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Evaluating the machine learning based Efficacy of Decision Tree and Support Vector Machines in Smart Irrigation Systems for Precise Irrigation Status Classification for Optimizing Water Management in Agriculture

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Abstract: - The research paper deals with the improvement of water management practices in agriculture through the use of machine learning in smart irrigation systems. The efficiency of the Decision Tree and the Support Vector Machine models with real-time sensor data was analyzed. The Internet of Things system was developed to analyze the data collected at the field with the help of various sensors, including temperature, humidity, and soil moisture sensors. The layout and choice of sensors were based on the official parameters required for most average plants and corps. After data collection and development of classifiers, the Decision Tree and Support Vector Machine models were used and analyzed regarding their efficiency for making irrigation-related decisions. As the result, it was found that both models showed a good performance, but the SVM model was slightly better due to a smaller number of false positives and false negatives, which allow it to divide the data into the corresponding categories more accurately. At the same time, both models use history data, and the more recent data are better for decision as it was also noted during the development when the use of models based on history data for irrigation decision result in regular irrigation, which in long term would cause the loss of productivity of plans, due to the issue that ancient and no crops are watered too. As the final results, it can be stated that the models show good performance, and the algorithms that were tested can be stated viable for the use at practice. At the same time, the SVM model shows slightly better performance than DT.

Keywords: optimization, agriculture, machine learning, water management, sustainability

I. INTRODUCTION

Smart irrigation systems are one of the most innovative solutions to water scarcity and sustainability in the agriculture industry. These systems utilize various technologies including sensors, actuators, and data analytics tool to track, collect and manage streams of real-time data about the water usage. By combining environmental data, such as soil humidity and weather, with the stages of crop growth, smart irrigation systems minimize the waste of water. The identified technology has numerous benefits including but not limited to water effectivity, controlled crop yields, and resources use. In addition, smart irrigation systems have potential for scalability and implementation in various climates [1]–[3].

Another major trend in the agriculture industry is the application of machine learning . The uses of such algorithms as decision trees, support vector machines, neural networks, ensemble, and other machine learning techniques has proven to be instrumental in analysis and predictions. In particular, the developed software for agriculture enables modeling, monitoring, and prediction of crop behavior and harvest to avoid numerous risks

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including diseases. By empowering farmers and related stakeholders with predictive tools, machine learning offers enhanced efficiency of resources use and the negative impact of agriculture on the environment [4]–[6].

Some of the most popular models such as decision trees and SVMs have been widely applied in agriculture for such purposes as crop yield prediction, disease diagnosis, and irrigation control. Because they are transparent and able to reflect the nature of decision-making processes, they are beneficial in several ways. The decision tree model is used to split the feature space into a tree which consists of nodes of decision where the hierarchical nodes are based on input variables. As the input variables are used to classify the target outcomes with high rates of accuracy, decision tree models are highly used in irrigation control to analyze the environmental inputs such as soil moisture, temperature, and humidity and analyze crop prediction and the amount of water consumed . Even though the decision tree model is simple, it generally overperforms and should be used if there is a transparency requirement for the nature of the training task. At the same time, support vector machine models are one of the most recent applications in agriculture for predictive analytics and classification task purposes [7], [8]. It works well when analyzing complex datasets by making generally good predictions. However, specifically, support vector machines are good at capturing nonlinearities and patterns in the input space. They make decisions by separating the different classes with lines maximally distant from each other . Hence, support vector machine models can be used to evaluate the input sensors of such as soil moisture, weather, or crop and predict irrigation requirements and water use by the farmers in a smart irrigation system. The robust and optimal nature of SVM models for water use is beneficial for operational tasks in agriculture [9]–[11].

