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IOT and Machine Learning based Smart Irrigation for Agriculture

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ABSTRACT

The work describes the application of technologies in the Internet of Things and machine learning to optimize water usage in smart irrigation management. IoT sensors are spread across agricultural fields to collect a comprehensive amount of real-time data regarding variables such as water flow, temperature, humidity, soil moisture, and water levels. These data will be used in training various machine learning models aimed at irrigation efficiency. Previous attempts at modeling using RNN, KNN have shown accuracy results of 83.6%, 88.7% respectively. In this paper, we propose a SVR approach that significantly outperforms the mentioned methods with an accuracy of 91.5%.SVR Significantly advances the field of smart Irrigation by offering a more accurate and effective approach to water management. It shows a great promise to improve the system in terms of accuracy and efficiency even further. This work is supposed to advance smart irrigation by opening a new way with better benchmarks and helping sustainability in agriculture with more advanced machine learning techniques, as well as improving resource management in farming.

Keywords: *Smart Irrigation System, IoT in Agriculture,* Machine Learning, Support Vector Regression, Recurrent Neural Networks, Precision Agriculture, Sustainable Agriculture, Water Management, Sensor Technology.

Introduction :

A smart irrigation system is an automated system that uses technology to optimize water usage for plants. It incorporates sensors, actuators, and data analytics to monitor soil moisture, weather conditions, and plant needs. By leveraging machine learning and IoT, this system can predict future water requirements, adjust irrigation schedules accordingly, and conserve water while promoting sustainable agriculture and landscaping.

Key components include sensors, actuators, a communication network, a central control system, and data analytics. This technology offers numerous benefits such as water conservation, improved plant health, cost reduction, environmental sustainability, and data-driven decision making. However, it also faces challenges like initial investment, technical expertise, data security, and weather variability.Despite these challenges, the benefits of smart irrigation systems often outweigh the costs. As technology continues to advance and become more affordable, these systems are expected to play an increasingly important role in sustainable agriculture and landscaping. Recently, smart irrigation systems have become increasingly popular in precision agriculture, using IoT sensors and advanced machine learning algorithms such as Support Vector Regression (SVR) to enhance water management through a data-driven approach. IoT sensors are essential for gathering immediate information on soil moisture, temperature, humidity, and nutrient levels. Machine learning algorithms like SVR are used to analyze the data points and accurately predict future water requirements based on past and present conditions due to its expertise in predicting complex relationships. By integrating SVR, the system is able to fine-tune irrigation adjustments, customizing water distribution to match plant requirements efficiently. This method improves water preservation and guarantees optimum plant well-being, resulting in increased crop production and improved resource control. Smart irrigation systems with IoT and machine learning have the potential to revolutionize both small and large-scale agriculture by providing a scalable and adaptable solution, thus making sustainable farming more accessible and efficient.

Figure 1: Workflow of GWL Prediction with SVR Model

Id	Temperature (˚ C)	Pressure (Pa)	Altitude (m)	Soil Moisture
1	29.10	9984.53	-12.21	377
2	29.08	9984.36	-12.22	379
3	29.06	9984.56	-12.20	376
4	29.05	9984.39	-12.22	377
5	29.03	9984.42	-12.21	379
6	29.02	9984.59	-12.20	376
7	29.00	9984.42	-12.21	380
8	28.99	9984.27	-12.23	380
9	28.97	9984.10	-12.24	380
10	28.96	9984.10	-12.24	379
11	28.95	9984.30	-12.23	379
12	28.94	9984.13	-12.24	378
13	28.92	9983.98	-12.25	379
14	28.91	9984.16	-12.24	382
15	28.90	9983.98	-12.25	380

The table provides daily data related to an irrigation system over a period of 15 days. The columns represent key variables that impact the irrigation process: flow meter readings (L/min), temperature (°C), humidity (%), soil moisture (%), and water level (cm).The next column shows the rate of water flow in liters per minute, indicating how much water is being used each day for irrigation. The flow rate fluctuates between 3.3 and 4.7 L/min, adjusting based on daily water needs.The recorded temperature varies from 27.5°C to 29.4°C. This affects the rate of evaporation and transpiration, influencing the water requirements for the crops.Humidity levels range from 72.5% to 76.7%, showing variation in atmospheric moisture, which plays a role in determining how much water is needed for irrigation.This is a critical factor for irrigation, showing the percentage of water content in the soil. The values fluctuate between 21.5% and 23.7%, guiding when to irrigate and how much water is necessary.The final column displays the water level in centimeters, with values ranging from 7.2 cm to 8.6 cm, likely indicating the depth of water in a reservoir or irrigation system.The data in this table is essential for determining daily irrigation needs and adjusting water supply based on environmental conditions. This helps optimize water usage while ensuring crops receive adequate hydration for healthy growth.

