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Global Challenges, Local Solutions: Engineering, Science, and Technology in Developing Regions and Technology

Advancing precision agriculture: Enhancing irrigation systems with IoT and machine learning

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Abstract Precision farming has revolutionized modern agriculture by focusing on the appropriate use of resources and limits to environmental impacts to produce higher yields from crops. The current research intends to look at the application of its many technological advances, namely the Internet of Things (IoT) and Machine Learning (ML), to better equip irrigation systems in precision agriculture to promote their efficient use, with the aim to develop a Hybrid cuttlefish search optimized radar support vector machine (HCSO-RSVM) model, which will facilitate the precision irrigation process through quantified data driven control actions, from real time data collected from the field through IoT-enabled sensors. The sensor data was pre-processed with Min-Max Normalization, depending on these coordinate signs for uniform input, hence promoting optimal processing and ensuring better system quality and efficiency. The current research represents a development by which irrigation management will be enabled for timely decision making by monitoring changes in environmental factors e.g., water levels, weather, and soil moisture content. The HCSO-RSVM model performance is so positive that it appears to have outperformed classic methods in high metric performance with 97% accuracy, precision turned out to be 94%, recall of 93%- which affirms its reliability in administration of irrigation processes. This present research provides a view of the way forward to improving water use efficiency in sustainable agriculture and food security in global environmental challenges by full integration of IoT in agriculture with intelligent application. The paper therefore, indicated the importance of data-driven models would help to reinforcement increasing precision agriculture and sustainability of agricultural practices as the agricultural landscape advances.

Keywords: internet of things (IoT), irrigation systems, precision agriculture, environmental impact, sustainable forming, smart integration

1. Introduction

Precision agriculture's basic concept has been that the first farmer decided to plant here instead of there, graze here instead of there and irrigate that field instead of this one. As farmers chose landraces for particular settings, the idea became more complex. For instance, there are many different landraces of sorghum and millet grown; certain landraces do well in the rainy lowlands but not in the dry uplands and vice versa (Evett et al., 2020). The majority of economies rely heavily on agriculture to produce food and create jobs in response to the world's expanding population. It is a vital economic sector that makes a substantial contribution to the GDP of the majority of nations. Because agricultural production naturally depends on water availability, the success of this vital industry is dependent on water resources (Abioye et al., 2020). Since agriculture produces food security and makes a substantial contribution to the GDP, it serves as the cornerstone of most economies around the globe. Unquestionably, population expansion and environmental degradation are putting pressure on essentials like accessibility to water, which is essential for agricultural productivity (Bwambale et al., 2022).

A correlation has been discovered between water management and climate policy. Water management can be influenced by a number of issues, which include the need for water from different businesses and the effect of different levels of global warming on hydrological resources (García et al., 2020). The primary industry impacted by water scarcity is irrigated agriculture, which accounts for the majority of water demand and reduces the ability to sustain food production per person (Bonfante et al., 2019). Food is directly produced by agriculture for the majority of living things, including people and animals. The world's agricultural industry is more important because of the paucity of food. The nation's economy, which

depends on agriculture, is determined by its yearly output (Mentsiev et al., 2019). The world's food security is constantly in danger due to population growth. Better farming practices can guarantee food security. The green revolution, which emerged in agricultural practices between the 1930s and the late 1960s, is a significant development. Since then, the use of hybrid seeds combined with regulated irrigation, chemical fertilizers and cultivation mechanization has contributed to an improvement in agricultural productivity throughout the world (Bhakta et al., 2019). The need for food has increased as a result of the world's population, which is increasing very rapidly. It is quite hard to meet the food requirements of our earth with the limited resources available. Precision agriculture (PA) monitors agricultural conditions during different growth cycles by combining near and far-reaching sensing techniques using Internet of Things (IoT) sensors (Shafi et al., 2019). A vital application for crop cultivation and production is agricultural irrigation, which is always considered. Large increases in agricultural productivity and water savings can be achieved with a dependable and appropriate irrigation water supply (Jamroen et al., 2020). In about 30 years, the world's population is anticipated to rise from 7-10 billion people. In addition, overuse of agriculture, urbanization, and climate change will result in significant losses of arable land for food production, which will negatively impact the balance between production and consumption (Loures et al., 2020). The research consists of an attempt at the combination of IoT and machine learning and applying it to improve irrigation systems with the goal of precision agriculture to optimize the water efficiency with crop development. Thus, this research intends toward a data-driven model using Hybrid Cuttlefish Search-Optimized Radar Support Vector Machine (HCSO-RSVM) for proactive, sustainable farming practices.

