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Sustainable Smart Irrigation in Precision Farming using IoT

Jagtap Sharad Sarjerao
Electronics and Communication
Bharat Institute of Higher Education and Research, Chennai, India
Anantrao Pawar College of Engineering and Research,
Pune, India
sharadjagtap0710@gmail.com

Dr. G. Sudhagar
Electronics and Communication
Bharat Institute of Higher Education and Research,
Chennai, India
sudhagar.ece@bharathuniv.ac.in

Rahul Namdeo Jadhav,
Electronics and Communication
Bharat Institute of Higher Education and Research, Chennai, India
AISSMS Institute of Information Technology,
Pune, India
jadhavrn@gmail.com

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***Abstract*—The current paper applies computational models based on machine intelligence to enhance the application of water in precision agriculture. This is to establish a reliable tool that can predict the most appropriate ambience of watering, hence enhancing sustainability. It includes what is referred to as sensor integration, and the establishment of a wireless sensor network (WSN). It gives analysis of a well-chosen data log containing essential sensor values like soil moisture, rain, humidity, wind speed and temperature. This paper work elaborates stages of Signal pre-processing, signal conditioning, training and testing performed for available stored dataset. Through the given 105,217 record dataset, smart irrigation accuracy compared using the support vector machine (SVM), random forest, decision tree, artificial neural network as well as other machine learning modes. Database are first trained then evaluated and finally samples are tested. The results of the current study depict that the random forest model is comparatively accurate than the other models with an accuracy of 92.68%. The second best performing method, which is only marginally less accurate than the random forest is decision Trees, with a success rate of 91.83%. SVM and neural network models also gave fairly good performance with accuracy of 90.78 and 90.21 respectively. The random forest model's accuracy in forecasting ideal irrigation conditions which 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*— *Support vector machine, random forest, decision Tree, wireless sensor network, Sustainable Water Management, Precision Farming, Smart Irrigation

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[1]. 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[2].

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 an internet of things. 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. Through these devices technology might be developed that will lead to has development of IoT[3]. Use of IoT in smart farming plays very crucial role which always helps for proper water management. With the help of IoT devices one can perform information transfer, information regulation by means of web pages or applications for portable devices[4]. The water management is one of the preconditions required for the health and the quality of the fields. However, the role of precision farming is overbearing to make the agriculture and this kind of crop financially viable. It means that people still engage with the management of water on relatively traditional, basic and mostly post-non-scientific levels, which results in loose and unrefined practices. Proper watering of crops can be facilitated or in other words, wastage can be prevented. Water being a natural resource and farmers require solution at a considerably lesser cost[2]. 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 possible to improve the watering system and inform the owner about other important factors e.g. the best time to water management done by using the collected practical data concerning the specific location in the field[5]. By using this strategy, farmers may learn more about their fields and save money on maintenance and water.

The detailed description of the system architecture follows, whereby all the hardware, software and the working systems are described. There will be a presentation of a study of machine learning techniques, the training procedure as well as the analysis of these techniques for irrigation[7], [8]. 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[9]. In this context, the development and application of sustainable water management strategies required due to health, environmental and social considerations[10].

II. RELATED WORK

The highlights of the advancements that have previously been documented in the literature are provided in this section. These include the use of machine learning and water conservation in agriculture [6].

R. Yacouby and D. Axman provides information on the swamp construction platform of farms and system with specific attention given to replicability of the unit[10]. It also examines how it performs the FIWARE components i.e. open source smart solution technique used in the Platform. Scalability is a critical factor in Internet of Things applications. The findings show that it can perform well for the swamp prototypes. To obtain more scalability with less computing resources, certain components need to be re-engineered and specifically designed configurations need to be implemented [1].

