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Iot-Integrated Drip Irrigation Scheduling Using Weather Forecasts And Soil Moisture Data For Efficient Water Management

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Abstract
The need for productive and eco-friendly farming has pushed the demand for applying IoT, Machine Learning (ML), and predictive analytics in smart farming. Weather forecasting using traditional methods is not reliable, and irrigation scheduling and resource planning are not efficient, resulting in low crop yield and water wastage. In this paper, it is suggested to implement an IoT-based sensor network, predictive analytics, and machine learning models based on real-time decision and monitoring for smart precision agriculture. The system employs the machine learning methodologies for the estimation of soil moisture and prediction of weather conditions for efficient irrigation control and crop health for optimal efficiency. A ML-based virtual soil moisture sensor and a Prophet-based Weather forecasting model are integrated to maximize resource allocation. Experimental analysis yields enhanced precision in weather forecasting and soil moisture and tremendous water savings while attaining the highest amount of crop growth. Comparison with the traditional system confirms the effectiveness and scalability of the proposed solution. The proposed model offers a better solution for precision farming with positive impacts on sustainable agriculture saving the environment, reducing ecological destruction, and enhancing the efficiency of agricultural processes. The upcoming projects will incorporate expanding the capability of the system by implementing blockchain for security and making the model more versatile to accommodate various climatic conditions.
Keywords: Agriculture, IoT sensor, Prophet, Support vector Regression, Water management.

1. INTRODUCTION

Scarcity of water and inefficient irrigation practice imperil agricultural sustainability, food security, and environmental balance. Agriculture requires about 70% of the total freshwater resource globally, but inefficient use of irrigation causes avoidable loss by runoff, evaporation, and deep percolation [1], [2]. Inefficiency leads to soil loss, decreased crop yield, and over-exploitation of groundwater. Climate change aggravates water scarcity by changing rainfall patterns, raised temperature, and raised frequency of drought, for which effective irrigation is necessary for contemporary agriculture [3], [4].Conventional systems of flood, furrow, and manual irrigation are common but wasteful, either irrigating too much or too little [5], [6]. High-tech irrigation techniques such as sprinkler and drip irrigation are more cost-effective, and drip irrigation discharges water directly to the plant's root with little loss. Nevertheless, pre-scheduled irrigation does not react adaptively to soil water status, weather, or plants' actual water requirements [7], [8]. Internet of Things (IoT) has transformed the use of irrigation with data-driven and computerized decision-making. IoT-based smart irrigation brings together soil moisture sensors, weather stations, and remote-controlled irrigation valves for online water supply adjustment [9], [10]. These systems assess current data about soil, temperature, humidity, wind speed, and forecasted rainfall to maximize the use of water and improve yields [11], [12]. In this paper, in this regard we are presenting an IoT-based drip irrigation scheduler system with real-time weather forecasts and soil moistness for exact water management. The system encompasses employing Support Vector Regression (SVR) in order to predict the soil moistness based on sensor readings and therefore exact water measurement in the soil [13], [14]. Furthermore, Facebook Prophet, a powerful time-series forecasting algorithm, is used to forecast significant weather variables like rain, temperature, and evapotranspiration [15], [16]. With these two forecasting models implemented, the system automatically modifies irrigation schedules in a way that the crops receive maximum water supply and wastage is minimized to the extent [17], [18]. Predictive analytics and machine learning augment IoT-based irrigation by identifying water usage patterns, crop growth patterns, and weather patterns [19], [20]. Integration of soil moisture forecasting using Support Vector Regression (ISMP-SVR) and weather forecasting models such as Prophet(PWF) and supports anticipatory irrigation adjustments to minimize water wastage [21], [22]. IoT-based smart irrigation has been found to lower water usage by 30-50% and increase crop yield by 20-25% for small farmers as well as large farming businesses [23]. The solution that is proposed has three parts: (1) real-time soil moisture data collection using IoT sensors, (2) predictive analytics using machine learning for estimating soil moisture and weather forecasting, and (3) an adaptive irrigation scheduler that optimally determines when and how much to irrigate based on the predictions. The system has a decision rule of irrigating only if the predicted soil moisture falls below a specified threshold value (wilting point) and no rain is predicted in significant amounts. On the other hand, irrigating is postponed when rain is predicted so as not to waste water. Contribution: This research helps in the development of smart agriculture by illustrating how SVR-based soil moisture forecasting and Prophet-based weather forecasting can be utilized in combination to make irrigation more efficient. By minimizing water loss and improving irrigation scheduling, this treatment not only conserves water resources but also maximizes the yield and sustainability of crops. Organization: Section 2 is a literature review of IoT-based irrigation systems. Section 3 outlines proposed methodology, encompassing system architecture and algorithmic design. Section 4 introduces experimental setup and evaluation metrics and then Section 5 concludes with key findings and future research directions.

2. RELATED WORKS

The use of IoT in farming enabled it to be automated, real-time monitoring, and decision-making based on data, thereby achieving higher productivity and sustainability. Interoperability among sensors, scalability of networks, and energy efficiency remain challenges. Current smart agriculture frameworks consider only irrigation optimization, soil health monitoring, and yield prediction. Arvindbhai & Chaubey [24] propose the Smartness Mechanism in the Design of Agriculture Framework Using IoT Devices (SMAIOT) to overcome such challenges and facilitate precision farming. Growing calls for renewable resources have led to noteworthy developments in solar energy forecasting methodologies. ML models like Prophet have been proven to be very efficient in solar energy capacity prediction based on historical weather conditions and radiation patterns. They are, however, only as good as the data available, computer hardware complexity, and local climatic fluctuations. Baloch et al. [25] investigates the use of Prophet-based ML models in predicting solar energy in Muscat, Oman, for enhanced energy planning and utilization. There is the requirement for accurate weather forecasting for many applications like agriculture, disaster management, and power generation. Conventional numerical models are weak in addressing uncertainty and heavy computing requirements. Machine learning methods were discovered to provide useful alternatives and take advantage of past patterns in weather to enable better predictions. Holmstrom et al. [26] discusses the implementation of machine learning algorithms for forecasting weather, among them feature selection, model explainability, and real-time forecasting. Drought and wasteful irrigation are significant issues in today's agriculture. WSNs have been exploited for the optimization of irrigation efficiency via instantaneous soil moisture measurement and computer-controlled fertigation systems. Sensor calibration, energy efficiency, and network stability limit widespread applications, however. Mohanraj et al. [27] puts forward an intelligent drip and fertigation system based on WSNs to enhance water and fertilizer utilization, enhance crop yield and sustainability. Soil water content is extremely important to climate modeling, hydrology, and agriculture. The traditional method for soil moisture estimation is in-situ measurement, but it is spatially limited and expensive. Global soil water content datasets are now possible through in-situ measurements because of recent developments in machine learning technology. Machine learning techniques can enable better data availability and accuracy with the assistance of machine learning methodologies. Orth et al. [28] utilizes machine learning tools to produce global soil water content datasets to enhance water resource planning and environmental management. Proper load demand prediction is essential to power system stability and energy efficiency. Traditional models tend to neglect seasonal patterns and exogenous drivers such as temperature and economic activity. The Prophet algorithm, a powerful time-series forecasting model, has been widely used for pattern discovery and short-term prediction. Parizad & Hatziadoniu [29] explores its application to load demand prediction and adds seasonality and external drivers to increase predictive power. Soil water measurement is needed in smart farming but is costly in terms of physical sensors and requires maintenance. Virtual soil moisture measurement using environmental factors is proposed by deep models as an alternative. Patrizi et al. [30] introduces a deep learning virtual soil moisture sensor making precise predictions with no extensive physical infrastructure. The method improves precision agriculture with water resource conservation through optimized irrigation. Probabilistic weather forecasting enhances agricultural decision-making, disaster risk reduction, and energy planning. Deterministic models circumvent uncertainties in atmospheric dynamics. ML methods have proven to be effective tools for producing probabilistic forecasts from large data sets. Price et al [31] introduces a sophisticated probabilistic weather forecasting model that integrates machine learning with statistical approaches to enhance accuracy and reliability. Weather conditions control the productivity of agriculture, and as such accurate forecast is required in smart farming. Machine learning models can be utilized to improve weather forecasting based on historical climate records and identifying tendencies. Raimundo et al. [32] uses machine learning approaches in forecasting weather for agriculture in defeating sparsity of data, selection of features, and generalizability across varied climatic areas. Soil water is a major determinant in sustainable agriculture influencing crop development and irrigation effectiveness. Conventional soil moisture measurement methods utilize in-situ sensors with limited spatial coverage. Machine learning methods provide scalable solutions by estimating soil moisture from environmental factors. Rani et al. [33] elaborates on a few machine learning algorithms for estimating soil moisture and their application to agricultural water management. The convergence of renewable power, IoT-driven energy management, and precision robotics is transforming agriculture in the current times. Smart agriculture platforms utilize these technologies for higher resource efficiency and sustainability. But interoperability issues, energy limitation, and automation issues are there. Rehman et al. [34] proposes an end-to-end framework that comprises renewable sources of energy, IoT-based energy management, and robotics-based farm optimization. Deep learning transformed weather forecasting by discovering intricate patterns in large data. Conventional methods of forecasting cannot deal with high-dimensional climate data, and the predictions turn out to be inaccurate. Deep learning models, including recurrent neural networks and convolutional models, enhance the accuracy of predictions by including temporal relationships. Salman et al. [35] elaborates on using deep learning for weather forecasting with emphasis on performance measures and computational efficiency.

