Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

A Comprehensive IoT-Based Automation System for Enhanced Productivity and Sustainability for Advancing Farming Efficiency

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The main objective of this research is to investigate the application of an IoT System coupled with machine learning models. The objective is using sensor data in real-time to determine the amount of water irrigation needed for a farm. The research uses a real dataset of different farming conditions such as temperature, humidity, and water level and conducts several pre-processing methods to the data to improve the quality of the input data. These methods include data cleaning, feature selection, normalization, and time-series analysis. Four machine learning methods are used to train and test the dataset. The results demonstrate that the Artificial Neural Network model is the most effective model in predicting results. It provides the best precision, recall, F1 score, and AUC-ROC curve which all amount to 98.5%, 97.5%, 98.0%, and 98.9% respectively. The model is also used in real-time for predicting irrigating pump operations from sensors. The research also presents its contribution as it integrates many sensors with renewable energy, solar panels, to support sustainability. The research has also assisted framers in obtaining valuable data to less the amount of water required in farm irrigation and helps with improving different farming techniques.

Keywords: Precision agriculture, IoT-based automation, Machine learning, Irrigation management, Sustainability.

1. Introduction

For effective crop growth, increased yields, and environmentally friendly water usage, optimum irrigation management is imperative in agriculture. However, current approaches to irrigation management are not adequately precise, resulting in over-irrigation, wastage of water resources, soil degradation, and reduced crop productivity. In order to overcome this problem, researchers and farmers are increasingly turning to technologies such as the internet of things and machine learning[1]–[3]. An IoT-based automation system, utilizing sensor data and predictive analytics in real-time to manage irrigation, may revolutionize the management of irrigation. The major objective of this research is to develop an IoT-based automation system for predicting irrigation requirements to optimize farming performance and evaluate its performance[4]- [7].

The specific objectives are the following: ascertain whether IoT -based automation system could be used in agriculture, evaluate the performance of various machine learning algorithms related to the prediction of irrigation demands. As a result, the present research is expected to expand the knowledge and promote further progress of similar fields of research as precision agriculture and environmentally sustainable agriculture[8]–[11].

Currently, in relation to agriculture, the development of IoT-based automation systems has become more widely used. These complex systems typically consist of sensor networks distributed in farming fields, which can measure a wide range of parameters including temperature, humidity, soil moisture, light levels, and water levels. The sensor data is then submitted to a control center output in real time, which can use it to inform automation decisions regarding irrigation schedules, fertilization, pest control and other operations. By automating these functions, IoT-based automation can simplify the lives of farmers and, more importantly, make farming operations more efficient by making them more timely[12]–[15].

The existing literature on IoT-based automation systems in agriculture can provide some valuable insights on the possible applications, effects, and difficulties of installing and using these systems throughout one’s farming business. There are many studies dedicated to the certainty whether the IoT-based systems can apply in irrigation management and how. The research has shown that many farmers and researches confirmed the opportunity to use IoT sensors in order to manage the irrigation effect as better as possible. Moreover, there are examples of using these devices in monitoring soil and water parameters i.e. nitrogen levels, water flow, and contaminant concentration. As a result, it seems clear that the installation of sensors and using them to deal with the water effect could be effective and useful for the majority of farmers[16]–[19]. The same could be addressed to the possibility to use IoT automation systems in monitoring crop health and optimizing the extent of pesticides used as it could help reduce the environmental pollution, open the ways for the further improvement of the environment and protect the population from the overuse of chemicals. As a result, the above examples prove that the IoT device could work and result in positive changes across the majority of farms[20]- [22].

Another solution that has already proved to be useful is the implementation of machine learning techniques to the array of sensor data and the requirement for future irrigation. Thus, the development is based on the use of the known data to create the model and train it in order to get the most accurate results in relation to future events. There are numerous machine learning algorithms that could be useful in this field among them are Support Vector Machines, Artificial Neural Networks, and Decision Trees. However, according to the practical examples, the Artificial Neural Networks are always the most effective option in a case when the training data is accessible and the training models could be run so that the necessary results could be acquired[23]–[25]. The similar ideas could be expressed as for SVM machines that were addressed. Finally, there is a lack of opportunities concerning the implementation and the installation of IoT devices as there is a clear difficulty to understand in what ways and how the new and toe old instruments could be integrated completing the synergetic action and networks. Similarly, the data resulting from the analyses could be immense so that the farmers will not be able to review it timely and make some decisions with references to the new steps.

