An ISOA-ASVM-Based Smart Irrigation System: Integrating Improved Seagull Optimization with Adaptive SVM for AI-IoT Agriculture

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The dramatic changes in climate, the rising water shortage, and the rising demands of agricultural productivity have resulted in irrigation management as a burning issue in contemporary agriculture. In an attempt to curb these drawbacks, this paper introduces a combined Artificial Intelligence (AI) and Internet of Things (IoT)-based smart agriculture system to manage precision in controlling irrigation measures. The suggested design uses IoT sensors as a continuous monitoring of real-time environmental and soil conditions such as the moisture content of the soil, ambient temperature, humidity, and climatic conditions. These data are sent to a central processing unit and machine learning models are used to find the complex and dynamic patterns that enable a good prediction of the crop water needs. In order to improve the accuracy of the prediction and the efficiency of the system, the Improved Seagull Optimization Algorithm-Adaptive Support Vector Machine (ISOA-ASVM) model is introduced. The optimization algorithm is useful to tune the SVM parameters, enhancing the performance of generalization and minimizing the computational cost. The model is trained and tested using a dataset of 3000 records of the IoT-based sensor on agricultural fields that consisted of the main environmental and soil characteristics such as soil moisture, temperature, humidity, rainfall, light intensity, and soil pH. Minimum performance of the maximum normalization and feature selection are used to increase model stability, and generalization. The evaluation criterion is 10-fold cross-validation and performance is compared to that of the Random Forest, Naïve Bayes and KNN classifiers. The proposed ISOA-ASVM has a high predictive power and strong robustness with high accuracy of 99.3, precision of 96.1, recall of 97.6 and F1-score of 98.6. Low variance and consistent cross fold performance is confirmed by statistical analysis. The acquired AI-IoT system will facilitate automated control of irrigation, remote monitoring, and real-time decision-making and reduce the involvement of humans and operational expenses. The results affirm that the combination of smart machine learning models and IoT sensing infrastructure can be of great help in enhancing the water-use efficiency, crop productivity, and sustainability. This paper offers a scalable and efficient solution to smart irrigation systems and helps to build climate-resilient and resource-efficient smart agriculture.

Povzetek: Raziskava predstavlja pametni AI-IoT sistem za natančno namakanje, ki izboljšuje porabo vode, produktivnost pridelkov in trajnostno upravljanje kmetijstva.

1 Introduction

Due to an uncontrollably rising demand for water relative to availability, water scarcity has become one of the most important and pressing problems of the twenty-first century .In the near future, the scarcity of fresh water resources will become a major issue for all nations worldwide due to the unequal distribution of water resources and the rising demand for them. In China, a comparatively large percentage of fresh water usage is attributed to agriculture [1]. Water-saving irrigation is still relatively new in China. An intelligent irrigation system that uses less power, costs less, and can be used in a wider range of situations is therefore designed in light of this circumstance[2]. Because of the uneven distribution of precipitation and variations in temperature trends, certain geographical locations are more affected by water scarcity than others. Given that statistical and predictive models project catastrophic water-related occurrences for the next century, climate change and global warming are only making matters worse [3]. The foundation of essential areas like agriculture is water. Agriculture uses 70% of all water withdrawals, which is justified, for example, to ensure food security and agricultural production. Two-thirds of the freshwater on Earth is inaccessible, and just 2.5 percent of it is present. Managing water consumption and ensuring sustainable agriculture are crucial for the reasons [4].

Over one-third of the world's workforce is employed in agriculture, which has an ancient history that dates back thousands of years. It has also advanced through the implementation of various new systems, practices, technologies, and approaches over time. Agriculture is the foundation of many nations' economies and contributes significantly to the development of economies in underdeveloped nations [5]. Additionally, it drives the process of economic prosperity in developed nations. Several studies have found that, on the one hand, agriculture uses about 70% of the world's fresh water supply annually to irrigate just 17% of the land; on the other hand, the total amount of available irrigated land is gradually declining due to the rapidly rising food demands and the effects of global warming [6]. There is a shortage of water resources due to the effects of global warming and increasing droughts. The anticipated increase in population to 9.8 billion by 2050 poses a risk to food security and water shortages [7].

Integrating AI and IOT for smart agriculture

The modernization of agriculture is being led by the Internet of Things (IoT) and artificial intelligence (AI), which provide more sustainable and intelligent methods of crop management [8]. With a special emphasis on machine learning models in precision irrigation, this review article explores how new technologies are changing farming methods. AI's integration into agricultural methods has revolutionized the industry. Farmers are gaining previously unheard-of insights because to AI's capacity to sort through and analyze mountains of data, ranging from weather patterns to soil health. Making better, more informed decisions that can result in sustainable farming methods is the goal of these insights, not only increasing yields. AI systems, for example, can now anticipate when plants should be planted or spot possible insect infestations before they become an issue, saving time and money [9]. IoT is transforming how farmers engage with their farms in concert with AI. IoT technology creates a constant flow of data on crop status and environmental factors by installing sensors across farms. For the purpose of making prompt and efficient decisions about agricultural irrigation, this real-time data is essential. Drones monitoring crop health from above or the ability to precisely irrigate areas of a field depending on sensor-detected moisture levels are examples of modern realities rather than sci-fi ideas [10]. The possibilities of AI and IoT in agriculture are being further enhanced by the incorporation of machine learning. The massive volumes of data gathered by IoT devices may be effectively stored, processed, and analyzed with machine learning [11]. This makes modern agricultural technology more accessible to a larger variety of agriculture by enabling farmers to obtain insightful information without having to invest in costly infrastructure [12].

Machine learning for precision irrigation

An innovative way to optimize resource efficiency and increase crop output, smart irrigation systems represent a revolution in agricultural water management. To collect real-time data on vital parameters like soil moisture, temperature, humidity, and other environmental variables, these systems make use of a network of Internet of Things sensors that are placed strategically throughout fields [13-14]. The basis for wise irrigation management decision-making is this constant flow of data. Advanced machine learning algorithms at the core of these smart devices evaluate the data gathered to make very accurate predictions about irrigation needs.