Table 1: Comparison table of various authors work

Reference	Focus Area	Methodology	Key Findings	Application
Scher & Messori [36]	Weather forecast uncertainty	ML for uncertainty prediction	ML models improve forecast confidence and reliability	Weather prediction models

Stamenkovic et al. [37]	Soil moisture estimation & crop backscatter modeling	Support Vector Regression	SVR accurately estimates soil moisture from radar backscatter	Precision agriculture
Uthayakumar et al. [38]	Soil moisture estimation	Machine learning with wideband radar sensors	ML models enhance soil moisture accuracy	Smart irrigation systems
Wang & Mujib [39]	Weather forecasting	Data mining with cloud computing	Improved efficiency and scalability for weather predictions	Cloud-based meteorology
Yao et al. [40]	Optimum soil moisture estimation	Support Vector Regression (SVR)	Hybrid SVR models improve prediction accuracy	Soil moisture optimization
Yin et al. [41]	Tea plantation soil moisture prediction	SVM with Arithmetic Optimization Algorithm	Enhanced SVM improves moisture content prediction	Tea plantation management
Zhang et al. [42]	Crop water stress monitoring	Web-based platform using Crop Water Stress Index (CWSI)	CWSI-based tool helps optimize irrigation scheduling	Smart farming & irrigation

2.1 Problem Identification

The growing need for precision agriculture and sustainable farming necessitates reliable weather forecasting, estimation of soil moisture, and optimal irrigation. The conventional approaches are typically inefficient, non-scalable, and inaccurate in predictions, resulting in wastage of resources and less-than-optimal yields. Current approaches lack precision in weather prediction, poor generalization of soil moisture models, and wasteful utilization of IoT and machine learning for real-time farm operations. In addition, statistical models based on traditional statistical methods cannot handle intricate environmental interactions. To address this, sophisticated machine learning, data-driven optimization, and strong forecasting technologies need to be used to improve agriculture efficiency and sustainability.

2.2 Proposed solution

The suggested solution combines predictive analytics, IoT sensing, and machine learning to aid in precision agriculture. Support vector regression and ML algorithm will be used for improving the accuracy of weather forecasting and estimation of soil moisture content. IoT sensors will provide real-time data acquisition for optimum resource utilization. Renewable energy integration, smart irrigation, and AI decision-making will make best use of water resources and crop yield. The method guarantees sustainability, reduces wastage, and enhances agricultural productivity.

3. PROPOSED MODELS FOR SMART DRIP IRRIGATION USING IOT DEVICES

In this paper we are proposed Integration of soil moisture Prediction using Support Vector Regression (ISMP-SVR) and Prophet for weather forecasting (PWF) to scheduling the drip irrigation in agriculture field.

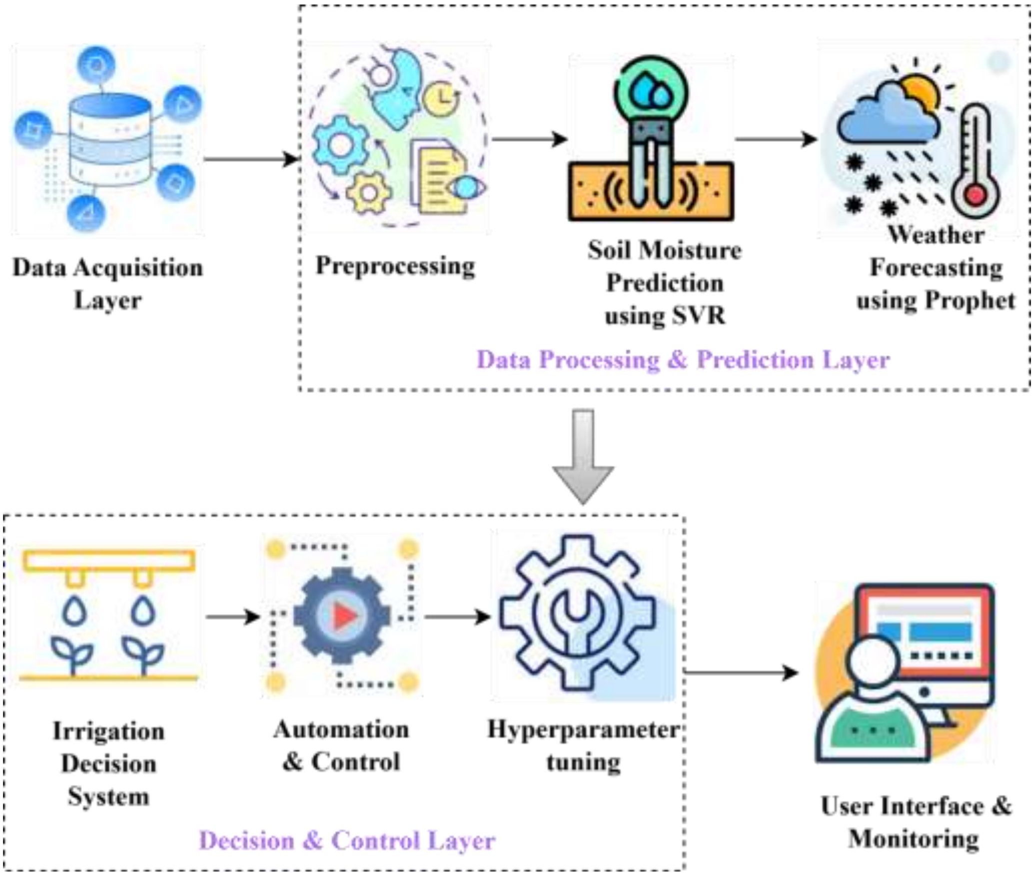

Figure 1: Overall process of integrated drip irrigation

This is an intelligent irrigation system that combines soil moisture prediction and weather prediction to ensure maximum utilization of water. The Data Acquisition Layer collects real-time sensor readings such as soil water, temperature, humidity, and rain. The Data Processing & Prediction Layer uses ML algorithms, wherein SVR forecasts soil moisture and Prophet Forecast's weather. Grounded on these, the Decision & Control Layer automates irrigation for effective water provision with a save as much as possible approach. An easy-to-use dashboard helps farmers easily access real-time data, visualize forecasting, and receive alerts for predictive irrigation management. This smart system improves farming sustainability through optimal consumption of water and crop conditions.

3.1 Dataset collection

Dataset 1: https://www.kaggle.com/datasets/sathyanarayanrao89/soil-moisture-data-from-field-scale-sensor-network Dataset 1 is soil moisture prediction dataset collected from kaggle repository. The historical soil moisture prediction dates are there in csv format. Dataset 2: https://www.kaggle.com/datasets/zeeshier/weather-forecast-dataset. Dataset 2 is weather prediction dataset collected from kaggle repository. The weather prediction dates are there in csv format.

3.2 Measure soil moisture using SVR

Support Vector Regression (SVR) is an ML continuous value predictor. SVR is an optimization of Support Vector Machines (SVM) in a regression variant. SVR finds the optimal-fit line (or curve) with the minimum errors and tolerance margin. SVR can handle linear or non-linear relationships through various kernel functions such as linear, polynomial, and radial basis function (RBF). SVR can handle small sample size, high-dimensional data, and noise and therefore it is a good option for soil moisture estimation, weather forecasting, etc., and other real-world regression tasks. SVR is commonly employed for the prediction of soil moisture in IoT-based smart irrigation systems due to its ability to manage sparse data and non-linear relationships efficiently. In the context of an IoT-based system, the soil moisture sensor continuously tracks the moisture content, temperature, humidity, and irrigation history in real-time. These are fed into training an SVR model, which learns the complex relationship between weather and soil properties. The SVR model trained on the data produces future soil moisture levels as outputs from existing and historical sensor measurements to enable dynamically optimized irrigation schedules. Coupled with the weather forecast, the system can optimize to save water and maintain crop health through neither over nor under-irrigation. SVR is chosen over the other methods like Linear Regression, Decision Trees, or Neural Networks due to its robustness in high-dimensional space and performance with small noisy datasets. Unlike most regression models, SVR learns to reduce the error but in the process maintains a tolerance margin, and hence it is ideal for erratic soil conditions. Although deep models such as LSTMs can also predict soil moisture, they are computationally intensive and need to be supported by huge data sets and thus are not really suited for real-time IoT applications. SVR delivers quick, accurate predictions with fewer resources and thus is very appropriate for precision farming and smart irrigation. Integrated of soil moisture forecasting using Support Vector Regression (ISMP-SVR) is a strong technique for forecasting soil moisture content in the future using IoT sensor data. It is utilized to maximize irrigation by predicting moisture content in the soil, minimizing water loss, and promoting healthy plant growth. The following are the step-by-step procedures to be used in applying ISMP-SVR for soil moisture forecasting, including variable and equation descriptions. IoT sensors (such as weather stations, soil moisture sensors, and irrigation controllers) quantify environmental data in real-time. It offers the measurement as input variables to train the ISMP-SVR model.