Kashyap et al. (2021) suggested an IoT-enabled deep learning neural network-based smart irrigation method for precision agriculture (DLiSA), which was an incorporated feedback system that maintained improved functionality over time, irrespective of the local climate. Karunathilake et al. (2023) outlined some of the most cutting-edge developments in precision farming, such as the application of big data and the IoT. The study offered a review of precision agriculture as it is today, taking into account the newest technological advancements, including machine learning, drones, and sensors. Fathy and Ali (2023) focused on smart irrigation systems, where the Message Queue Telemetry Transport (MQTT) protocol was used as an application messaging platform. Through enhancing agricultural irrigation efficiency, smart irrigation seeks to minimize natural resource waste. Murugamani et al. (2022) examined a broad approach, covering problems like soil sensing, temperature, leaf disease detection, moisture sensing, and server-based remote monitoring systems. Plant illnesses that, if not treated in a timely manner, lower productivity is usually caused by insects and infections. Jiménez et al. (2022) outlined how to create and implement an intelligent IoT-multiagent precision irrigation strategy to increase the water consumption efficacy of irrigation systems. The technology offered a cutting-edge method to assist district and field level decision-making in water resources management applications. Singh et al. (2022) described how to construct a smart irrigation system that takes the weather and soil into account. Using a variety of research publications in Agriculture 4.0 and ML, the soil and meteorological characteristics are chosen. The difficulties potato farmers confront in raising yields, enhancing quality, and cutting expenses of production were covered (Ahmad et al., 2023). A potential answer to these issues is the adoption of precision agricultural technologies (PATs), which include remote sensing, variable rate input application, yield monitoring systems, and precision planting, among others. Anjum et al. (2023) offered a thorough analysis of precision irrigation technologies and techniques. Precision irrigation, which is a portion of precision agriculture systems, has not gained much attention despite the widespread promotion and implementation of precision agriculture in arid land areas by (Garcia et al., 2023). Concentrated on precision irrigation using remote sensing technologies to measure agricultural characteristics, crop water status, vapor-transpiration, and infrared thermography Samreen et al. (2023).

1.1. Key contributions

To obtain the hydrometeorological data and address misplaced values, outliers, and discrepancies, the gathered data first need to be cleaned.

Once the data is cleaned, Min-Max normalization is used to preprocess the data.

To evaluate each parameter used for the assessment, in Part 4 the performance of the proposed HCSO-RSVM combined method is assessed against other models.

The remaining parts of the paper are structured as follows: Part 2 provides a thorough review of the HCSO-RSVM approach. Part 3 discusses the experiment design, results, and performance evaluation of the proposed system. Part 4 summarizes the overall results. Part 5 concludes the paper and offers suggestions for future research.

1.2. Problem statement

In agriculture, modern irrigation practices are not prevalent, despite the potential upside of leveraging IoT and ML. Further implementing these practices is disallowed by the lack of suitable research and working solutions that are aimed at the variety of crop types, environmental conditions, types of sensors used, and geographies. The development of a framework that effectively combines data analysis, IoT Sensors, and machine learning (ML) practice is needed to create a

smart irrigation system that would be able to run a distributed watering system dynamically and in real-time to monitor crop needs and environmental variables.

2. Materials and Methods

This section covers how the IoT and ML techniques are employed to improve irrigation systems and advance precision agriculture. The methodological design is displayed in Figure 1.