Combining machine learning learning techniques with smart irrigation systems could significantly contribute to enhancing the quality of agricultural water management practices. Machine learning models, which analyze real-time sensor data and develop predictions on irrigation demand in the future, can be particularly impactful in minimizing water waste and, correspondingly, maximizing crop yields [12], [13]. While different models can be used in the context of machine learning, including decision tree and support vector machine models, the implementation of machine learning algorithms to process complex environmental data and large amounts of historical information proves particularly beneficial. The high accuracy of machine learning models' predictions and their sophisticated and in-depth insights into irrigation demands can be particularly advantageous. Moreover, the possibility to incorporate machine learning into existing smart irrigation systems is another notable advantage as it streamlines the implementation process. Overall, the applicability of machine learning algorithms to agriculture manifests itself in smarter and environmentally sounder irrigation system that helps to address the pressing issue of water scarcity in the context of an ever-warming climate change [14], [15]. Although there have been a significant number of studies conducted in the field, a gaps still exist in our understanding of the broader social and technical context in which machine learning models are used.

This research investigates the application of machine learning models, such as decision tree and support vector machine, in smart irrigation systems in agriculture in order to optimize water management. These models analyze real-time sensor data to make the most accurate prediction of irrigation needs. The outcomes of the research are expected to fill the gaps in the available research and provide a view of the application of machine learning in agricultural practices, the benefits it may bring, and the challenges it may impose. The utilization of experimental tools, analysis, and frameworks is going to contribute to the development of smart irrigation systems and technologies as well as have implications on increased crop yields and elimination of water scarcity in agriculture.

II. METHODOLOGY

In the first phase of our research, we devised an IoT system for smart irrigation in agriculture. This system aims to improve water management by exploiting real-time data acquisition from sensors installed or distributed in various locations within an agricultural field to collect. Temperature sensors were devised to measure temperatures, water level sensors to measure water levels and humidity sensors to measure humidity among the other environmental parameters. These sensors were installed to monitor the environmental parameters affecting their crops continuously. These sensors would then send the data to the controller unit for evaluation. Controller unit being the heart of our IoT system, receives the readings of environment parameters through sensors and manages iterations using predefined algorithms . The controller unit then manages pump operation conducting the desired volume of water for the crops . Continuous monitoring of the data ensures that the crops get the exact amount of water necessary.

In the second phase, the DT and SVM models have been employed in conjunction with the IoT system to increase the predictability and performance of the system. We could reasonably conclude that the data train in the DT and SVM models was done on the feature set of historical data acquired on the field. The target, on the other hand, was to supervise the actual necessary amount of water to apply on the crops obtained from historical data acquired previous to the given field. The sensor data was input on the models and used to calculate the relation of the environmental parameters to the amount of water necessary to apply to crops. Thereafter, the data was used to predict the currently necessary amount of water. To test the usability of the employed models, we used varied performance measures , accomplished by observation on the predictability of the usage of DT and SVM models to predict the amount of water to apply based on environmental parameters. Furthermore, the DT and SVM models' training-scheduled performance was embedded on our system's decision-making process. The models' training scheduled time is used to compute the advance analysis of when the pump should be put on or off. Our system continuously monitors the environment parameters and computes/predicts when the amount of water is low. Then the controller changes the operation of the pump by initiating the pump operation. Over-pumping is prevented; the controller stops the pump operation in advance before any application of water. Using a DT and SVM models-vis IoT system through an advanced analysis of water management is sustainable and minimizes wastage of water. It additionally enhances resource management, thus increasing the crop yield.