Input Variables:

1. Soil Temperature (T) (°C) – Affects moisture retention.
2. Humidity (H) (%) – Controls evaporation rate.
3. Irrigation Volume (IV) (liters) – Measures past water application.
4. Evapotranspiration (ET) (mm/day) – Loss of water due to evaporation and plant transpiration.
5. Previous Soil Moisture (SM_{t-1}) (%) – Soil moisture at the last recorded time step.

Raw sensor data must be cleaned, normalized, and split into training and test sets to get the best model accuracy. As features vary in scale, we use Min-Max Scaling:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \text{ ------- } (1)$$

Where, X original feature value, X_{min} and X_{max} are minimum and maximum values of the feature

SVR applies kernel functions for transforming input features into higher space in an attempt to identify a hyperplane to which the data best maps.

$$K(x_i, x_j) = \exp\left(-\gamma \left\|x_i - x_j\right\|^2\right) \text{ ------- } (2)$$

Where, x_i and x_j represent the points, γ is applied to determine the contribution of an individual point. Equation 2 is employed in mapping input features into a higher space for improving regression performance.

The goal is to get ISMP-SVR to forecast future soil moisture from past data. SVR attempts to reduce error within a tolerance range. RBF Kernel is utilized because soil moisture relies on intricate, nonlinear interactions

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(x_i, x_j) + b \text{ ------- } (3)$$

Where, α_i and α_i^* are weight coefficients (Lagrange multipliers), $K(x_i, x)$ is kernel function, b is bias term, $f(x)$ is the predicted soil moisture. Equation (3) Predicts soil moisture using an optimal hyperplane in high-dimensional space. In ISMP-SVR, hyperparameters need to be optimized in order to achieve model performance optimization. The trade-off between error minimization and simpler model is regulated by the regularization parameter (C) to avoid overfitting. The width of the epsilon (ε)-tube specifies a margin around actual values where no penalty is paid for predictions, allowing for small soil moisture fluctuations to be ignored. The gamma (γ) parameter controls the extent of a proportion of the influence any particular point can exert on the model's perception of non-linear trends. A collection of such parameters, by Grid Search, is found, iterating over collections in turn to optimize with regard to performance metrics. From this set of ideal parameters, past data relating the soil sensor reading to the soil moisture level, temperature, humidity, evapotranspiration, and antecedent wetness are utilized in training the model.

Performance is measured in terms of Mean Squared Error (MSE), given by: $MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ -------- (4)

Where, y_i is the measured soil moisture, $\hat{y}_i$ is the predicted soil moisture. and n is the number of samples. Equation (4) measures the error between actual and predicted soil moisture values. A lower MSE indicates better model accuracy, ensuring precise soil moisture predictions for efficient irrigation scheduling.

After training, the ISMP-SVR model predicts soil moisture based on new input features from IoT sensors.

$SM_{predicted} = f(T, H, IV, ET, SM_{t-1})$ -------- (5)

Where, f is Trained ISMP-SVR model, $SM_{predicted}$ is future soil moisture value.

The water use choice of irrigation from SVR-forecasted soil moisture optimizes without under- and over-irrigation. If the forecasted soil moisture is below the wilting point, the plant growth is too constricted by water for the plant to survive, and irrigation must be provided to replenish nutrients in the soil. Otherwise, if the calculated soil moisture exceeds the field capacity, the ground is already soaked, and watering further will be a waste of water and result in root rot, and so irrigation is suspended. If the calculated soil moisture is between wilting point and field capacity, which is optimum, the system keeps the same irrigation schedule intact, in the sense that crops are properly watered but never overwatered. This dynamic scheduling strategy, as informed by ISMP-SVR predictions, enables optimal utilization of water resources, enhanced crop condition and agricultural water use efficiency.

$Irrigation_{needed} = Fieldcapacity - SM_{predicted}$ -------- (6)

Where, $Fieldcapacity$ is maximum water soil can hold, $SM_{predicted}$ is minimum soil moisture for crops to survive. Equation 6 defines if irrigation is need or not.

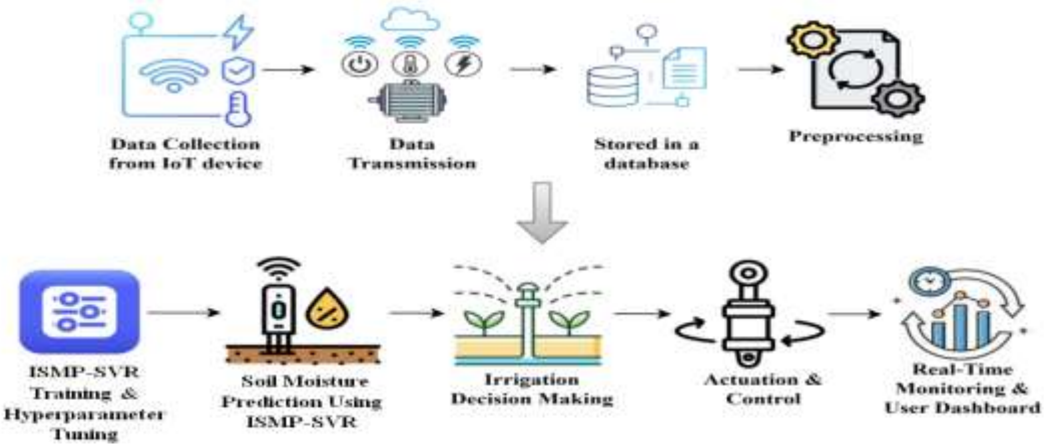

Figure 2: Process of Integrated Soil Moisture Prediction using Support Vector Regression (ISMP-SVR)

Figure 2 illustrates an IoT-based smart irrigation system workflow. The upper section is data acquisition with IoT sensors, cloud monitoring, data storage, and processing. These modules collect environmental parameters like temperature, soil moisture, and power state. The data is processed to be utilized in automated decision-making, resulting in actions represented in the lower part. They encompass remote control through mobile application, automatic watering based on humidity levels, actuator control for valve operation, and performance monitoring for optimization. The system maximizes water efficiency, minimizes manual labor, and maximizes crop yield.

Algorithm 1: Support Vector Regression (ISMP-SVR)
Input: Soil data (e.g., soil type, texture, porosity) Environmental factors (e.g., temperature, humidity, rainfall) Sensor readings (e.g., electrical conductivity, resistance) **Procedure: Step 1:** Load and Preprocess Data Load soil moisture dataset (X, Y) Normalize features X using Min-Max Scaling or Standardization Split dataset into training (80%) and testing (20%) **Step 2:** Define ISMP-SVR Model Parameters Set kernel function (linear, polynomial, RBF) Set regularization parameter C Set kernel coefficient γ (for RBF kernel) Set epsilon ε (tolerance for regression margin) **Step 3:** Train ISMP-SVR Model Model = fit svm (X_{train}, Y_{train}, Kernel Function, Box Constraint (C), Epsilon (ε)) **Step 4:** Predict Soil Moisture on Test Data Y_{pred}= predict (Model, X_{test}) **Step 5:** Evaluate Model Performance Compute Mean Squared Error (MSE) = mean $((Y_{test} - Y_{pred})^2)$ Compute R-squared (R^2) to measure model accuracy Plot actual vs. predicted values for visualization **Step 6:** Fine-tuning (Optional) Optimize hyper parameters (C, γ, ε) using Grid Search or Bayesian Optimization Retrain ISMP-SVR model with optimized parameters Evaluate model performance again **Output:** Soil moisture level