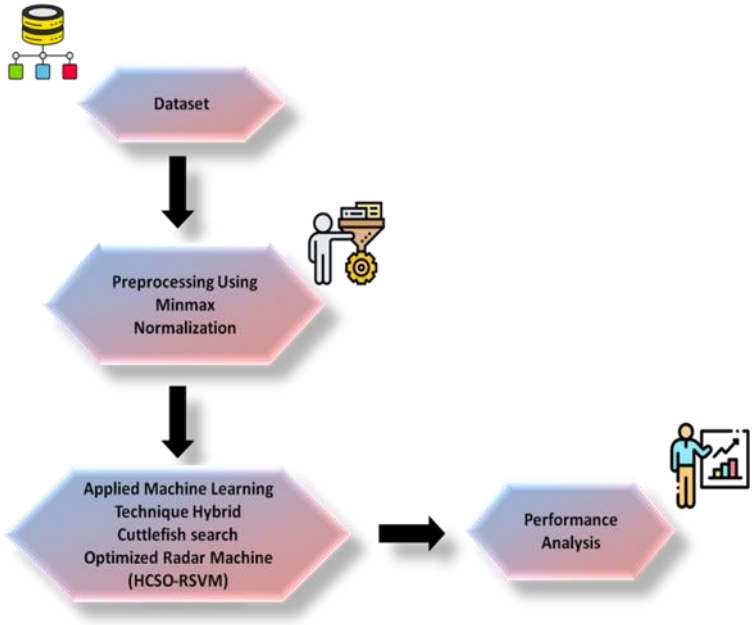


Figure 1 Methodological Design.

2.1. Dataset Collection

The auto irrigation dataset on Kaggle includes sensor readings for soil moisture, temperate and humidity, along with timestamps. It is intended to support the usage of automated irrigation systems by providing real time environmental data for training machine learning models in precision agriculture. Source: Kaggle (https://www.kaggle.com/datasets/harshilpatel355/autoirrigationdata).

2.2. Min-max normalization

A common method for scaling the numerical properties in a specified range is min-max normalization. It uses the original data, which has been converted linearly, to allow for a meaningful comparison of scores before and after the process. The formula of min-max normalization can be given by Equation (1).

$$Z_{new} = \frac{z - min(z)}{max(z) - min(z)} \quad (1)$$

Z_{new}= The modified value which is obtained after scaling the dataset.
z = The value which is outdated.
$max(z)$ = Maximum value of the dataset.
$min(z)$ = Minimum value of the dataset.

2.3. Hybrid cuttlefish search optimized radar support vector machine (HCSO-RSVM)

The term Hybrid Cuttlefish Search Optimized Radar Support Vector Machine refers to a theoretical amalgamation of many technologies motivated by the adaptable characteristics of cuttlefish, optimizer radar systems, and support vector machine techniques employed

2.3.1. Radar Support Vector Machines (RSVM)

SVM is used to evaluate the data's accuracy in classification and regression tests. Similar learning mechanisms are used by SVMs and supervised learning models. Under these circumstances, a non-linear kernel RSVM model, such as the Radial Basis Function (RBF), would be more suitable. The RSVM is a variation of support vector classification model, which is

introduced based on a specific kernel-based feature space expansion technique. The space where a linear support vector classifier can operate is depicted in Equation (2).

$$e(v) = \beta_0 + \sum_{j=1}^{m} \alpha_j \langle v, v_j \rangle \quad (2)$$

where $\alpha_1, \cdots, \alpha_n$ and β_0 are variables, which are determined by $(\frac{m}{2})$ internal products (v_i, v_j') of training observational pairs. The kernel is a process, where we replace an inner element with $L\ (v_i, v_i')$, where L is a kernel. The representation of the linear kernel is illustrated in Equation (3).

$$L(v_j, v_j') = \sum_{i=1}^{o} v_{ji} v_{ji}' \quad (3)$$

To describe a polynomial kernel of degree d, we have to use Equation (4).

$$L(v_j, v_j') = \left(1 + \sum_{i=1}^{o} v_{ji} v_{ji}'\right)^e \quad (4)$$

RSVM classifier belongs to the family of supervised learning methods based on kernels, which have been developed mainly for binary classification. When there are numerous training samples, this kind of classification divides the data into two or more groups. A kernel function is used to map the training set to a set of data that will be linearly separated. The performance of the RSVM classifier may be determined by utilizing the kernel parameter and the regularization parameter. Nonlinear classification is another application for RSVMs. Text and hypertext classification, language recognition, image recovery, financial ruin prediction, remote sensing assessment of visual data, biological, time series estimation, data privacy, including bio informatics and protein classification, and chemical-based science, including spectrum analysis and chromatography-mass spectrometry, have all benefited from the successful application of RSVM.