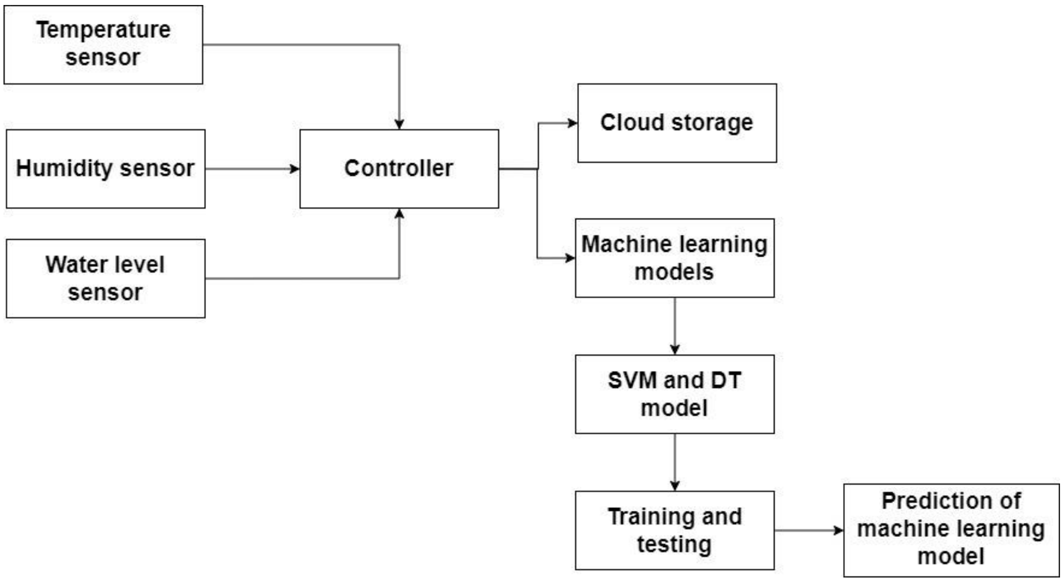

Figure 1. Methodology of machine learning model

A. Sensor and communication

In our study, we focus on the critical role of sensor selection and deployment, which allows realizing real-time data acquisition and monitoring toward the efficient management of smart irrigation. Sensors are widely used to collect the data on temperature, levels of water, and humidity; more importantly, these devices are chosen to meet a specific amount of parameters that should be measured to observe the most decise aspects of the environment, determining plant health or water needs. Among the key sensors integrated within our IoT-based smart irrigation system used in the environment are temperature sensors, water level sensors, and humidity sensors, which may serve various goals and, simultaneously, support even more accurate and carefully examine the characteristics of the agricultural field environment.

Temperature sensors are positioned to be appropriate for monitoring temperature parameters in the field. Temperatures are likely to increase by varying water amounts and conditions of the environment. Measuring temperature range, these sensors provide information about water volumes needed for the plants through the data of plant conditions and stress levels observed due to temperature changes. Also, when speaking about temperature characteristics, it would also be crucial to detect any possible frosts that can affect the plants and be prevented.

Water level sensors are used to evaluate moisture in the soils to give data on water levels needed for the agricultural field. These sensors are typically located at 10, 20, and 30 cm depths and measure soil water concentration at different levels. Based on the proportions of soil moisture capacity, the irrigation water might be employed to ensure the normal soil profile moisture reach . Due to such systems, water availability is assessed and managed to prevent being under-watered or over-watered. Humidity sensors are used to evaluate humidity in the atmospheric air. Humidity ranges usually affect the velocity of the plant's transpiration and the levels of moisture stress. At the same time, humidity sensors are used collectively with temperature sensors to define evening moisture gain ranges.

Such collected data are sent with the use of Wi-Fi connectivity to the central unit of the IoT system. The central controller provides the processing of this data with the use of an artificial neural network, which would allow realizing the decision-making process. The results of this data acquisition are observed in three datasets to show some data calculations, measures, and important events. In this system, we pay critical attention to the timely process of information acquisition and sending.

B. Machine learning models

For our research, the existing machine learning models are a foundation to enhance capabilities of our IoT-based smart irrigation system. Specifically, we use two powerful algorithms, Decision Tree and Support Vector Machine , that determine water requirement from real-time sensor data. While historical sensor data is used to train them, these models can accurately predict a tendency based on complex patterns and relationship between inputs and outcomes present in the agricultural environment.

Firstly, we use Decision Tree algorithms that are known for their interpretability and simplicity in use. The trained DT model partitions feature space into separate areas, similar to a tree structure, through sequential binary data splits. For our system, the implication of this decision structure serves as the advantage by receiving an intuitive report reflecting the description of necessary features to manage irrigation regulating and planning. Therefore, we train a DT model through historical sensor data analysis, which helps the model accurately and effectively classify specific states and determine outcomes.

