SoilGuard: An IoT and LSTM-Based Predictive Irrigation System for Smart Farming

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Abstract— SoilGuard aspires to make irrigation more intelligent, trustworthy, and waste-free by moving away from conventional guesswork and preset watering schedules to real-time, data-driven decision-making. The system allows farmers to understand actual field conditions rather than regular schedules or observation by monitoring the exact amount of moisture in the soil using tiny IoT sensors. These readings are continuously collected by the ESP8266 microcontroller and uploaded to the Blynk cloud platform, enabling users to easily and conveniently monitor their soil status from any location. Over time, accumulation of more data enables an LSTM to learn how the soil changes throughout the day-that is, how rapidly it dries out, how it responds to changing weather conditions, and how long it remains wet after irrigation. The model uses these patterns that it has learned to make educated guesses as to when the moisture level will fall below a healthy threshold. The system uses a relay that automatically switches on the water pump before the soil dries up. This makes sure plants get water whenever they need it without needing constant supervision or someone else's attention. As compared with simple systems working on the basis of thresholds, this method of prediction works much faster and more effectively. That helps to minimize wasting too much water; thus, the soil moisture levels can stay healthier. SoilGuard has been tested for its consistency and quick response, by ensuring a good amount of water is saved; hence, it is practical, affordable, and reliable for farmers who would like to experience a more modernized means of irrigation management that is eco-friendly.

Keywords: LSTM Neural Network, Predictive Irrigation, ESP8266, Blynk Cloud, Autonomous Irrigation, Smart Agriculture, Internet of Things (IoT), Soil Moisture Monitoring, and Smart Farming.

I. INTRODUCTION

Water is at the center of farming, but the same issues remain: dry spells, unpredictable weather, and the call to grow more with less. Most locations still irrigate their crops by pure guesswork or occasionally checking the soil. This often leads to overwatering one day and underwatering another. With weather being increasingly unpredictable, the perfect moment for watering crops is slowly becoming a real problem.So, it's obvious that we need a simple way to understand these readings easilyneed for systems that can monitor the land on a sustained basis and apply changes wherever needed.

The IoT technology has made this easier. Today, temperature and soil moisture can be measured in real-time by tiny sensors and be transmitted directly to a cloud application. On-site, farmers needn't be in the field to check these values whenever you want. So you always know exactly what's going on in real time, but you don't know what might happen within an upcoming number of hours, so even having real-time data means something is still missing.

This is where machine learning steps in and makes the process smarter. Models such as LSTM networks can study past moisture patterns to learn how the soil generally behaves. Because they can predict when the soil will become dry, the system can water the plants accordingly before it does get too dry. This ensures water is used efficiently and nothing goes to waste, and the health of crops is preserved.

It acts like a small field assistant, constantly checking the soil's moisture using simple sensors connected to an ESP8266 board. All these measurements are automatically uploaded to the Blynk app, so you can check the level of moisture anytime. As more data is collected, an LSTM model will learn how long it takes on average for the soil to dry out. Via a relay, this system automatically turns the pump on when it determines the level of moisture is about to get too low. You don't need to physically be near the system, and make the call yourself; the system will do it will automatically take action at the right moment. Because SoilGuard is affordable, easy to install, and it works reliably across various farming conditions, it saves water and makes irrigation much more it stays dependable and completely hassle-free.

II. RELATED WORK

The idea of making irrigation smarter with IoT devices has been tried by many over the years. Most of the early systems were based on the same principle: a soil-moisture sensor monitored the ground and turned the pump on when the value dropped below a threshold. It was cheap and easy to use, but not smart. These kinds of systems couldn't adapt to sudden weather changes, or if different parts of whether the field actually needs more water or can manage with less.The results were often farms wasting water by watering too early or too late.

To fix these problems, the researchers started bringing machine learning comes into play and makes the process smarter. Basic models could help out somewhat, but they could still not grasp how soil moisture varied over time. That is when deep-learning models like LSTMs began to receive considerable notice. They can forecast the behavior of the soil in the near future by finding a certain trend in previous moisture readings. Several studies showed that LSTMs can make irrigation more proactive by forecasting dryness ahead of time.