Another article presents 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[10]. This article elaborates identification of species, the forecasting of agricultural production, and the finding of pests and illnesses in crops. To track the efficiency of crops grown and analyse the quality, the work is carried out on identifying a specific set of crop images using computer vision and machine learning. Using colour sensor data for linear regression models of fertility patterns, feeding disorders' diagnosis, cattle's behaviour, and others, this strategy can be applied to enhance the level of livestock production[8]. Drip irrigation and other smart ways of watering crops together with smart ways of harvesting that eliminate the use of manpower are also described. To sum up, this article shows that concepts of knowledge-based agriculture can contribute to the improvement of such agriculture's quality as well as to making it more sustainable [2].

Hence, this paper explores the general employment of artificial intelligence approaches in sensor data processing for agriculture[4]. This paper also presents a scenario of Internet of Things (IoT) intelligent farm prototype for water, energy and foods [3].

The questionnaires of this work include the one related to the monitoring of precision agriculture utilizing airborne platforms featured with visual cameras which are thermal or multispectral. In each case, application key limits and flight criteria are defined [4].

The role of sensors in precise agriculture and wireless sensor network with its application on the areas of agriculture are discussed in this article [5].

This research provides useful recommendations concerning the technical aspects of the unmanned aerial vehicles (UAV), which is a common tool in the sphere of public administration. This paper helps in identifying the right Unmanned Aerial Vehicles (UAVs) Featuring on-board sensors for various farming tasks and at the same time taking into account all the constraints. More than one hundred research articles were examined based on the applications of Unmanned Aerial Vehicle UAVs in precision farming[11], [12]. The 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[11], [12]. The purpose of this research is to create a detail overview in 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 various applications, which involves several procedures and approaches [7].

III. METHODOLOGY

System Architecture:

To facilitate the transmission of information, it was imperative to establish many nodes, each dedicated to a certain input, so forming a wireless sensor network (WSN) with a star topology[13]. This configuration enables seamless sharing of essential data among the nodes. The system needs an aggregate node for network administration and server connectivity, various nodes of sensor for information gathering and other node of an actuator for irrigation system are used for switch control[5].

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[14]. As a result, each node has a common base comprised of long range (LoRa) transceiver and ESP32 or dual-core microcontroller and other interfacing 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 the power consumption ratio of 70 mA, the RFM95W module enables to establish wireless communication with the maximum distance of up to 2km.

Aggregation Node:

The Aggregate Node is responsible for the establishment of data exchange within the network with the server and the other two types of nodes. The node's main components consist of an ESP32 module and RFM95W LoRa module, which provide message exchange across network nodes[10]. Additionally, message queuing telemetry transport (MQTT) was used to establish communication with the server[16].

MQTT uses an internet network connection to function remote monitoring and its remedy proved to be the most practical choice for implementation of server with nodes interfacing. Due of the growing coverage in Portugal, narrowband internet of things (NB-IoT) technology was used for precision farming. 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[9]. This module has the capability to operate via either NB-Internet of Things as well as 2nd generation mobile technologies. The use of 2G technology in this module offers benefits due to the limited network coverage often seen in agricultural regions[17].

Wireless Sensor Nodes:

Sensor Nodes are termed as such due to the fact that these nodes are direct interfaces to sensors and are responsible for collecting field data. These nodes have to include sensors to collect data, an integrated LoRa radio module for the transmission of data to the control board, and a power source. Similar with the aggregation node (AN), the ESP32 microcontroller is used to control the all of the modules[16]. While the AN must always be listening, this node might employ the ESP32 deep sleep to save energy as the collection of the values is at specific intervals and the node can be in deep sleep while waiting for the next interval. It's configuration has already been explained in the previous section, an RFM95W radio is used to transmit the collected data to an Aggregation Node through LoRa [9].

SI7021, a temperature and humidity sensor whose precise temperature and moisture measurement include temperature accuracy of + -3%RH and + - 0. 4 C when operating within a temperature of 40 C - 125 C and moisture measurement accuracy of 0-100%[18].

Another sensor used to measure analogue soil moisture is a humidity waterproof sensor which is very accurate in data collection. Using capacitive sensing, this collection was built.

