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IoT and Machine Learning based Precision Agriculture through the Integration of Wireless Sensor Networks

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Abstract: - In this study, the integration of IoT technology and machine learning (ML) algorithms with precision agriculture are studied, with an emphasis on optimizing irrigation management through wireless sensor networks. Data are collected in real time from various sensors that measure temperature, humidity, moisture in the soil and water levels. Such data is used to predict the demands for water and control pump operations based on them. They employed different machine learning (ML) models, including Support Vector Machine (SVM), Decision Trees (DT), Random Forest (RF) and Naive Bayes (NB). The accuracy of pump operation predictions is then evaluated. SVM presents the highest overall accuracy. Followed closely by DT and RF. Confusion matrices can be used to glean insights into the misclassification patterns of each model, guiding the selection of the most effective ML approach for precision agriculture applications. IoT and ML technologies together enable real-time monitoring, adaptive control, and data-driven decision-making in agriculture, all of which can help towards efficiently using water resources in dealing with climate change and rapidly growing food demands.

Keywords: precision agriculture, Internet of Things, machine learning, wireless sensor networks, irrigation management.

I. INTRODUCTION

Lately agriculture has become a radical method with which to farm. Modern agricultural technologies are used to make farming more effective in cultivating resources and freeing land for production. The basic idea behind precision agriculture is that with traditional farming practices or even green agriculture practices farmers have been processing land for years perhaps centuries. But the farmland has itself changed nowadays [1]–[3]. In this respect, sensors are able to help farmers figure out they should do next. As global food demand continues to increase under the pressure of growing challenges including those brought on by climate change as well as limitations on resource precision agriculture is increasingly seen as not just desirable but essential for sustainable food production and agricultural resilience [4], [5].

Although countless IoT devices have been reckoned up, both about the house as to other homes, and for food and industry, the precise of the IoT device remains important. Some of these devices are weather resistance or have a cosmic history of expansion or contraction [6]–[8]. For example, a home security system that monitors an individual's health constitutes an IoT device as well as a smartwatch. Similarly, a toothbrush that can be

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operated by voice input has been connected to a network and can communicate the internal temperature outside to a much lower value. Some are equipped with a variety of sensors, while others may be embedded in the environment [9], [10].

Furthermore, precision agriculture research has made clear the importance of wireless sensor network for the smooth collection and transmission of data inside agricultural landscapes. With advances in sensor technology, low-cost, energy-efficient sensors can monitor all sorts of environmental parameters in real-time. The rapid spread of IoT platforms and cloud-based services means that data can now be stored, processed, and analyzed all centrally; farmers can access this actionable sentiment at a distance--far, far from home--and perhaps manage to drag it onto a decision-making platform for negotiations with stakeholders [11], [12].

Even with improvements in these areas, challenges still persist when it comes to the generalization and widespread implementation of precision agriculture technologies. These challenges include issues concerning the privacy and security of data, as well as the compatibility between different devices and interfaces for the IoT [13]- [15]. In addition, other obstacles such as scalability of ML algorithms and even getting hold of technology and infrastructure in rural areas are to be addressed. Efforts to deal with the problems require the interdisciplinary collaboration of agriculture, engineering, and policy; these domains will also need investment in research, education, and infrastructure development. Besides, to bring out the full potential of precision agriculture in enhancing agricultural productivity, sustainability, and resilience against a world full of new challenges, measures to promote digital literacy and encourage technology adoption among farmers are extremely important [16]- [18].

II. METHODOLOGY

In this research an Internet of Things (IoT) system was developed that linked many devices across the world with different sensors such as temperature harmonizers and humidity sensors, providing constant environmental data to precision farming. Figure 1 shows the architecture of the system. The sensors installed in sensitive crop areas, such as vegetables, bananas, and cut flowers, are used to collect information on plant growth and health. Then, via wireless transmission, the sensor readings are sent directly to a central controller-- the nerve center of the IoT system.

The controller's main purpose is processing sensor inputs in handling and managing data. It uses advanced algorithms to turn this information into actionable insights about the data of the day. These insights are then transmitted to the cloud infrastructure and are stored also the user can access these data. This cloud-based method permits farmers and agricultural practitioners to access the data remotely.