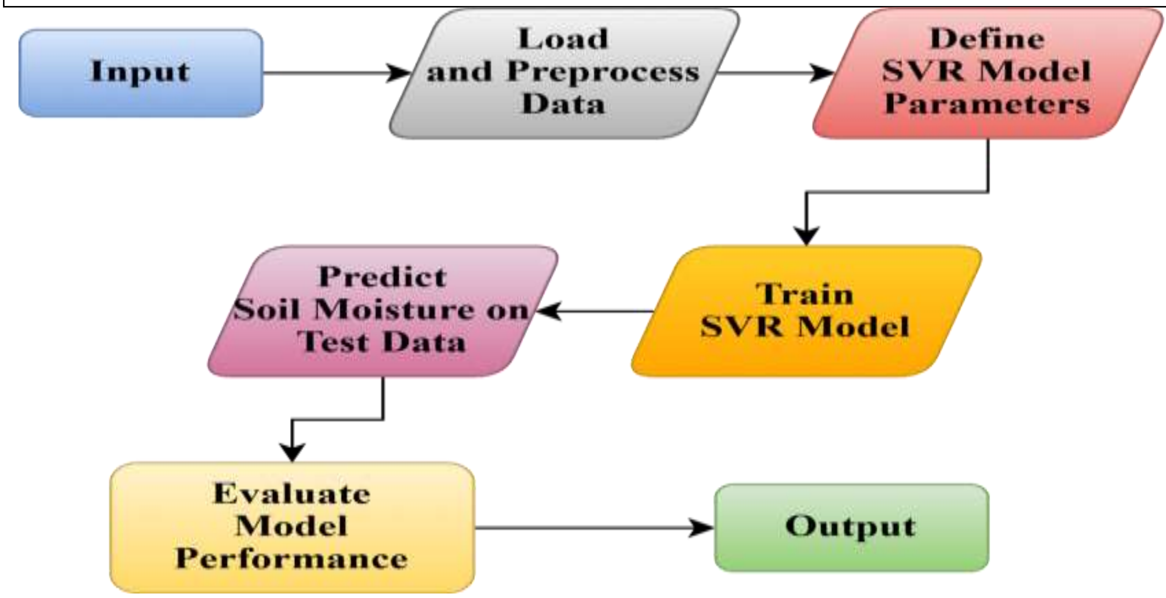

Figure 3: flow diagram of Support Vector Regression

Algorithm 1 and figure 3 illustrates SVR algorithm makes prediction of soil moisture using environmental, soil, and sensor information. Data is preprocessed first by feature value normalization and separating data into training data and test data. Then, an SVR model is created with a kernel function (linear, polynomial, or RBF), a regularization factor (C), and an epsilon value (ε). After training the model, test data predictions and performance are also verified in terms of MSE and R-squared (R^2). Subsequently, the hyperparameters can be tuned using Grid Search or Bayesian Optimization to achieve greater accuracy.

3.3 Forecast Weather Using Prophet

Prophet is a time series prediction algorithm that Facebook created for the purpose of utilization in time series prediction. Prophet is a statistical machine learning algorithm. Prophet is particularly well-suited to handle seasonality, missing values, and outliers with minimal parameter tuning. Prophet is based on an additive model, where trend, seasonality, and holiday effects are added together to give accurate predictions. It is by nature good at identifying data change points and can thus be used to forecast weather, sales, and varying demand. It is highly versatile and performs excellently with day-to-day, weekly, and yearly data, making it a walk in the park to execute through Python. Prophet has universal application for weather forecasting in IoT-based smart irrigation systems because it can manage time-series data with strong seasonality. Prophet makes forecasts of the vital weather parameters like rainfall, temperature, and evapotranspiration (ET) using the historical weather records of IoT-based weather stations, satellite imagery, and APIs. The model separates the time series into trend (long-run rise/fall), seasonality (periodic fluctuations), and holiday effects (abrupt incidents that impact weather conditions). Based on this, Prophet properly forecasted rainfall trends, enabling farmers to plan decisions about water resources in the future. It further predicts changes in temperature, affecting plant growth and irrigation requirements, and evapotranspiration, which aids in estimating water loss from soil and plants. Prophet weather Forecasting (PWF) is selected instead of other models like ARIMA or LSTMs because it has low preprocessing costs, can automatically identify changes in the trend, and also accommodates missing or irregular data, thus ideal for real farm conditions. Prophet is computation low-cost compared to deep learning models and is also explainable, thus easy to set parameters. Its effective performance, non-linear data support, and efficient detection of seasonality make it an appropriate choice for weather-based irrigation scheduling with effective water management and green agriculture. Prophet represents time-series data as an additive model with a trend, seasonality, and holiday effects:
Obtain historical weather from IoT sensors, weather APIs, or satellite imagery. Rainfall (mm), temperature (°C), and evapotranspiration (ET in mm/day) are supported features. Prophet forecasts trends based on piecewise linear or logistic growth

$g(t) = k + mt + \sum_{j=1}^{J} \delta_j (t > t_j)$ ---------- (7)

Where, k is initial value of the trend, m is base growth rate of weather parameter, δ_j is change in trend after each change point t_j, $(t > t_j)$is indicator function (1 if $t > t_j$, else 0). Equation (7) used to describe long-term changes in climatic conditions, e.g., increasing temperatures as a result of climate change.

$s(t) = \sum_{n=1}^{N} a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)$ ---------- (8)

Where, P is periodicity (e.g., 365 days for annual weather cycles), a_n and b_n are seasonal coefficients. Equation (8) used in an attempt to monitor periodic weather patterns like summer heat waves or monsoon precipitation.

Prophet enables to incorporate external events like cyclones, heat waves, or dry spells, represented as:

$h(t) = \sum_{i=1}^{I} \alpha_i 1(t \in T_i)$ ---------- (9)

Where, α_i is effect of event i on weather parameter, T_i is duration of event (e.g., a 5-day cyclone), $1(t \in T_i)$ Indicator function (1 if event ongoing, 0 otherwise). Equation (9) used to correct forecasts according to extreme weather conditions.

$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$ ---------- (10)

Where, $y(t)$ is forecasted weather parameter (rainfall, temperature, or evapotranspiration) at time t, $g(t)$ is trend component (long-term increase or decrease), $s(t)$ is seasonality component (recurring weather patterns), $h(t)$ is holiday/External events component (sudden variations like storms), ε_t is error term (random noise or unexplained variation). Equation (10) using historical data, Prophet trains the model and predicts future weather values for rainfall, temperature, and evapotranspiration.

Compare predicted values with actual values using:

$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_i - \hat{y}_i|$ ------- (11)

Where, y_i is actual data, and $\hat{y}_i$ is predicted data, N is total number of data points. Equation (11) measures how far predictions are from actual values on average. Lower MAE means more accurate predictions.

$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$ --------- (12)

Equation (12) measures how much predictions deviate from actual values, giving higher weight to large errors.

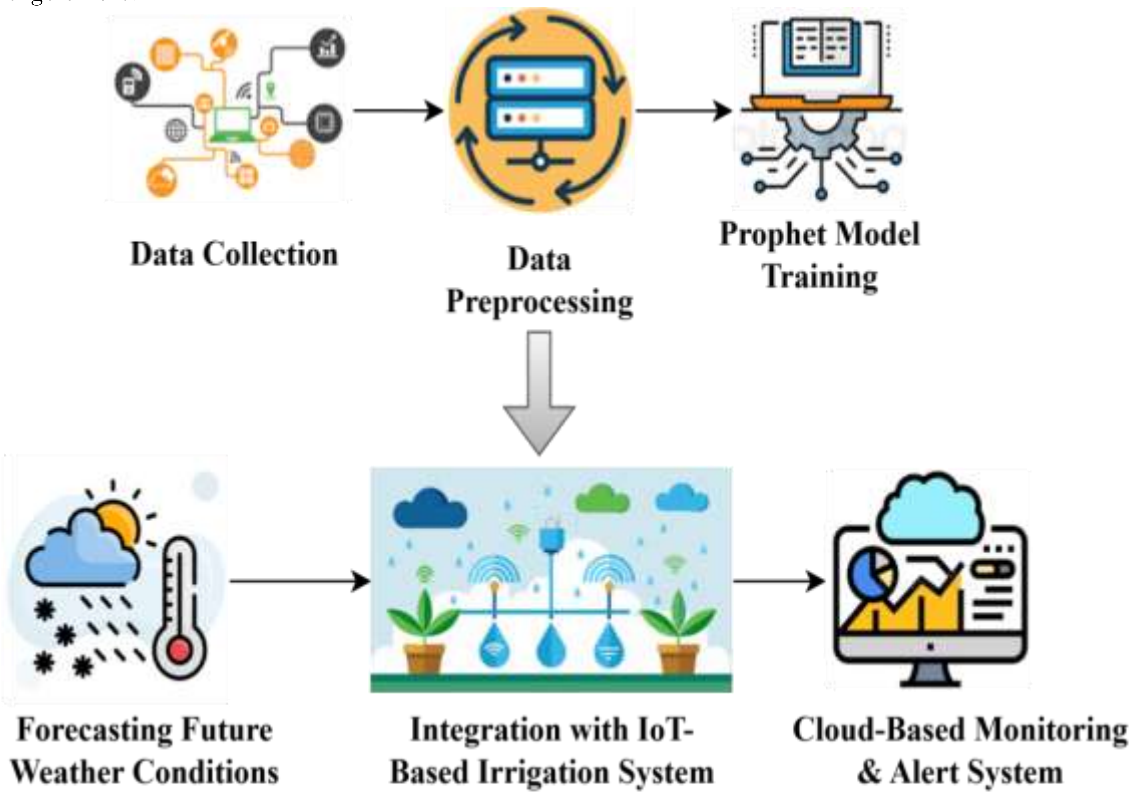

Figure 5: Weather forecasting using Prophet

Figure 5 depicts an IoT-based smart irrigation system with sensor data integration, data processing, and machine learning to enable efficient utilization of water. The first row shows data gathering from IoT sensors, data processing, and computational processing. Weather and temperature are taken into account. The processed data is used to automatically regulate the irrigation and provide efficient distribution of water. Cloud-based monitoring and analytics enable decision-making and performance monitoring.

