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Hybrid ABC-WOA based Machine Learning Approach for Smart Irrigation System

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Abstract: An important development in contemporary farming methods is the smart irrigation system, which integrates technology to maximize crop productivity and conserve water. Utilizing state-of-the-art technologies like sensors, data analytics, and machine learning algorithms, smart irrigation systems revolutionize traditional farming methods this study presents a novel approach to irrigation prediction that makes use of machine learning algorithms to process temperature and moisture data from the soil. The study's goal was to provide a flexible, reasonably priced autonomous irrigation system for intelligent agricultural management. Finding out how successfully various models predicted the ideal times to irrigate a soil given its features involved assessing and training them using collected data. These models included KNN, Logistic Regression, Neural Networks, SVM, and Naïve Bayes. After a thorough examination, the Support Vector Machine (SVM) model continuously performed better in terms of sensitivity, specificity, and accuracy metrics, with scores of 97.29%, 98.17%, and 97.46%, respectively. Due to its strong performance, SVM is now the most trustworthy predictor for irrigation management, particularly when it comes to controlling pumping operations in response to temperature and soil moisture fluctuations. This method uses real-time environmental data to optimize irrigation systems, which should lead to improvements in resource efficiency and production in sustainable agriculture practices.

Keywords: *Irrigation prediction, Machine learning, Support Vector Machine, Soil moisture, Temperature.*

I. Introduction

The main sector of the Indian economy and its cornerstone is agriculture. In almost every nation, agriculture automation is a hot issue and a developing idea. Every country in the globe has a fast growing population, and this increases the need for food. Farmers are refusing to let those who meet the requirements because of the need for food and customer demand [1].

A smart irrigation system has also been proposed as an IoT-based irrigation system. Irrigation system built in this work uses open-source software to predict a field's watering demands by monitoring several ground characteristics such as moisture in the soil, temperatures, and ambient variables, as well as information gathered from online weather forecasts. In, a deep learning incorporated IoT smart built system was created. In this study, the author presented a deep learning-based irrigation system which can recognize different plant varieties and modify watering requirements for each type of plant appropriately. .. A crop monitoring system linked to agricultural irrigation was developed by the author [2].

Water is a finite and valuable natural resource that has to be carefully planned for, produced, growing needs and limited supply necessitate making the greatest use of the water resources presently accessible at the farm level. In a situation when water is scarce, raising agriculture attended to, controlled, and above all utilized. Due to rising demand to fulfil the demands for food in the future, agricultural yields must rise despite water shortages. Handling the limited water supply wisely is necessary in order to irrigate greater regions with the same amount of water [3].

Water shortage is developing on a worldwide scale, making the achievement of sustainable agricultural output challenging. By 2050, it is anticipated that the lack of agricultural water would get worse Growing needs and limited supply necessitate making the greatest use of the water resources presently accessible at the farm level. In a situation when water is scarce, raising agriculture attended to, controlled, and above all employed. Owing to increased demand in about 80% of the world's nations. This puts food security at risk in addition to the consequences of climate change and competition from other businesses. A little over 70% of freshwater withdrawals are linked to irrigate farming. 9.7 billion People will need to be fed by 2050, and as irrigation generates 40% of the food and fiber produced worldwide, it will be essential to meeting this target. By 2050, irrigation water extraction is predicted to reach 29000 km3, which would cover the majority of the expanding demand in emerging nations, from 20 million hectares under irrigation [4]. The application of smart technology in agriculture holds the potential to address these issues The Internet of Things (IoT), which links different devices to the internet and enables data sharing between them, is one example of this technology. Another technique that enables machines to learn from data and gradually enhance their performance is machine learning. [1].

Numerous research have employed the Internet of Things (IoT) to lessen overwatering. These studies concentrate on smart irrigation methods that predict irrigation requirements using machine learning algorithms and data from soil moisture

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sensors and meteorological sources. Smart irrigation minimizes water loss while maintaining the visual appeal and health of the plants without sacrificing watering efficiency. Therefore, water usage outside can be decreased with the use of intelligent irrigation systems. This method works well for small, medium, and large landscapes, including ones that are professionally maintained. [2].