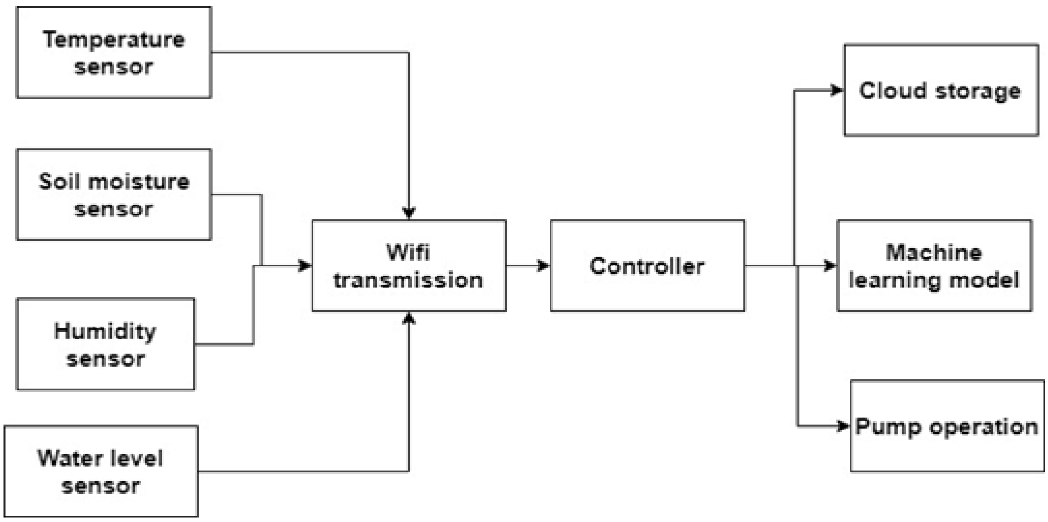

Figure 1. Architecture of the System

Based on sensor meter readings, the IoT system can carry out certain agricultural activities. Water level sensors produce data that is useful to the IoT controller, which is able to monitor soil moisture. If the earth appears too dry or in need of watering the crops, then the controller will turn on the tap automatically. When the temperature is above or below what is ideal for crop growth temperature sensors also allow the controller to control cooling or heating systems. In fact, it is not only water levels in the soil.

In addition, the Internet of Things system also includes predictive analytics capabilities. These take advantage of machine learning to predict environmental changes. From analyzing history's data patterns to today's sensor tests, the system can predict trends in coming times. It also provides early warning of frost or dry spells among other potential hazards. Farmers are able to anticipate risks in this way so that precautions can be taken and risks more acceptable.

An IoT system that was designed to encompass many different types of agricultural environments, as well varying workloads is one well-known example. Also, farmers can add or subtract sensors to suit the crops that are actually grown, even varying environmental factors. This will allow complete farm management and optimization. Other IoT devices and agricultural machinery can be seamlessly integrated into the system architecture.

2.1 Machine Learning Approach

For handling overshoot with control actions based on sensor readings, especially of the motor on and off in switch used for irrigation, this paper describes a predictive algorithm using machine learning (ML). Sensor-based this research, in the context of many things it does, such as a: Soil moisture level detector, is, in other words, far from perfect. Often, the motor switch-off depends on reading from sensors. So by the time the control signal is released, it may all be too late. Let's put it this way: If the sensor indicates a low soil moisture content prompting the maker to start supplying water for plants, the soil may have become moist by the time Lifeless hard soil is unable to absorb into, and on the flip side, rain dripping airplane oil mops into real gutters rather than down their slopes this overhead machine can only be wasteful tapped resources. If, for example, the sensor detects adequate soil moisture and sets the motor off, there may still be a subsequent irrigation irrigation to achieve the desired result before the motor reaches this and turns off. This insufficient water supply may be harmful to the health of crops.

In order to solve these problems, the research aims to insert a predictive algorithm into the IoT system, and utilize ML methods. It trains the ML model by feeding it historical sensor data in order to forecast water needs for the future under present and future environmental conditions. The model is able to predict changes in soil moisture levels or the optimal time for controlling a motor by analyzing patterns and trends in the data. This predictive ability of the machine learning model helps the irrigation system to schedule and ensure the motor running at appropriate time.

A predictive algorithm constantly monitors sensor data and forecasts in real time. When the ML model predicts that future crops will need irrigation according to anticipated soil moisture trends, it starts early by initiating the necessary control action to activate the motor before any water shortage occurs. On the other hand, if the model foresees that moisture levels will suffice in the imminent future, then it maintains the motor's power to keep irrigating water without prematurely ending infant growth.

2.2 Various Model used in this research

In this research, machine learning (ML) models are widely used in the prediction of water requirements in precision agriculture.

