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Implementation of smart irrigation using IoT and Artificial Intelligence

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Water management is crucial for agriculture, as it is the primary source of irrigation for crops. Effective water management can help farmers to improve crop yields, reduce water waste, and increase resilience to drought. This can include practices such as precision irrigation, using sensors and technology to deliver water only where and when it is needed, and conservation tillage, which helps to reduce evaporation and retain moisture in the soil. Additionally, farmers can implement water-saving techniques such as crop selection, crop rotation, and soil conservation to reduce their water use. Thus, studies aimed at saving the use of water in the irrigation process have increased over the years. This research suggests using advanced technologies such as IoT and AI to manage irrigation in a way that maximizes crop yield while minimizing water consumption, in line with Agriculture 4.0 principles. Using sensors in controlled environments, data on plant growth was quickly collected. Thanks to the analysis and training of these data between several models among them, we find the K-Nearest Neighbors (KNN), Support Vector Machine (SVM) and Naive Bayes (NB), the KNN has shown interesting results with 98.4 accuracy rate and 0.016 root mean squared error (RMSE).

Keywords: *artificial intelligence; AgriTech; internet of things; smart agriculture; smart irrigation.*

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1. Introduction

A smart irrigation system is an innovative technology that uses advanced technologies such as IoT (Internet of Things), artificial intelligence (AI), and machine learning (ML) to optimize the use of water in agricultural fields. These systems are designed to improve water use efficiency, reduce labor costs, and increase crop yields, while also reducing the potential for water waste.

The Internet of Things (IoT) refers to the interconnected of physical devices, such as appliances and machinery, which are embedded with sensors, software, and network connectivity that enable them to collect and exchange data. This allows for the automation and remote control of these devices, as well as the ability to monitor and analyze the data they generate. In our context, IoT-based systems utilize sensors to gather real-time data on soil moisture, weather conditions, and other factors that affect plant growth. This data is then transmitted to a central hub where it is analyzed by AI and ML algorithms. These algorithms are able to make predictions and adjust irrigation schedules in real-time, based on the specific needs of the crops and the local environment. For example, the system can predict the weather and adjust the irrigation schedule accordingly, or detect when the soil is already saturated and stop irrigation [1].

Artificial Intelligence (AI) is the simulation of human intelligence in machines that are programmed to think and learn like humans. It encompasses a wide range of technologies and techniques, including machine learning, natural language processing, robotics, and computer vision. AI systems can be trained on large datasets to perform tasks such as recognizing speech and images, making predictions, and controlling machines. The goal of AI research is to create systems that can perform tasks that typically require human intelligence, such as recognizing objects in images, and making decisions. AI has a wide range of application in areas such as healthcare and AgriTech. In this way we have a Smart irrigation systems with AI and ML that can help farmers to identify and manage potential issues such as pests, diseases, or nutrient deficiencies. These systems can also provide farmers with detailed information on water usage and crop yields, which can be used to make informed decisions about planting, fertilization, and other farming practices. Additionally, the use of IoT allows for remote monitoring and control of the irrigation system, saving time and resources for farmers [2].

Machine learning (ML) is a method of teaching computers to learn from data, without being explicitly programmed. It is a subset of artificial intelligence that allows systems to automatically improve their performance with experience. It useful in Smart irrigation systems to optimize the watering schedule for crops, based on factors such as weather, soil moisture, and plant type. This can help to conserve water and improve crop yields. Some examples of machine learning techniques used in smart irrigation include decision tree algorithms, that make possible to predict when to water based on weather forecasts, and neural networks to estimate soil moisture. Additionally, computer vision can be used to monitor crop health and detect signs of disease or stress. Overall, the goal of machine learning in smart irrigation is to automate the process of determining how much water to apply, and when, to ensure that crops receive the optimal amount of water while minimizing waste [3].

Agriculture 4.0 is a term used to describe the application of technology to agriculture, it refers to the use of technology in agriculture to improve efficiency, productivity, and profitability. This can include precision farming techniques, such as data analysis and IoT to optimize crop yields. Drones and autonomous vehicles can be used for tasks such as crop spraying and monitoring. Robotics can be used for tasks such as harvesting and planting. Livestock monitoring systems can track the health and productivity of animals. Climate and weather monitoring systems provide farmers with real-time data on conditions in the field. Smart irrigation systems can help farmers to conserve water. Crop disease and pest detection systems can detect and respond to problems early. Advanced data analytics and machine learning in agri-tech can help farmers make data-driven decisions [4].