2. Methodology

In our research focused on improving the farming efficiency through IoT-based automation, a complex system was implemented where various sensors in different fields of the farming area were integrated. As mentioned, these sensor types, such as temperature, humidity, or water level sensors, were crucial in providing real-time data on the conditions of crops. There are 16 sensors installed in the whole crop field, which are distributed in the area to cover all relevant environmental parameters where the crops are located. These sensors are connected with a central controlling unit using the wireless communication capabilities between them, which ensures that all farming operations can be monitored from one centralized location. Figure 1 shows the methodology of proposed research.

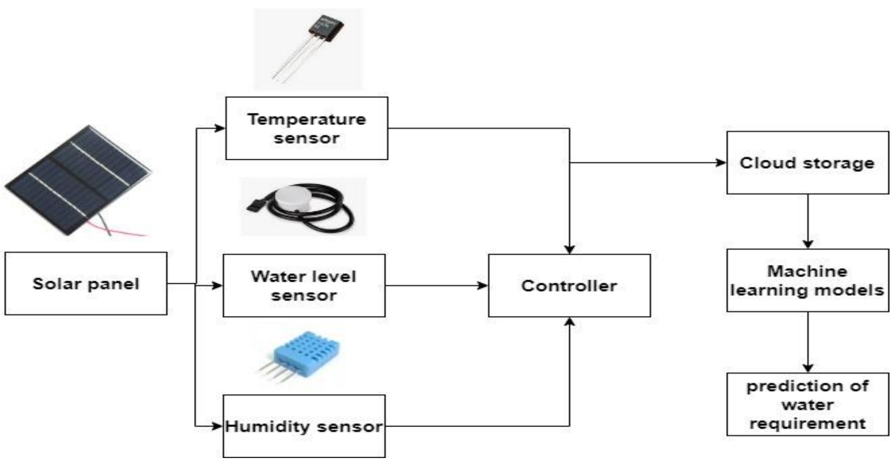

Fig. 1. Methodology of the Proposed Research

At this central controller, the data from sensors are received, and machine learning algorithms are applied to understand the optimal operation of irrigation systems in advance to adjust it accordingly. In the scope of this research, four different machine learning algorithms were used for this purpose, such as Artificial Neural Networks, Decision Trees, Linear Regression, and Support Vector Machines. They were trained with 3200 readings from the sensors where the data were divided into 70% for training purposes and 30% to validate the results of analytics. Using the real-time data from sensors as input, these machine learning algorithms can help in prediction of the needed water for crops because they can learn from historical data and the development of patterns in cases. Finally, the best machine learning model is selected for implementation to ensure that there are not under or over-irrigated crops in the system based on real-time data using IoT technologies.

The most specific feature of our research is the integration of the renewable energy sources to power the network of sensors to monitor the farming conditions. In the scope of sustainable farming, the solar panels were included to provide power to these sensors located in the crop areas. This means that the system is not only automating the irrigation management of the farms, but the technology used is helping to avoid any resource wastage used and obtain cost savings in the operations as a result.

3. Various Sensors Used In This Research

As for our research associated with enhancing farming efficiency through IoT-based automation, we benefited from a wide range of sensors that were located at different sites throughout the farm. As a kind of eyes and ears, the sensors capture monitoring data that cannot be visually observed and provide us with an effective monitoring strategy to ensure proper crop conditions and farming efficiency. First, we relied on temperature sensors that were located within the site of the crop fields to understand whether there were any changes in terms of temperature regimes. This is particularly important as temperature has a significant impact on crop development and growth so that there should be certain measures to control temperature fluctuations. In this way, our decision to install temperature sensors and locate them at special sites allows us to evaluate whether measures should be taken to prevent potential risks, such as frost or heat. Regardless of the type, we obtain opportunities to know about potential risks and make a decision before it is too late.

In a similar manner, humidity sensors were also used to monitor changes in terms of moisture that can be found in the atmosphere above the crops where plant transpiration is expected to occur. Moreover, only by accurately assessing moisture levels the farmworkers have a possibility to decide on the optimal timing for watering plants and adjust the performance of the ventilation system. As a result, we avoid potential risks of plant dehydration, root production, and spreading of fungal diseases. In conclusion, we would like to stress the importance of using a water level sensor that can help measure the level of water in reservoirs or soil moisture. At the same time, the decision to use solar panels that were intended for the supply and production of energy presents a special value.