Support Vector Machine (SVM) is a powerful supervised learning algorithm extensively utilized in a variety of classification and regression tasks. So in the end, SVM—applicable to fields as diverse as genetics or hydrology—does a fantastic job predicting water needs because it finds an optimal hyperplane which sorts points according their features. In addition, the maximization of the margin between classes allows SVM to effectively capture complex relationships among environmental variables such as soil moisture, temperature or crop type longer than half a meter. SVM can handle high-dimensional data sets and relate them nonlinearly, making it ideal for predicting water requirements in different types of agriculture [19]- [21].

Decision Trees (DT), offers a clear and understandable way of determining water needs in precision agriculture. Decision trees continuously divide the feature space into different parts, guided by the most informative features. Ultimately, they yield a tree-like system which represents rules of decision. For irrigation management, DTs can effectively determine the key environmental factors that affect water requirements, such as soil moisture content, weather and crop species. In addition, DT models reveal insights Enjoying the decision-making process, farmers can see which underlying environmental factors drive crop irrigation recommendations and change their management strategies accordingly [22]- [24].

A Naive Bayes (NB) classifier can be interpreted as a probabilistic classifier based on Bayes' theorem and the assumption of conditional independence among features. In spite of its simplistic assumptions, Naive Bayes (NB) turns out to be quite effective at determining the water requirements of precision agriculture. Based on historical data, Naive Bayes (NB) estimates the likelihood of certain environmental characteristics by calculating their probability. The proposed ML model tells us the water requirement of the plants. The simplicity of NB and its computational efficiency, as well as the capacity to handle continuous and categorized variables, make it an important tool for real-time irrigation management systems [25]–[27].

The Random Forest (RF) is a composite learning algorithm that uses many different decision trees to raise its predictive performance and robustness. It holds several advantages for precision agriculture including high accuracy, scalability, resistance to overfitting. To get the best prediction from the environmental model, you need to train many decision trees on random subsets of this data and then aggregate their predictions. Also, as for the accuracy of prediction models, they reveal feature relevance which will permit the farmer to give weight to important factors that control water and meanwhile make better use of resources [28]- [30].

2.3 Communication System

The research depends on wireless technologies like Wi-Fi and 4G to convey field-collected data to their control nodes, then onwards to the cloud. Sensor nodes gather data about the environment like temperature, humidity, and soil moisture levels. This data then travels across the 4G network directly to the ACU. The high-speed, large area coverage of 4G allows efficient and reliable communication in the lower-density regions where agriculture is carried out. When the controller gets sensor data, it first performs some simple processing and conforming of these data to standards before putting them up to the cloud platform over a Wi-Fi link. WiFi technology offers a rich channel and low latency that allows for fast and smooth data transmission between the controller and the cloud server. The sensor data will be stored, analyzed and presented in real time on the cloud. This gives farmers valuable information on environmental conditions and allows them to use data for precision farming. In this mesh of WiFi and 4G technologies, sensor data is easily transmitted in IoT systems. Agricultural operations can be conducted at a distance and take little time; the system is most dependable.

2.4 Training of ML Model

Based on a dataset comprising 3587 readings of sensor values from field-deployed sensors, this study used machine learning (ML) for model training. The training process includes several steps designed to optimize predictive capability. First, the data is preprocessed for database insertion to make it available. Preprocessing will insert the null and normalize the features, with outliers being removed for quality control purposes. The dataset is then divided into a training set for modeling and a validation set. This is to test and prevent so-called "overfitting" to the data. Support Vector Machine (SVM), Decision Trees (DT), Naive Bayes (NB), and Random Forest (RF) are just a few of the machine learning algorithms that have been trained using the training data. These are employed to find patterns or relationships between sensor inputs and water requirements. The models gradually adjust their parameters in order to minimize errors and increase accuracy, as they are trained. Several different types of cross-validation methods like k-fold cross-validation may be employed. Models' performance is further improved through hyperparameter tuning. Once these ML models have been trained, the validation sets can be used to verify their robustness and accuracy in water supply forecasting.

III. RESULT AND DISCUSSION

To train AI models, a standard data-splitting technique was used, with 70% of the data chosen for training and the remaining 30% used for testing. Table 1 shows real-time sensor data from the wheat production season in the field. Based on this, predictive algorithms that are highly accurate and reliable can be developed, as we tested ML models on this data. As a result, precision agriculture's water management is effectively optimised through irrigation. In this study, the data was divided into two independent sets: training and testing.