Secondly, considering that DT model does not satisfy all the necessary requirements of achieving high productivity, we additionally introduce a Support Vector Machine learning algorithm. SVM can effectively reach high predictive performance by mapping inputs and outputs into a higher-dimensional feature space thanks to the division of various classes through the use of core functions. In this way, we can improve classification efficiency and ensure accurate prediction when dealing with sensor data. By training the SVM model, we strive to identify complex non-linear relationships among parameters outlined and between them and water requirements. In general, we want to model a complex system that consists of various interacting elements which is, however, captured and presented comprehensively and efficiently in such a format. Since the models are trained with previous sensor data, it allows them to generalize results on unseen data. We use a range of objective performance metrics to guarantee the effectiveness of training efforts, like accuracy, precision, recall and F1-score.

C. Dataset

The first step in our research is the implementation of an IoT system. Sensors and data collection are a fundamental prerequisite for the realization of the objectives in our research investigation. With sensors implementing across the entire field, such a system can quickly gather invaluable data on the current environmental conditions inside the field. The first dataset contains a sample of this data and shows the status of the system at a given time in the morning, the afternoon, or the evening. The sample data shown in table 1 shows collected from the various sessions are shown in table 1.

TABLE 1. SENSOR DATA AND THE ACTUATOR RESPONSE

Time	Temperature (°C)	Humidity (%)	Soil Moisture (%)	Pump Operation
6:00 AM	22	65	40	On
7:00 AM	24	68	42	On
8:00 AM	26	70	45	Off
9:00 AM	28	72	48	Off
10:00 AM	30	75	50	On
11:00 AM	32	78	52	On
12:00 PM	34	80	55	Off

1:00 PM	36	82	58	Off
2:00 PM	38	85	60	On
3:00 PM	36	82	58	On
4:00 PM	34	80	55	Off
5:00 PM	32	78	52	Off
6:00 PM	30	75	50	On
7:00 PM	28	72	48	On
8:00 PM	26	70	45	Off
9:00 PM	24	68	42	Off
10:00 PM	22	65	40	On

This dataset contains different readable variables, such as time, temperature, soil moisture, humidity, and pump status. Combining such data allows one to observe the relationships that exist between the condition of the soil, the temperature, and other factors. A more applicable dataset which consists of 2100 observations combines the above-described factors and has an additional pump status variable. The dataset is split with a traditional 70-30 split, with 70 percent being used for training and 30 percent being applicable for testing. Such a ratio will allow a model to receive training by being tested on a variety of conditions.

D. Preprocessing of dataset

As a part of our research, dataset preprocessing is an important part of our machine learning models' training. It presupposes a range of important procedures closely related to cleaning, transforming, and enhancing the dataset, which would contribute to the models' improved performance and robustness. There are several typical steps that need to be completed before the data can be utilized to train the models, including data cleaning and separation, feature scaling, and feature engineering. In addition, normalization is also a new type of processing, which is often recommended to be completed in combination with these stages for the sake of the improved performance and generalization capacity of the models. Moreover, as a part of our additional preprocessing, we complete data partitioning as a crucial element, which is irreplaceable to help the models avoid overfitting and be trained on the one subset of the data while being tested on another.

Data cleaning is the first stage we utilize to identify and handle missing or erroneous data. Missing data is one of the most serious problems associated with machine learning since it can have a negative impact on the models' performance leading to their being biased and inaccurate. To improve the situation, we utilize imputation, which is a general technique used to replace missing values with their estimates derived from the existing data. Outliers, which are the extreme values differing significantly from themselves, are also detected and emended or, if it is impossible, removed. The following feature scaling stage presupposes the standardization of values or the completion of the 0 to 1 range across all the features. It is essential for the models, which are sensitive to the scales of input variables, such as for Support Vector Machines. Feature scaling is important since it does not allow some variables to take over others with smaller values, ensuring that the model learns from all the features equally.

The second stage is so-called feature engineering, which means data transformation for the more comfortable learning from it for the models. We create new features in this process, extracting the existing ones to be more consistent with the inherent patterns of the data. For example, the difference of soil moistening or the average temperate in the tank can be transformed into a new meaningful factor. As well, we usually normalize the data, it making its distribution normal if our models need it. The Decision Tree, for example, usually perceives the assumption that the data is normally distributed. However, usually, it is not the case. Normalization helps to make models more adequate and generalizes properly.