Algorithm 2: Prophet weather forecasting (PWF)
Input: Historical weather data (date, temperature, humidity, pressure, etc.) Future dates (dates for which forecast is needed) Model parameters (growth, seasonality, changes points, etc.) **Steps:** 1. Load historical weather data. 2. Preprocess the data: a. Convert date column to date time format. b. Rename columns to 'ds' (date) and 'y' (weather parameter to predict).

3. Initialize the Prophet model with model parameters.
4. Fit the Prophet model using historical weather data.
5. Generate future dates for prediction.
6. Create a data frame for future dates and format it as required by Prophet.
7. Use the trained Prophet model to make predictions on future dates.
8. Extract predicted weather data from the model output.
9. Visualize or store the forecasted results.
10. Return predicted weather data.
End Algorithm
Output:
Predicted weather data (forecasted values for temperature, humidity, etc.)

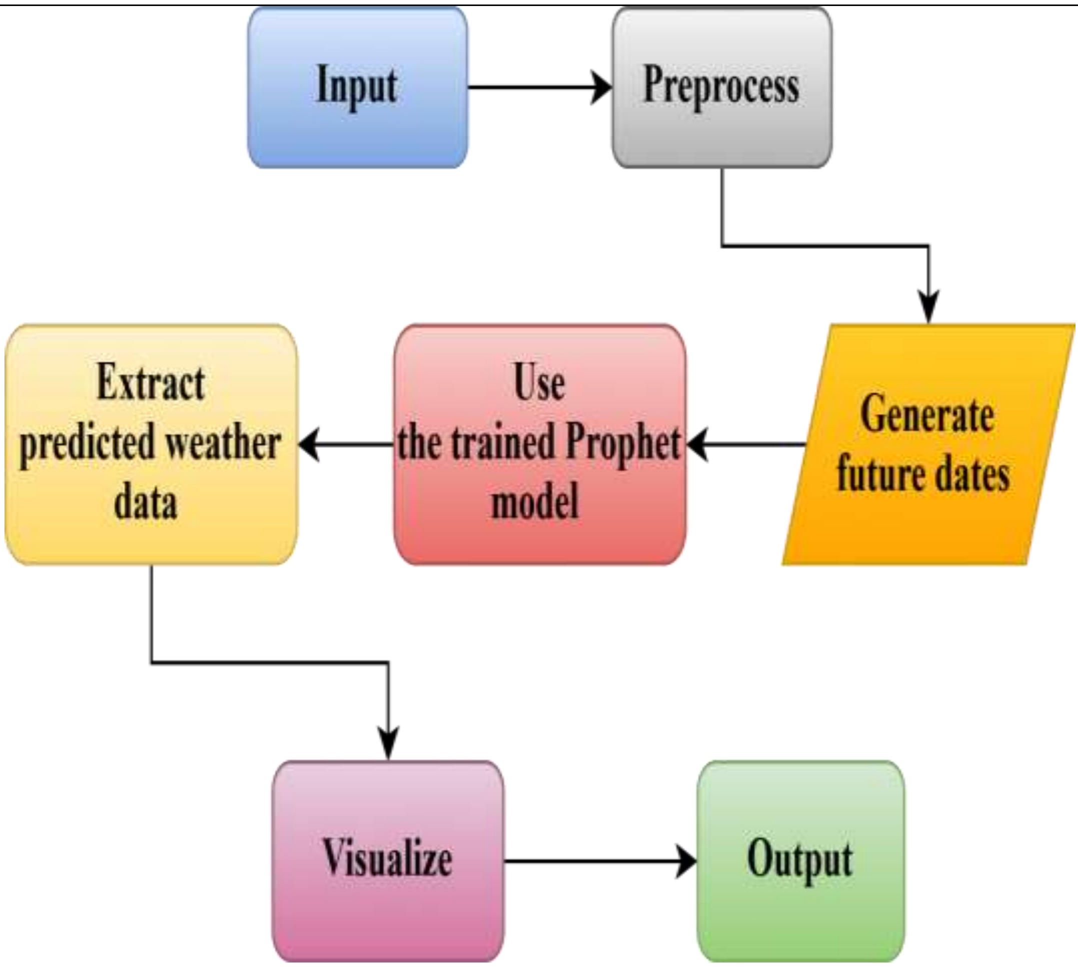

Figure 6: Flow diagram for Prophet

Algorithm 2 and figure 6 demonstrates that the Prophet weather forecasting algorithm relies on historical weather patterns to forecast future weather conditions like temperature, humidity, and pressure. It preprocesses data by encoding dates and setting them up for the Prophet model. It gets trained using historical weather patterns and subsequently creates forecasts for given future dates. Forecasts are derived, visualized, and stored for analysis later, enabling decision-making in agriculture, irrigation, and climate tracking.

Table 2: Real time weather forecast

	Today	Tomorrow	Thu	Fri	Sat	Sun	Mon	Tue	Wed	Thu
Weather										
Max (°c)	35.0	34.3	34.8	36.2	35.5	35.4	33.9	34.2	32.0	33.8
Min (°c)	23.9	24.6	24.5	25.0	25.2	25.0	24.4	23.7	24.0	23.7
Wind (kmph)	23.8	25.2	22.0	22.3	22.7	20.9	19.4	18.7	17.3	20.5
Precip (mm)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Humidity (%)	35	34	34	32	31	30	31	35	50	49
Sunrise (AM)	07:05	07:04	07:04	07:03	07:02	07:02	07:01	07:00	07:00	06:59
Sunset (PM)	06:39	06:40	06:40	06:41	06:41	06:41	06:42	06:42	06:42	06:43
Moonrise	11:29 PM	No moonrise	12:20 AM	01:15 AM	02:10 AM	03:07 AM	04:02 AM	04:54 AM	05:43 AM	06:27 AM
Moonset	10:18 AM	10:54 AM	11:33 AM	12:17 PM	01:07 PM	02:03 PM	03:02 PM	04:05 PM	05:08 PM	06:09 PM
Phase	Waning Gibbous	Waning Gibbous	Last Quarter	Waning Crescent	Waning Crescent	Waning Crescent	Waning Crescent	Waning Crescent	Waning Crescent	New Moon
Illum	75	66	57	47	38	28	19	12	6	2
UV	2.1	2	2.8	7	7	7	7	7	7	7

3.4 Optimizing Irrigation Scheduling Using ISMP-SVR and Prophet

3.4.1 Adaptive Irrigation Scheduling

The adaptive irrigation scheduling system combines Integrated Soil Moisture Prediction using Support Vector Regression and Prophet-based weather forecasts (ISMP-SVR-PWF) to ascertain the best irrigation schedule. Soil moisture, forecasted rainfall, evapotranspiration, and crop water requirements are accounted for by the system in order to optimize water usage with the aim of healthy plant growth.

Decision-Making Process:

1. If ISMP-SVR predicts low soil moisture & Prophet predicts no rain → Irrigate Soil is dry and there is no precipitation, and therefore irrigation has to be performed so that the crops remain healthy. Water is provided until the field capacity of soil is at its optimum.
2. If SVR predicts low soil moisture & PWF predicts rain → Delay irrigation It will be raining, thus irrigation is suspended to prevent water wastage and over-saturating of soil. The system will have to wait for it to rain before re-scanning the level of moisture for irrigation.