2.3.2. Cuttlefish Search Optimization (CSO)

The blue bodies and patterns of the cuttlefish are replicated light from the numerous cell layers of cuttlefish that includes leucophores, iridophores, and chromatophores. Visibility and reflection are both considered by the CSO. The method of reflection process is a process that reflects the light toward the surface, but the visibility is a process that mimics the visibility of the pattern. These two procedures are employed as a search method for finding the best answer. Figure 2 shows the CSO flow chart.

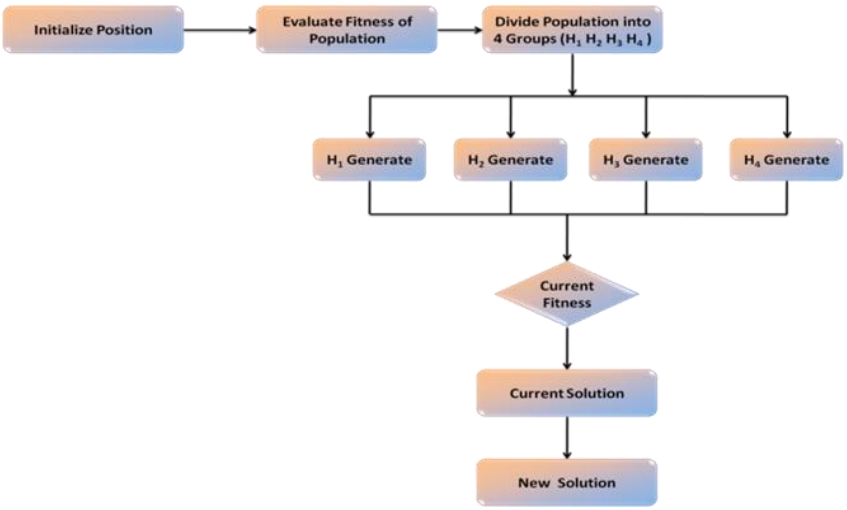


Figure 2 Flow chart for CSO.

$$new_population = ref \quad (5)$$

The combined visibility and reflection processes together yield six distinct conditions and Equation (5) expresses a new possible resolution.

$$ref[i] = Q \times H_1[j].points[i] \quad (6)$$

$$vis = W \times ([Best.Points\ [i] - Q \times H_1[j].points[i]) \quad (7)$$

The values of Rand (q_1 and q_2) are acquired using Equations (6) and (7), respectively.

$$R = rand() \times (q_1 - q_2) + q_2 \quad (8)$$

$$W = rand() \times (x_1 - x_2) + x_2 \quad (9)$$

We need to use Equation (8) to compute how detectable the appropriate background is. These points indicate the places of the optimum solutions. The saccule stretches or shrink interval is set by R, and how high the pattern is seen is governed by V. An interval around the best response resulting from Equation (9) is a new search area.

$$ref[i] = Q \times Best.points[i] \quad (10)$$

Equation (10) employs the Leucophore cells for improvement in the pattern visibility, analogous to Equation (11), by reflecting light from the near locality of the solution that is Best ($BXbest$).