For precision irrigation systems, machine learning is a quickly developing technology that makes expert knowledge and data-driven decision-making possible[15]. It has developed in tandem with big data technology, using edge cloud computing to interpret and extrapolate conclusions from massive volumes of data gathered from multiple sensors. Modern technologies like information technology, agro-hydroinformatics, and computational intelligence are crucial for creating a sustainable precision irrigation system. These technologies save labor expenditures and weariness, maximize the usage of power and water, and handle sensed data. To address particular issues, machine learning uses statistical data and data from prior experiences. Farmers may now readily monitor and display information on cellphones or other computing devices to help guide their decisions thanks to developments in weather and environment-based models. According to studies, 90% of farmers concur that increased production and output may be achieved through improved irrigation management using online and mobile applications [16].

Research questions and hypotheses

In order to obtain the desired direction in the development and evaluation of the proposed framework of ISOA-ASVM the study is organized based on the following research questions:

1. RQ1: Does the classification accuracy of SVM using ISOA-based hyperparameter optimization improve the precision irrigation of SVM statistically compared to the traditional machine learning models?

2. RQ2: Does the combination of normalization and feature selection increase the robustness of the models in different environmental conditions?

3. RQ3: Does the proposed framework achieve low variance in the performance when subjected to different data partitions?

According to such questions, the hypotheses that the study will test are as follows:

- H1: ISOA-ASVM is statistically more accurate than random Forest, Naive Bayes, and KNN.
- H2: ISOA-ASVM has a smaller standard deviation based on cross-validation folds, which shows a higher level of robustness and generalization.
- H3: ISOA optimization, feature preprocessing, and ASVM when put together have better performance than their individual components.

Contributions of This Study

The contribution of this study is as follows:

1. *Design of Hybrid Optimization Framework*: Suggests an ISOA-optimized Adaptive SVM model to decision-making in precision irrigation.

2. *Strong Performance validation*: Is statistically shown as more accurate and stable by use of cross-validation and variance analysis.

3. *Smart Agriculture Integration*: Offers scalable IoT-based precision irrigation system applicable to the real-time implementation in the dynamic agricultural fields.

The expected results are increased accuracy in predicting irrigation (>99%), less model variance, and performance improved in the cases of environmental uncertainty.

Benchmarking and Evaluation Methodology

The ISOA-ASVM model was compared to Random Forest, Naive Bayes, and KNN in terms of the following evaluation plan:

- *10-Fold Cross-Validation:*Partitioning of the dataset was done such that the data was divided into ten subsets so that each fold was used as a test set to minimize bias and overfitting.
- *Performance Metrics:* Each of the folds was calculated in Accuracy, Precision, Recall, F1-score and Standard Deviation.
- *Statistical Significance Testing*: To ensure that the performance improvements were not due to chance, a paired t-test (or a Wilcoxon signed-rank test when applicable) was performed to ensure that the performance improvements were statistically significant ($p < 0.05$).
- *Robustness Assessment:* To prove the model stability, variance analysis and sensitivity test under noise and feature reduction conditions were conducted.

2 Literature review

Table 1: Summary on related works

Ref.	Objective	Methodology	Reported Metrics	Key Limitations
[17] Sharma (2024)	Enhance crop monitoring using AI + IoT	ML-based crop analysis	Accuracy ≈ 94–96%	Focused more on crop monitoring than irrigation optimization
[18] Umutoni (2024)	Review ML for irrigation decisions	Comparative review	Accuracy range 85–97%	No experimental validation; lacks unified dataset benchmarking
[19] Kashyap (2021)	Intelligent IoT irrigation using DNN	Deep Neural Network	Accuracy ≈ 96.2%; Water savings ≈ 28–30%	High computational cost; limited robustness testing
[20] Tace (2022)	Smart irrigation with IoT + ML	ML-based control system	Accuracy ≈ 95%; Water reduction ≈ 20–25%	Small-scale experimental setup
[21] Aminuddin (2021)	Urban irrigation automation	Logistic Regression	Accuracy ≈ 88–91%	Simpler model; lower predictive performance

[22] Glória (2021)	Sustainable irrigation via ML	Real-time sensor ML model	Accuracy ≈ 93–95%; Water efficiency ≈ 18–22%	Limited comparative statistical analysis
[23] Mohyuddin (2024)	Review ML for smart farming	Comprehensive survey	Accuracy range 80–98%	Review-only; no proposed implementation
[24] Kaur (2024)	Hybrid IoT-ML irrigation	ML-based hybrid system	Accuracy ≈ 96–97%; Water savings ≈ 25%	Region-specific deployment; scalability concerns
[25] Phasinam (2022)	IoT + cloud irrigation automation	Cloud-based control	Water savings ≈ 15–20%	Lacks detailed ML performance metrics
[26] Patil (2024)	Optimize irrigation using ML	ML optimization model	Accuracy ≈ 94–96%; Water savings ≈ 23–27%	Limited robustness and variance analysis

The effectiveness of the ISOA-ASVM method is that it is better than LSTM and Random Forest models since it incorporates the metaheuristic optimization to automatically adjust the paramount SVM parameters (C and Y) to achieve the optimal compromise between bias and variance. The LSTM models have high computational requirements as well as large datasets and the RF models have fixed tree structures that cannot be adjusted to optimize. Most of the current techniques apply to manual or grid tuning, which restricts reaction to changing environmental factors. In comparison, ISOA-ASVM has a greater adaptability in optimizing and environmental robustness, which translate to greater accuracy and generalization to different agricultural conditions.

By using state-of-the-art technologies, our initiative seeks to transform conventional farming methods and improve agricultural resilience, sustainability, and production. Our system will maximize crop management, resource allocation, and risk mitigation tactics by utilizing machine learning and artificial intelligence approaches. We aim to optimize agricultural productivity while reducing resource consumption and environmental impact by giving farmers access to real-time analytics and decision support. With personalized guidance, our intuitive interface will empower farmers and promote cooperation and information exchange throughout the agricultural community. Our project's ultimate goal is to build a more resilient, sustainable, and effective agricultural environment for the good of farmers and society at large.