The data from the sensors is collected throughout the day, as both the changes of the environment and the crops are subject to change at any moment. Thus, the sensors are active from morning to evening, collecting information on such parameters as temperature, humidity, and water levels. The information is checked at regular intervals, ensuring that the entire range of interaction between crops and their environment is covered. As a result, a dataset that displays the diurnal span of data gathered by the sensors is created. The environmental changes and the way they affect crops throughout the day can be seen in Table 1, which shows only a small fraction of collected data.

Table 1. Sensor Readings

Time	Temperature (°C)	Humidity (%)	Water Level (cm)
07:00 AM	22	65	12
07:30 AM	23	64	11.5
08:00 AM	24	63	11
08:30 AM	25	62	10.5
09:00 AM	26	61	10
09:30 AM	27	60	9.5
10:00 AM	28	59	9
10:30 AM	29	58	8.5
11:00 AM	30	57	8
11:30 AM	31	56	7.5
12:00 PM	32	55	7
12:30 PM	33	54	6.5
01:00 PM	34	53	6
01:30 PM	35	52	5.5
02:00 PM	36	51	5
02:30 PM	35	52	5.5
03:00 PM	34	53	6
03:30 PM	33	54	6.5
04:00 PM	32	55	7
04:30 PM	31	56	7.5
05:00 PM	30	57	8
05:30 PM	29	58	8.5
06:00 PM	28	59	9
06:30 PM	27	60	9.5
07:00 PM	26	61	10

A. Preprocessing of dataset

In our research, preprocessing of the dataset was critical to the accuracy and validity of the machine learning models used to predict agriculture irrigation needs. The dataset underwent various complementary preprocessing steps aimed at cleansing the raw sensor data and preparing it for analysis. First, data cleaning was performed on the original data to identify any inconsistencies, missing values, or outliers. The analysis ruled out any inconsistencies and implemented missing value imputation, where the data's missing values were filled with the mean or median of the feature. Next, several additional preprocessing steps were taken to improve the predictive power of the model by manipulating the nature of the features.

Feature engineering involves manipulating the features of multi-dimensional data to improve the performance of machine learning models. It can involve adding new features or deleting irrelevant ones. In our research, new features were constructed, helping to inform the predictiveness of the machine learning models used. For example, the rate of change of temperature and humidity over time was extracted from the original data to provide additional comparative parameters for understanding the variables. The effect was normalized on the new features, where the original features were uniformly transformed to ensure uniform effects during model development. It helps improve data generalization capabilities and improved the model's performance by allowing all features to play an equally significant role.

Moreover, there were aspects that needed to factor in the nature of the data. Since we were working with sensor data that relies on changes or ratios in data levels over time, it was necessary to consider time series. Typically, time-series analysis helps to determine whether the data is periodic or trended. The outcomes enabled the determination of whether specific features depend only on past data and their implications. Additionally, in feature selection techniques, various processes were also considered in preprocessing. It includes comparing the correlation matrix with the VIF of each feature, retaining only features that have no multicollinearity. Overall, we sought to reduce the dimensionality of the features, allowing only informative features. Following this step, the dataset was split to allocate the training dataset and testing dataset. This is done by the stratified random sampling method. Finally, given that each of the three classes had few samples that were prone to class imbalance, the dataset was balanced using the oversampling method. Figure 2 shows the architecture of preprocessing.

