, respectively. The Random Forest model's better predictive potential is further validated by the accuracy and F1-Score measurements. These results imply that Random Forest's ensemble learning technique is useful in identifying ideal irrigation conditions, which makes it a viable option for precision agriculture's water management strategy optimizations. For practitioners looking for effective and dependable models to improve agricultural practices' productivity and sustainability, the research offers insightful information.

VI. CONCLUSION

Several important results were drawn from the thorough investigation and assessment of machine learning algorithms for precision agriculture's prediction of ideal irrigation conditions. When comparing to other models like Decision Tree, SVM, & Neural Network, the Random Forest approach shows the highest level of accuracy (92.68%), making it the most effective and promising option. This great accuracy suggests that the model is capable of accurately determining the ideal irrigation conditions, which is a crucial component of precision agriculture.

Even with its little lower accuracy of 91.83%, the Decision Tree approach performs well, suggesting that it may be a viable option. Despite attaining accuracy rates of 90.78% & 90.21%, respectively, SVM along with neural network models demonstrate competitive performance, indicating their possible use in certain scenarios.

The Random Forest model is better because of its focus on accuracy, which is further supported by the precision metrics and F1-Score. In agricultural contexts, minimizing false positives & false negatives is critical for optimizing irrigation techniques. This ensemble learning methodology shows promise in this regard.

The study's conclusions emphasize the use of machine learning in precise agriculture, particularly with regard to water management. The aforementioned models provide significant assistance in forecasting ideal irrigation circumstances, hence supporting the overall objective of sustainable and effective farming methods. With its exceptional precision and accuracy, the Random Forest algorithm shows out as a very appealing option for making irrigation decisions in real time. This study offers insightful information that may help academics and practitioners use machine learning to improve agriculture's sustainability and accuracy.

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