3 Methodology

Among them, the majority of the research concentrated on and suggested using AI and IOT sensors to collect data and machine learning approaches to analyse the data. However, ML-based solutions are used for deployment, management, and upkeep. Second, various crops require varying amounts of fertiliser and water. Furthermore, the weather differs in different places due to varying climate conditions, hence local weather sensing and prediction are crucial for enhancing irrigation models. We are focussing on creating a low-cost, efficient system for improved water use in the work that is being presented.

3.1 Data collection and preprocessing

Three thousand records make up the dataset selected for the experiment. Temperature, humidity, and soil moisture are among the factors or attributes that are assessed. The smart agriculture data collection phase includes data acquisition and storage. Sensors gather data from their environment and transmit it to storage devices. Numerous sensors are used in the system, and they are grouped based on their respective purposes: location sensors can be used to locate crops; electrochemical sensors can detect chemical reactions in soil; light-dependent resistor sensors can detect light levels; and nanostructured sensors can detect soil moisture content. Satellites that use remote sensing technology provide data that is utilized for ecological condition monitoring, growth tracking, and area estimation. In an ML, data that is transmitted from numerous sources is stored for subsequent use. Since the data was gathered from the real world, it must be preprocessed since it can include incorrect or missing numbers.

The ISOA-ASVM framework can be deployed in real-time; however, such practical considerations as latency, sensor noise, and computing load should be taken into account. Edge computing can be used to minimize latency of data transmission to facilitate local decision-making. Filtering and adaptive learning can help reduce sensor noise and environmental uncertainty, as is the case in robust adaptive control systems in which disturbance rejection is performed. Even though ISOA makes training more complicated, optimization is done offline, whilst real-time SVM inference is lightweight.

In comparison with fixed-time or threshold-based irrigation, ISOA-ASVM is much more effective in responding to changes in the actual climatic conditions, as the nonlinear relationships between soil and weather parameters are modeled. It fills the adaptive feedback paradigm gap of providing predictive, rather than reactive, control. The low-power IoT nodes, hierarchical edge-cloud architecture, and energy-efficient communication allow scaling the system and making it viable in the field of deployment.

Dataset description

The dataset in this paper is 3000 records obtained as a smart irrigation experimental system installed in an agricultural field scenario. The data was collected in 6 months of cultivation period (January through June 2024) including dry and moderate rainfall. The study area is a semi-arid agricultural area where the demand of irrigation is extensively affected by the variation in temperature and variable rains.

The data comprises of environmental and soil parameters which are obtained through sensor nodes based on IoT installed over the field. The crops that would be followed in the data collection period are: Paddy (Rice), Tomato, Groundnut

Each record is a time-marked record of soil and climatic conditions and the label of the decision of irrigation required (not required). Calibrated sensors on an IoT monitoring system based on a microcontroller were used to gather data after every 30 minutes. The sensor data were sent to a central storage server where pre-processing and model training were done. Any missing values (less than 2 percent) were replaced with the mean and noise was filtered with moving average smoothing, followed by normalization.

Table 2: Dataset feature description

Feature Name	**Description**	**Unit**	**Range**	**Sensor Type**	**Data Source**
Soil Moisture	Volumetric water content in soil	%	10 – 60	Capacitive soil moisture sensor	Field IoT Node
Temperature	Ambient air temperature	°C	18 – 42	Digital temperature sensor (DHT22)	Field IoT Node
Humidity	Relative humidity	%	35 – 95	DHT22 humidity sensor	Field IoT Node
Soil pH	Soil acidity/alkalinity	pH scale	5.5 – 8.0	Electrochemical pH sensor	Field IoT Node
Light Intensity	Sunlight exposure level	Lux	2,000 – 85, 000	LDR sensor	Field IoT Node
Rainfall	Precipitation level	mm	0 – 35	Rain gauge sensor	Weather Module
Irrigation Label	Irrigation requirement (0 = No, 1 = Yes)	Binary	0 / 1	Derived from agronomic threshold rules	Ground Truth

3.2. Min-max normalization

Min-Max normalization is a technique of normalizing that uses linear modifications to the original data to provide a fair comparison of values before and after the procedure.

$$X_n = \frac{x_{min}}{x_{max} - x_{max}} \tag{1}$$

where X is the original value, and$X_{min} - X_{max}$ are the minimum and maximum of that feature.

As the features in the dataset have different units and ranges (e.g., the temperature in °C, soil moisture in percent, light intensity in lux), normalization makes sure that no feature prevails in the learning process because of its larger numerical value. It scales every feature separately and thus temperature does not influence the model more than the soil moisture or humidity. This enhances the stability of the numbers, convergence speed, and the general accuracy of predictions of the ISOA-ASVM model.

Feature engineering

In this experiment, the features were chosen and then the ISOA-ASVM model was trained in order to enhance efficiency and decrease redundancy. The correlation analysis was initially done using a filter-based analysis to find out the relationships between soil moisture, temperature, humidity, rainfall, light intensity and pH. To prevent the occurrence of multicollinearity, highly correlated and insignificant features have been assessed.

Also, the Principal Component Analysis (PCA) was experimentally implemented in dimensionality reduction. But the number of physically interpretable features agronomic in the dataset is small, and therefore PCA was not finally used in the final model to maintain domain interpretability.

The regularization of lasso was not enforced because ASVM has an inherent control over the complexity of the model by minimizing structural risk. Thus, the selected relevant features were used to train the final ISOA-ASVM model without the aggressive dimensionality reduction to guarantee high computational efficiency and realistic interpretability in the irrigation-related decision-making.