Data erasing is carried out after five minutes to ensure the set data of the field under study is updated in every ten minutes. To save the battery technique in which battery precisely used to power the node before the next collection is made, the circuit is put in deep sleep mode in which the power consumption is set to 100µA[17], [19].

Actuator Node:

The task of the actuator node was to perform the action that came with the data received from the sensor node. This node consists of a microcontroller that is the ESP32, a LoRa communication module that is the RFM95W, a weather station and irrigation pumps. RFM95W will be responsible for sharing the pertinent communication for the given node as well as the aggregation node[16]. It helps in receiving irrigation commands and transmitting the status of each pump.

Irrigation updates messages will be send by the system to the microcontroller where the microcontroller will in turn process the messages to adjust the pumps for the necessary period for each zone[16]. It will also be hooked to a weather station the SEN0186 and this will be able to provide information of wind speed, direction and precipitation. These sensors are not connected with a Sensor Node since they require to collect data all the time and cannot work with batteries[9].

A. Data Collection:

1) Deployment of Sensors and Network Creation:

In the first step of this smart technique, systematically, sensors are planted and wireless sensor network (WSN) is formed to collect important data for sustainable water management in precision agriculture. This involves searching for and using sensors that would measure other aspects that include the soil and air, amount of rainfall and wind direction and its velocity[13], [16]. The use of these sensors around the agricultural site, ensuring that every area of the site is covered with the sensors' field of vision necessarily factors in topographical nuances in the layout of the crops to be planted. At the same time, firming up WSN is carried to allow for easy interaction between installed sensors for real-time data collection and improving precision farming activities[10].

2) Transmission and Aggregation of Data:

After the sensors have been put in place, the data generated is transmitted and integrated to constitute a holistic dataset. This implies the use of efficient transfer protocols like MQTT or constrained application protocol (CoAP) to ensure intermittent linkage between the central database and the sensors[17], [20]. When the above aggregation techniques are applied, several data collected from sensors are integrated into one data set. These methodologies provide a more complex understanding on the agricultural field through giving detailed view on the environmental situation and the gathered data from various sources are integrated[8], [21].

B. Dataset Description

The initial source of data on which the further analyses are based is a set of 105,217 records that has been preliminarily compiled so as to contain the most relevant parameters necessary for the functioning of precision agriculture[22]. The type of data is arranged systematically and applies temporal variables including Year, Month, Day, and Hour in its structure. This configuration helps to maintain record with documented observation in timely perspective. The same needs to be complemented by other environmental parameters such as temperature, humidity, rainfall, wind speed, wind direction and moisture content of the soil, among others[8]. This list of parameters is exhaustive and does not give a mere point-in-time view of the environment that affects the precision agriculture domain but tries to encompass all the parameters that may influence it. Therefore, temporal and environmental interactions of this dataset can form the basis of analysis and assessment of the components that are critical in sustainable and efficient water management in precision agriculture[2], [5].

C. Data Analysis

Data analysis of information collected through the enlisted sensors in the context of enhancing the effectiveness of irrigation by using IoT and WSN are involved in pre-processing of gathered information. Additionally, cleaning and refining of the data acquired with the help of sensors to manage the presence of outliers and missing sensor data is one more step here[13]. The general approach of the investigation is focused on developing a machine learning model, which has to employ the sensor data storage to predict the optimal watering hours. This is integrated with the irrigation management system so that the amount of water can be regulated in a precise manner in real time[10]. Feedbacks ensure that the machine learning model is updated regularly and thus the system is self-governing and enhancing the irrigation systems in the agricultural areas[9].

D. 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: It is essential to examine and possibly complete any values out of range because of missing or broken sensors and compute by using mean, median and regression[9].

- Outlier Identification and Removal: For the outliers' detection and exclusion in a proper manner in correlating with further analysis, one can use the mere statistical and visualization methods.

- Data Formatting and Consistency: Ensure that all sorts of data feed into the method are standardized for an output that is pre-cleaned and ready for analysis. There is a conflict in the data structures, fix every issue that stems from different data type, date format or other irregularities in a normalized dataset[19].

