Automated Plant Care System for Smart Homes Using IOT

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Abstract — The rise of smart home technologies and the hectic urban life has led to a rise in the demand for automated and intelligent solutions to plant care. Most of the homeowners find it difficult to have a regular watering system for the plants in the house and along the balconies, thereby leading to overwatering or underwatering. The study introduces an intelligent Internet of Things (IoT) Smart Home Plant Care System based on the idea of machine learning (ML), which will help to optimise watering processes and enhance the condition of plants due to automated control. This system uses the IoT sensors that constantly monitor the key parameters like soil moisture, the ambient temperature, humidity, water tank levels, and the real-time weather conditions. Machine learning models based on the sensor data available in history and patterns of watering are trained to avoid unnecessary watering during high humidity or rainy weather. Weather-aware predictive logic is added to avoid unnecessary watering in case of high humidity or rain. The system combines automated pumping manipulation with a web application based on Flask, which will monitor the process in real-time, make predictions and warning messages, and manage the system. The effect of testing performance has shown better water-use efficiency, maintenance of stable soil moisture, correct prediction performance, and operational latency. The proposed solution is a scalable, cost-effective, and intelligent solution to the automation of the smart home plant, improving the health of the plant and saving on water resources.

Keywords— Smart Home Automation, Internet of Things (IoT), Plant Monitoring, Automated Watering System, Machine Learning, Predictive Analytics, Soil Moisture Sensing, Weather-Aware Control, Flask Web Application.

I. INTRODUCTION

Plants located indoors and on the balconies are relevant to improve the air quality, beautify the homes, and improve their psychological well-being. Nevertheless, healthy plants need consistent monitoring of soil moisture and environmental conditions in order to remain healthy. Most of the homeowners depend on manual watering or on a fixed schedule that tends to cause over watering, under watering, root rot, soil erosion and wasting of water. These conventional methods are not flexible and fail to take into consideration the fluctuation in temperature, humidity or seasonal variations indoors.

The temperature of the environment, moisture levels, exposure to sunlight, and climatic conditions of the environment also play a great role in determining the water needs of plants.The decisions made in watering in most households rely on the games of guesses other than data-based understanding, which leads to poor plant care. As smart home automation and sustainable living become more popular, the necessity to have intelligent systems of caring about plants that can adjust to the current environmental conditions increases.The Internet of Things (IoT) allows constant tracking of the conditions in the plants due to interconnected sensors to measure soil moisture, ambient temperature, and humidity, as well as the level of water tanks. IoT-based plant monitoring systems offer real-time information, but most of the solutions available today utilise only a basic form of threshold-driven control programming, in which the watering is activated when the soil moisture is below a pre-determined value. Although simple to apply, these types of systems are not flexible, do not record long-term moisture patterns, and do not look at interactions of the environment or weather predictions.Machine learning provides a strong solution to these shortcomings that learns complex patterns based on historical sensor data. Temporal, nonlinear relationships, and interactions among environmental parameters can be used to predict watering requirements more precisely using ML models. In combination with weather data and IoT monitoring, ML-based systems can help to make watering more efficient and healthy in general.The present research is based on an end-to-end Smart IoT-Based Home Plant Care System that will be integrated with machine learning-based prediction and automatic decision-making. There is real-time monitoring of the system, predictive watering control and intelligent activation of the pumps. It has a secure Flask-based web interface on top to provide interface visualisation, manual control, prediction insight, and system diagnostics. The proposed system is scalable, inexpensive, and best suited for a smart house environment.

II. LITERATURE SURVEY

The development of smart plant monitoring and intelligent watering machines has greatly evolved in the last ten years due to the improvement of sensing technology, wireless communication, embedded systems and intelligent information-processing methods. Initial plant automation systems were mostly rule-based, and fixed soil moisture sensors, predetermined watering schedules, or manually programmed. Though these systems minimised the human effort and made a certain level of automation possible, they were not flexible to changing environmental conditions in the interior, like changes in temperature, humidity, and season. Consequently, such systems tended to lead to over-watering or under-watering, which had a negative impact on plants.