However, Smart irrigation systems are an innovative technology that can revolutionize the way water is used in agriculture. They use IoT, AI and ML to optimize irrigation schedules, improve water use efficiency, increase crop yields, reduce labor costs, and provide farmers with detailed information on water usage and crop yields, that can help them make informed decisions and improve their farming practices.

The goal of this paper is to present a method for predicting irrigation needs and managing automatic irrigation systems efficiently. The approach includes four steps: installing sensors to measure soil moisture, temperature, and rain, linking the sensors to an acquisition system, using the Node-RED platform for monitoring, storage, and notifications, and analyzing the collected data using various algorithms such as K-Nearest Neighbors, support vector machine, and Naive Bayes. This method can be useful for large-scale irrigation systems or domestic applications, making plant watering easier and improving water management. The paper includes related works, methods used, discussions, as well as results, and conclusions.

2. Related works

In recent years, the use of smart irrigation systems has gained popularity as a means to conserve water and improve crop yield. Smart irrigation systems utilize various technologies such as weather forecasting, soil moisture sensors, and evapotranspiration (ET) data to optimize irrigation schedules and reduce water waste. These systems can also be integrated with other agricultural technologies such as precision farming and crop modeling to further enhance their effectiveness. The implementation of smart irrigation has been shown to not only improve water use but also increase crop and reduce costs for farmers.

For this, many researches came to existence like (M. Al-Sakib Khan Pathan and M. Rokibul Islam) in 2016. This study reviewed various IoT-based smart irrigation systems that have been developed for use in precision agriculture, including systems that use wireless sensor networks, cloud computing, and machine learning. The study found that these systems can significantly improve water use efficiency and crop yields, but also highlighted the need for further research to address issues such as sensor reliability and data privacy [5].

The paper "Smart Irrigation System Using IoT and Machine Learning" by Gore S., et al. presents a system that uses IoT and machine learning to optimize water usage in agriculture by predicting the water requirements of crops based on weather conditions and soil moisture levels. The system utilizes sensors to collect data and transmit them to a cloud server for processing by machine learning algorithms. This allows the system to control irrigation automatically, turning it on or off as needed. The authors conducted an experimental evaluation of the system on a farm, and found that it was able to accurately predict the water requirements of crops, reducing water usage by up to 30% and improving crop yield by up to 15%. The authors conclude that the system can be an effective tool for reducing water usage and improving crop yield in agriculture and suggest that the system can be further improved by incorporating more sophisticated machine learning algorithms and incorporating data from additional sensors [6].

Another one, presented in 2018 proposed a smart irrigation system that uses IoT and machine learning to optimize irrigation schedules based on real-time data on soil moisture, weather conditions, and crop growth. The system was tested on a small scale and found to significantly improve water use efficiency and crop yields.

Table 1. Comparative table that present many studies.

Date	IA Model	Model	Plant	Data type	Technology	Accuracy	Ref.
2016	Machine learning	Random Forest (RF)	No specific	Images	Multi-temporal satellite imagery	85%	[9]
2018	Machine learning	Support Vector Machine (SVM)	Citrus Orchards	Numeric data	Remote sensing data	91%	[10]
2020	Machine learning	Artificial Neural Networks (ANN)	Vineyards	Numeric data	Remote sensing	96%	[11]
2017	Machine learning	Decision Tree (DT)	Corn	Numeric data	Remote sensing and Meteorological data	88%	[12]
2017	Machine learning	K-Nearest Neighbors (K-NN)	No specific	Numeric data	Wireless sensor network	96%	[13]
2018	Machine learning	Random forest (RF)	No specific	Numeric data	Decision support system for precision agriculture	92%	[14]
2018	Machine learning	Support Vector Machine (SVM)	Wheat	Numeric data	Remote sensing data and Weather forecasts	78%	[15]
2016	Machine learning	Neural Network (NN)	Corn	Numeric data	Soil moisture sensors	86%	[16]
2018	Machine learning	Neural Network (NN)	No specific	Numeric data	Remote sensing data	94%	[17]
2020	Machine learning	RF & SVM & DT	No specific	Numeric data	Multi-temporal remote sensing	RF.A 96%	[18]

We continue with the study that compare the performance of three different IoT-based smart irrigation systems, including one that uses wireless sensor networks, one that uses cloud computing, and one that uses both wireless sensor networks and cloud computing. The study found that the system that used both wireless sensor networks and cloud computing performed the best, with the lower water consumption [7].