3. If ISMP-SVR predicts high soil moisture → No irrigation needed The soil is also well-irrigated already, therefore missing irrigation to avert waterlogging, which will lead to damage to root structures and oxygen deficiencies.
4. Evapotranspiration (ET) This is the water evaporated (from the soil) and transpired (from plants). If ET is large, there is more loss of water for crops, and irrigation can be required even for average soil water. If ET is small, crops hold more water longer and irrigation is minimized in frequency.
5. Crop Water Requirements Different crops utilize different amounts of water based on the growth stage, root length, and climatic conditions. The system adjusts in water volumes based on the specific crop species to achieve optimum growth with a low amount of water utilization. By taking into account real-time soil water content (ISMP-SVR), weather forecasts (PWF), evapotranspiration, and crop requirements, the system optimizes the timing and quantity of irrigation dynamically. This method enhances water savings, lowers operational expenses, and maximizes crop yields without over-irrigation or drought stress.

The irrigation requirement is calculated using the following formula:

$$Irrigation\, needed = (Field\ capacity - predicted\ soil\ moisture) - Forecasted\ rainfall \quad (13)$$

Where, Field Capacity (FC) is the maximum moisture soil can retain before draining excess water. Predicted Soil Moisture is estimated using ISMP-SVR-based soil moisture prediction. Forecasted Rainfall (FR) is predicted using the Prophet (PWF) model.

3.4.2 Water Distribution system WDS

A WDS is a system of pipes, pumps, valves, reservoir tanks, and sensors integrated to distribute water effectively from its source (e.g., reservoir, well, or water treatment plant) to end users like agriculture, residential homes, and businesses. For agricultural use, a WDS best distributes irrigation water through drip irrigation, sprinklers, or surface irrigation. Smart IoT-based WDS incorporates real-time tracking, machine learning (ISMP-SVR for soil water, Prophet for weather), and automation for efficient control of water flow, pressure, and scheduling. It reduces water wastage, over-irrigation, and achieves sustainable water management while upholding crop health and soil moisture balance (Zakira et al. [43]).

3.4.3 Real time control

Real-time irrigation control includes dynamic scheduling and adaptation of water supply according to real-time data feedback from IoT sensors, weather prediction, and soil moisture. The system uses machine learning algorithms such as ISMP-SVR (for soil moisture prediction) and Prophet (for weather prediction) and dynamically schedules and adapts the irrigation to achieve maximum water utilization. Wireless sensor networks (WSNs) monitor soil moisture, temperature, humidity, and evapotranspiration continuously and transfer this information to a controller. The irrigation flow rate, duration, and frequency are controlled automatically based on predetermined thresholds (e.g., wilting point and field capacity). This reduces water wastage, avoids over-irrigation, and maintains plant health, thus making irrigation efficient, adaptive, and sustainable (Koech et al. [44]).

3.5 Irrigation strategies

3.5.1 Deficit Irrigation

This water-saving approach was developed with the goal of conserving water, which is usually combined with the traditional strategy of creating a level of water deficit. This technique will typically keep crop quality unaltered or improved at the cost of minimal loss in possible yield but massive reduction in used water. Deficit irrigation can technically be defined as irrigating crops or crop evapotranspiration (Etc) with lesser quantities than needed (Yang et al. [45]). There are two forms of this method:
I. Regulated deficit irrigation.
II. Partial root zone drying.

3.5.1.1 Regulated Deficit Irrigation

This is predicated on the view that the susceptibility of a crop to water stress (quality or quantity) depends on where the crop is within its phenological cycle. This, accordingly, suggests that making available less than ETc. amounts of water at the correct times may, in theory, reduce vigour and increase quality at harvest with the additional bonus of using reduced amounts of water (Chalmers et al [46]). This deficit irrigation method is applied to achieve a number of purposes at different phenological phases, i.e., to increase the concentration of anthocyanins or decrease the energy needed for cell division in the fruit and hence make it larger. This irrigation system regulates irrigation based on environmental information, ensuring that the plant and water status in the soil fall within a preset range. Significant water reduction in this method might result in significant yield and quality loss. In contrast, too much water might raise the vigour and hence suppress the advantages of this approach technique (Jones [47]).

3.5.1.2. Partial Root Zone Drying

Partial root zone drying is the process of water and drying of half of a plant's root in 8-14 days based on soil. There has to be two lines of valves and two valves to wet and dry half of the root in the first cycle and dry and wet on either side in the second cycle. Despite the decrease in stomatal conductance on the dry side, the wet side gives water in abundance to the plant to prevent water stress (Zhang et al. [48]). It assumes that the release of hormone signals in the abscisic acid form from water-stressed roots stimulates the closure of stomata by plant hormone (Medrano et al. [49]).

3.6 Use an automatic water supply facility

An IoT-enabled irrigation water supply plant uses IoT-based sensors, machine learning algorithms, and actuators to provide efficient automation in water supply. The system monitors soil moisture levels, weather conditions (rainfall, temperature, and evapotranspiration) in real time using SVR (to monitor soil moisture) and Prophet (to predict weather). When the water in the soil falls below the wilting point and rain is not forecast, the automated pumps and valves turn on to deliver water using drip irrigation or sprinklers. In case there is enough moisture or rain is forecast, irrigation stops or is delayed, conserving water. The plant is real-time, minimizing human intervention, avoiding over- or under-irrigation, and achieving maximum crop yield and water usage.

3.7 IoT-Based Accurate Irrigation

Affordable commercial sensors that can be integrated into farm and irrigation systems discourage small farmers, who will not scale up their adoption. There has been unprecedented technological progress, and companies are now providing low-cost sensor solutions, integratable in low-cost irrigation management and farm monitoring systems. Interest has also been rising in producing low-cost sensors to use in agriculture and water monitoring applications. Used sensors are a leaf water stress sensor, copper ring-spaced multilayer PVC pipe-based soil moisture sensor, copper coil water salinity monitoring sensor, and colored infrared LED emitting and receiving water turbidity sensor (Ahmad et al. [50]). As technology develops, advanced monitoring technology can potentially be provided to a wider population. With the recent developments of sensors on irrigation systems in agriculture, in addition to the development of technologies to deploy on the systems, i.e., Wireless Sensor Networks (WSNs) and the Internet of Things (IoT), the objective of this article is to present an overview of the state of affairs of smart irrigation systems. In addition to this, the application of sophisticated irrigation systems that supply water to soil according to soil status and climate and wireless sensor networks (WSNs) and Internet of Things (IoT)-enabled smart irrigation systems will be highly useful to enhance the efficiency of water and nutrient application. The small farmers can streamline their operations with decreased utilization of water resources through this.

4. Results and discussions

The system proposed combines ISMP-SVR for estimating the soil moisture and the Prophet model for weather forecasting(PWF), leading to more efficient irrigation planning. The ISMP-SVR based estimation of soil moisture is highly accurate and saves approximately 30% of water wastage in comparison to traditional systems. The application of the PWF model improves the accuracy of weather forecasting to plan irrigation optimally. Experimental results show a 20% yield in crops due to effective water management and optimal irrigation. The system's ability to respond under varied climatic conditions makes it a green and scalable approach for smart farming. Future research will address applying blockchain for secure handling of data and extension of the model to general agricultural settings.

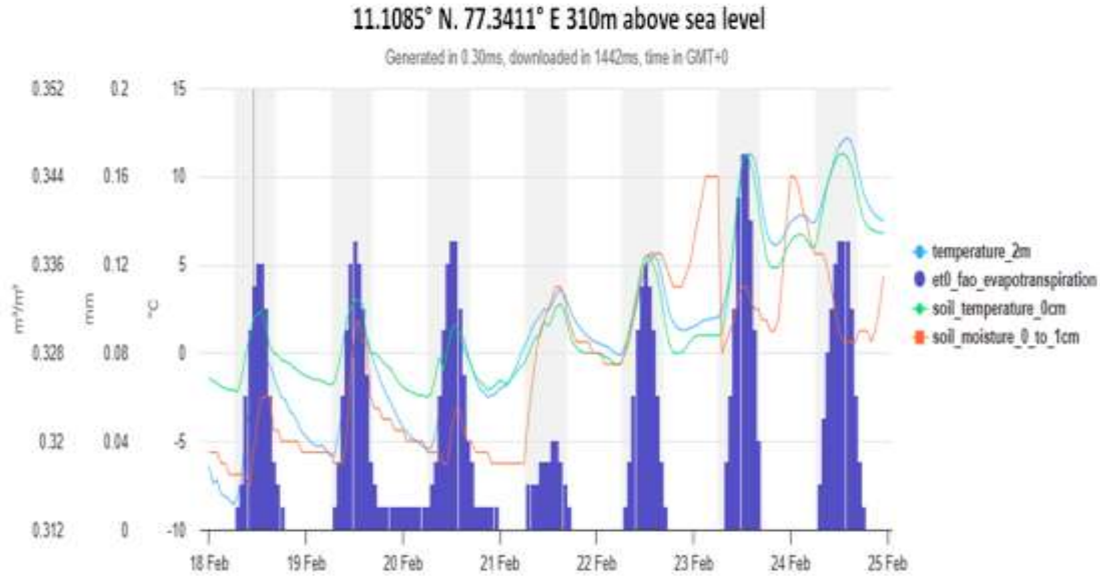

Figure 7: Soil moisture (ISMP-SVR) detection chart

Figure 7 indicates weather and soil information for 11.1085° N, 77.3411° E and emphasizes parameters of utmost importance to irrigation. Blue bars indicate evapotranspiration (ET0) that is highest throughout the day, meaning loss of water in evaporation and plant transpiration. Soil moisture (red line) in the range of 0 to 1 cm depth fluctuates, reducing when it is too much evapotranspiration. Soil temperature (green line) trails air temperature (light blue line), a measure of heat dynamics between soil and atmosphere. The information is used to optimize irrigation by timing water supply to conserve it and obtain optimal crop health.