$$vis[i] = X \times (Best.Points[i] - BXbest) \quad (11)$$

2.4. IoT networks and sensors

Wireless sensor networks are used in many agronomic applications, such as remotely monitoring soil and ambient conditions to predict crop health. Irrigation schedules for agricultural areas are projected using WSN, which is cognizant of environmental elements such as humidity, temperature, pressure, soil salinity, soil moisture, and soil conductivity. Wireless sensor networks make it possible to monitor spatiotemporal climate, hydrography, pressure, movement, soil moisture, eco-psychological plants and epidemics to report the best options to farmers. It would be immensely beneficial for them to possess such knowledge. Farmers can take advantage of automatic control systems to regulate adverse situations through control of irrigation, fertilizer and insect management in a farming system. Irrigation maintenance is one of the most comprehensive and detail-oriented tasks in farming (IORLİAM et al., 2022). There are a lot of improvements that can be made in the irrigation system to increase the efficient use of water and agricultural output. Another factor that necessitates an update of the system is declining groundwater levels. The set-up uses a water and cost-effective micro-irrigation system.

2.5. Farming System Surveillance

In agriculture, a number of modern technology and tools are currently in use. Thus, the improved way of operating the apparatus provides autonomy for hunger and improves the ease of operation. Remote observation technology improves large-scale farm management. In addition, the quality of the method can be enhanced by including more information, such as weather prediction and satellite images. Efficient use of pesticides and fertilizers leads to decreased farm costs and increased crop quality. For this, it is necessary to understand the temperature, moisture and wind speed of the surrounding environment. A WSN could track and predict these events from a field of interest autonomously. Plant growth and quality are impacted by fertilizer application. On the other hand, feeding fertilizers optimally on good fields is hard labor. Using fertilizers for agriculture allows for the monitoring of variations in land nutrition, including pH, phosphorous (P), potassium (K) and nitrogen (N). Thus, both the crop's quality and the balance of soil nutrients can be maintained. The quality of groundwater is decreased by the increased use of pesticides and fertilizers. Wireless technology improves the control of water quality through the placement of sensor nodes.

3. Result

The suggested technique was implemented using Python 3.11 on Windows 10 OS with a 32 GB solid state-drive, which was utilized throughout the research process. This section assesses the functionality of the suggested system. The performance metrics include precision, accuracy and recall. that are used in the evaluation. Currently used approaches for comparison are Random Forest (RF) and Naive Bayes (NB) K-Nearest Neighbor (KNN), (Sharma et al., 2023). Table 1 displays the performance outcomes of the suggested and current methods.

Table 1 Outcomes of data compression time & radio.

Methods	Accuracy (%)	Precision (%)	Recall (%)
NB (Sharma et al., 2023)	94.23	92.59	91.32
KNN (Sharma et al., 2023).	95.85	90.45	90.81
RF (Sharma et al., 2023).	93.45	89.67	91.76
HCSO-RSVM (proposed)	97	94	93

The precision, F1 score, recall, and accuracy of the proposed model are shown in Table 1. It reveals that, in terms of all the performance parameters, the proposed model categorized COVID-19 bacterial infection accurately. The (YOLO+VGG-19) model was able to identify COVID-19 ARDS considerably more accurately than DenseNet201, ResNetv2, and InceptionResNetv2.

3.1. Accuracy

Accuracy is the process of identifying the total number of incidents. The accuracy of the existing and proposed approaches is defined in Table 1 and illustrated in Figure 3. The HCSO-RSVM has been suggested for use in irrigation systems because of its accuracy. The proposed approach, has an accuracy rate of 97%, while the accuracy rates of RF, NB and KNN are

93.45%, 95.85% and 94.23%, respectively. From the findings shown it demonstrates that the proposed method outperformed the previous approaches.

$$Accuracy = \frac{t_p+t_n}{t_p+t_n+f_p+f_n} \quad (12)$$

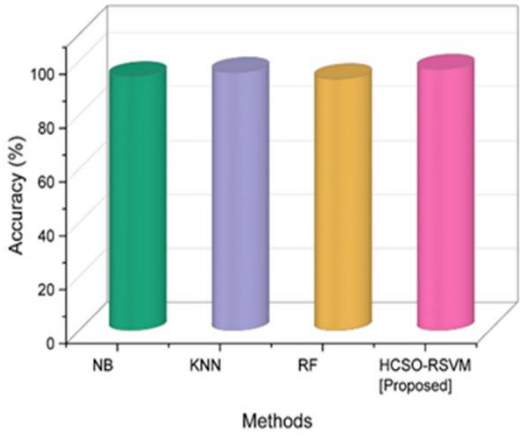


Figure 3 Accuracy.