In 2020, (A. A. El-Shafie, H. M. El-Sayed, and E. A. El-Sayed) developed a smart irrigation system that uses IoT and artificial intelligence to optimize irrigation schedules based on real-time data on soil moisture, weather conditions, and crop growth. The system was tested on a small scale and found interesting result [8].

Generally smart irrigation system based on the Internet of Things (IoT) and machine learning can help to optimize the water use and improve crop yields. By using sensors to gather data on soil moisture, temperature, and weather conditions, and then applying machine learning algorithms to analyze this data, such a system can automatically adjust irrigation schedules and amounts to match the specific needs of the plants. This can lead to significant water savings and improved crop yields, while also reducing the risk of over-watering or under-watering. Additionally, such a system can also enable farmers to monitor and control irrigation remotely, improving efficiency and reduce labor costs.

Finally we present a comparative table that presents studies that have used artificial intelligence methods for smart irrigation detection, along with their results, technology used.

These studies present different machine learning techniques, data sources and evaluation methods, thus the results can be hard to compare. That is why our research presents data of different plants and uses several machine learning models to have a better basis for comparison.

3. Methods

Based on the AI and IoT ecosystem, our research consists of intelligently managing plant irrigation by focusing primarily on domestic plants to help manage these plants as well as to collect data from concrete way and train them in supervised learning models with a labeled data (input = Sensor value – output pairs = Decision of pump) to make predictions about new, unseen data. The goal is to learn a general rule, or model, that maps inputs to outputs. The trained model can then be used to make predictions on new, unseen data.

There are two main types of supervised learning: classification and regression.

— In classification, the goal is to predict a categorical label for a given input. For example, an email classifier would take an email as input and predict whether it is spam or not spam. Common classification algorithms include logistic regression, decision trees, k-nearest neighbors, and support vector machines (SVMs).

! In regression, the goal is to predict a continuous value for a given input. For example, we would take a sensor value of temperature, soil humidity, rain, humidity as input and predict whether it is time for pumping or not. Common regression algorithms include linear regression, polynomial regression, and random forests.

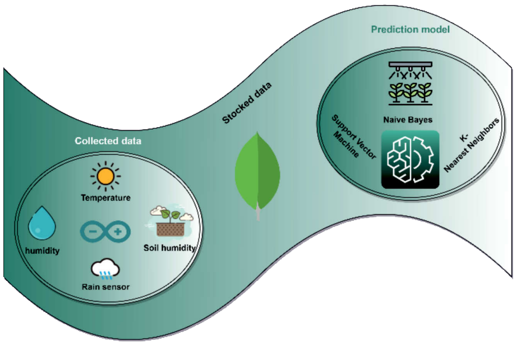

Fig. 1. Global schema of our realization.

After that moving on to the next step which consists in generalizing these models to serve a large category of plants.

To serve this need, we went through different steps as shown in Figure 1:

! Realization of an intelligent model that includes several sensors (soil humidity sensor, air humidity sensors, temperature sensor, rain sensor) to serve data collection with the use of a programmed Arduino card through the acquisition of different information about plants from agricultural engineers.

! Use of the Node-Red framework to collect, process, split and visualize this data.

! Store our data in the MongoDB Cloud database to have access at all times and in real time.

! Train our data in machine learning models (Support Vector Machine, K-Nearest Neighbors, Naive Bayes).

3.1. Support Vector Machine

The Support Vector Machine (SVM) algorithm is a supervised machine learning algorithm that is used for classification and regression tasks. It is based on the idea of finding a hyper-plane that maximally separates the different classes in the data. The basic idea behind the SVM algorithm is to find the best decision boundary (or hyper-plane) that separates the different classes with the largest margin. The margin is defined as the distance between the hyper-plane and the closest data points of each class [19].

The mathematical function that represents the SVM algorithm is called the primal optimization problem, which can be written as the following optimization problem:

$$\text{Minimize } \frac{1}{2}\|w\|^2$$
$$\text{Subject to } y_i(wTx_i + b) \geqslant 1 \text{ for all } i = 1, 2, 3, \ldots, n.$$

Where w is the normal vector of the hyper-plane, b is the bias term, x_i is the feature vector for the ith data point, y_i is the class label for the ith data point, and n is the number of data points.