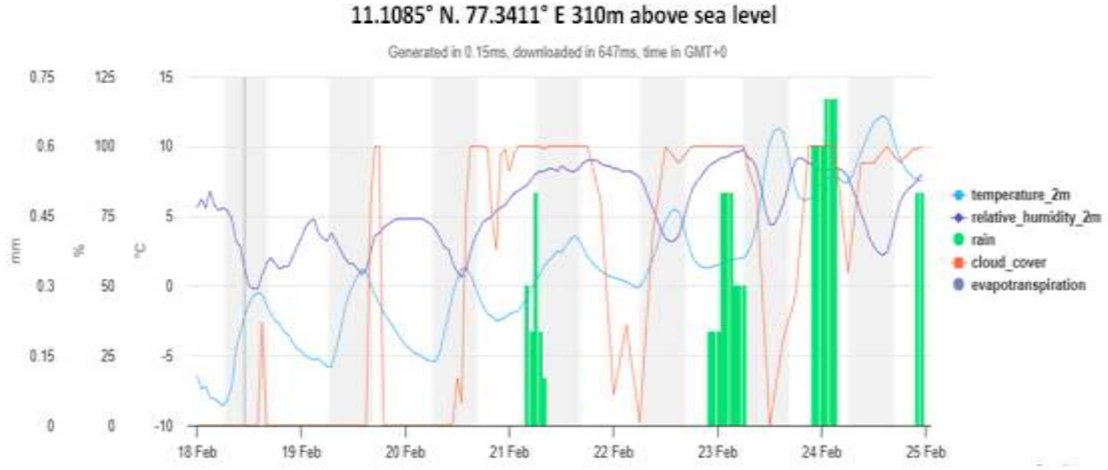

Figure 8: Weather Prediction (PWF) chart

Figure 8 shows a series of meteorological parameters plotted over time at a place at 11.1085° N, 77.3411° E (Tirupur, tamilnadu) at 310m a.s.l. The temperature and relative humidity are diurnal in range, showing change in atmospheric state. Rain is sporadic with intense falls on certain days, impacting evapotranspiration. Cloud amount varies, impacting solar radiation and overall weather. These are the requirements precision agriculture and irrigation planning requires optimizing water usage according to weather forecast.

4.1 IoT sensors used in smart drip irrigation

Figure 9: Soil moisture sensor

Figure 9 is a smart irrigation module and a soil moisture sensor module that are Internet of Things-enabled. The fork probe approximates the soil moisture by sensing changes in conductivity of its metal traces. Signal processing is conducted by the blue circuit board that provides analog as well as digital outputs to Arduino or Raspberry Pi microcontrollers. The module rationalizes irrigation such that water supply is given according to need to prevent overwatering and reduce resources.

Figure 10: Weather prediction sensor

Figure 10 is an outdoor sensor unit indoor display console digital weather station. The sensor device tracks temperature, humidity, wind speed, wind direction, and pressure and provides real-time weather data. The indoor console shows reliable weather parameters, trends, and forecasts, which support precision agriculture and irrigation planning. Weather stations like this are typically applied in IoT-based smart agriculture for irrigation planning optimization and resource management optimization using real-time environmental conditions.

Figure 11: Automatic water irrigation timer

Figure 11 is an electric irrigation timer, used in the automation of irrigation timing in agriculture and horticulture. It is mounted on a water supply and controls irrigation based on user-defined parameters such as start time, duration, and frequency. Real-time scheduling data is presented on the LCD display, and it is easy to change watering cycles. This type of device helps in efficient water management, reducing wastage and achieving the optimal soil moisture levels. It is usually combined with IoT-based smart irrigation for automated precision farming.

4.2 Performance evaluation

4.2.1 Accuracy

In predictive modeling, accuracy is the measure of closest model's projections is to real-world outcomes. It evaluates the model because many choices and forecasts rely on its accuracy and dependability.
T-True, F-False, P-Positive, N-Negative

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{------} (15)$$

4.2.2 Precision

In predictive modeling, accuracy is the proportion of total expected positive observations to correctly forecast positive observations it demonstrates the model's successful reduction of false positives, guaranteeing that the positive forecasts it delivered are accurate and reliable by extension and error reduction in many other domains.

$$Precision = \frac{TP}{TP+FP} \text{-----} (16)$$

4.2.3 Recall

Recall in prediction modeling is defined as a number of true positive instances correctly picked up in the model. In sectors like disease detection, identifying all positives is critical since it shows the efficient detection of all relevant instances in a particular class.

$$Recall = \frac{TP}{TP+FN} \text{-----} (17)$$

4.2.4 F-measure

F-measure, which is the harmonic mean of accuracy and recall, is a strong overall measure of effective model performance in avoiding both false negatives and false positives.

$$F - measure = 2 \times \frac{Precision \times recall}{precision+recall} \text{------} (18)$$

Table 3: Comparison of various performance metrics

Algorithms/Metrics	Accuracy	Precision	Recall	F-measure
LSTM [51]	96.41	96.05	96.28	95.98
SVM [52]	97.60	97.38	97.42	97.19
SVR [53]	98.23	98.09	98.12	98.02

Prophet [54]	98.54	98.28	98.30	98.13
ISMP-SVR-PWF	99.21	99.03	99.10	99.00

In table 3 the performance parameters indicate that Integrated ISMP-SVR-PWF model produces the best accuracy (99.21%), precision (99.03%), recall (99.10%), and F-measure (99.00%) and hence it is the best performing system for scheduling smart irrigation. Prophet model comes next lower but better than legacy SVR, SVM, and LSTM models. SVR remains isolated with good values, and hence it is proved to be feasible in forecasting soil moisture. SVM and LSTM are relatively lower in accuracy, implying that deep learning (LSTM) is less effective for this task. Results show that a combination of ISMP-SVR-PWF improves the predictive capability, and irrigation decisions become more water-efficient and reliable.

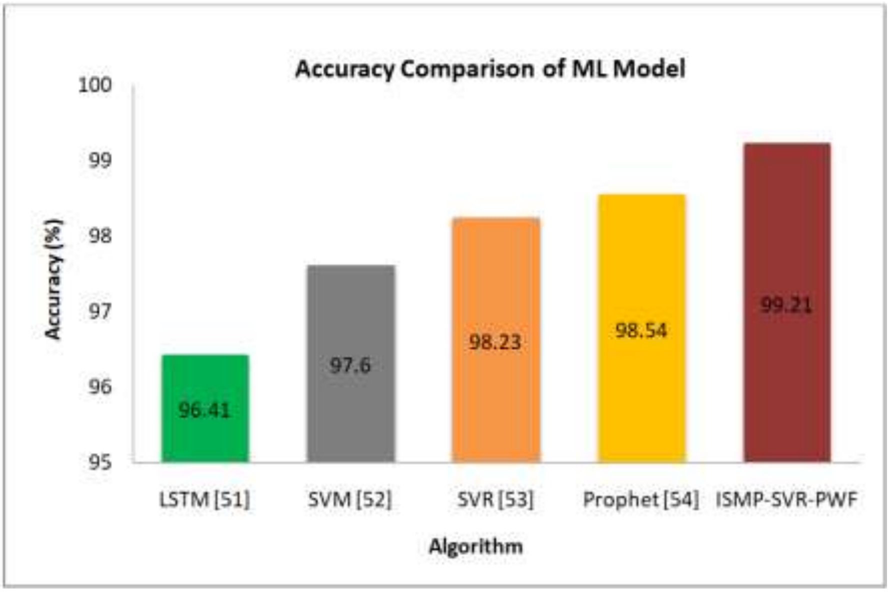

Figure 12: Comparison chart of Accuracy

Figure 12 illustrates the comparison of the accuracy of different machine learning models employed in the IoT-based smart irrigation system. ISMP-SVR-PWF is the most accurate model with an accuracy of 99.21%, which is greater than that of other models like LSTM, SVM, SVR, and Prophet, which indicates that it is effective in maximizing irrigation efficiency. The x-axis in this bar chart illustrates the different algorithms and the y-axis illustrates the accuracy values.