Table 1comparison of existing studies

Reference	Author/year	Model	Result	Limitations
[3]	Ramya et al., 2020	This system introduced the notion of training an ensemble method in ML with real-time data acquired to produce an optimised conclusion.	This system delivered a low-cost prototype model with sophisticated technical characteristics and a fully working system, with optimal outcomes with 90% accuracy.	The gap of this research is author didn't mentioned about prototype model mixes open standard technology with commercially accessible sensors.
[4]	IORLİAM et al., 2022	According to author the random forest accuracy is more in the ML for the Smart irrigation data for agriculture purpose	The data from Internet of Things-enabled smart irrigation equipment was categorised using four different algorithms: CNN, LR, RF, SVM, and SVM.	This study investigates machine learning techniques for categorising (dividing) data from IoT-enabled smart irrigation equipment.
[5]	Shetty & Smitha, 2021	The classification process uses the artificial algae algorithm (AAA) with the least squares-support vector machines (LS-SVM) model to assess if irrigation is necessary.	The suggested IoT ML-SIS strategy outperformed the other techniques in performance validation, with a maximum accuracy of 0.975.	The experimental findings demonstrated that the IoT ML-SIS approach is a suitable tool for smart irrigation in precision agriculture.
[6]	Optoelectronics, 2023	For accurate decision-making in an irrigation management plan, an LSTM model that learn from a crop recommendations dataset has been constructed.	The experiment findings show that the LSTM model was trained with an accuracy of roughly 96.98% for irrigation decision-making.	LSTM models are used as a spot interpolation technique for crop water need prediction using data from a current network of smart irrigation.

A. Research Gap/ Problems Identified:

The research highlighted in the four studies demonstrates the effectiveness of various machine learning models for smart irrigation systems. However, a prominent gap across these studies is the limited exploration or explicit mention of feature selection methodologies. Feature selection plays a pivotal role in enhancing model performance by identifying and utilizing the most relevant data attributes for predictive accuracy. Despite achieving impressive accuracies ranging from 90% to 97%, the studies fail to delve into the critical process of feature selection. Neglecting this aspect could lead to potential issues such as overfitting, increased computational costs, and suboptimal model generalization. Future research in this domain should focus on a comprehensive investigation of feature selection techniques specifically tailored for smart irrigation systems. By integrating robust feature selection methodologies, researchers can potentially improve model interpretability, efficiency, and overall performance, thus contributing significantly to the advancement and reliability of smart irrigation technology.

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Organization of the study

The following part is how the paper is structured:
The method for artificial algae (AAA) using least squares-support vector Studies that are pertinent to the topic of machine learning techniques used to intelligent irrigation systems are

outlined in Section 2, along with their limits and findings. Section 3 presents a method based on the use of machine learning in conjunction with smart irrigation systems. Section 4 displays the results of this technique, and Section 5 offers a discussion section.

II. Background

A. Support Vector Machine:

A discriminative classifier using the separation hyperplane is how SVM is properly defined. Using labelled training data, support vector machines (SVMs) may construct a hyperplane to categorize the freshly discovered unlabeled data. Creating a training set (yi; xi); i=1,2,..., n is the next stage, in which xi R n is the itch vector and yi R n denotes the target element. Support Vector Machines (SVMs) have been developed in several iterations to address a range of problem categories and, more importantly, varying degrees of complexity. The optimal hyperplane generated by this investigation's linear SVM is shown below.

$$f(x) = \omega^T * x + b \quad (1)$$

Where: $yi(\omega^T * x + b) \geq 1 - \xi_i ; \xi \geq 0;$ or

Each i = 1, 2, n

SVM models may be employed with a variety of kernels, including sigmoid, polynomial, linear, and radial basis functions. The kernel function is a point product of the input data points once they have been transformed into a higher dimension feature space. [11].