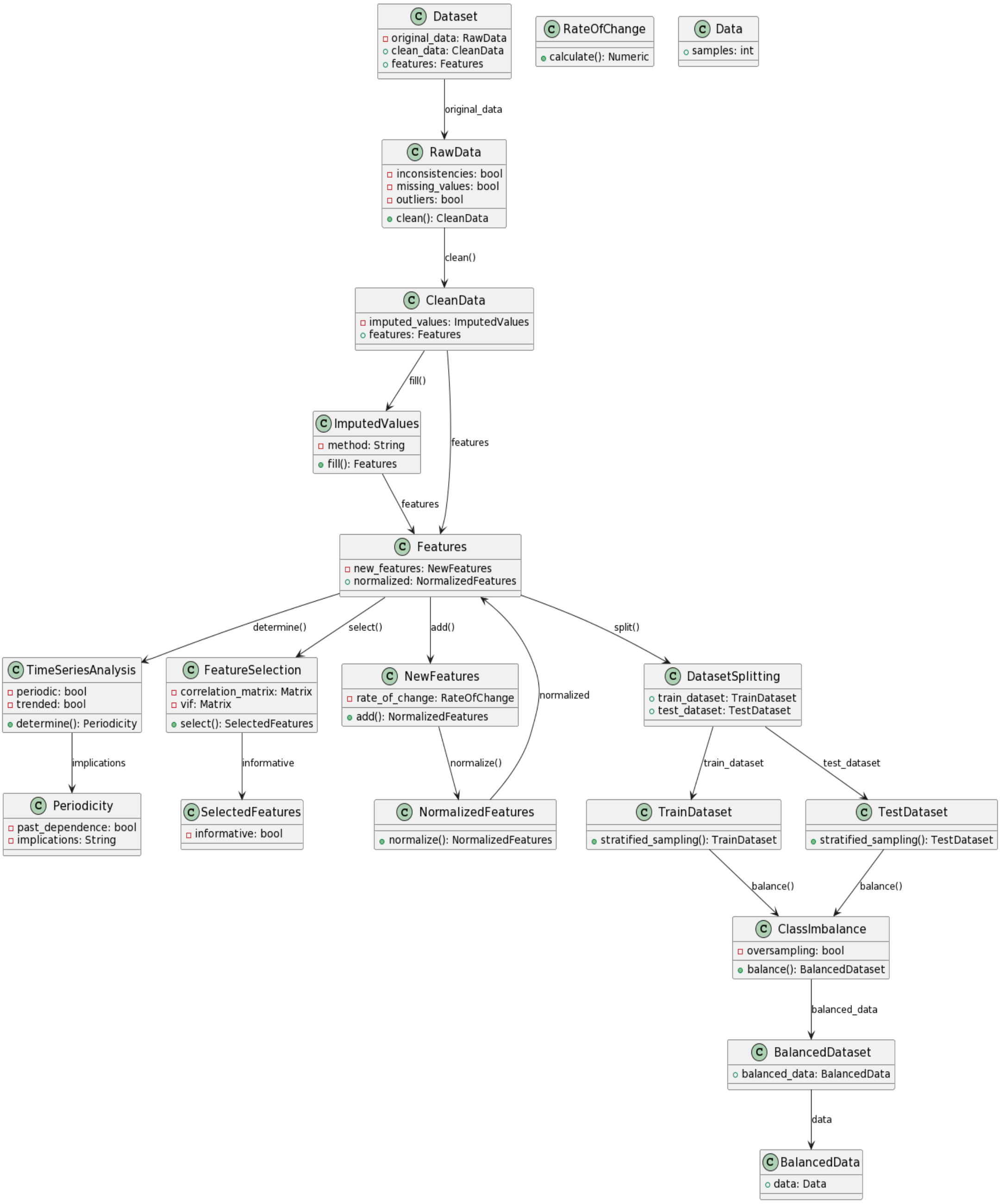

Fig. 2. Architecture of Preprocessing Of Dataset

B. Machine learning models

Artificial Neural Networks represent a category of machine learning models that are based on the structure and functions of biological neural networks. In the context of the research on IoT-based automation for farming efficiency, ANNs are used to process the real-time sensor data and predict irrigation requirements for crop. They consist of several layers of interconnected artificial neurons, which process input data, identify specific patterns or features and output the results. The network is trained on labeled data, meaning that with each iteration, it can generalize and predict results for the previously unseen data. The benefits of using ANNs are explained by the need to process complex, non-linear data in the area of agriculture: by inputting the sensor readings into the input layer and adjusting the weights of the network, it can emulate the multitude of interactions between input and output data, pertaining to the effects of various environmental conditions on the water needs of crops. In this way, we can predict the irrigation demands of crops with a high degree of accuracy, reducing the overall amount of water spent and promoting sustainable practices.

Another class of models we use in our research are decision trees, which we use to predict irrigation requirement levels using features extracted from controller sensor data. Decision trees create a structure in which a series of decision nodes are organized in hierarchical form splitting the input space into more and more homogeneous subsets. Most importantly for this research, this approach generates transparent and easy to interpret decision rules. Thereby, decision trees have proven quite useful for farmers and other practitioners in agriculture.