In the case of non-linearly separable data, SVM algorithm uses the kernel trick, a technique that maps the input data into a higher dimensional space where it can be linearly separated. The kernel functions can be linear, polynomial, radial basis function (RBF) or sigmoid. These functions are used to compute the inner product between the inputs in a higher dimensional feature space, without actually computing the coordinates of the data in that space. The SVM algorithm has a lot of mathematical derivations, it is a powerful algorithm that has been widely used in many applications, and it has proven to be very effective in practice.

3.2. Naive Bayes

The Naive Bayes algorithm is a probabilistic algorithm that uses Bayes' theorem and probability density functions to classify data. The algorithm makes the assumption that all features in a dataset are independent of each other, which is often not the case in real-world data. Despite this assumption, the algorithm is often very effective in classifying data and is used in a variety of applications such as spam detection and text classification [20].

The mathematical functions used in a Naive Bayes algorithm include:

1. Bayes' theorem, which is used to calculate the probability of an event occurring based on prior knowledge of conditions that might be related to the event.
2. Probability density functions (such as the Gaussian distribution for continuous data or the multinomial distribution for discrete data) are used to model the likelihood of different features given a certain class.
3. Conditional probability is used to calculate the probability of a certain class given a set of features.
4. The algorithm then uses these probabilities to classify new data points, where it calculates the posterior probability of a class given the features and the prior probability of the class.
5. The probability estimates used in the algorithm are often calculated using maximum likelihood estimation (MLE) or the method of moments (MOM).

In summary, the Naive Bayes algorithm is a simple yet effective method for classification tasks, which uses Bayes' theorem, probability density functions and conditional probability to estimate the probability of a class given a set of features, and uses these estimates to classify new examples.

3.3. K-Nearest Neighbors

K-Nearest Neighbors (KNN) is a non-parametric, instance-based, supervised machine learning algorithm. It is used for classification and regression tasks. The basic idea behind the KNN algorithm is that an object is classified by a majority vote of its neighbors, which are the k closest training examples in the feature space [21].

The mathematical functions used in the KNN algorithm include:

1. Distance functions, such as Euclidean distance, Manhattan distance, or Minkowski distance, are used to measure the similarity between a new data point and the training examples.
2. Sorting algorithms, such as quicksort, are used to find the k closest training examples to a new data point.
3. A voting process, typically based on majority vote, is used to classify the new data point based on the class labels of its k closest neighbors.

4. In the case of regression problems, the average of the k closest neighbors can be used to predict the target value for the new data point.

The KNN algorithm is a simple and intuitive method, which does not make any assumptions about the underlying data distribution. It is often used as a benchmark method, it is simple and easy to understand, however, it requires a lot of computational resources and does not work well with large datasets.

4. Discussion and result

In this paragraph, we will discuss the results of our study. Through analysis and experimentation, we have been able to draw several conclusions about the topic at hand. These results will be presented in detail, along with any relevant data and statistics. Additionally, after providing a brief overview of the methodology used in our research. Overall, this paragraph will provide a comprehensive look at the findings of our study, and highlight the significance of these results within the field. We started with talking about our data as shown in Table 2.

Table 2. Table presents analysis data.

Data	Temperature	Air humidity	Soil Moisture	Pump
Min	12°C	38.2%	310.26	0
Max	40°C	82.3%	979.55	1
Mean	27.08°C	67.5%	380.50	***

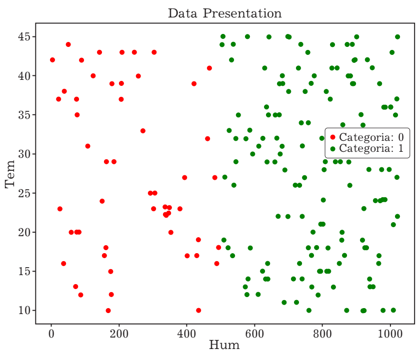

Fig. 2. The chart presents a part of the collected data.

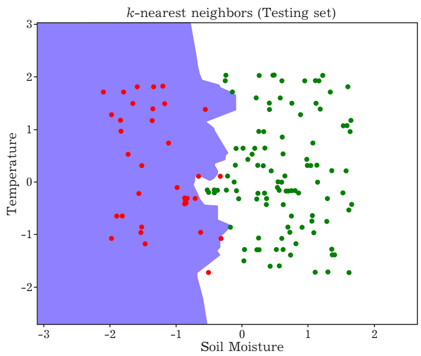

Fig. 3. The chart presents the result of KNN in test set.