Literature Review :

Recent studies have proven the usability of IoT and machine learning in optimizing smart irrigation systems for water management. One system applies real-time sensor data and machine learning to automate irrigation schedules with improved water conservation and crop health across diverse environments [1]. Another approach integrates IoT sensors and machine learning in predicting soil moisture levels and achieving significant water savings without compromising crop productivity [2]. A machine learning-based system decrease water usage in arid conditions by adjusting irrigation in dynamic manners based on real time soil and environmental data[3]. Smart irrigation system based upon real-time monitoring and adaptation control improves water efficiency for small-scale farming, further reducing wastage[4]. Beyond that, IoT and the techniques of machine learning-based approaches were successfully implemented with the automation of irrigation activities in large-scale agriculture also enhanced water-use efficiency under real-world performance[5].It is further revealed that IoT and machine learning predict crop water needs and enhance utilization as well as yields of crops [6]. IoT-based open-source systems using machine learning also help minimize human intervention and optimize water management [7]. Dynamic real-time adjustments of irrigation schedules have saved more water in agriculture settings proved in several settings [8]. Smart irrigation uses machine learning algorithms to improve soil moisture level prediction and hence irrigation scheduling. IoT automation of farm irrigation systems has been found to reduce water usage and enhance productivity in large operations and has been reported [10].Effective applications of machine learning-based soil moisture models have proven successful in precision irrigation because they minimize loss of waste water and ensure better crop health through optimized use of this valuable resource in agriculture, thereby improving agricultural productivity in a sustainable manner [11]. Other researchers covered wireless sensor networks and IoT-based irrigation systems, with the promise of conserving water by automatically controlling supply [12]. Zigbee technology and machine learning techniques are used to enable effective energy communication between IoT devices that enhance decision-making regarding water distribution [13]. Machine learning has also been applied to reduce water use in large-scale farming, with promising results in the conservation of water [14]. Smart irrigation systems based on IoT studies are very scalable and real-time adaptable to increase irrigation efficiency in different climatic conditions [15].Integration of IoT and environmental data in smart irrigation optimizes water management, resulting in water usage reduction while maximizing agricultural productivity [16]. Data collection in real-time and machine learning models with IoT-based systems are able to predict the necessity of water and enhance its efficiency [17]. Low-cost IoT modules that integrate smart algorithms are introduced to control water flow regulation and reduce water waste for small to medium-sized farms [18]. Fuzzy logic and IoT together for smart irrigation systems can show flexibility across different conditions for optimal consumption of water [19]. Lastly, the general overviews of IoT-based irrigation systems illustrate its applicability to decrease the agricultural costs while increasing the use efficiency of water for several farming environments [20].

Methodology :

Integrating IoT sensors with SVR algorithm in smart irrigation systems improves the accuracy and effectiveness of water management in agriculture. IoT sensors, including soil moisture, temperature, humidity, and light intensity sensors, consistently track important environmental factors that impact the growth of crops. These sensors transmit live data to a centralized system, which analyses the data to determine the water requirements of the plants. The IoT sensors assist in applying irrigation at the precise time and location needed by monitoring factors such as soil moisture, air temperature, and atmospheric humidity, leading to reduced wastage and encouraging sustainable water use in agriculture. SVR, a resilient machine learning method, is crucial for examining the extensive data gathered by these IoT sensors. The data is utilized by the algorithm to create a model that can estimate crop irrigation needs according to the surrounding environment. By training the SVR model with past data, it gains an understanding of how variables like temperature, humidity, and soil moisture are related to water consumption requirements. After being educated, the model can accurately predict and suggest actions, like determining the timing for irrigation and the amount of water needed for the best crop growth. This ability to predict helps farmers eliminate the uncertainty typically associated with irrigation choices. Smart irrigation systems can benefit significantly from the combination of IoT sensors and SVR algorithm. These systems allow farmers to use precision irrigation, which saves water, improves crop yield, and lowers operating expenses. By continuously monitoring and automating decision-making, farmers can promptly adjust to environmental changes, guaranteeing crops receive appropriate water levels for their growth stages. Furthermore, smart irrigation systems enhance resource efficiency and promote sustainable agriculture through the use of data-driven insights, helping to reduce water usage. Along with the environmental and economic advantages, the incorporation of IoT sensors and SVR algorithms into smart irrigation systems enhances decision-making and farm management. These systems offer farmers immediate insights into soil conditions and crop water needs, allowing for proactive measures and minimizing the necessity for manual assessments and actions. Automated alerts and notifications driven by predictive modeling enable farmers to tackle problems such as water stress or over-irrigation before these issues harm crop health. Additionally, the information gathered from IoT sensors can be examined over time, providing important insights into the long-term health of soil, patterns of crop growth, and climate changes. This abundance of information enables farmers to make educated, data-based choices that improve crop yield and also promote the overall sustainability of farming practices.