With the introduction of the Internet of Things (IoT), the smart home plant monitoring became significantly transformed as it brings with it the possibility to respond to changes in the environment in real-time and across all its aspects, as the sensor networks connected to each other continuously. Plant care systems based on IoT are equipped with low-power sensors and microcontrollers used to monitor the soil moisture, ambient temperature, humidity, light intensity, and water availability. Information obtained through these sensors can be transferred using wireless devices to cloud computing systems to store the information and monitor it remotely. The framework of the IoT provided by Xu et al. [1] as a basis of distributed sensing and scalable monitoring systems established the foundation of the current smart monitoring systems. Ayaz et al. [2] also showed that the IoT-based systems are effective in facilitating real-time monitoring and automated control of the environment.

Although such systems are effective in the acquisition of data, most of the IoT-only plant monitoring systems use fixed threshold-based decision logic. These systems activate watering in situations where the soil moisture levels are lower than a specified value. Although it is simple and inexpensive, the method can not record complex and nonlinear interrelations among soil moisture, temperature, humidity, and environmental dynamics. Ray [3] pointed out that the IoT systems should incorporate smart analytics in order to cease reactive automation to predictive decision-making.

In order to limit these constraints, scholars have continued to integrate machine learning (ML) models in the framework of smart plant care. The article by Liakos et al. [4] has examined the use of machine learning in environmental monitoring and has outlined the uses of predictive irrigation scheduling as an important field where machine learning models have been successful compared to the rule-based system. Machine learning models are based on historical sensor data, adjust to dynamic conditions and are elastic to change with proactive predictions rather than reactive responses.

Several supervised learning algorithms have been considered in watering prediction, such as Linear Regression, Support Vector Machines, k-Nearest Neighbours, Artificial Neural Networks, and decision tree-based ones. As proved by Garcia et al. [5], predictive models are much more efficient in watering than the conventional methods based on thresholds. It was demonstrated by Rahman et al. [6] that IoT sensor data is more effective in terms of watering accuracy and water wastage when accompanied by an ML model.

Ensemble learning algorithms like Random Forest and Gradient Boosting have been considered as one of the strongest algorithms available and have been observed to have high prediction accuracy and the capability to deal with noisy sensor data. These models are good in nonlinear interactions with soil moisture, temperature, and humidity and can be used in smart homes to monitor the well-being of the house plant.

Another significant research direction has become watering control, which is weather-conscious. Use of weather forecasts and humidity prediction in watering logic will avoid unnecessary watering during times of high moisture. Lopez-Mata et al. [7] have shown that scheduling according to the weather is much more effective in terms of water-use efficiency. Most systems are, however, based on heuristic rules as opposed to predictive machine learning models, which restricts adaptability.

Recent studies have paid attention to integrating IoT sensor data, cloud systems, and predictive analytics into integrated systems. In a paper by Kamilaris and Prenafeta-Boldu [8], the authors emphasised that deep learning and data-driven models are increasingly becoming relevant in smart monitoring applications. Ferantinos [9] also showed that highly trained ML models are effective in monitoring plant health.

Scalability and system deployment are still crucial issues. Most intelligent plant monitoring systems are prototypical and do not have scalable web interfaces. Sharma et al. [10] highlighted the importance of lightweight frameworks like Flask in the implementation of ML-based IoT solutions that have real-time dashboards and remote control functionalities.

In the case of smart homes based on IoT, security and data integrity have also become paramount issues. Unauthorised access and data manipulation may affect the reliability of the system. Hence, the contemporary implementations include authentication systems, secured application programming interfaces and encrypted communication messages to maintain the stability of the system.

Lack of automated model retraining is another weakness of the current systems. With varying patterns of the environment over time, these fixed ML models can be inaccurate in making predictions. Long-run performance and flexibility are supported by continuous learning models that retrain models on a periodical basis with new sensor information.

The research gaps highlighted must be filled in this paper since it will offer a full-fledged Smart Home IoT-Based Plant Care System that comprises real-time sensing, predictive watering based on machine learning, weather-sensitive logic, automated pump control, secure communication infrastructure, and scaled-out Flask-based Web deployment infrastructure. The proposed system is a solution of smartness, versatility and feasibility in automated attention of the home plants and amplification of water consumption and well-being of the plants.

III. METHODOLOGY

The proposed Smart Home IoT-Based Plant Care System is created in a multi-stage manner that includes real-time environmental monitoring together with smart data processing, prediction and control of the machine learning approach, automated watering regulation, and web-based deployment. The entire labour process will aim at providing correct watering determinations, water use, and dependability of the system functioning in both indoor and residential settings.