III. RESULT AND DISCUSSION

To predict irrigation responses using real-time sensor data, the performance of each machine learning model was tested. The results of the testing phase confirmed that both Decision Tree and Support Vector Machine models were highly accurate. The testing of the Decision Tree model revealed that the level of precision reached 94.5 percent. Although this was an excellent result that showed the model's high degree of proficiency in the classification of irrigation responses, the machine learning model made a decision on this task based on the classification patterns and decisional rules. The results of this work demonstrate that the testing data revealed that the Decision Tree model did not have higher precision values when it came to the task of classifying irrigation responses in smart irrigation systems. It may, therefore, be assumed that the model now meets the need for interpretable results and a high level of actionability, suggesting a simple way to make decisions about irrigation. A similar decisional task was conducted regarding the outputs of the Support Vector Machine model, and the result is 98.94% precision. In sum, the tested machine learning model was able to classify irrigation responses with high precision because it had more complex relationships with the sensor data. This model was able to reveal the high-precision data necessary to identify more intricate relationships and patterns observed in the environmental parameters and enhance the irrigation schedule in terms of accuracy and precision. The figure 2 shows the accuracy of the machine learning model used in this research.

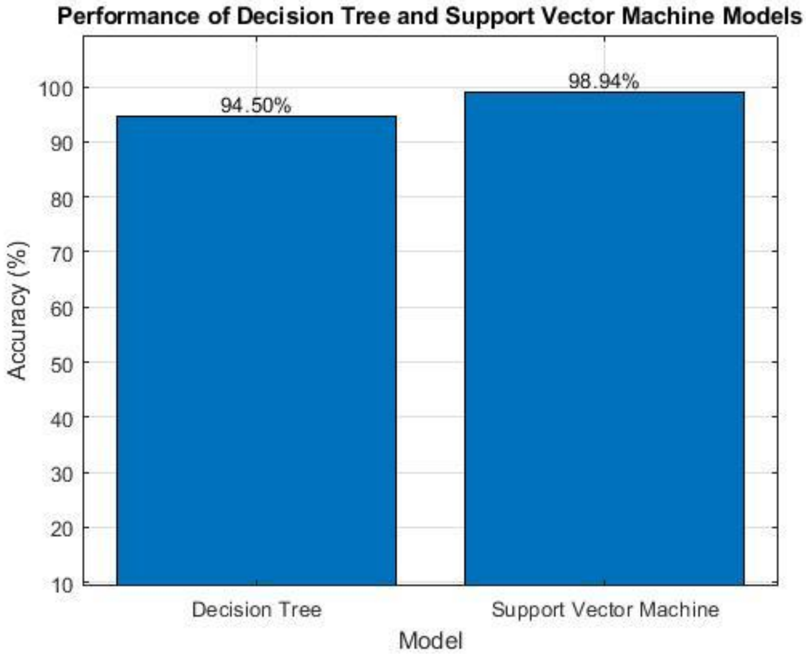

Figure 2. Accuracy of each model

This figure 3 presents a summary of the performance metrics of the models. In the Decision Tree model, the precision is at 0.92, and this means that nineteen out of twenty positive instances or 92 percent were correctly classified as positive. The associated recall is 0.96 showing that the model was able to correctly classify 96 percent of actual positive instances . As for F1 score, it is 0.94 and represents the harmonic mean of recall and precision, and as a result, a balanced accuracy measure . Finally, the AUC ROC is 0.88 or 88 percent, showing that this model has high discriminative power, as it has a high probability of distinguishing between negative and positive instances. As for the performance of the Support Vector Machine model, all the indicators are higher. Specifically, precision is at 0.97, and recall is at 0.99, and F1 score is at 0.98, meaning that this model is better at accurately classifying irrigation responses. Finally, the value of AUC ROC is 0.94, showing that the SVM model is also more effective at correctly allocating positive and negative instances. Overall, this table evidences that both models are nearly equally effective in improving agricultural water management and the later is slightly better.

In Figure 4 confusion matrices provide information on the performance of the Decision Tree and the Support Vector Machine models when classifying irrigation responses. In the confusion matrix of the first model, the top-left cell indicates that the number of instances correctly classified as negative is 450 . The top right states that the number of instances classified incorrectly as positive 20 units. Also, the bottom left indicates the number of instances classified incorrectly as negative 30 units. In the bottom-right cell, 500 means that the number of instances that have been correctly classified as positive is 500.