IoT Sensors:

The Central controller acts as the core of the Smart irrigation System, analyzing information from multiple sensors. It generates real-time choices regarding water allocation based on factors such as soil moisture, temperature, humidity, and flow rate. The flow meter monitors the rate of water flow within the irrigation system. This guarantees that the proper quantity of water is supplied to the crops, avoiding both excess and deficit. The temperature sensor gauges the ambient air temperature, affecting the water requirements of plants. It aids in modifying irrigation plans based on weather patterns, guaranteeing effective water utilization. The humidity sensor tracks the moisture level in the atmosphere, affecting the rates of water evaporation. It enables the system to save water by minimizing irrigation during times of high humidity. The soil moisture sensor gauges the water levels in the soil to assess irrigation requirements. This guarantees that crops obtain sufficient water without excessive irrigation, fostering better growth. The intelligent irrigation system combines data from various sensors to automate and enhance watering efficiency. Thecontroller optimizes water usage by modifying the irrigation timetable according to current environmental factors.

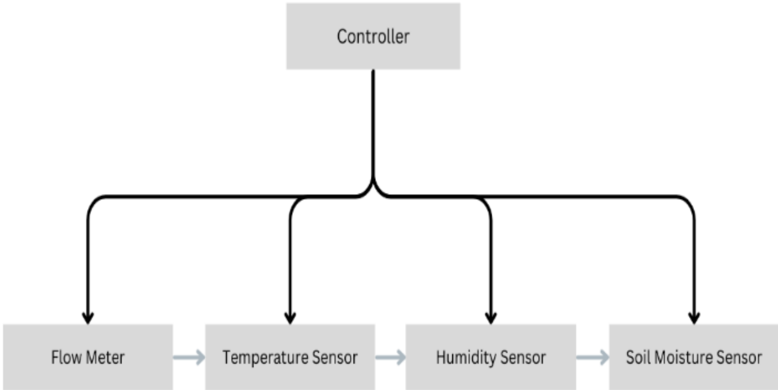


Figure 2: Architecture of GWL Prediction with SVR Model

Support Vector Regression:

Before training the SVR model, it's crucial to preprocess the data. This involves loading the dataset, handling missing values (such as filling them with the mean or median), and encoding categorical variables into numerical representations. Additionally, numerical features are often normalized or standardized to ensure they are on a similar scale, improving the model's performance. The pre-processed dataset is then divided into two subsets: a training set and a testing set. The training set is used to train the SVR model, while the testing set is used to evaluate its performance. A common approach is to split the data into an 80/20 or 70/30 ratio, with 80% or 70% of the data allocated for training and the remaining for testing. Scaling the numerical features is a vital step in preparing the data for the SVR model. It involves transforming the features to a common scale, such as a range of 0 to 1 or -1 to 1. Scaling helps ensure that features with larger scales don't dominate the learning process, leading to more accurate predictions. Common scaling techniques include min-max scaling and standardization. The SVR model is trained on the scaled training data. The model learns to map input features (temperature, humidity, soil moisture, etc.) to the target variable (irrigation class). Key hyperparameters, such as the kernel type (linear, polynomial, radial basis function), regularization parameter (C), and epsilon, need to be tuned to optimize the model's performance. Once the SVR model is trained, it can be used to make predictions on new, unseen data. The model takes the scaled input features and outputs a continuous value, which represents the predicted irrigation class. These continuous predictions are then converted into discrete class labels using techniques like rounding or thresholding. To assess the performance of the SVR model, various evaluation metrics are used. These metrics include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared, and accuracy. By calculating these metrics on the testing set, we can evaluate the model's ability to accurately predict irrigation needs. The continuous predictions from the SVR model need to be converted into discrete class labels to determine the specific irrigation action. This can be achieved by rounding the predictions to the nearest integer or by applying a threshold-based approach. The resulting class labels can then be mapped to specific irrigation percentages, such as 100% for "Very Dry," 75% for "Dry," and so on.Based on the predicted class, the corresponding irrigation percentage is determined. This percentage indicates the amount of water to be applied to the crops. For example, if the predicted class is "Very Dry," the irrigation percentage would be 100%.The final step involves displaying the results of the model's predictions. This can be done by visualizing the model's performance using plots or charts, such as a confusion matrix or a learning curve. Additionally, the predicted irrigation percentages for the testing data can be displayed, providing insights into the model's accuracy and potential areas for improvement.