It is also important that decision trees can process both numerical and categorical data, which is the case for the set of sensors. More specifically, this type of machine learning models can split the data based on the feature threshold and keep splitting recursively creating decision rules based on environmental features. In similar fashion, the system generates decision rules, which can be readily used by farmers.

Linear Regression is one of the simplest statistical techniques applied in our research to define water requirement on the base of sensor inputs. It utilizes min square optimization to compute the coefficients for a linear equation that explains the dependence of an independent variable one multiple dependent ones. This method is far from perfect as some limitations come into the equation, although it provides a clearer insight into sensibility and weights of the relation between factors and H2O requirement. It defines and quantifies effects on the need for irrigation caused by each sensor reading, which ensures a more precise evaluation of factors that should be counted the most and more accurate decision making. Besides, it is more convenient to use in practice when it comes to communication and explanation of findings. Through this method used to convey the results, farmers can get a better understanding of data output, spot trends, and compile the results for the comparison with machine learning techniques and more sophisticated metrics.

A support vector machine is a strong machine learning model that is used in the research to categorize sensor data points and predict the required amount of irrigation. The working principle of the model is finding the hyperplane to separate data points of different classes and maximize the margin of separation. In this research, the model was used for regression, and the model predicted the value of required irrigation as continuous value based on farm inputs. Since a support vector machine uses regularization parameter, it is relatively immune to overfitting. Moreover, the SVM model is justified by its flexibility in modeling complex relationships, which can be carried out using a kernel. Thus, the main idea is to map the features of interest to a higher dimension, which can be used to identify patterns or interactions in the data. Ultimately, it makes possible to analyze multisensory inputs which are abundant in the research and should be analyzed in higher dimensions.

4. Result and Discussion

Once the machine learning models have been trained on the dataset, the performance of each model has been rigorously tested to assess their predictive performance. The results of the testing phase show considerable differences in the accuracy of the models. In particular, the prediction accuracy of the Artificial Neural Network model is the highest, at 98.45%. This result is expected and indicates that the ANN is exceptional at capturing complex patterns and relationships in the sensor data to predict irrigation need in the crops. The Support Vector Machine model also shows very good predictive performance, at 94.55%. Thus, while slightly inferior, the accuracy of the SVM model also indicates good capacity of this model to handle high-dimensional data and nonlinear relationships, making it a suitable decision for real-time applicability in farming situations. The result of the accuracy are shown in figure 3.

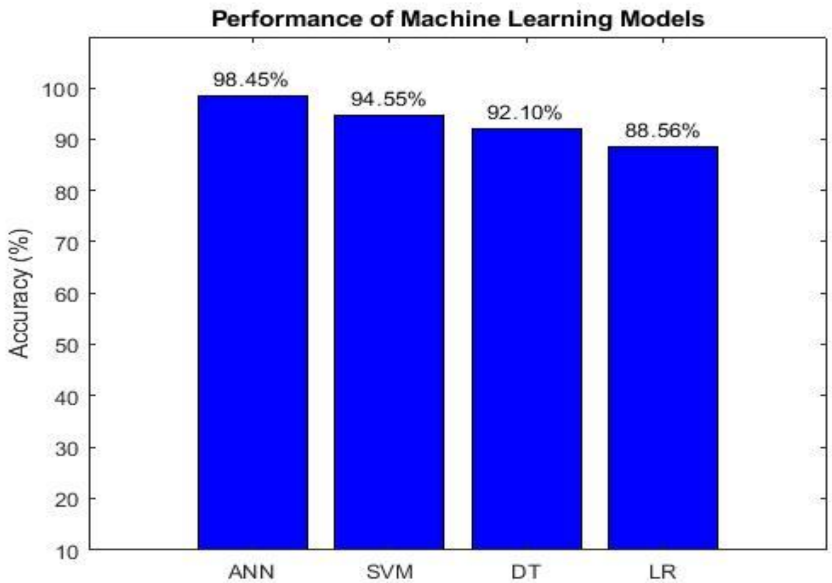

Fig. 3. Accuracy of Each Model

Moreover, the DT and LR models also show good results, though with slightly lower accuracy. In particular, the accuracy of the DT model is 92.10%, which reflects its ability to capture decision rules and hierarchy relationships in the data. Finally, the accuracy of the LR model is 88.56%, which also shows good capacity of this model to learn linear patterns and relationships in the sensor data.