Table 1. Sensor Readings

Time Stamp	Temperature (°C)	Humidity (%)	Soil Moisture (%)	Water Level (%)	Pump Operation

2024-02-21 08:00	25.6	68	42	65	Off
2024-02-21 08:15	26.1	66	41	63	Off
2024-02-21 08:30	26.5	65	40	62	Off
2024-02-21 08:45	27.0	64	39	60	Off
2024-02-21 09:00	27.4	63	38	58	On
2024-02-21 09:15	27.8	62	37	56	On
2024-02-21 09:30	28.2	60	36	54	On
2024-02-21 09:45	28.6	59	35	52	On
2024-02-21 10:00	29.0	58	34	50	Off

In real time, you can rigorously test various machine learning (ML) models. It assesses their ability to predict pump operations in three dimensions using sensor readouts. Once testing is complete, the results show that our sensor-based predictive algorithm outperforms individual machine learning models. The Support Vector Machine (SVM) has 95.86% accuracy, Decision Trees (DT) have 92.34% accuracy, Random Forest (RF) has 90.23%, and Naive Bayes (NB) has 88.76%. These performance indices also show how well our sensor-driven predictive algorithm determines the pump's operational condition based on its sensors, which is far superior to current technology in terms of comprehensiveness and accuracy. The higher accuracy achieved by our integrated sensor-driven approach emphasises the importance of combining multiple ML techniques with real-time sensor readings when optimising farm irrigation management practices. Farmers can make better decisions about when to water and when not to by combining sensor-driven prediction algorithms with various types of ML models, saving money. They will also be able to improve resource utilisation, crop harvests, and environmentally friendly protective practices. Overall, these results highlight precision agriculture's potential to revolutionise traditional irrigation systems while increasing efficiency.

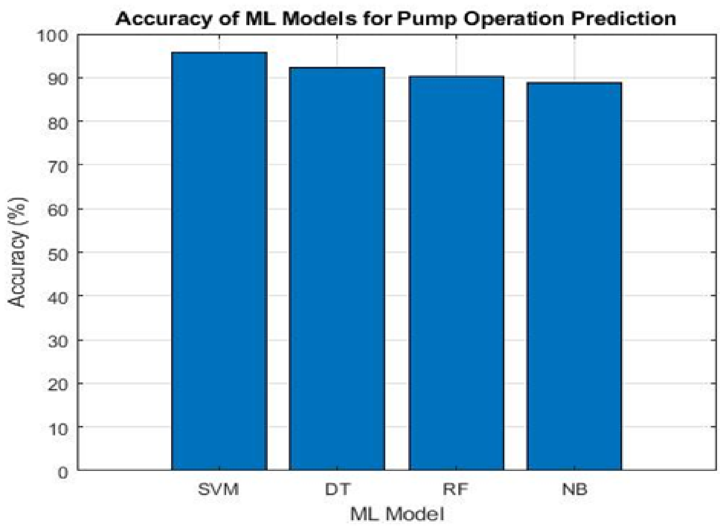

Figure 2. Accuracy of the Each Model

The performance score of each ML model are shown in figure 3. The SVM model predicts the pump operation with the highest precision of 95.86% indicating its correct identification in positive prediction. The model DT exhibits the highest performance compared to the SVM which as the recall of 90.12% and F1 score of 91.22% and has the acceptable range of precision and recall. RF shows the accuracy of 90.23% in prediction of the response and the NB has the lowest performance compared to the SVM and DT and has the F1 score of 87.63%. These variations shows that the proposed models excels in prediction of the pump operation and can be used in real time.

The confusion matrices shown in figure 4, which highlight the performance of each machine learning (ML) model in forecasting the pump operation status from real-time sensor data. The Support Vector Machine (SVM) model is 730 right in predicting that the pump is Off, and 710 right in predicting the pump is On. But there are 20 instances misclassified as Off when in fact they were On; also, there were 40 instances misclassified as On when they were Off. The Decision Trees (DT) and Random Forest (RF) models also perform well, with similar levels of accuracy, but have slightly different classification errors. The Naive Bayes (NB) model, although in general its predictions are correct, nevertheless there is a higher rate of misclassifications compared to the other models. Such figures illustrate the good and bad points of each ML model in predicting pump status, thus guiding the choice the most suitable model for managing water resources with maximum precision in precision agriculture programs.