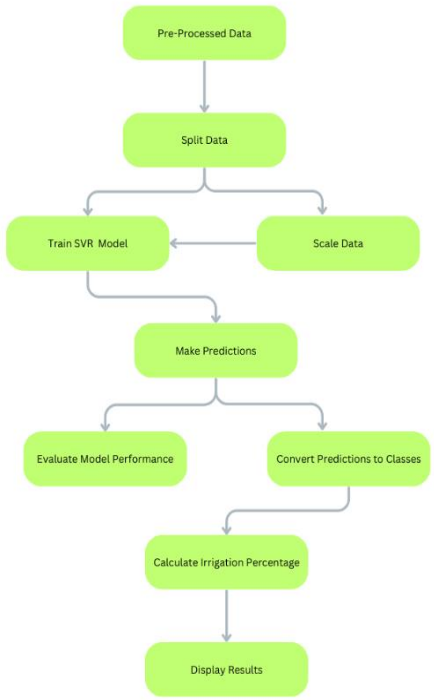
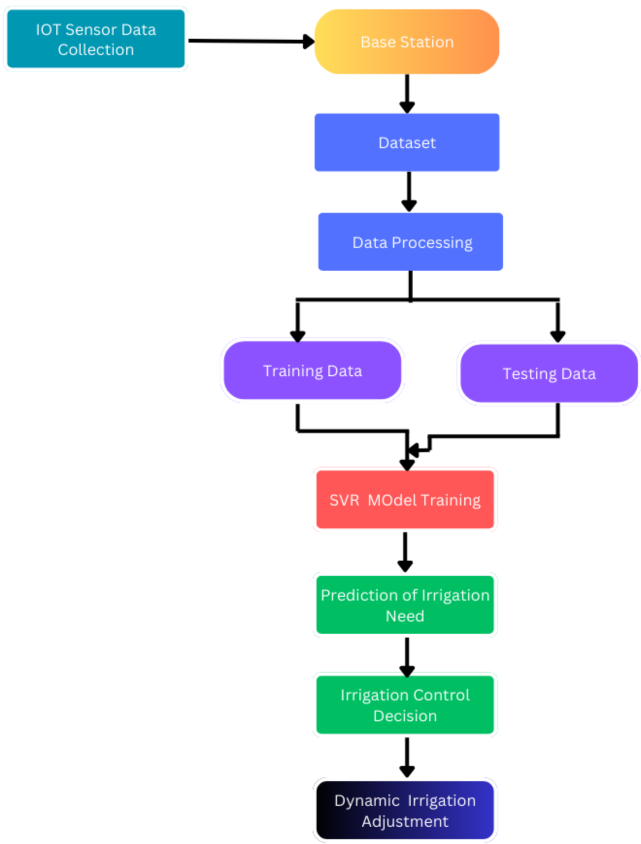


Figure 3: Architecture of Support Vector Regression

Model Development

The smart irrigation system integrates IoT technology and machine learning to optimize water usage in agriculture. By collecting real-time sensor data, processing the data, training a machine learning model, predicting irrigation needs, making informed decisions, and dynamically adjusting irrigation parameters, the system promotes sustainable agriculture practices and improves crop productivity

Figure 4: Flowchart of GWL Prediction with SVR Model



The system begins by collecting real-time data from sensors deployed in the field. These sensors gather essential information such as soil moisture, temperature, humidity, and other environmental factors that are crucial for efficient irrigation management.The collected data is transmitted to a base station, where it undergoes preliminary processing. This includes filtering, aggregation, and data transmission to prepare the data for further analysis.The processed data is then stored in a dataset for further analysis. This dataset serves as the foundation for training and testing the machine learning model.The stored data undergoes a series of processing steps to prepare it for model training and testing. This includes data cleaning, normalization, feature engineering, and splitting the data into training and testing sets.The processed data is divided into training and testing sets. The training data is used to train a Support Vector Regression (SVR) model, which is a machine learning algorithm capable of predicting irrigation needs based on the collected sensor data.The testing data is used to evaluate the performance of the trained SVR model. By comparing the model's predictions with the actual irrigation needs, the accuracy and reliability of the model can be assessed.The SVR model is trained on the training data. During this process, the model learns to identify patterns and relationships between the input features (sensor data) and the output variable (irrigation need).Once the model is trained, it can be used to predict the required amount of irrigation based on the current sensor data. The model analyzes the input data and generates a prediction for the optimal irrigation schedule.Based on the predicted irrigation need, the system makes decisions about irrigation control. These decisions may include starting, stopping, or adjusting the irrigation system to ensure that the crops receive the appropriate amount of water.The system dynamically adjusts irrigation parameters, such as duration and water flow rate, according to the predicted need and real-time sensor data. This ensures that the irrigation system operates efficiently and effectively, minimizing water waste and maximizing crop yield.