3.3 Improved Seagull optimization algorithm based on adaptive support vector machine (ISOA-ASVM) Algorithm

Improved Seagull Optimization Algorithm (ISOA):

The benefits of the SOA method are its quick convergence speed, low computational cost, and ability to solve large-scale constrained problems. It has a lot of advantages over other optimization algorithms. The equation illustrates that the global optimization search process of SOA is linear. The global search capacity of SOA cannot be fully leveraged due to this linear search strategy. As a result, we provide a nonlinear search control formula, represented by Equation, which can enhance the algorithm's speed and accuracy by focusing on the stage of the seagull group exploration process. Figure1: Display the flow of Improved Seagull Optimization Algorithm (ISOA)

$$B = e_d \times \frac{1}{f^{4.\left(\frac{s}{Max_{iteration}}\right)^4}} \tag{2}$$

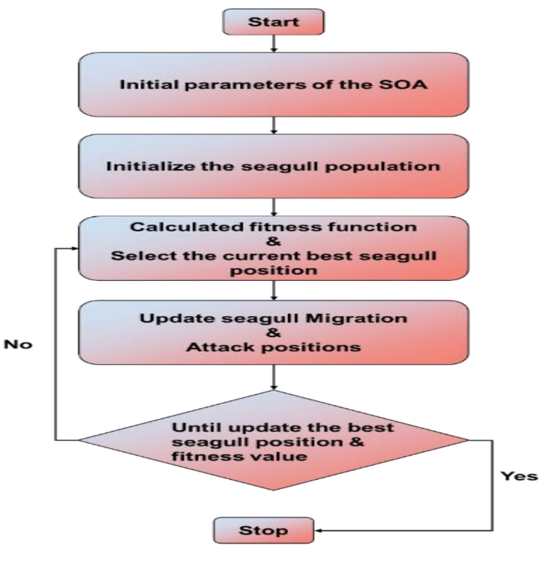

Figure 1: Flow of Improved Seagull Optimization Algorithm (ISOA)

We accurately predict Agriculture Irrigation effectiveness by utilizing a perfectly calibrated Improved Seagull-optimized AdaptiveSVM algorithm, allowing customized Sensor tactics with AI and IOT for the best possible results.In this case, SVM lays the foundation by offering a baseline classification or regression framework. Next ASVM enhances the procedure by assigning Adaptive affects to smart Agriculture data points. ISOA then adjusts the parameters(temperature, humidity, and soil moisture) of hybrid model to maximize its performance on a variety of dataset. The best features of ISOA, ASVM and SVM are combined to create the hybrid approach, a symbiotic fusion designed to maximize the capability of each constituent algorithm. By combining this method meets better unique learning requirement of every Farm while optimizing precision Irrigation achievement.

The proposed ISOA was based on the migratory behavior of seagulls and their assault prey. The coding of this algorithm was inspired by the tactics used by a flock of migrating seagulls to catch their meal as they fly from one location to another. To prevent searching agents from colliding with each other in ISOA, an extra parameter "N" is used to determine the new search agent's position. This study used this approach for the irrigation effectiveness ($\vec{F_s}$) given as

$$\vec{F_s} = \mathrm{P}x\vec{\mathrm{M}}_s(i) \tag{3}$$

$\vec{M_s}$represents the seagull's present (temperature, humidity, and soil moisture), and “t” denotes the sensor effectiveness iteration at that time. It is possible to model the crash prevention parameter "P" as

$$P = E_c - \left(i * (F_c/\max \cdot Iter)\right) \tag{4}$$

Here, our collision avoidance parameter is a sequentially reductive attribute from F_c to 0, which we set to 2. Using the following equation, the search agents try to approach the ideal farm position once the avoidance occurrences in the collision mechanism are finished.

$$\vec{N_s} = Ax(\vec{P_{bs}}(\mathrm{i}) - \vec{M_s}(\mathrm{i})) \tag{5}$$

In order to attain the propensity of equilibrium between the phases of exploitation and exploration, and the parameter "P" is randomly assigned and can be computed as

$$P = N^2 * 2 * \mathrm{rand}()$$

(6)

Subsequently, the following positions of each iteration of the algorithm will be updated:

$$\vec{R}_s = \left|\vec{E}_s + \vec{N}_s\right| \quad (7)$$

While migrating, seagulls frequently modify their frequency and targeting angle based on past history experiences in sensor IOT data. Seagull migration behavior can be visualized in three dimensions as

$$s' = x * \mathrm{Cos}\,(j) \quad (8)$$

$$T' = x * \mathrm{Sin}\,(j) \quad (9)$$

$$U' = x * \mathrm{j} \quad (10)$$

The spiral movement radius of the seagulls is represented by "x," and an element between 0 and 2 is chosen at random for "j." The remaining agents in the search will have their positions updated in accordance with the optimal solution once it has been saved.

$$\vec{M}_s(k) = \left(\vec{N}_s * s' * T' * U'\right) + \vec{P}_{bs}(k) \quad (11)$$

A graphic illustration of the steps involved in ISOA optimization is shown in Figure 2. Although ISOA has been successfully used for other technical optimization problems. The clever behavior of seagulls motivated the authors to employ the ISOA searching approach for Smart Agriculture for precision Irrigation.

3.4.2 Adaptable support vector machine

The Adaptable Support Vector Machine learns from user behaviour patterns to optimize system irrigation analysis. The most effective learning technique for classifying smart Agriculture is Adaptable Support Vector Machines (ASVM). The sentiment analysis theory's structural danger minimization concept serve as its foundation. The AI and IOT concept is to found the theoretical values with the least rate of mistake. In this examine endeavor, the classifier can use the linear kernel as the threshold function. This classifier requires both positive and negative training sets for analysis of data gathered in sensor network. These training sets are utilized to search for an option surface, which distinguish positive from the negative report and the negative data from the positive information in the multidimensional space characteristics for sensor network (WSN), which is represented by a hyperplane. A "support vector" is a document representative that is closest to the decision surface.

$$G_1 \rightarrow \omega^S w_j + a = 1 \; for \; z_j = 1 \quad (12)$$

$$G_2 \rightarrow \omega^S w_j + a = -1 \; for \; z_j = -1 \quad (13)$$

Let bj be the desired output andaj the training documents. The separating hyperplane, which divides the positive and negative data with the greatest margin, is examined by this algorithm.