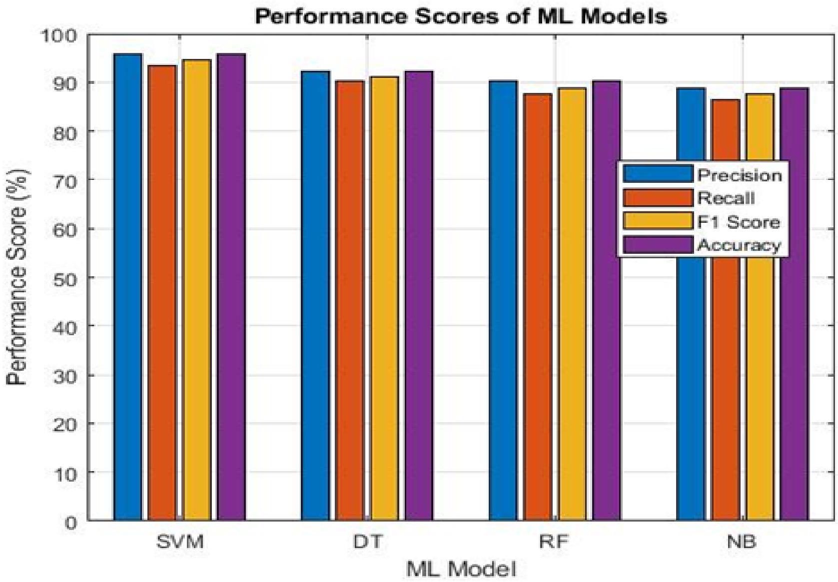

Figure 3. Performance Score of Each Model

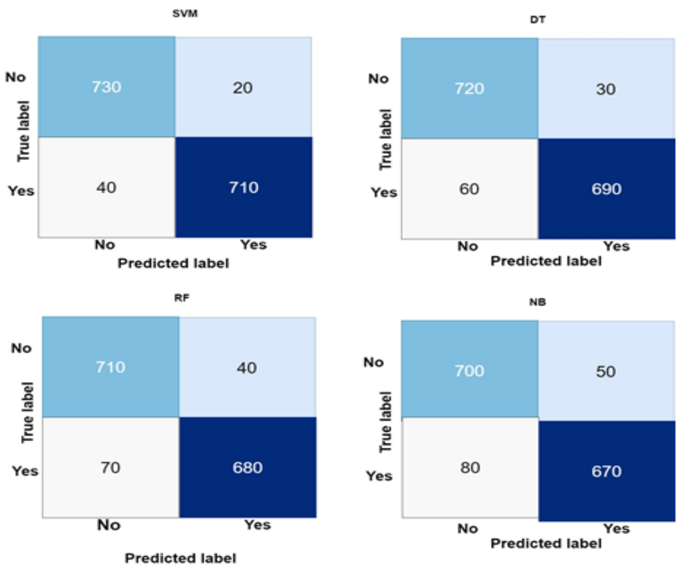

Figure 4. Confusion Matrices Result

IV. CONCLUSION

In summary, this study shows that the IoT and machine learning (ML) can be used in precision agriculture for better irrigation management, and specifically for water-saving irrigation technologies. Real-time monitoring, control, and adaptive management of water resources were shown by an experiment that employed wireless sensor networks and predictive algorithms. The investigation's evaluation of different kinds of ML models, among them Decision Trees (DT), Support Vector Machine (SVM), Random Forest (RF), and Naive Bayes (NB), demonstrated the accuracy with which each performed in predicting water requirements or controlling pumps. SVM achieved the highest accuracy; DT and RF were close behind, while NB lagged somewhat behind. Moreover, by analyzing confusion matrices we could learn something about the misclassification patterns of the models, which enabled us to select the most appropriate ML method for precision farming apps. These results have very important implications for earth-friendly agricultural practices--they show how we can save water or preserve materials while getting higher yields from crops. It sets the environmental protection aspect that both helps manage water resources and improves agricultural productivity. Also, it was shown via experiments that combining IoT technology with ML can not only provide intelligent guidance but also allows for expansion and adjustment in agriculture. And the future work, the future advancements in this field will have to deal with challenges such as food and environment. Changing climates and growing world population needs require us to look into how people in rural areas can make more efficient use of land. By making use of the Internet of Things (IoT) and machine learning (ML) in agriculture, farmers can rationally allocate resources, increase production yields. And so are contributions to creating a human agriculture that is more resilient rather than degrading.

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