- Duplicate Removal: This will eliminate the problem of having two records of the same data in the database which wastes database space. To ensure every record is unique, its required to remove duplicates in the sensor data[23]. This will improve the dependability of the dataset as well.

- Feature Engineering: Employ feature engineering to create other features that could enhance the feature set that are feeding into the machine learning model and gather relevant information[24].

- Normalization/Scaling: To ensure that some characteristics do not dominate due to their range, standardize or normalize numerical features in the sensor data is in accordance with the same scale[11].

- Temporal Alignment: To maintain the temporal context that is required in irrigation forecasts, the sensor data should be aligned temporally yet the chronological order of observations is important.

E. *Train-test split*

In this paper seamlessly incorporated the crucial train-test split after completing sensor data preparation procedures. In this work irrigation improves effectiveness of using an IoT and WSN system. In this split, the pre-processed dataset is classified into many testing as well as training sets. Subsequently, we trained the machine learning model using 80% of the data applying the scikit-learn toolkit's feature dataset variable named X_train and the related target variable named Y_train[25]. The remaining 20% of data are original testing samples named 'X_test,' 'Y_test.' This unavoidable isolation ensures a diverse set of data is used in training the model while at the same time ensures that a more strict and clean set of data is reserved for testing the model[6]. Then this split provides the basis for the selection of models, further checking, validation, and training – all of these constitute the process of building effective and efficient irrigation optimization system.

The subsequent phases include creating and training of machine learning models using the training set after the completion of train-test split[12].

F. *Selection of machine learning model*

1) *Feature Selection:*

However, before actually training the model, you may want to do additional analysis of the training set in order to enhance the set of features[21], [24]. The goal of feature selection is to improve the model's prediction skills by concentrating on the most important variables.

2) *Model Selection:*

As this depends on the various types of models that are available to learn to find their own strengths as well as their drawbacks. Therefore, selecting the best of algorithm for the given assignment is a challenge. Each of the 4 models—Random Forest, Decision Tree, SVM, & Neural Networks—brings something unique to the table [25].

- Random Forest: random forest (RF) is a tree-based technique where a multiple learning decision trees are combined. It is thus possible to identify which is the best among the many trees with the aim of getting one of pure. A node that is formed by a single class enhancing its skills of prediction[21].

- Decision Tree: It is a family of models which is based on the trees and all tree beginnings has the root that divides the data and all trees have the features which in result gives the leaf nodes with Boolean output[2], [16]. Both, classification and regression may be performed using these approaches. The idea of this method is to develop a model which will predict the search value in such situation with the help of obtaining elementary decision-making rules.

- Support Vector Machines: Basic on classification, regression and outlier detection, the Support vector machines also known as SVMs are a type of supervised machine learning algorithms [24]. Some of the algorithms are quite famous because of their outstanding outcome in large dimension space and for their efficiency in uses of training points in decision functions and memory.

- Neural Networks: The multilayer perceptron (MLP) method is a supervising learning based on the function f (). Various functions are used for the study of the neural network algorithms for the research[25]. They were received by the training on the given data set; neural networks are defined as mathematical models of the nervous system. These MLP networks are also referred to as non-linear, universal, general or flexible and adaptable. Because of their complexity, the discussed structures may be modified in the application by increasing or decreasing the number of layers and units involved[21].

G. *Model Training*

The process of model training is considered as the key phase of the overall machine learning model. Moreover, in this phase, the model is fed to label dataset, thus enabling it to determine aspects such as the links between various inputs and specific outputs. In other words, in order to reduce the gap between the forecasted probability for the training data and the actual labels employs an iterative process of modifying internal settings[21], [22]. This procedure enables the model to extend the learning obtained from known datasets on new which is previously unseen data in order to make precise predictions. The trained model is normally tested with a different validation dataset in order to be sure that it performs much better than the training data. Recurrent training is aimed at enhancing the model's ability to learn complex relations and make rational decisions in the environment [25].