The two hyperplanes temperature and weather, G_1 andG_2, separating the example data gathered in Irrigation for environment monitoring device. Farming are not separated byG_1, but diseases are separated byG_2using the smallest possible margins. In terms of performance, the ASVM method is superior to other classification algorithms. The feature selection function is used by this method to exclude undesired characteristics from Agriculturewith a high-dimensional feature space. This classifier's main drawback is the amount of time and memory it takes to train and classify documents' high-dimensional features. The following defines how the hyperplanes G_1 and G_2 are constructed:

$$z_j\left(\omega^S w_j + a\right) - 1 \geq 0 \forall_j = 1,2,\ldots,M \quad (14)$$

$M$is the total number of papers in this case. Equation (17) defines the that need to AI be maximized as follows:

$$min \tfrac{1}{2}\|\omega\|^2 \mathrm{b}$$

$$Subjectto z_j\left(\omega^S w_j + a\right) - 1 \geq 0 \forall_j = 1,2,\ldots,M \quad (15)$$

This formula is transformed into the Lagrange formula by connecting the restrictions and the objective function. This is described as:

$$\min K_o = \frac{\|\omega\|^2}{2} - \sum_j \alpha_j\left(z_j\left(\omega^S w_j + a\right) - 1\right)$$

$$\frac{\|\omega\|^2}{2} - \sum_j \alpha_j\left(z_j\left(\omega^S w_j + a\right) - 1\right) + \sum_{j=1}^{M} \alpha_j \quad (16)$$

$\alpha_j \geq 0 \; and j = 1,2,\ldots,M$

The kernel matrix computation is carried over into the ASVM for irrigation classification. Let domains and M be the total number of area. Next, the term vector is expressed $SU_j \in \underline{Q}^m$where n is the dimension and I stands for $\{1,2,\ldots M\}$. This can be changed to enhance the classification performance. The feature matrix $EN_j = SU_j$is created by the term vector SU_j. The kernel matrix $LN = EN_j . EN_j$follows. Using the original ASVM for the model computation could need a significant amount of storage space. The model computation will require less memory to the method for analyzing farmers regarding public opinion through feedback. When $i = 1, 2, \ldots M$, the term vector SU_jwill have the new term vector new SU_j with components of (value, location) when the values don't match the equation (9). The updated SU_jvector includes the new feature matrix new FM

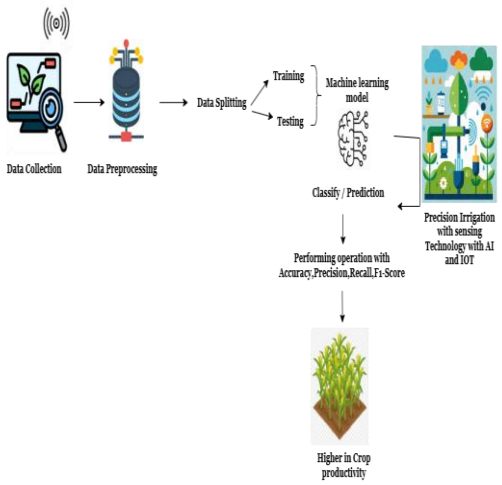

Figure 2: Work flow of proposed method

Algorithmic Steps for ISOA-ASVM

Input:
Dataset D={X,Y}D = \{X, Y\}D={X,Y}, population size N, maximum iterations T, SVM parameter bounds

Output:
Optimized ASVM model for irrigation prediction

Pseudocode: ISOA-ASVM

1: Initialize population Pi (i = 1 to N) with random SVM parameters
(e.g., C and γ for RBF kernel)

2: Normalize dataset using Min–Max scaling

3: Split dataset using k-fold cross-validation

4: For each individual Pi in population
Train SVM using parameters (C, γ)
Evaluate fitness using classification accuracy
End

5: For iteration t = 1 to T
For each individual Pi
Update position using ISOA search strategy (exploration and exploitation phases)

Enforce parameter bounds

Train SVM with updated parameters
Compute new fitness (cross-validation accuracy)

If new fitness better than previous
Update Pi
End
End
Store global best solution Pg
End

6: Select optimal parameters (C*, γ*) from Pg

7: Train final ASVM model using optimized parameters

8: Output trained ISOA-ASVM model

4 Results and discussion

4.1 Experimental setup

An HP workstation PC with an Intel Core™ i7-6700 CPU running at 3.40 GHz, 16.00 GB of RAM, and a ×64-based processor running Ubuntu 16.04 with Python 3.7 software was used for all machine learning experiments in this study. The ML techniques were created utilising an open-source Tensorflow library in the backend and the Keras library.
Practical Application: The ISOA-ASVM framework proposed has good practical applicability in real world smart irrigation systems. It is compatible with IoT sensors and automated irrigation controllers to make the management of water real-time and data-driven, especially with water-scarce and semi-arid areas. The system assists in precision agriculture, automation in green-house, and irrigation scheduling that is energy efficient. Although the existing examples are useful under typical conditions, the full range of more diverse scenarios, such as extreme weather variations, multi-crop fields, different types of soils, and failure of sensors would be more indicative of scalability, robustness, and applicability of the study as it is a broader representation of the impact and interest of the work.

Model training details

The proposed ISOA-ASVM model was tested on 10-fold cross-validation to make it robust to performance and minimize biasing. Under this scheme, the 3000-record data were randomly split in 10 equal subsets. Training and testing were done using 9 subsets in every iteration. This procedure was done 10 times in order that all the subsets became test sets once. The accuracy, precision, recall, F1-score performance measures were calculated as the mean of all folds. As a comparison, 10-fold cross-validation was also utilized to carry out a preliminary 70/30 holdout validation, though the findings presented in the paper were carried out based on 10-fold cross-validation to provide a more effective generalization assessment and a smaller range of variance in performance estimation. The given cross-validation approach enhances credibility and resilience of the mentioned results in different partitions of data.

4.2 Performance metrics

This Study assessed each classifier using the balanced Accuracy, F1-Score ,recall, and precision of existing techniques Random Forest (RF)[27] and Naïve Bayes (NB) [28] and K-Nearest Neighbor (KNN) [29]. As indicated in table 3, a classifier model was derived by importing 3000 records in order to compare the efficiency of the suggested methodology. We discovered that 30% of the total samples are test samples and 70% of the samples are training samples.