Contrary in the confusion matrix of the source decision tree model, the top left has 470 meanings that there are 470 instances classified correctly as negatives. The top right cell, meaning zero, shows that no instance is classified as positive. The bottom, left meaning 10, indicates the number of instances classified as negative. The bottom right shows that the number of instances classified correctly as positive is 520.

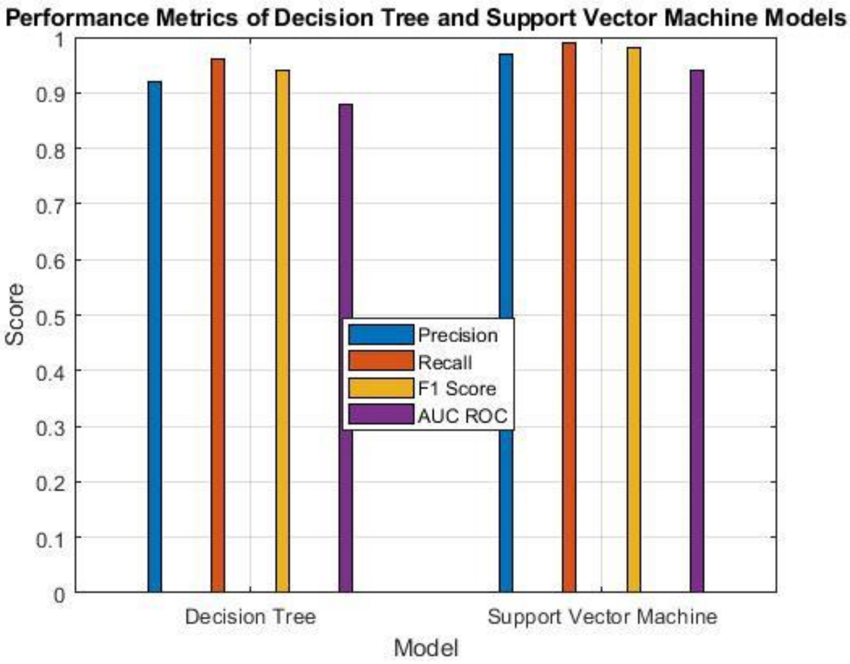

Figure 2. Performance score of each model

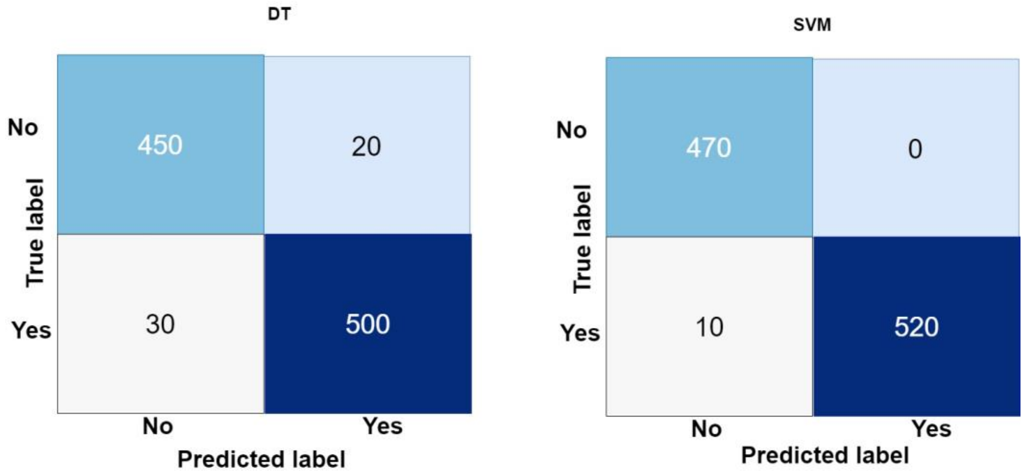

Figure 4. Confusion matrices of each model

Figure 5 displays a comprehensive representation of the performance of both models, Decision Tree and Support Vector Machine, over the course of 270 epochs, with values of data loss and accuracy registered for every 30 epochs. As can be seen, both models exhibit a similar pattern characterized by a relatively uniform decrease in data loss and a corresponding increase in accuracy. However, a detailed analysis of the values provides a different perspective, as, at every epoch from 30 to 270, the Support Vector Machine model had a lower value of data loss and a higher rate of correct data representation. It is essential to note that these characteristics are indicative of the quality of a model, as a lower data loss point to a minimal rate of prediction errors, and higher accuracy suggests a more significant number of correct predictions.