H. Model Evaluation

Subsequently, new unseen data used to assess how the developed model holds up to the new data. As accuracy, precision and different validation set are applied in order to evaluate its real life performance. Consequently, fine-tuning may be done in the perspective of the model's fine-tuning for different purposes.

I. Accuracy

Accuracy is a most simple measure that suggests how often a classifier provides correct labels. [8] The measure of accuracy is determined by the figures arrived at by dividing the number of true positive and true negative predictions by the number of total predictions done by the model.

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

Where S= Total predictions done by model

J. Precision:

It is the genuine ratio of occurrences of accurately classified events to the total number of cases that fit into such classifications [9].

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

K. F1-Score:

The F1 score is obtained by finding the average of the reciprocal value of its two components of the recall and the accuracy scores into one formula that will act as the measure of variability [10].

$$F1 = \frac{2 * \Pr ecision * \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call}$$

F1 is ratio of 2 times product of precision and recall to the sum of precision and recall..

IV. Results

The findings section provides an analysis and evaluation of the applied procedure for saving water in precision agriculture and can be considered as the culmination of a very detailed research approach which was followed in the process of this work. The research carries out a thorough process of gaining insights for efficient irrigation through the models, preparing the data and then collecting it keenly. This section indicates the results of selected Machine learning algorithms, as Random forest, decision tree models, support vector machine and neural networks. For this reason, the primary goal of the study is to assess the performance, efficiency, and reliability of the developed algorithms in achieving the aimed goal of optimal irrigation timing. The implications of the results revealed will be significant for understanding the relevance and efficiency of the selected machine learning concept in precision agriculture as well as for creating new approaches and methods in the framework of self-adequate and eco-friendly irrigation practices.

Looking critically at the decision tree model, the efficiency got revealed to be a highly accurate one with a 91.83%. This precision shows the degree to which the algorithm is capable of distinguishing situations to be either irrigation friendly or on the contrary unfriendly. More specifically, the presented model achieves True Positive (TP) count equal to 80,500. This means that the model 'understands' that precise irrigation is useful in particular cases. Conversely, for this model, the identified 7,000 False Positives (FP) meaning that it wrongly categorizes some negative cases as favourable.

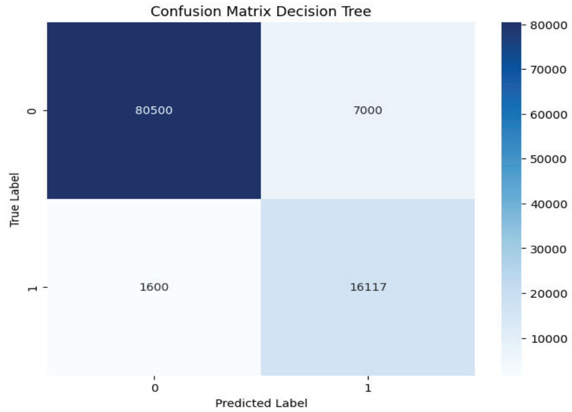

Fig. 1. Confusion matrix of decision tree

Moreover, 1,600 False Negatives (FN) are the cases of the situations that were classified as unfavourable though they were actually favourable or benefited[22]. On the same note, 16,117 cases are correctly diagnosed by the model as non-favourable (True Negatives, TN). The present work provides a detailed analysis of the TP, FP, FN, and TN measures. The findings of the paper reveal the overall effectiveness of Decision Tree model and its limitations when applied to precision agriculture[25].