B. Native Bayes:

Thomas Bayes's (1702–1761) ideas serve as the foundation for the probabilistic machine learning technique known as the naïve Bayesian algorithm. This theorem may be expressed as the probability that, in the event that B has already happened, A will follow. Think about the attributes X = (x1... xn) and the class variable Y. The NB algorithm is unique in that it views each attribute as independent of the others, meaning that altering one would not have an impact on the others. Notwithstanding its simplicity, NB has shown to be a reliable classifier. [7].

Neural Network:

Any kind of mapping from one vector space to another may be accomplished using a neural network. These neural networks are not able to recover information from data, but they may utilize previously unknown information hidden in it. It should be noted that in order to comply with specific requirements, learning in mathematical formalism necessitates altering the weighting factors. [13]. In order to create a neural network, we start with the linear model, which has the following specifications:

$$g(x,\omega) = \sum_{i=1}^{p} \omega i f i(x) \quad (9)$$

Procedures for the x variable. Neural networks belong to the class of models with non-linear parameters. The two most prevalent forms of static neural networks are: basic expansions of the preceding relationship:

$$g(x,\omega) = \sum_{i=1}^{p} \omega i f i(x,\omega') \quad (3)$$

Where parameterized functions are "Neurons". The formula provides the neuron's output.

$$y = f[\omega_0 + \sum_{i=0}^{n} \omega i x i] \quad (4)$$

C. Logistic regression:

When the dependent variable is categorical, such as (0 or 1), (True or False), or (On or Off), a logistic regression model is employed. [14].

This is how the logistical role appears.

$$p(x) = p(x) = \frac{1}{1+e^{-(x-\mu)/s}} \quad (5)$$

Where μ is a location parameter (the curve's midpoint, where $p(\mu) = \frac{1}{2}$ and s is a scaling parameter

D. K-Nearest Neighbors:

K-Nearest Neighbors is a straightforward method that maintains all of the existing instances while ranking new cases based on a similarity metric.
When classifying a case using the KNN technique, a distance function is employed to determine which of the k closest neighbors the case belongs to. The case is classified by a majority vote of the adjoining properties. [15].

Among the on-site distance functions are: Euclidean:

$$\sqrt{\sum_{i=1}^{k} (xi - yi)^2} \quad (6)$$

Manhattan: $$\sum_{i=1}^{k} |xi - yi| \quad (7)$$

Murkowski: $$\left(\sum_{i=1}^{k} (|xi - yi|)^q \right)^{1/q} \quad (8)$$

This section introduces two optimisation techniques: Artificial Bee Colony (ABC) and Whale Optimisation Algorithm (WOA). Flowcharts and algorithms are given for both techniques.

E. Artificial Bee Colony (ABC) algorithm

There are three different species in ABC's mechanical bee colony: worker bees, who observe the utilized bees dancing around the hive in search of food, server bees, who are tasked with finding specific food sources, and scout bees, who search for food sources at random. Observers and observers are sometimes referred to as unemployed beekeepers due to their unemployment. The scout bees have the first task of finding every food source.

Here is how the ABC algorithm often works[8]:

Initialization phase-

The scout bees set the $\vec{y}_m$ control parameters and initiate the population of food source vectors (m=1....SN, SN). Each nutrient source, denoted by $\vec{y}_m$, represents a vector solution to an optimization problem $\vec{y}_m$ where the objective function is minimized by optimizing a set of an independent variables, denoted by $(y_{mx}, i = 1...n)$.[9] It's possible to use the following definition while setting things up:

$$y_{mx} = l_x + rand(0,1)*(u_x - l_x) \tag{10}$$

Employees Bees Phase-

Makes use of When new nectar-rich food sources are close to ones they have already visited and remembered, bees will seek them out. They search the surroundings for potential food sources and evaluate their viability (fitness). [18] For example, they may utilize the formula included inside the equation to identify a food source nearby.

$$\upsilon_{mx} = y_{mx} + f_{mx}(y_{mx} - y_{kx}) \tag{11}$$

Where is a randomly chosen food source, is a randomly chosen parameter index, and is a randomly chosen integer between and [-a, a]. When fitness is determined, an avaricious decision is made between it and the food supply. For minimization problems, the fitness value of the solution may be computed using the formula below.

$$fit_m(\vec{y}_m) = \begin{cases} \dfrac{1}{1+f_m(\vec{y}_m)} & \text{if } f_m(\vec{y}_m)^3 0 \\ 1+abs(f_m(\vec{y}_m)) & \text{if } f_m(\vec{y}_m)<0 \end{cases} \tag{12}$$

Where $f_m(\vec{y}_m)$ is the value of solution $\vec{y}_m$'s objective function.