3.2. Precision

Precision is a metric for evaluating a classification's accuracy for a model context in statistics and machine learning. It calculates the ratio of positively predicted cases that were identified out of all positively predicted situations. Figure 4 and Table 1 provides the precision of the proposed and current systems. Application of the proposed HCSO-RSVM precision has been suggested for the irrigation systems. The precision of RF is 89.67%, NB is 92.59%, KNN is 90.45% and precision of our proposed approach is 94%. The result indicates that the proposed HCSO-RSVM achieved higher precision than the other methods.

$$Precision = \frac{TP}{TP+FP} \quad (13)$$

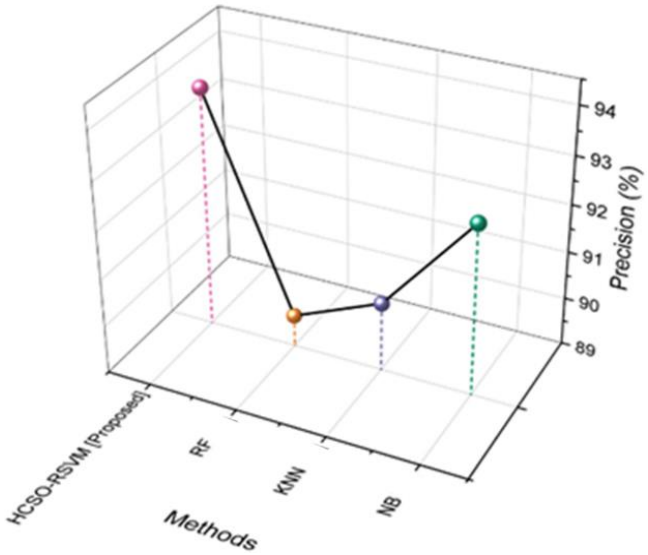


Figure 4 Precision.

3.3. Recall

Recall is mathematically characterized by the difference between inaccurate negatives from the sum of true positives. The model could serve as the basis for being able to identify relevant occurrences in a collection of industrial product data. The recall for the suggested and current approaches is presented in Table 1 and Figure 5. Precision of the suggested method is 93% whereas RF's recall is 91.76%, NB's recall is 91.32% and KNN's recall is 90.81%. Our experiments show that the HCSO-RSVM is more precise than other approaches.

$$Recall = \frac{TP}{TP+FN} \quad (14)$$

The equivalent results for the recall measures are shown in Figure 5. The suggested method's value is 92%, which is superior to existing approaches like DenseNet201 at 80%, ResNetv2 at 40%, and InceptionResNetv2 at 71%. The recommended YOLO+VGG-19 outperforms other approaches and has greater recall in detecting bacterial infection.

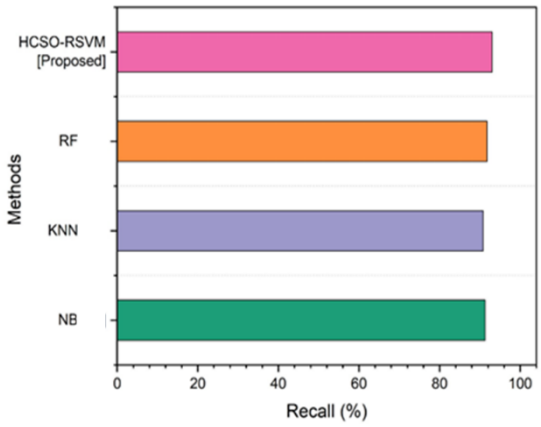


Figure 5 Recall.

4. Discussion

Using remote-sensing technologies for precision irrigation can improve water-use efficiency due to its ability to provide real-time information about crop water status. By employing measurements of evapotranspiration and using infrared thermography, farmers can optimize irrigation decisions and minimize water waste. Both techniques produce a more spatially accurate picture of soil moisture and plant health making it particularly useful to optimize yield. Samreen et al. (2023) describe the critical role remote sensing plays in sustainable agriculture through large-area implementation. Leveraging remote sensing techniques into agro-techniques can significantly improve resource management and climate resiliency in new-age agriculture.