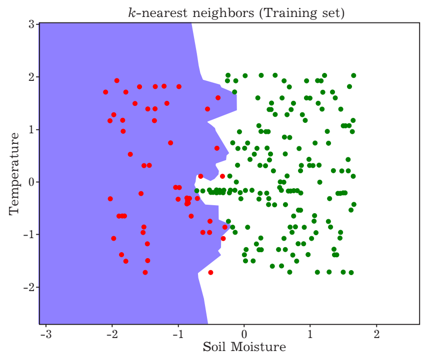

Fig. 4. The chart presents the result of KNN in training set.

This table presents a small analysis of these data, we find in this table two different data: the incoming data such as the soil moisture data, the air humidity data, and outgoing data which is presented by a single type of data which is the pumping data.

After that, we find part of this data present in the form of a point chart between the pumping value "0 or off" presented in red and the pumping value "1 or on" presented in green (see Figure 2).

For result of our model, we see in Table 3, it presents the different models with their parameter, their accuracy, and their (RMSE) which is the root mean squared error according to an overall analysis of the latter, we find that the most efficient model with good accuracy and low RMSE is the Naive Bayes with an accuracy of 98.4% and the RMSE of 0.016.

Table 3. The table presents the parameters used in our models and result.

Algorithm	Params	Accuracy	Root-Mean-Squared-Error
K-NN	K = 5	98.4%	1.6%
Naive Bayes	Gaussian NB	97.1%	2.9%
SVM	Linear SVC	96.7%	3.2%

The graphs (see Figures 3, 4) illustrate the results of the best model employed, namely, the K-Nearest Neighbors (KNN) model. The blue points in the training and testing sets represent pumping points of "0", while the white points represent pumping points of "1". The line in the graph demonstrates how the model effectively integrates all the red data points into their surroundings and the opposite for the green data points, resulting in a 98.4% accuracy rate.

5. Conclusion

AgriTech is a rapidly growing field that combines agriculture and technology to improve crop yields, reduce labor costs, and increase efficiency. Examples of AgriTech include precision agriculture, controlled environment agriculture, and the use of drones and robots in farming. The use of technology in agriculture has the potential to address many of the challenges facing the industry, such as climate change, water scarcity, and population growth. However, it is important to note that the implementation of AgriTech must be done in a sustainable and responsible manner, taking into account the potential impact on small farmers, rural communities, and the environment.

The use of intelligent irrigation is an important part of Agritech systems and it is vital to meet the increasing demand for food. By gathering data on irrigation usage, farmers can optimize their resources and make more informed decisions. A recent study suggests utilizing a database created with Node-RED and a data acquisition card to predict irrigation system efficiency and through machine learning, models providing decision support can be trained with an accuracy rate exceed 98%. We are currently working on expanding the database by incorporating more data and researching other algorithms to ensure the most accurate and efficient models are used. We also plan to integrate semi-supervised learning into our decision-making process. Intelligent irrigation plays a crucial role in meeting the world's growing food needs by allowing farmers to make more informed decisions and use resources more efficiently.

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Впровадження розумного зрошення з використанням інтернету речей та штучного інтелекту

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Керування водними ресурсами має вирішальне значення для сільського господарства, оскільки це основне джерело зрошення сільськогосподарських культур. Ефективне керування водними ресурсами може допомогти фермерам підвищити врожайність, зменшити витрати води та підвищити стійкість до посухи. Це може включати такі практики, як точне зрошення, яке використовує датчики та технологію для доставки води лише туди і тоді, коли це необхідно, і консерваційна обробка ґрунту, яка допомагає зменшити випаровування та зберегти вологу в ґрунті. Крім того, фермери можуть застосовувати методи економії води, такі як вибір культур, сівозміна та збереження ґрунту, щоб зменшити споживання води. Отже, з роками зросла кількість досліджень, спрямованих на економію використання води в процесі поливу. У цьому дослідженні пропонується використовувати передові технології, такі як IoT та AI, для управління зрошенням таким чином, щоб максимізувати врожайність сільськогосподарських культур і мінімізувати споживання води відповідно до принципів Agriculture 4.0. Використовуючи датчики в контрольованому середовищі, дані про ріст рослин були швидко зібрані. Завдяки аналізу та тренуванню цих даних між декількома моделями, серед яких знаходимо K-найближчі сусіди (KNN), метод опорних векторів (SVM) та наївний Байєс (NB), KNN показало цікаві результати з рівнем точності 98.4 і 0.016 середньоквадратичною помилкою (RMSE).

Ключові слова: *штучний інтелект; AgriTech; інтернет речей; розумне сільське господарство; розумне зрошення.*