Onlooker Bees phase-

Bees who are unable to find employment fall into two categories: scout bees and spectator bees. The term provided in the equation may be used to determine the likelihood value that an observer will select.

$$p_m = \frac{fit_m(\vec{y}_m)}{\sum_{m=1}^{SN} fit_m(\vec{y}_m)} \tag{13}$$

A food source is selected by an observation bee. $\vec{y}_m$ at random, and then uses the equation to find a nearby source $\vec{v}_m$ and assess its fitness. Between $\vec{v}_m$ and $\vec{y}_m$, Similar to the utilizing bee's phase, self-absorbed selection is utilized during this phase.

F. Whale Optimization Algorithm (WOA)

The Whale Optimization programme (WOA) is an optimization programme that is built on how humpback whales interact with each other and how they hunt. The WOA programme tries to find food in the water like humpback whales do. In the WOA algorithm, a point vector in the search space is used to show each possible answer. The algorithm starts with a group of possible answers that are generated at random from the search field. A possible solution's quality is judged by how well it answers the optimization problem[10]. This is done with a fitness function. The algorithm works by going through a number of steps called iterations. Each iteration has three main steps: Search, surround, and bubble are all options. During the search stage, the position of each feasible solution is modified such that it is closer to the best answer identified so far. [11]. This step is a simulation of how humpback whales look for food. They do this by following the best available signs.

The WOA algorithm has been shown to be effective at solving a wide range of optimization problems, such as those in engineering design, data mining, and machine learning. The method is easy to use and only has a few settings that need to be tweaked. But, like other optimization algorithms, the WOA algorithm's success depends on the problem being solved and how the algorithm settings are set[12]. So, to get the best results for a given problem, it is important to carefully tune the algorithm's settings[13].

Algorithm 1 The Standard Whale Algorithm

```
Initialize a population of random whales
W* = the best search agent
t = 0
While (t < iterations)
    for each whale
        Update WOA parameters
         and p)
        if (p < 0.5)
            if (|B| < L)
                W^{t+1} = W* - B.Dis
            else if (|B| ≥ L)
                W^{t+1} = W_rand - B.Dis
            end if
        else if (p ≥ 0.5)
            W^{t+1} = Dis'.e^{x.r}.cos(2πr) + W*
        end if
    end for
    Evaluate the whale W^{t+1}
    Update W* if W^{t+1} if better
    t = t + 1
end while
return W*
```

III. Methodology

This study presents a novel method for predicting irrigation schedules that estimates when to start and stop pumping based on temperature and soil moisture measurements. Our goal is to provide an intelligent and reasonably priced autonomous irrigation system that can be intelligently managed and adjusted to various situations. This strategy's cornerstone is the application of machine learning algorithms designed specifically to maximise agricultural operations. We employed a variety of models, including KNN, Logistic Regression, Neural Networks, SVM, and Naïve Bayes, all of which were trained on the gathered dataset. This broad variety of models serves as the foundation for our recommended intelligent irrigation system for efficient water utilisation in agriculture.

A. *Dataset Description*

In this paper, data collected from the websites listed below: https://www.kaggle.com/code/triptmann/irrigation-scheduling-for-smart-agriculture/input.

This dataset comprises a collection of images capturing moisture and temperature information. It includes numerical data representing various features such as meteorological conditions, soil moisture levels, and the identification of specific crop types. The primary goal of this system is to facilitate automatic water supply management based on the gathered information.

B. *Pre-processing steps for classification*

This paper aims to investigate the impact of various pre-processing techniques on the precision of the outputs of multiple core convolutional networks. There are several pre-processing methods presented in the next section.