The downside to Naive Bayes (NB) (Sharma et al., 2023) for a MANET application is that NB assumes independent features. This is unlikely to hold true in real-world network data where features sometimes exhibit correlation. These reduced assumptions can shorten detection accuracy as a whole, particularly for intricate network cases that have dynamic flow patterns and correlated behavior. NB may find high dimensional datasets taxing because NB works by estimating conditional probabilities, which can also lead to overfitting or poor performance. NB cannot be reliable in performance because it is prone to noise and does not cope well with unbalanced data. The model also lacks flexibility to adapt to changing network topologies, which as noted, compromises effectiveness.

One major limitation of KNN (Sharma et al., 2023) for detecting anomalies in MANET is the computational costs are generally pronounced in larger networks with dynamic topologies and change vectors. The networks become larger, the more computation needs to go to the calculations of distances that relates to the nodes, which further contributes to eliminating desirable detection timeframes. KNN drastically struggles with scalability, as real-time changes made to the networks means a new/current calculation must be made every time. Additionally, the effectiveness of KNN diminishes greatly in noisy environments with incomplete or inaccurate data, potentially causing KNN to inaccurately label something as an anomaly (false-positive) or miss properly identifying an anomaly because of identifying a greater number of false anomalies (false-negatives). KNN also relies a great deal on the distance metric used meaning KNN performance could be greatly impacted potentially by distance metric selection. KNN does not work well below high-dimension feature spaces when applied to MANET for anomaly detection which could adversely affect detection capabilities.

The application of RF (Sharma et al., 2023) when considering resilience improvements of MANET based losses of detection have limitations, especially considering training considers with computationally intense capability in order to make a large MANET. RF must also take enormous memory ingestion and must take average processing resources of memory as it trains multiple decision trees, thus working against the integrating infrastructure where the decision trees are not in the domain (limited resources).. In addition, the decision making would also take considerable time as RF time for anomaly detections will present the associated decision making. The performance of RF will also be detracted by noise in the data or if there are too many irrelevant features. The RF has can further demonstrate challenges when using imbalanced dataset, impacting the influence of the results. There was also challenges from the interpretability aspect of model regarding how to communicate the result to an average user.

The results show that the HCSO-RSVM method demonstrates higher classification performance with higher accuracy (97 %), precision (94 %), and recall (93 %) than the alternative approaches to the model. This underscores that HCSO-RSVM is a successful model at obtaining improved predictions from irrigation systems with the provided service from previous models. The suggested HCSO-RSVM addresses these issues as it relies on feature selection and feature optimization. While

HCSO accounts for feature dependency which helps to mitigate the curse of dimensionality, RSVM is robust to noisy and imbalanced data. The hybrid method has better computational efficiency, allowing for the anomaly detection of MANETs in real-time. Furthermore, RSVM's ability to adapt to dynamically evolving network topologies improves both detection accuracy and resilience.

5. Conclusions

A viable approach for attaining sustainable and effective agricultural practices is the incorporation of IoT and machine learning techniques to improve irrigation systems in the environment of precision agriculture. This study has shown the potential for maximizing agricultural output, minimizing water waste and optimizing irrigation systems through the use of predictive modeling and advanced data analytics. The aforementioned statistics indicate that the HCSO-RSVM technique's accuracy, precision, and recall are 97%, 94%, and 93%, respectively. Precision agriculture promises to be a sustainable, resilient and high-yielding agricultural practice in the face of changing global issues through continuing innovation and collaboration in the fields of IoT and machine learning. The constraint indicates that the sensor data were used and could possibly be influenced by environmental factors. Future research could demonstrate the viability of multi-sensor integration and real-time adaption to further precision in irrigation practices.

Ethical considerations

Not applicable.

Conflict of Interest

The authors declare no conflicts of interest.

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