A. Data Collection and Preprocessing

The IoT sensors on the plants located either indoors or on the balcony constantly gather environmental and operational data. Some of the key parameters that the sensing layer is used to measure include soil moisture, ambient temperature, relative humidity, water tank level, pump status, and the length of time during which the water is sprayed. These sensors are interconnected with low-power microcontrollers, which send data back to the backend server at fixed intervals by wireless communication protocols like Wi-Fi.

Besides sensor data, weather APIs receive external data on weather, such as the probability of rainfall, forecasts of humidity, and predictions of temperature. When combined with real-time and forecast, based on weather data, it would be possible to make decisions related to watering in advance and avoid unnecessary watering in humid or rainy weather.

Raw sensor values can be contaminated by noise or lack of values, or time difference due to sensor inaccuracy, network latency, or environmental perturbations. To guarantee the reliability of data and the accuracy of the model, a preprocessing pipeline is introduced, which comprises the following steps:

- Interpolation or elimination Techniques used to deal with missing or corrupted sensor values.
- Silencing by means of smoothing and filtering.
- Continuous features are normalised and scaled to ensure that the inputs of the model are constant.
- Time-based feature (e.g. hour of day, day of the week) to describe the watering habits.
- Connection of sensor data with weather information.
- Nominal variables such as the pump status are coded into numbers.
- The phase of preprocessing offers consistency of data, model performance and real-time prediction and automated watering decision-making performance.

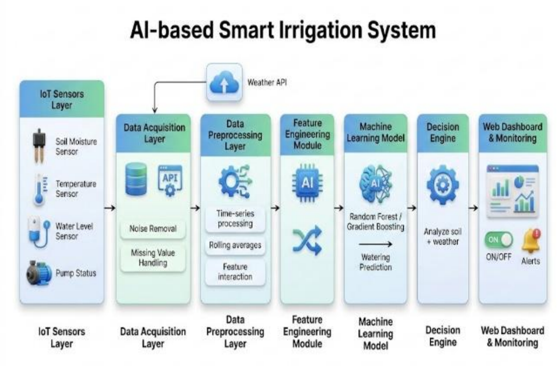

Fig. 1. Workflow of the Proposed ML-Based Smart Home IoT Plant Care System

B. Feature Engineering

The importance of feature engineering is that it increases the predictability of the models used to predict the watering of the plant. In addition to the raw sensor measurements, several derived characteristics are also generated to represent the time behaviour, interaction with the environment and soil moisture with time dynamics of the interior.

Time variables, such as the number of hours in a day and days in a week, are also solicited to influence the daily regimes of watering that tend to be typical of the indoor environment. The trends in the soil moisture are computed using rolling averages and rate of change indicators to determine the short term changes and the slow changes in soil moisture. These features help the model to be aware of the rate at which the soil gets dry in various surroundings that can be located within the house.

The interaction features are derived on the basis of temperature, humidity and soil moisture measurements combination to determine the dynamics of water uptake in plants and the influence of evapotranspiration within the house with greater accuracy. Weather indicators such as the possibility of rain, the amount of humidity that is predicted, and the amount of temperature are also provided to prevent unnecessary watering in the high moisture.

Features generated are much more context-filled, and the machine learning models will more effectively learn the intricate environmental conditions, including watering and planting requirements.

C. Machine Learning Model Training

With historical sensor data, weather information and watering action information, machine learning models are trained in a supervised fashion. The dataset is further divided into training and testing to ensure objectivity in the assessment of the model and the predictive ability, and the ability to handle the nonlinear relationship and $noisy measurements of the IoT sensors. Random Forest and Gradient Boosting are ensemble learning algorithms that are utilised as they are robust, have high predictive accuracy, and nonlinear sensor data can be used as well as nonlinear relationships. The models would be appropriate in smart homes where sensor measurements may vary due to interior noise.

The models learn to predict the sensitivity of the requirement to water (Yes/No) and approximate the probability of pump activation based on the current and anticipated environmental situations. Hyperparameter tuning is performed to maximise the performance, and feature importance analysis is performed to find out the most important factors that change the watering decision. This enhances the model interpretability as well as assisting in system transparency.

D. Model Evaluation

Model performance is measured on several classification measures such as accuracy, precision, recall, F1-score and confusion matrix analysis.

It gives special attention to the reduction of:

- False positive (unnecessary pumping and wastage of water)
- False negatives (felt that watering was skipped, which can cause stress to plants)

Besides conventional evaluation metrics, the consistency and stability of prediction with time are also examined to guarantee that there is consistency in performance under varying indoor environmental conditions. The methods of cross-validation are implemented to test the robustness and generalisation of models in other time intervals.