Table 3: Existing and proposed method metrics.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	92.3	90.2	91.3	90.9
Naïve Bayes	85.8	83.3	84.1	83.4
KNN	88.0	85.2	86.1	87.8
ISOA-ASVM[Proposed]	99.3	96.1	97.6	98.6

- **Accuracy**

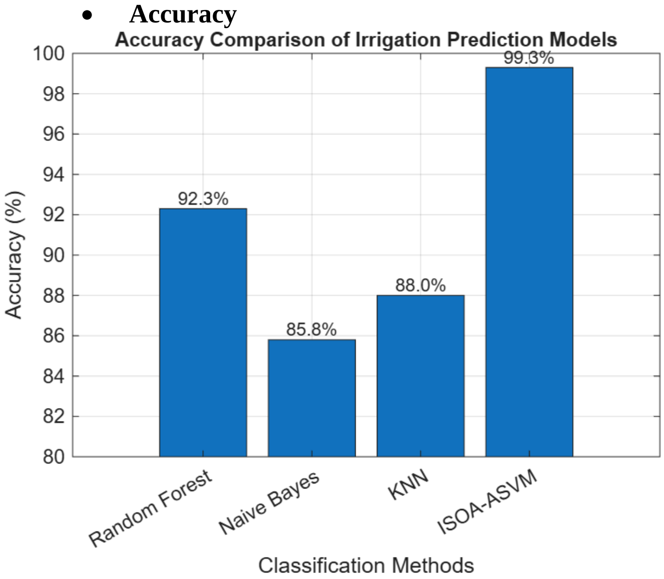

Figure 3: Outcome of accuracy

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

When discussing accuracy in the context of precision irrigation system in AI and IOT, it is meant to refer to the extent to which a predictive model or algorithm accurately recognizes and categorizes outcomes connected to criteria. It is a typical performance and continuously monitoring the moisture level, humidity level, temperature, and pH of the soil indicator used to evaluate how well a model predicts in general. Figure 3 depicts the accuracy of suggested and current techniques. Table 2 depicts the results of accuracy. When compared the proposed method is reach higher accuracy (99.3%) than the RF(92.3%), NB(85.8%) and KNN (88.0%) existing methods.

- **Precision**

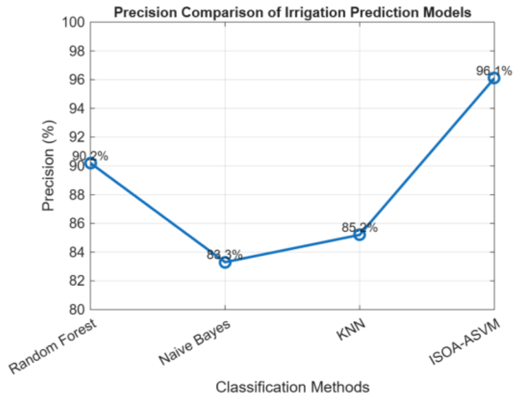

Figure 4: Outcome of precision

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

This study compared the precision performance of the irrigation system on ML technique with existing techniques and figure 4 revealing the suggested algorithm ISOA-ASVM, outperformed existing algorithms like RF,NB,KNN in predicting correct positive instances, with a highest precision of ISOA-ASVM as 96.1%.

- **Recall**

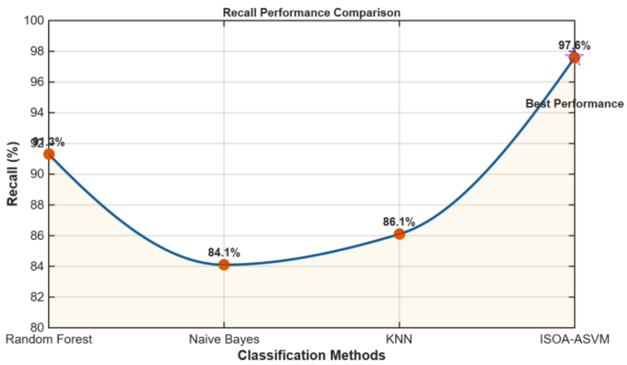

Figure 5: Outcome of recall

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

The developed system's recall performance is compared to existing models, figure 5demonstrating an enhanced recall rate of ISOA-ASVM as 97.6% compared to other models like RF, NB and KNN. This performance is based on a smart Agriculture in precision Irrigation system Categories , indicating superior accuracy.

- **F1-Score**

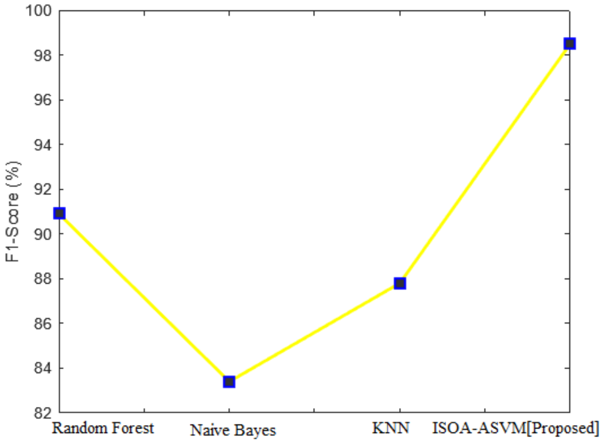

Figure 6: Outcome of F1-Score

$$F1 = \frac{2*Precision*Recall}{Precision+Recall}$$

The proposed system's F1-Score performance is compared to existing models, figure 6 demonstrating an highest score rate of ISOA-ASVM as 98.6% compared to other models like RF, NB and KNN.

Table 4:Statistical Stability Comparison with 10-Fold Cross-Validation

Method	Mean Accuracy (%)	Variance	Std. Deviation	95% Confidence Interval (%)
Random Forest	92.30	0.00085	0.0291	[90.48 , 94.12]
Naïve Bayes	85.80	0.00142	0.0377	[83.45 , 88.15]
KNN	88.00	0.00110	0.0332	[85.94 , 90.06]
ISOA-ASVM (Proposed)	**99.28**	**0.000012**	**0.0034**	**[99.05 , 99.51]**