Figure 3 displays the full performance metrics of each machine learning model used in our experiments to predict irrigation requirements using sensor data. First, the results show that precision is extremely high for the Artificial Neural Network model – namely, 98.5%.

Essentially, this implies that almost all positive predictions of the model are correct. At the same time, the recall value of ANNs is also high at 97.5%, meaning that such systems can correctly identify almost all positive instances in the dataset. As a result, the F1 score for the given model is 98.0%, suggesting that the model is effective. Finally, the value of the AUC-ROC curve is 98.9% for the Artificial Neural Network. The next model, Support Vector Machine, also demonstrates satisfactory performance, although precision, recall, F1 score, and the value of the AUC-ROC curve are slightly lower for this system in comparison to the previous one. In all other cases, the differences between the values characterizing the performance of ANNs and SVMs are not significant, with the specificity of SVMs being slightly higher than that of ANNs. The Decision Tree and especially LR can be characterized as models with good performance since all values of precision, recall, the F1 score, and the AUC-ROC curve are high.

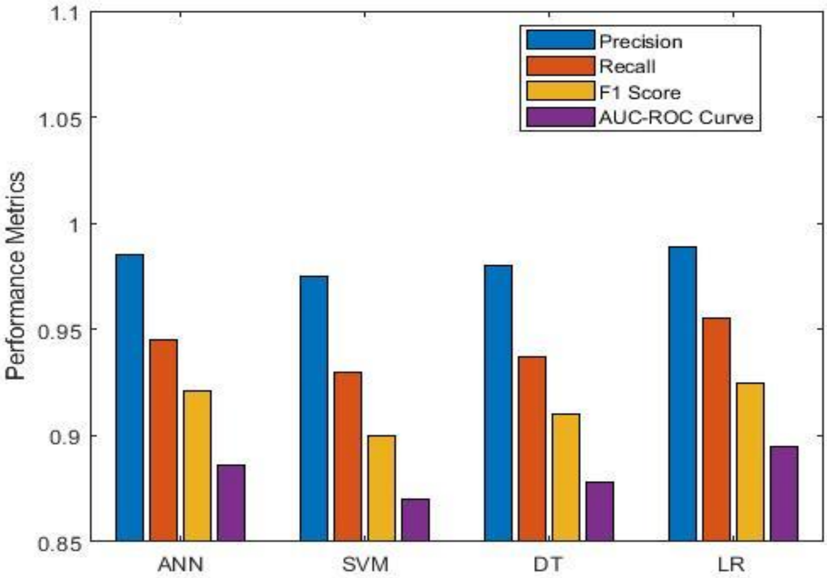

Fig. 4. Performance Score of Each Model

Figure 5 Confusion Matrices, presents a detailed explanation of how each machine learning model was able to correctly and incorrectly classify instances. Specifically, each cell of the table depicts how many instances were correctly classified as either positive or negative compared to the actual class to which they belong. With respect to ANN, the model showed 1480 of true negatives and 1470 of true positives. It is clear that most of the instances were correctly classified to both of the classes. Additionally, it is demonstration that 20 of examples were falsely classified to the positive class and 30 were falsely classified to the negative class.