E. Automated Control and Web-Based Deployment

The trained machine learning models are deployed over a Flask-based system of back-end, which provides real-time inference with incoming sensor and weather data. According to model projections, the water pump is automatically activated by the system using actuator interfaces, and watering occurs at the right time and in the most efficient manner.

The interface of a web-based application is interactive to the homeowners and administrators and provides:

- Real-time sensor monitoring
- Data representation- visualisation of historical watering.

- ML-based predictive outcomes of watering.
- System configuration settings System configuration settings are found under the Administration View menu.
- Alert notifications
- Manual override controls

Scalable architecture means that new sensors, sophisticated models, mobile applications, or cloud-based services can be added to the architecture easily because it is modular. This provides flexibility and usage in the long-term in smart home environments.

IV. IMPLEMENTATION

The proposed Smart Home IoT-Based Plant Care and Monitoring System is deployed as an entire end-to-end solution comprising IoT-based sensing, machine learning-based prediction, automated watering control, weather integration, and a web-based monitoring terminal. Its implementation focuses on real-time functionality, scalability, low-cost deployment and reliability, which is applicable in indoor plants and balcony gardens as well as residential smart home settings.

A. System Architecture

The system has been layered over the client-server architecture that consists of three major layers, viz. the Sensing Layer, the Application Layer and the Data Layer. This modular design adds to the scalability and fault tolerance.

Sensing Layer (IoT Layer)

This layer will be a cluster of IoT sensors, which will be located near the plants, either inside the plants or on a balcony, to monitor them frequently:

- Soil moisture
- Ambient temperature
- Relative humidity
- Water tank level
- Pump status

The sensor data is communicated with the server using the assistance of Wi-Fi-based HTTPs. Such values are in real-time and reflect the environmental status of the plant, and become the foundation of automatic watering.

Application Layer (Backend Processing)

The application layer has been done using Python and the Flask Web Framework. It handles:

- Sensor data ingestion
- Machine learning inference
- Watering decision logic
- Weather data integration
- Pump control operations

The backend opens API endpoints that are made in a RESTful manner to receive sensor data, make predictions, and control the water pump, as well as to serve data to the frontend dashboard.

Data Layer (Storage and Logging)

The lightweight SQLite database is used to store the persistent storage:

- Sensor readings
- Watering actions
- Weather information
- Training logs of machine learning
- Prediction results
- System alerts

The schema is biased towards real-time queries, historical analysis and retraining models. It is a methodical kind of logging that ensures system analysis and transparency in the long-term.

B. Backend Implementation

The main control system point of the system is the backend, which is put in place to make smart watering decisions and organise the actions of elements. Flask is selected because it is light and just fits machine learning models.

Sensor Data Handling

The data of incoming sensors through API endpoints is checked, pre-processed, time-stamped, and stored in the database. The records contain soil moisture, temperature, humidity, water level and pump state.

Watering Decision Logic

The system has both automatic and manual watering modes.

In automatic mode, the backend evaluates:

- Present moisture content of soil
- Output machine learning prediction
- Weather conditions
- Water tank availability

The pump is triggered only when it is needed, avoiding excessive water and wastage.

Weather Integration

The weather data is periodically retrieved with the help of a weather API. Rainfall probability, humidity predictions, and temperature forecasts are among the data that are stored and used to inhibit watering in the high-moisture or rainy seasons.

Alert Management

The system creates alerts when there is a critical situation as follows:

- Extremely dry soil
- High temperature
- Low humidity

- Empty water tank

The database keeps the alerts and sends them out through email notification to alert the users in real time.

C. Machine Learning Model Integration

The machine learning models are embedded in the backend and are therefore able to make predictions in real time with very low latency.

Model Training

Training of supervised learning models is done using historical sensor and watering data that is stored in the database. The aspect of feature engineering involves:

- Time-based features
- Rolling moisture averages
- Interaction terms
- Lag-based features

The use of ensemble models like Random Forest and Gradient Boosting is because of the strength and high predictive abilities.

Model Deployment

The trained models are coded and loaded into memory when the application is started to minimise the inference latency. The preprocessing that was applied when training is also applied when performing inference in real time.