Eliminate noise:

The process of noise elimination, especially in image datasets, often involves various techniques and methods specific to the characteristics of the images. The information regarding which images are considered for noise elimination, the criteria for selection, or the methodology used to eliminate noise would typically be documented or described in the methodology section, associated documentation, or supplementary materials provided with the dataset.

C. *Feature Selection*

This study utilized a hybrid ABC-WOA optimization method to specifically select relevant features associated with soil moisture and temperature data from the provided dataset. Through this approach, we effectively isolated critical information, essential for subsequent analysis and modeling. This feature selection process aimed to enhance the accuracy and efficacy of our study's predictive models in the context of smart irrigation systems.

Algorithm: Hybrid ABC-WOA Optimization

Initialization: Initialize ABC and WOA populations randomly:
- ABC population: N_ABC bees
- WOA population: N_WOA whales

Repeat for a maximum of max_iterations or until termination criteria are met:
For each ABC bee in ABC population:
    Employed bees explore solutions locally:
        Modify the position of bee using a local search strategy.
    Calculate the fitness of each employed bee.
    Onlooker bees select employed bees based on fitness and perform global search:
        Select employed bees probabilistically.
        Apply global search strategy.
    Evaluate fitness of onlooker bee.
    For each WOA whale in WOA population:
        Update whale position using WOA equations:
    X_WOA_j = A * sin(B) * |C * X_rand - X_WOA_j| - X_WOA_j
        Evaluate fitness of WOA whale.

D. *Train _test split*

The dataset has been partitioned into separate test and training sets based upon the user-specified splitting ratio after all preparation procedures are finished. During the training phase, our primary task was to train the models using the available dataset. This enabled us to develop predictive capabilities within the models, specifically geared towards determining when to initiate or cease pumping activities based on the varying levels of soil moisture and temperatures.

Train the network:

The train dataset is used to train the proposed Support Vector Machine (SVM) and other machine learning methods, including Nave Bayes, logistic regression, and the K-Nearest Neighbors (KNN) model. The suggested model's effectiveness is evaluated and contrasted with existing models.

The quality of the suggested algorithm is assessed using the performance indicators shown below.

E. ***Performance metrics***

Evaluation metrics like as F1-Scores, accuracy, sensitivity, and precision are often used to assess how well an algorithm performs in relation to performance indicators that are obtained from the confusion matrix.

Accuracy: What is meant by "identification rate" is the proportion of correctly recognized subjects to all disciplines.

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

Sensitivity: Minimum value sensed is known as sensitivity, It characterizes the ratio. The computer system in question is quite accurate in identifying and classifying labels as positive.

$$Sensitivity = \frac{TP}{TP+FN}$$

Precision: One way to evaluate a prediction's accuracy is to count the total number of accurate forecasts. Another name for this idea is predictive value.

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

F1-Score: The F1score is a numerical measure of accuracy and memory combined.

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

Specificity: Specificity has been correctly identified by the system as a negative**.**