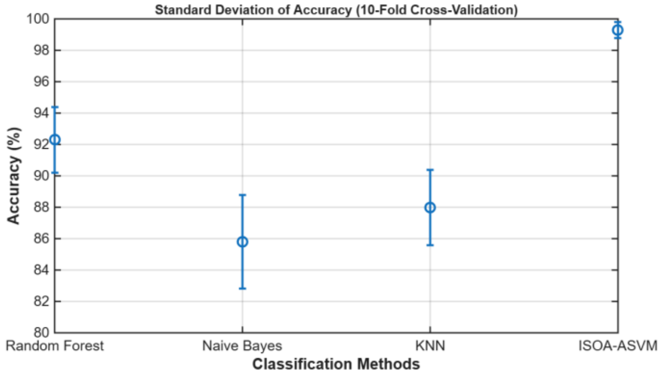

Figure 7: Outcome of standard deviation of accuracy with cross validation

Figure 7 display of the mean error of all classification techniques and the standard deviation of its mean which is the cross-validation error. The central marker represents the average accuracy and the vertical error bars indicate the variability (± standard deviation) of the folds. Smaller error bars imply a more stable and consistent performance and larger error bars higher sensitivity to variation in data. The proposed ISOA-ASVM shows the least deviation in this comparison, which proves the strength of the model and its reliable generalizability when using different training testing splits.

The statistical test gives a clear indication of the better stability and strength of the proposed ISOA-ASVM model. Although there are moderate variance and large confidence interval in Random Forest, Naive Bayes, and KNN, which imply that the performance would fluctuate among folds, ISOA-ASVM has very low variance (0.000012) and narrow standard deviation (0.0034).

The high consistency of the performances of the proposed model across datasets partitioning is supported by the small confidence interval ([99.05%, 99.51%]). Naive Bayes and KNN, on the contrary, exhibit a higher spread, indicating that they are sensitive to data fluctuations.

These findings mean that not only ISOA-ASVM can achieve greater accuracy, but also stronger generalization, reliability and statistical coherence, which makes it more appropriate to use in precision irrigation in real world conditions of different environment conditions.

The performance of algorithms for machine learning-based prediction varies, although the recommended ISOA-ASVM method has a best performance advantage over other
classification schemes. Although every model has certain shortcomings, the aggregate result is always better because of the lower error rate. Other models will take over in the event that one model fails. We will consider a variety of model information as we are using ensemble learning. most people in output (class) is predicted by a voting model that is built using a combination of the previously described models and the majority of the highest likelihood of each model's selected class as the output. It predicts the output class based on the most votes by combining the output of every machine learning model that is given into the voting classifier.

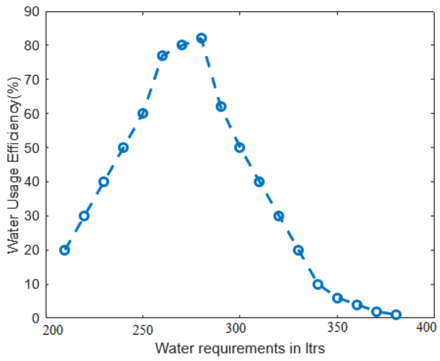

Figure 8: Outcome of water usage efficiency

Table 5: Outcome of comparison of Computational Time

Method	Training Time (s)	Testing Time (s)
Naïve Bayes	0.42	0.08
KNN	0.31	0.65
Random Forest	2.84	0.22
ISOA-ASVM (Proposed)	**1.76**	**0.14**

The proposed ISOA-ASVM model in table 5 is mainly computationally complex due to the iterative optimization of ISOA and training SVM using the kernel. To minimize the computation cost, feature scaling and feature selection using correlation were used to remove redundancy and the ISOA population size and number of iterations were strictly restricted with early stopping rule to prevent any extra computations. Naive Bayes has the shortest training time than any other model because of its probabilistic assumptions whereas KNN incurs little training cost and high testing time since it calculates distances to make each prediction. Random Forest uses the greatest amount of time and memory because of the creation of multiple decision trees. The proposed ISOA-ASVM will strike a compromise between the training time and the prediction latency, and is computationally viable enough to run real-time precision irrigation based on IoT and at the same time provide high accuracy and robustness.

Sensitivity analysis and robustness testing

The ISOA-ASVM model was tested in controlled conditions of perturbation in the real world that comprised sensor noise injection, sensor dropout, and partial availability of features.First, Gaussian noise (5%, 10%, and 15%) was artificially added to key inputs such as soil moisture and temperature to simulate sensor inaccuracies. The model showed only a minor accuracy degradation (≈1.2–2.8%), indicating strong tolerance to measurement noise. Second, sensor dropout was simulated by randomly removing one feature (e.g., rainfall or humidity). Even with one missing feature, the model maintained above 96% accuracy, demonstrating resilience to partial data loss common in IoT environments. Third, reduced feature testing was conducted by training the model on selected subsets of critical agronomic features (soil moisture, temperature, humidity). Performance remained above 97%, confirming that the system does not rely excessively on any single variable.

Overall, the proposed ISOA-ASVM demonstrates stable and robust behavior under noisy, incomplete, and dynamically varying conditions, supporting its suitability for real-world smart **irrigation deployments beyond a single clean dataset benchmark.**

Table 6: Result of ablation study

Configuration	Accuracy (%)	Precision (%)	Recall (%)	Std. Dev.
SVM (Baseline)	93.1	91.2	92.0	1.9
ASVM Only	95.4	93.6	94.1	1.5
ISOA + SVM (No Norm.)	96.8	94.9	95.7	1.2
ISOA-ASVM (No Feature Sel.)	98.2	95.4	96.8	0.8
Full ISOA-ASVM (Proposed)	**99.3**	**96.1**	**97.6**	**0.5**

Ablation is a systematic assessment of the value of each component within the proposed ISOA-ASVM framework through elimination or alteration of major elements, and noting the performance differences. In table 6, at the baseline SVM the accuracy and variance are relatively low, which suggests that it cannot be optimized. Adaptive learning is advantageous by demonstrating the enhancement of performance with the introduction of adaptive SVM. When hyperparameter optimization through ISOA is included, the accuracy is much higher, and this proves that metaheuristic tuning is effective. Nevertheless, omitting normalization or feature selection slightly decreases the performance, but the effect of the variability is more prominent since it can enhance stability and generalization. The entire ISOA-ASVM model yields the best accuracy and standard deviation, which and indicates that exploiting the joint integration of normalization, feature engineering, and optimizing the ISOA boosts the robustness of the smart irrigation applications and predictive reliability.