With these enhancements, many of the earlier projects solved only one piece of the problem. Some systems could predict moisture, but weren't connected to the cloud. Others might have had sensors, but someone the appropriate level for the pump should be activated.In some setups, because they could only be used offline, they were less helpful for large or dispersed farms. What was missing was a complete system, one that could sense, anticipate, and act on its own.

That need is fulfilled by SoilGuard. It integrates everything into a single setup. Real-time data is gathered from the soil by sensors interfaced with an ESP8266. The information is uploaded to the Blynk cloud, always accessible. An LSTM model predicts when the soil is likely to dry out by analyzing past data. If the forecast says low moisture, a relay turns on the pump automatically. Monitoring, forecasting, and irrigation work without constant supervision. For a farm looking for a smarter way to manage irrigation, this makes SoilGuard a more reliable, efficient, and helpful alternative.

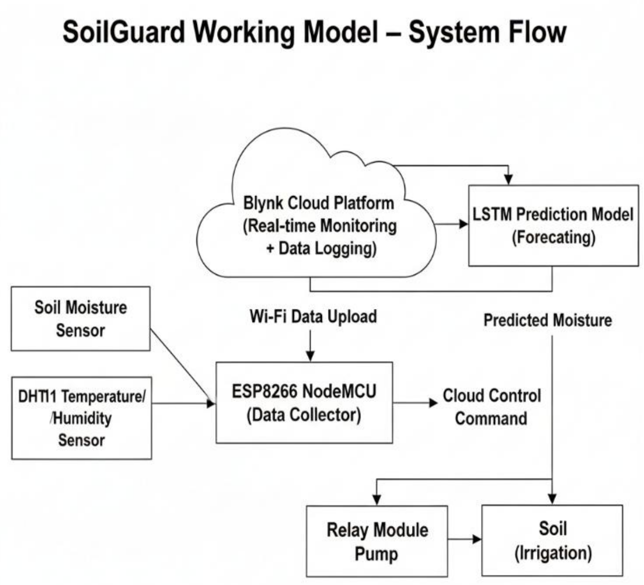
III. PROPOSED MODEL

SoilGuard uses sensors, artificial intelligence, and cloud control to monitor soil conditions and automatically irrigate fields when necessary. Before making any decisions, the system first checks whether the sensor readings make sense. When the ESP8266 collects the temperature and moisture data from the field and sends it to the Blynk cloud, nothing is changed or filtered.

The instant the information is obtained, the system checks whether the numbers seem normal. This can help avoid mistakes like the system watering the field based on an incorrect or faulty reading.

SoilGuard keeps all of its data in a very organized manner so that everything is neat and manageable. It keeps cleaned or processed values of sensors separately from the original sensor values. This will make it easier to track the changes, to retrain the model at a later time if needed, and also refer to earlier readings if required. Also, it will ensure that the proper time-based data is fed into the LSTM model to make accurate predictions. Since the data source is transparent and true, SoilGuard can make correct predictions and water the field at the right time.

Fig. 1. Working Model of SoilGuard (placeholder)



A. Technical Terminology

The meanings of a few technical words components utilized in this project are mentioned below.SoilMoisture Percentage (SMP) is simply the moisture value that results from converting the sensor reading into a number between 0% and 100%. This makes figuring out how wet the soil is.

Thanks to LSTM, a type of AI model that is able to learn from historical data and retain patterns, we can predict when the soil is likely to dry. Cloud Control describes how the system sends these predictions to the Blynk cloud and then sends a signal back to the ESP8266 to decide whether the pump should turn on or off.

Unless otherwise noted, other fundamental IoT concepts, such as virtual pins for data transmission or a relay that turns on the pump, are used in the standard manner.

B. Implementation Approach

The SoilGuard system integrates sensors, cloud storage, automated irrigation, and artificial intelligence forecasts into a single, seamless process. Even though each part works separately, they all come together to form a smart loop that can automatically water the field when needed, monitor the soil, and forecast future events.