$$Specificity = \frac{TN}{TN+FP}$$

Where,
TP= True Positive
TN= True Negative
FP= False Positive
FN= False Negative

IV. Results and Discussion

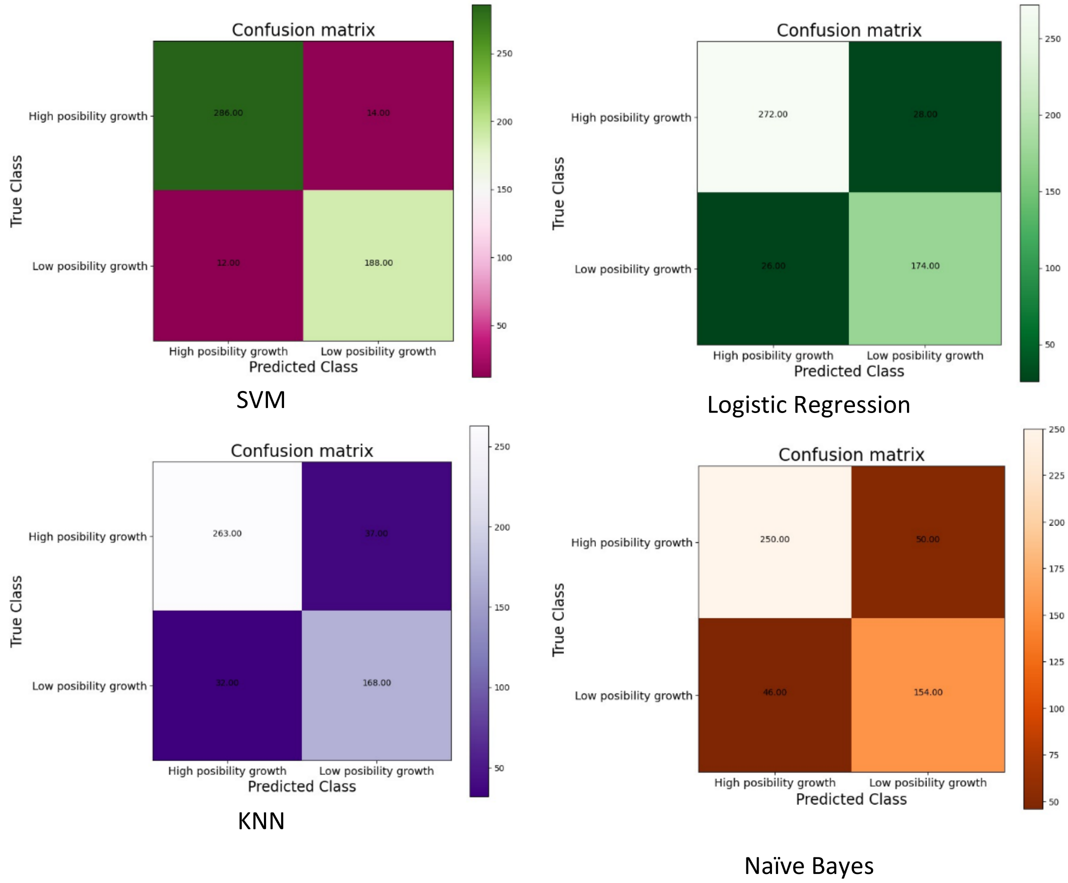

Figure 1 Comparison of proposed and existing methods

SVM correctly detected high possibility growth data 286 times but incorrectly identified 14 instances of low probability growth. It successfully predicted 188 high-probability growth cases and 174 low-probability growth instances, however it made 12 and 26 misclassifications, respectively. Logistic regression shown strength by detecting 272 high and 174 low probability growth data, but it also had 28 and 26 misclassifications, respectively. KNN identified 263 high and 168 low likelihood growths with 37 and 38 misclassifications, indicating opportunities for improvement. With 46 and 50 misclassifications, Nave Bayes detected 250 high and 154 low Probability growth occurrences, indicating overall strong accuracy in differentiating defective photos.

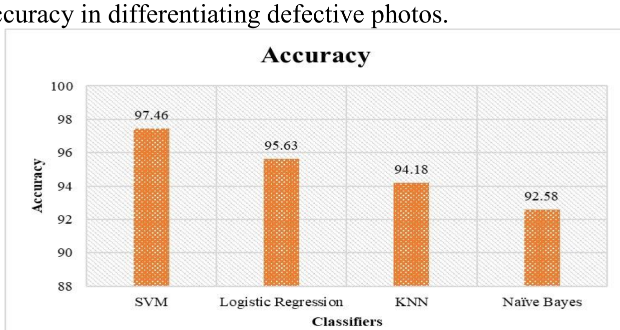

Figure 2 Accuracy

The above graph clearly shows that the recommended (SVM) precision is the evaluation and comparison were carried out using two more models, namely Logistic Regression and (KNN). As a result of this phenomena, the suggested model outperformed the Logistic Regression and KNN, Nave Bayes, yielding an accuracy score of 97.46 as opposed to the recommended model's scores of 95.63, 93.18, and 92.58.