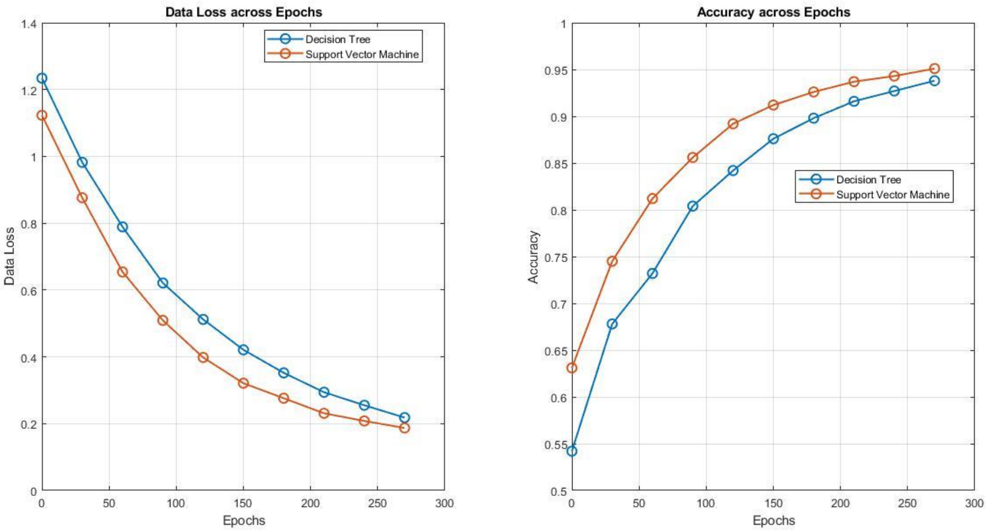

Figure 5. Data loss and accuracy at each epochs

The significance of the fact that most of the provided values characterize the SVM model as superior is that the model is more capable of recognizing complex patterns between data. As a result, its predictions have a lower error category, meaning that it is more able to accurately predict the irrigation response to a set of weather variables. Therefore, the essential conclusion that can be drawn from the provided information is that the Support Vector Machine model is more effective in optimizing water management in agriculture.

IV. CONCLUSION

The following research aims to provide smart irrigation systems in order to optimize water management practices in agriculture with machine learning models. Specifically, by implementing Decision Tree and Support Vector Machine algorithms, the research aimed to predict irrigation responses over the sensor data. It comes out that results are appealing as both models can be used efficiently in each case and can deliver highly accurate classifications on irrigation. When tested, SVM outperformed better than DT with its higher values of precision, recall, F1 score, and AUC ROC. The results of the confusion matrices showed how SVM managed to eliminate false positives and false negative to low levels, which in turn ensured high accuracy of irrigation response classification from the real-time sensor data. The tracking of both models for the 270 epochs showed how SVM outperformed DT in terms of loss of data reduction and in terms of increase of accuracy as it had the less data loss for the majority of epochs and had increased accuracy levels, which showcase how well the model can efficiently capture complex patterns in sensor data. The results suggest that it is possible to provide IAD systems with advanced analysis through machine learning algorithms where SVM model can be of most use.

REFERENCES

[1] K. Koteish, H. Harb, M. Dbouk, C. Zaki, and C. Abou Jaoude, “AGRO: A smart sensing and decision-making mechanism for real-time agriculture monitoring,” *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 9, pp. 7059–7069, 2022, doi: 10.1016/j.jksuci.2022.06.017.

[2] A. Raghuvanshi *et al.*, “Intrusion Detection Using Machine Learning for Risk Mitigation in IoT-Enabled Smart Irrigation in Smart Farming,” *Journal of Food Quality*, vol. 2022, 2022, doi: 10.1155/2022/3955514.