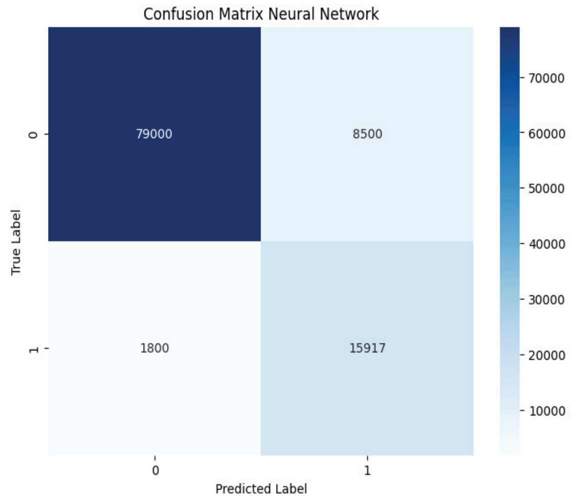

Fig. 2. Confusion matrix of neural network

With an impressive accuracy of 90.21%, the Neural Network model proves to be effective in forecasting irrigation favourability. These are confirmed by a TP total of 79,000 for the broad overview of assessment indices identified as decisive factors for the favourable irrigation time. However, the observation of the model shows that it gives out 8500 False Positive (FP). Those observations that have been classified as Having Favourable Status, Additionally 1800 FN are outputs indicating that the result is unfavourable when the actual is favourable. On the positive side, 15,917 cases are correctly deemed unfavourable by the model, (True Negative TN). With the help of TP, FP, FN, and TN values incorporated in this study, the investigation contributes to the current attempts in enhancing the efficiency of the irrigation system by providing tangible information about the net benefit of the NN model, including its utilization and potential shortcomings in the large system.

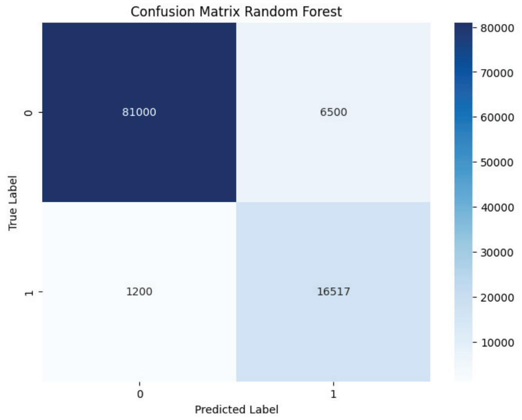

Fig. 3. Confusion matrix of random forest

In terms of irrigation favorability prediction, the Random Forest model performs well, with an astounding accuracy 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 False Positives (FP), which are examples that were incorrectly identified as favourable[25]. There are also 1,200 False Negatives (FN), which are examples of cases that were erroneously classified as unfavourable. On more positive note 16,517 cases where classified as unfavourable by the model are indeed unfavourable (True Negatives, TN).

When used with priority in the field of precision agriculture, this detailed evaluation which indicate TP, FP, FN, and TN values provides a comprehensive assessment of the Reno Random Forest model strength and weakness and benefit to elaborate ways of achieving the best reasonable volume of irrigation[20], [22], [23].

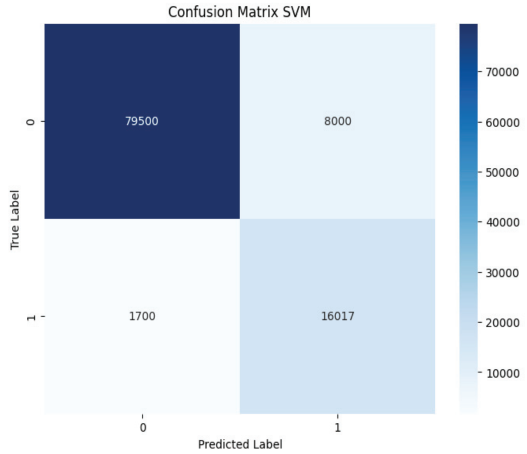

Fig. 4. Confusion matrix of SVM

The Support Vector Machine or SVM model gives a high accuracy in the prediction of irrigation favourability 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 false positives (FP), on the other hand, indicate that the model has mistakenly forecasted 8,000 cases as favorable[20], [21], [23] 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[22], [23].

A. 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

Kaggle database used for this study.

V. CONCLUSION

This article concludes emphasize 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 manuscript offers insightful information that may help academics and practitioners to use machine learning to improve agriculture's sustainability and prediction accuracy.

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