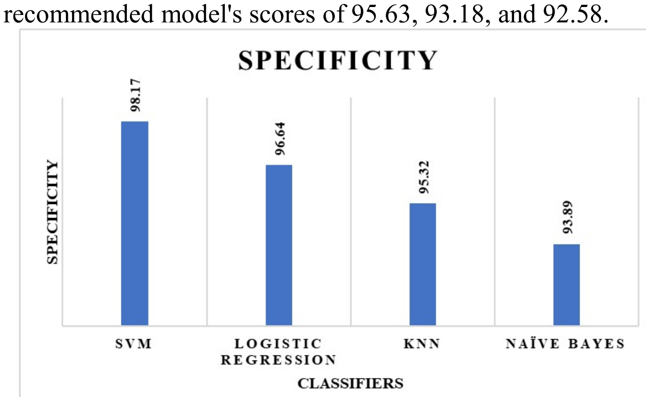

Figure 3 Specificity

The suggested SVM's performance the context following graph clearly shows the assessment and comparison of two additional models, Logistic Regression, KNN, and Nave Bayes. SVM has a specificity rating of 98.17. As a result, the recommended model outperformed Logistic Regression, KNN, and Nave Bayes, with specificity scores of 96.64, 95.32, and 93.89, respectively.

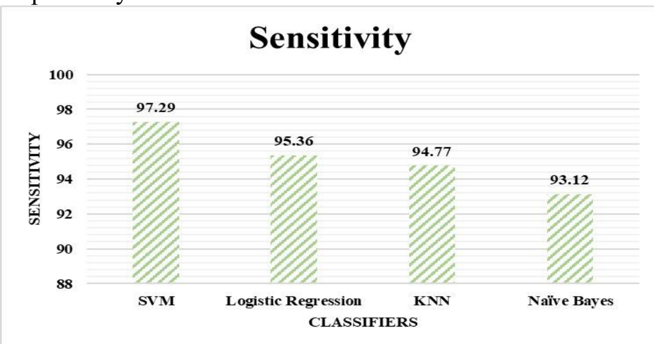

Figure 4 sensitivity

The graph above compares and contrasts the performance of the Logistic regression, KNN, and Nave Bayes models with that of the suggested model SVM. SVM has a sensitivity of 97.29. The proposed model outperformed Logical Regression (95.36), KNN (94.77), and Nave Bayes (93.12).

Table 2 Architectures and values

Architectures	Accuracy (%)	Specificity (%)	Sensitivity (%)
SVM	97.46	98.17	97.29
Logistic Regression	95.63	96.64	95.36
KNN	94.18	95.32	94.77
Naïve Bayes	92.58	93.89	93.12

Future Scope: In this proposed system Integration of Remote Sensing and IoT for Real-Time Monitoring of Irrigation in Smart Farming can be developed as further study.

Conclusion:

The study introduces an innovative approach to irrigation prediction by harnessing soil moisture and temperature data to forecast pumping initiation or cessation. Its main goal is to suggest a flexible, reasonably priced autonomous irrigation system that can be intelligently managed using machine learning algorithms designed specifically for agricultural optimization. Using the data gathered during the evaluation process, a number of models, including Naïve Bayes, KNN, SVM, Logistic Regression, and Neural Networks, were rigorously trained and analyzed. SVM was consistently shown to be better, as evidenced by scores of 97.17%, 97.29%, and 97.46% for accuracy, specificity, and sensitivity, respectively. The lower scores of the Logistic Regression, KNN, and Naïve Bayes models verified the robustness of the SVM model, which predicted the optimal irrigation timings depending on soil conditions. The SVM model was shown to be the best accurate predictor of irrigation management as a result. Its exceptional performance demonstrates how perfect it is to include with an automated watering system. This method makes it possible to effectively control the amount of water used for agriculture, which lowers waste and enhances resource utilization. The suggested SVM-based strategy provides some important advantages over traditional methods. It assists farmers in making well-informed decisions that enhance crop output and protect water resources by accurately forecasting when to start or stop pumping operations in response to variations in temperature and soil moisture content. The article ends by suggesting that SVM be the preferred approach for developing intelligent irrigation systems. It is a helpful tool for sustainable farming methods that boost productivity and conserve resources because of its capacity to precisely predict irrigation needs based on existing environmental conditions.

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