[3] R. K. Jain, “Experimental performance of smart IoT-enabled drip irrigation system using and controlled through web-based applications,” *Smart Agricultural Technology*, vol. 4, no. May 2022, p. 100215, 2023, doi: 10.1016/j.atech.2023.100215.

[4] A. J. Rau, J. Sankar, A. R. Mohan, D. Das Krishna, and J. Mathew, “IoT based smart irrigation system and nutrient detection with disease analysis,” *TENSYMP 2017 - IEEE International Symposium on Technologies for Smart Cities*, pp. 3–6, 2017, doi: 10.1109/TENCONSpring.2017.8070100.

[5] A. Chinasho, B. Bedadi, T. Lemma, T. Tana, T. Hordofa, and B. Elias, “Response of maize to irrigation and blended fertilizer levels for climate smart food production in Wolaita Zone , southern Ethiopia,” *Journal of Agriculture and Food Research*, vol. 12, no. March, p. 100551, 2023, doi: 10.1016/j.jafr.2023.100551.

[6] A. Katimbo *et al.*, “Evaluation of artificial intelligence algorithms with sensor data assimilation in estimating crop evapotranspiration and crop water stress index for irrigation water management,” *Smart Agricultural Technology*, vol. 4,

no. October 2022, p. 100176, 2023, doi: 10.1016/j.atech.2023.100176.

[7] E. Delpiazzo *et al.*, "The economic value of a climate service for water irrigation. A case study for Castiglione District, Emilia-Romagna, Italy," *Climate Services*, vol. 30, no. May 2022, p. 100353, 2023, doi: 10.1016/j.cliser.2023.100353.

[8] E. Bojago and Y. Abrham, "Small-scale irrigation (SSI) farming as a climate-smart agriculture (CSA) practice and its influence on livelihood improvement in Offa District, Southern Ethiopia," *Journal of Agriculture and Food Research*, vol. 12, no. February, 2023, doi: 10.1016/j.jafr.2023.100534.

[9] R. Shukla, N. K. Vishwakarma, A. R. Mishra, and R. Mishra, "Internet of Things Application: E-health data acquisition system and Smart agriculture," *International Conference on Emerging Trends in Engineering and Technology, ICETET*, vol. 2022-April, pp. 12–16, 2022, doi: 10.1109/ICETET-SIP-2254415.2022.9791834.

[10] A. A. Junior, T. J. A. da Silva, and S. P. Andrade, "Smart IoT lysimetry system by weighing with automatic cloud data storage," *Smart Agricultural Technology*, vol. 4, no. November 2022, 2023, doi: 10.1016/j.atech.2023.100177.

[11] R. H. Wadghane and O. Madguni, "Agriculture water poverty status of sugarcane cultivation along canals of Jayakwadi Dam, Maharashtra, India," *Smart Agricultural Technology*, vol. 6, no. May, p. 100369, 2023, doi: 10.1016/j.atech.2023.100369.

[12] C. Catalano, L. Paiano, F. Calabrese, M. Cataldo, L. Mancarella, and F. Tommasi, "Anomaly detection in smart agriculture systems," *Computers in Industry*, vol. 143, no. January, p. 103750, 2022, doi: 10.1016/j.compind.2022.103750.

[13] N. Chamara, M. D. Islam, G. (Frank) Bai, Y. Shi, and Y. Ge, "Ag-IoT for crop and environment monitoring: Past, present, and future," *Agricultural Systems*, vol. 203, no. April, p. 103497, 2022, doi: 10.1016/j.agsy.2022.103497.

[14] K. Phasinam, T. Kassanuk, and M. Shabaz, "Applicability of Internet of Things in Smart Farming," *Journal of Food Quality*, vol. 2022, 2022, doi: 10.1155/2022/7692922.

[15] A. Washizu and S. Nakano, "Exploring the characteristics of smart agricultural development in Japan: Analysis using a smart agricultural kaizen level technology map," *Computers and Electronics in Agriculture*, vol. 198, no. November 2021, p. 107001, 2022, doi: 10.1016/j.compag.2022.107001.