Prediction Logic

The model gives the probability of watering according to prevailing conditions and predicted conditions of the environment. When the probability is above a setting threshold, watering is suggested, and the pump time is calculated.

Auto-Training Mechanism

A scheduler periodically inspects sensor data collected through the accumulation of new sensor data and re-trains the model when more new samples are available. Accuracy and error rate are performance metrics that are recorded to check the quality of the models and avoid degradation.

D. Database Design and Logging

The main storage engine is SQLite. The database contains table structures on:

- Sensor readings
- Watering history
- Weather information
- Machine learning training history
- Prediction outputs
- Alert records
- Configuration settings

The hierarchical structure allows effective real-time updates to the dashboard, the analysis of trends over time, as well as optimization of the model in the future.

E. Frontend Implementation

The user-friendly interface will be on the front end, which will enable the homeowners to monitor and control the plant care system. It is composed in HTML, CSS and JavaScript.

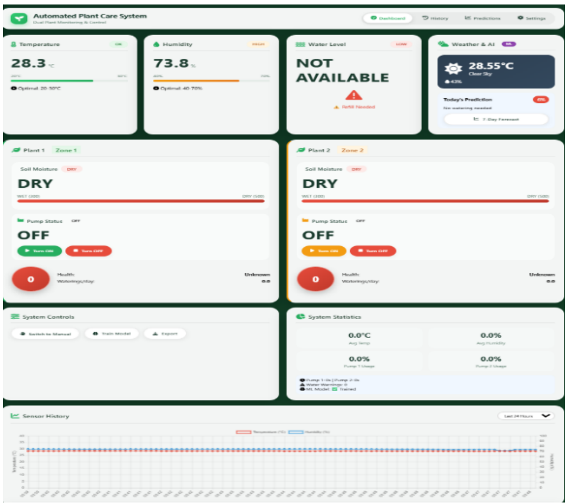

Fig. 2. Smart Home Plant Monitoring Dashboard with Real-Time Control Interface

Frontend features include:

- Soil moisture, temperature and humidity in real-time.
- Live pump status monitoring
- History and alerts of watering visualised.
- Predictions of watering based on machine learning.
- Systems configuration and manual override controls.
- Asynchronous API calls, currently used to communicate with the backend, allow JavaScript to update the page without having to reload the page.

Graphical signs like probability levels of watering and recommendation labels help users to make meaning out of those system decisions.

V. RESULTS AND DISCUSSION

The Smart Home IoT Plant Care System based on the proposed ML was tested on the basis of the real-time sensor data gathered throughout several operational cycles in an indoor and a balcony plant setting. The performance analysis was on the accuracy of decision making, efficiency in water usage, reliability of the prediction, system responsiveness and stability in the system's operation. The system was experimented with in the conditions of different indoor environment such as changes in soil moisture, temperature, humidity, and weather predictions.

A. Watering Decision Accuracy

The machine learning models showed high capability of separating between the conditions that needed watering and the ones that did not. Through the study of historical soil moisture patterns, environmental parameters and temporal characteristics, the system forecasted watering needs with high precision.

The proposed system minimised the unwarranted activation of the pump as compared to the conventional threshold-based watering systems. The models of classification demonstrated better accuracy in determining the real conditions of dry soil, so the watering was carried out in cases when it was necessary. This reduced excessive watering and aided in the maintenance of the optimum soil moisture content to support the growth of healthy plants.

B. Water Usage Efficiency

One of the objectives of the system was to maximise the use of water within a home set-up. The experimental findings show that there is a significant decrease in water consumption as a result of smart prediction of watering processes. In addition to this, the use of weather forecasts enhanced efficiency since the watering was prevented during a rainy or high-humidity day. Moreover, automated watering time was also applied to turn on watering according to the degree of soil dryness, rather than applying a pre-set duration of watering. This adaptive process helped a great deal with water wastage and avoiding oversaturation of soils.

C. Prediction Reliability and Stability

T It was observed that the machine learning models were able to stay predictive over time even when the indoor environment conditions changed. This was made possible through the application of the ensemble learning methods that allowed the system to learn nonlinear relationships between the soil moisture, temperature and humidity parameters through the use of newly gathered sensor data. The ability to continuously learn enabled the system to handle seasonal variations and long-term indoor environmental variations, which made the prediction consistency better, and the degradation of the model was also lower.