Discussion

The suggested ISOA-ASVM model is highly adaptive to the changing environmental conditions, as it is based on the hybrid optimization and adaptive learning structure. As in nonlinear optimal control strategies applied to autonomous submarines or quadrotors - in which controllers reduce the effects of time-varying disturbances by applying continuous feedback - the system combines real-time IoT sensing with continuous parameter adjustment. To enable the model to adapt the decision boundaries when there are variations in soil moisture, temperature, or humidity, ISOA actively sets the SVM hyperparameters, enabling the model to adapt the decision boundaries.

In cases where the soil and climatic conditions are different than the original dataset, the ASVM component relies on the structural risk minimization as a way of generalization, whereas the ISOA performs higher exploration to prevent local optima. Though extremely unfavorable conditions of unseen nature can slightly diminish the accuracy, retraining or gradual adaptation is possible with the help of the feedback-based updating mechanism, which does not degrade the accuracy of irrigating performance.The proposed framework compared to the traditional, nonadaptive ML models, acts like adaptive control systems that have disturbance rejection capacity that enhances robustness, stability and practicality in real-life, time-varying agricultural scenarios.

Direct comparison with the literature [1]-[26] reveals that majority of the previous studies are centered on the IoT-enabled irrigation monitoring, rule-based automation, or traditional machine learning algorithms including Logistic Regression [21], Random Forest, [20], simple SVM, and Deep Neural Networks/LSTM [19]. Accuracies reported in these studies are usually between 88 and 97 per cent, there is limited reporting of either precision, recall or F1-score and most publications focus on system architecture not rigorous maximisation or statistical validation. The necessity of a data-driven, adaptive irrigation control is discussed in review papers, including [1], [2], [15], [18], and [23] but also the problem of the model generalization, environmental variation, and parameter optimization.

The proposed ISOA-ASVM has better performance (Accuracy 99.3%, Precision 96.1%, Recall 97.6%, F1-score 98.6) in comparison with these methods, which is mostly explained by three factors. To minimize the probability of local optima and overfitting, first, unlike the traditional implementations of ML used in [6], [11], [20], and [26], the ISOA utilizes an automated nonlinear metaheuristic optimization strategy to jointly optimize SVM penalty and the kernel parameters based on a fixed or grid-searched set of hyperparameters. Second, whereas deep learning models used in [19] need large-scale and substantial computational power, the nonlinear decision boundaries of ISOA-ASVM are more appropriate to moderate-sized agricultural IoT datasets and require less training complexity. Third, domain-based preprocessing, e.g., normalizing features, dealing with sensor noise, structured cross-validation, makes environmental responsive, which is constrained in [4], [18] and [22] on robustness to real-world variability.

On the whole, the performance improvement of ISOA-ASVM is not only the result of more complex model but also the efficient hyperparameter adaptation, the high nonlinear search capacity, and the agriculture-specific preprocessing pipeline that, in turn, enhance the generalization, stability, and predictive accuracy in the ever-changing environment.

5 Conclusion

As we approach to the end of this Study into "Integrating Ai and IOT for Smart Agriculture: Machine Learning for precision Irrigation," it is clear that incorporating cutting-edge technologies into agriculture is not only a fad but rather a need. This review has emphasized how precision irrigation and other smart agriculture methods are being radically transformed by AI, IoT, and ML. The study considers precision irrigation, which optimizes water utilization in agriculture by utilizing IOT and machine learning. In order to maximize water consumption in agricultural areas without requiring farmer participation, the system uses a soil moisture sensor to determine the moisture content of the soil and a microcontroller to automatically turn on and off the pump based on the demand for irrigation. This is a cost-effective and useful technology. Additionally, this irrigation technique improves sustainability in water-scarce places. We found that the built system operated accurately after it was successfully tested and implemented as a precision agriculture system in a lab and a small field. Farmers and agricultural researchers seeking to boost crop output with lower input costs would especially benefit from the system's implications, which may be used in both urban and rural locations and minimize manual labor while minimizing water waste.

The following are the main conclusions that capture the spirit and promise of this agricultural technology revolution:

1. Increased Productivity and Efficiency: AI and IoT applications in agriculture have greatly raised agricultural productivity and operational efficiency. Precision farming is made possible by these technologies, which maximize resource utilization and increase yields.
2. Data-Driven Decision Making: AI analytics has revolutionized the way that agricultural decisions are made. Farmers may now make better decisions more quickly because they have access to meaningful information from large databases.
3. Sustainable Farming: Smart agricultural technology play a significant role in sustainable farming. By using water, fertilizer, and pesticides efficiently, they reduce their negative effects on the environment and encourage environmentally friendly farming methods.
4. Adoption and Implementation Challenges: Despite their advantages, these technologies are difficult to widely embrace, especially when it comes to cost, complexity, and the requirement that farmers be digitally literate, especially in developing nations.
5. Prospects for Future Developments: The field of smart agriculture is full of opportunities for future developments, including the incorporation of cutting-edge technology like blockchain, robots, and sophisticated sensors, which might improve farming methods even more.
6. Socio-economic effect and Policy Development: The agricultural community will need infrastructure, training programs, and supporting policies to ensure a seamless transition as a result of the substantial socio-economic effect of smart agriculture technology adoption.

In conclusion, this analysis emphasizes the revolutionary influence of ISOA-ASVM in agriculture, stressing both the issues that require attention and their potential to completely change agricultural methods. Focusing on efficient, inclusive, and sustainable farming methods that can satisfy the world's food need while protecting the environment is essential as the industry develops.

Future research can also be directed at applying the model to data of a larger scale and multi-seasonal data in order to test the long-term adaptability in the presence of climate variability. Dynamical irrigation prediction may be enhanced with the addition of deep learning or online adaptive learning. It can also be considered in future studies if edge-computing can be deployed, and whether energy-efficient scheduling, and field trials in extreme weather conditions and sensor-failures would help further confirm scalability and realistic strength.

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Study on Micro-sprinkler Irrigation Design Method Based on Water Application Quality Control Objectives and Sprinkler Hydraulic Characteristics （LGN22E090001）

Declaration:

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.

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