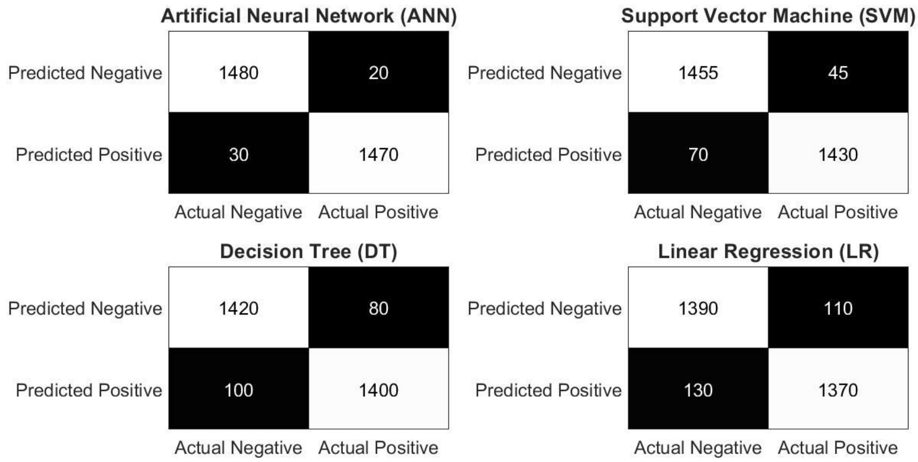

Fig. 5. Confusion Matrices of Each Model

Similarly, the percentage associated with the correct classification of the negative class by the Support Vector Machine is high with 1455, while 1430 instances were correctly classified as positive. However, 45 were misclassified as negative and 70 were misclassified as positive. At the same time, Decision Tree had 1420 of correctly classified true negatives and 1400 correctly classified examples as true positives. In turn, the Linear Regression model showed only 1390 of correctly classified instances belonging to the negative class, while only 1370 instances were classified as positive. Additionally, all of the models except ANN showed the number of falsely classified examples.

The most applicable model for prediction response in our research is the Artificial Neural Network model. Therefore, based on the extensive analysis, this model is implemented with regard to predicting the operation of the pump. The best performance in providing an accurate prediction of the irrigation need thus classifies this model as the most preferable for optimizing farming processes and, therefore, improving practice efficiency.

The following table 2 presents the dynamic interrelation between some sensor readings and the activation of the water pump by the Artificial Neural Network model. Throughout the day, the values of the three sensors fluctuate with the temperature, humidity, and water level surveyed every half-hour. At the same time, the ANN model continuously processes this information analyzing the necessity of irrigation. When the temperature and humidity start decreasing, at the same time as the water level, it implies the deficiency of moisture in the soil, which is a signal for the starting point of the irrigation process. Therefore, as soon as the water level begins increasing, one can deduce that the artificial water delivery for this portion of soil is over. Conversely, in cases when the sensors are stable, signifying the presence of adequate characteristics for proper crop growth, the model does not need to switch on the water pump since the optimal level of soil moisture is already achieved. Therefore, these real-time responses of the system activated by the ANN model guarantee proper and effective irrigation.

Table 2. Sensor and the Operation of Pump

Time	Temperature (°C)	Humidity (%)	Water Level (cm)	Pump Operation
07:00 AM	22	65	12	OFF
07:30 AM	23	64	11.5	OFF
08:00 AM	24	63	11	OFF
08:30 AM	25	62	10.5	OFF
09:00 AM	26	61	10	ON
09:30 AM	27	60	9.5	ON
10:00 AM	28	59	9	ON
10:30 AM	29	58	8.5	ON
11:00 AM	30	57	8	ON
11:30 AM	31	56	7.5	OFF
12:00 PM	32	55	7	OFF
12:30 PM	33	54	6.5	OFF
01:00 PM	34	53	6	ON
01:30 PM	35	52	5.5	ON
02:00 PM	36	51	5	ON
02:30 PM	35	52	5.5	ON
03:00 PM	34	53	6	OFF
03:30 PM	33	54	6.5	OFF
04:00 PM	32	55	7	OFF
04:30 PM	31	56	7.5	OFF
05:00 PM	30	57	8	ON
05:30 PM	29	58	8.5	ON
06:00 PM	28	59	9	ON
06:30 PM	27	60	9.5	ON
07:00 PM	26	61	10	OFF

5. Conclusion

The present research proves that an IoT-based automation system along with machine learning models can do a lot to make farming more effective and sustainable. Throughout the data analysis and model evaluation, we have chosen the Artificial Neutral Network model as the best solution for predicting the preferable time for irrigation using data collected from sensors. It is remarkable that the performance of the ANN model in terms of precision, recall, F1 score, and AUC-ROC curve is better compared to the performance of other machines learning models, including Support Vector Machine, Decision Tree, and Linear Regression. The use of the ANN model proves that the great potential for this tool to become a trustworthy method to manage irrigation in various types of farming. In addition, our research shows that the analysis of the data in real time plays a critical role in supporting correct irrigation-related decisions at the farm and improving the effective use of resources. Thus, by installing sensors on their fields, farmers will apply the readings to the corresponding machine learning algorithm and define the best time to irrigate their crops in accord. In this case, the work of the ANN model to predict the operation of the water pump using the collected data is a notable example of our research. Also, the use of solar panels as the source of energy for the sensor network adds to the value of our research in terms of sustainability.

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