D. System Response Time and Real-Time Performance

The system was shown to have low-latency, which can be used in real-time smart home implementation. The sensor data ingestion, prediction computation, and control decision of the pumps were carried out over short time intervals, and the response to the soil dryness was instant.

The Flask backend was used to process numerous API calls without apparent delays. Because trained models had been loaded into memory at the time of application startup, there was minimal inference time and therefore real-time functionality.

E. Plant Health and Soil Stability Analysis

Trend analysis of soil moisture indicated that the system was more stable than a manual or rule-of-thumb watering system. By keeping the soil in ideal water content levels throughout longer periods of time, the system prevented the sudden fluctuations in water levels that can impose stress on the roots of plants, and ensured a healthier growth of plant roots, as well as reduced the chances of overwatering or extended dry periods. The predictive strategy was proven to be effective as the correlation between the environmental conditions and watering actions was established.

F. Alert Accuracy and System Reliability

This alert system was able to identify critical conditions, such as:

- Extremely dry soil
- High indoor temperature
- Low humidity
- Low water tank level

Alerts were created in real time, stored in the database and sent out through email notification (optionally). This system was shown to be capable of stable continuous operation and did not lose data or have critical failures. Background activities like weather notification and model retraining worked simultaneously and did not affect the main watering service.

G. Comparative Performance Analysis

Compared to the traditional method of threshold-based plant watering systems, the suggested ML-based method has proven to be better in the sense of:

- Watering decision accuracy
- Water conservation
- Flexibility to changes in the environment
- Long-term stability

Conventional watering systems are based on defined moisture levels, whereas the new system uses past data and predictive analytics to make rational decisions on watering. Such a smart combination of IoT sensing with machine learning scales up the level of automation and positively influences the overall quality of taking care of the plant.

Overall, the results demonstrate that IoT surveillance and machine learning-based prediction could be rather useful in improving the efficiency of watering plants in the smart home, the level of system intelligence, and the extent of reliability in its functioning.

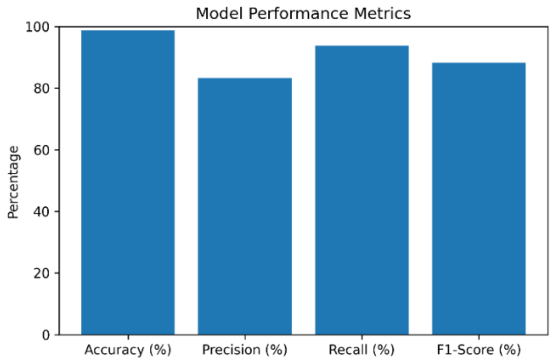

Fig. 3. Performance Metrics of the Proposed Model

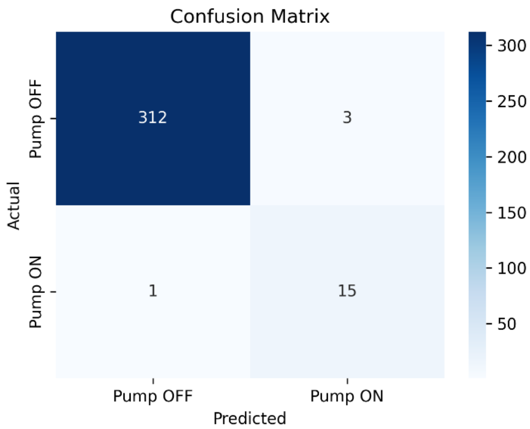

Fig.4. Confusion Matrix of the Proposed Random Forest Model

VI. CONCLUSION

This paper presents a Smart Home Plant Care System powered by the IoT, which involves machine learning to give a prediction regarding the watering schedule and plant status. The proposed system will enhance the accuracy of water delivery, optimise the utilisation of water and reduce the number of people in the process of caring and keeping the indoor and balcony plants in a healthier state by applying the predictive analytics and adaptive control systems along with the real-time sensor in terms of sensor data and weather conditions. The use of automated pumping, weather thinking and real-time monitoring that is controlled by the use of a Flask-based web interface will ensure that the plant is maintained regularly with the help of soil moisture; a healthier plant will grow.

The system is customizable, inexpensive and applicable to smart homes. It is a modular structure to enable a simple connection with other sensors and advanced analytics. It may be extended to the future by the use of deep learning models to enhance the accuracy of the prediction, the creation of mobile applications, the incorporation of voice assistants, the deployment of their models to the cloud on a multi-user basis, and the adaptation of the models to the plant-to-plant.

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