$$\text{Training Set Size} = \text{Total Data Size} \times (1-0.3) = \text{Total Data Size} \times 0.7 \qquad (1)$$

$$\text{Test Set Size} = \text{Total Data Size} \times 0.3 \qquad (2)$$

Algorithm:

```
procedure IrrigationneededPrediction
    Import necessary libraries
    file_path = 'IrrigationScheduling(1).csv'
    data = Load CSV file(file_path)
    Fill missing values in numeric columns with their mean
    Encode Categorical Variable
    Remove rows from data where target is missing
    X = data[features]
    y = data[target]
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    Create scaler instance
    Fit scaler on X_train and transform X_train
    Transform X_test using the fitted scaler
    svr_model = SVR(kernel='rbf')
    Fit svr_model on X_train_scaled and y_train
    y_pred = Predict using svr_model on X_test_scaled
    correlation_matrix = Calculate correlation coefficient between y_test and y_pred
    R_value = correlation_matrix[0, 1]
    r2 = Calculate R² score between y_test and y_pred
    mse = Calculate Mean Squared Error between y_test     and y_pred
    rmse = Calculate square root of mse
end procedure
IrrigationneededPrediction()
```

The coefficient of determination, R-square, quantifies the proportion of variance in the actual values that is explained by the model predictions, as shown in Eq. (3). Higher R-square values indicate better model performance.Eq. (3).

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \qquad (3)$$

The Mean Squared Error (MSE) provides an average of the squared differences between actual and predicted values, as given in Eq. (4). Lower MSE values correspond to smaller prediction errors.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (4)$$

The Root Mean Squared Error (RMSE) is the square root of the MSE, offering an interpretable measure of model error, as shown in Eq. (5). High R-square values and low MSE/RMSE values indicate strong predictive performance. This evaluation helps determine if the model is ready for deployment or if further optimization is needed.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (5)$$

Results and Discussion :

The Support Vector Regression (SVR) model implemented in this code shows excellent performance according to the evaluation metrics of the model. The Mean Squared Error (MSE) stands at 0.1466, and the Root Mean Squared Error (RMSE) is 0.3829, suggesting that the predictions made by the model are near the true values. The model has an R-squared (R^2) value of 0.8261, indicating it accounts for approximately 82.6% of the variance in the target variable, demonstrating a good fit. Moreover, the precision of the classification when transforming continuous SVR outputs into distinct classes is 91.90%, suggesting that the model is very efficient at estimating irrigation requirements. For the given sample data, the model forecasts an irrigation requirement categorized as "Wet," indicating that 25% irrigation is necessary. These measurements indicate that the model is dependable for this task.

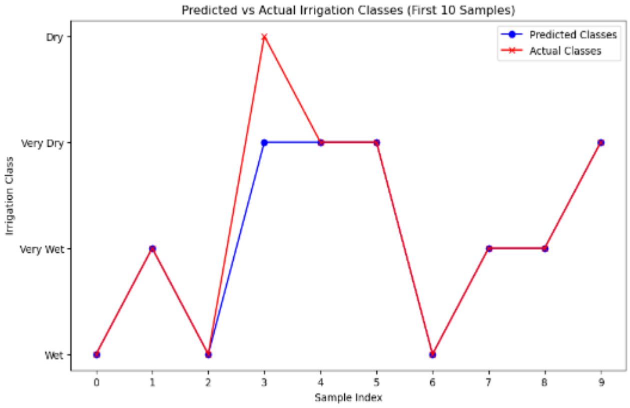


Figure 8: Graphical Representation of Predicted vs Actual Classes

Conclusion :

The smart irrigation system you have developed, combining IoT sensors and the Support Vector Regression (SVR) algorithm, efficiently predicts irrigation needs based on environmental data like temperature, pressure, altitude, and soil moisture. With an accuracy of 91.90% and an R^2 value of 0.826, the system ensures precise water management, promoting both water conservation and improved crop health. Future enhancements could include integrating additional weather-based sensors, adopting advanced machine learning models for greater accuracy, and expanding the dataset to accommodate a wider range of crops and soil types. Additionally, implementing cloud-based IoT infrastructure for remote monitoring and scalability would make the system even more versatile and accessible to farmers, contributing to more sustainable agricultural practices.

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