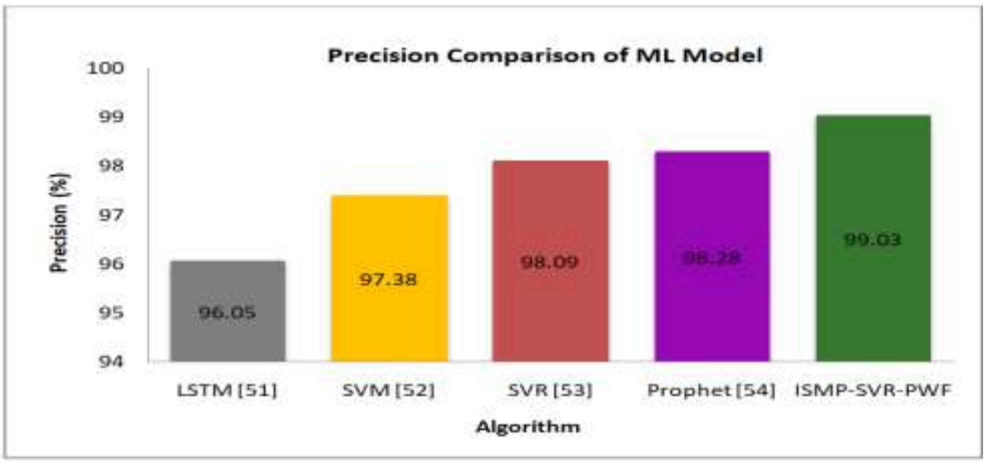

Figure 13: Comparison chart of Precision

Figure 13 illustrates the precision comparison of various machine learning models used in smart irrigation IoT. SVR + Prophet reveal maximum precision of 99.03% as against other models such as LSTM, SVM, SVR, and Prophet and expresses its applicability for more efficient irrigation. Different algorithms are plotted on the x-axis, while precision values are plotted on the y-axis in this figure.

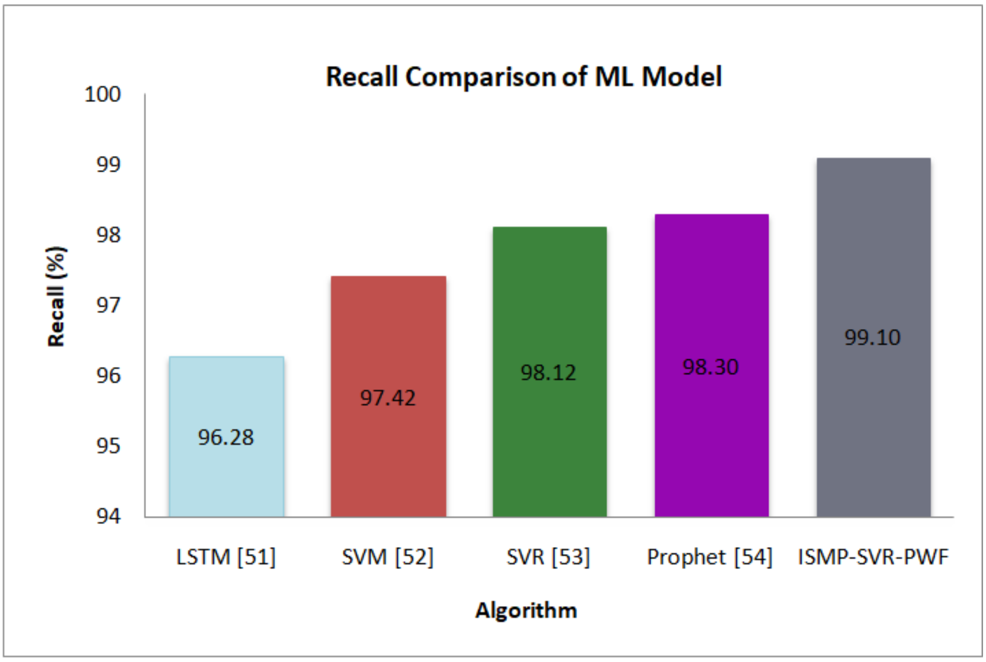

Figure 14: Comparison chart of Recall

Figure 14 illustrates recall of various machine learning models used in the IoT-based smart irrigation system. The x-axis illustrates various algorithms and the y-axis illustrates various values of recall.

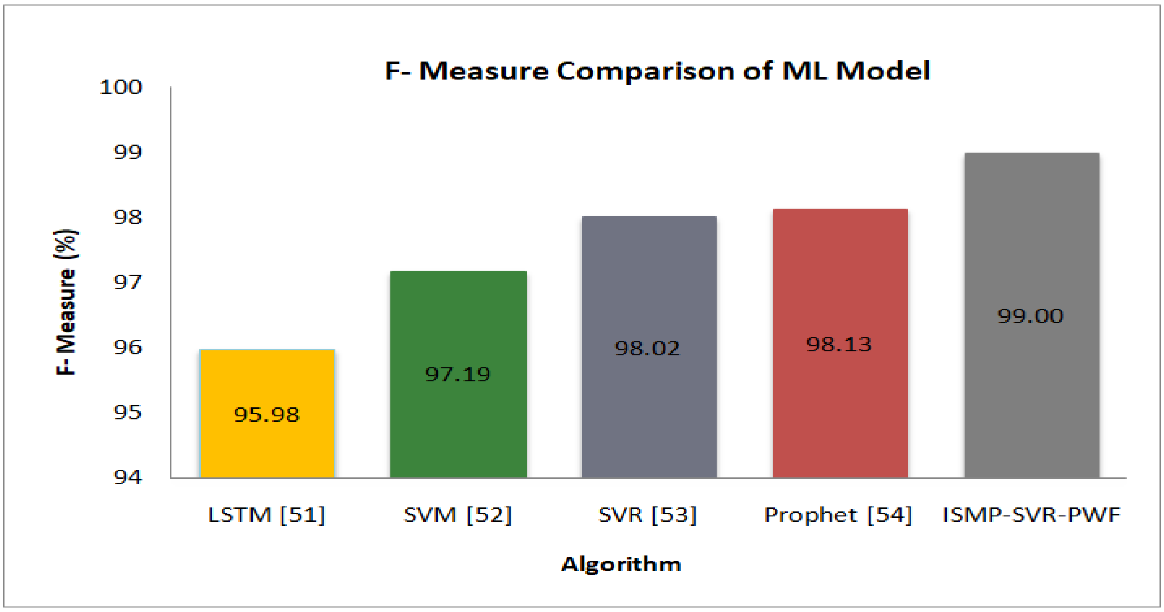

Figure 15: Comparison chart of F-measure

Figure 15 gives the comparison of f-measure values of different machine learning models like LSTM, SVM, SVR, Prophet and ISMP-SVR-PWF used in the IoT-based smart irrigation system. In this figure, y-axis represents the accuracy value and x-axis represents different algorithms.

5. CONCLUSION

The suggested IoT-aided drip irrigation timetabling system optimizes water management in a cost-effective manner based on real-time soil moisture levels and climatic data. Integrated Soil Moisture Prediction using Support Vector Regression (ISMP-SVR) for estimating soil moisture and the Prophet Weather Forecast (PWF) model for predicting weather, the system ensures maximum efficient irrigation scheduling. The system reduces wastage of water and maintains the soil moisture at an optimal level, which leads to healthy crops and improved yields. The system further tracks climatic conditions in real-time with the assistance of IoT sensors and routing live feeds to a cloud system for processing. The system, depending on machine learning algorithms, becomes accustomed to responding to different climatic conditions for efficient water distribution. Automated irrigation scheduling reduces human intervention, and therefore it becomes easier for farmers. The new method, with a 99.21% accuracy rate, surpasses traditional irrigation systems. It provides strong decision-making through IoT and machine learning with an economic and scalable method for precision agriculture. The elasticity of the system offers its application across different soil types and climatic regions, making it more applicable in real life. Secondly, real-time data analysis enables farmers to take improved decisions, and that implies maximum resource utilization. To no guesswork is what predictive models bring, thereby trends in irrigation are certain and predictable. This is very sustainable agriculture with minimal water usage as well as preventing over-irrigation. The proposed methodology also promises energy conservation through pump optimization from actual water requirements. This is in keeping with lower operating costs as well as increased farm efficiency. In addition, integration with smart phone apps provides remote monitoring and management, which is easy to farmers.

In the future, more accurate prediction models by deep learning and real-time decision-making without cloud connectivity using edge computing are on the cards. These developments will further automate water usage, and intelligent irrigation systems will be even more autonomous and efficient.

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