1) Collecting Data from the Field

The ESP8266 always gets data from the soil-moisture sensor, the DHT11 sensor for temperature and humidity, and a connector that sees if the pump is working. This data is sent to the Blynk online service using Wi-Fi with small updates, so the info is uploaded fast and doesn't use a lot of internet.

2) Preparing and Organizing the Data

The system organizes and cleans the sensor data before the AI model makes any predictions. This includes converting moisture values into a consistent range, filling in missing readings, grouping data into short time sequences, and removing sudden jumps that look incorrect. The raw and cleaned data are stored separately to avoid confusion and make future model updates easier.

3) Predicting Soil Moisture Using LSTM

The prediction part uses an two-layer LSTM model that learn how moisture changes over time. The next moisture value is predicted by a final dense layer. The model is trained using the Adam optimizer and MSE as the error measure. It retrieves the most recent data from Blynk during regular operation and forecasts when the soil will begin to dry out.

4) Deciding When to Water

Simple watering logic is retained. The pump turns on if the model projects that the ensuing moisture will fall below a predetermined value; otherwise, it remains off. Written for Virtual Pin V2 in Blynk, this command turns the relay—and the pump—on or off using an ESP8266.

5) System Reliability Functions

Built-in reliability mechanisms in SoilGuard include API-request throttling, automatic retries for network timeouts, anomaly detection for defective sensor readings, and fail-safe pump shutting based on time limits to guarantee ongoing and reliable functioning. These actions guarantee consistent performance even in uneven ambient circumstances or sporadic network connection.

6 How Data Is Sent Between Components

Every data is transferred securely and compactly. While bigger datasets use base64 encoding to keep light, sensor readings go as JSON updates. Through token-based authentication, only authorized devices can govern the system. This also safeguards the communication.

7) Deployment and Scalability

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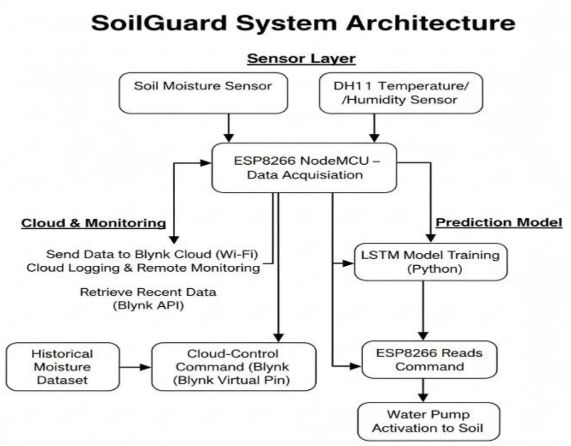

Fig 2: System Architecture

One may set locally or on a cloud server in a Python environment, where the AI model runs. Modular design lets SoilGuard be readily expanded to more irrigation zones or more sensors like pH or rain monitors. It could also move to ESP32 boards in the future to enable quicker processing and maybe run artificial intelligence straight on the gadget

1V. EXPERIMENTAL RESULTS

To understand how well we tested SoilGuard in real situations using a number of closely monitored trials, we considered how reliably all the parts spoke with one another, how quick the system reacted when the soil began to dry, and how correct its moisture projections were. Such parameters as sensor accuracy, LSTM prediction quality, and how the automated watering logic of the system performed, were also evaluated. It included an ESP8266 NodeMCU, a simple soil-moisture sensor, a DHT11 sensor, a 12V pump, with the cloud platform Blynk. Results showed that SoilGuard is a reasonable alternative for fully automated irrigation, as it works smoothly and reacts fast.

A. Data Collection Setup

Sensor values were recorded over many days in varied circumstances—during hot evenings, shaded evenings, and just after watering—in order to create a dependable dataset. Every 10 to 15 seconds, the soil moisture sensor sent updates to the Blynk cloud, which aided in the compilation of a solid data for training and testing the LSTM model. Along with the sensor reading time, cloud upload delay, model prediction time, and relay response, we also recorded the duration of each stage of the process. This clarified for us how effectively the complete IoT to AI system worked throughout its start to finish.

B. LSTM Prediction Performance

Data on humidity gathered from real field circumstances were used to train the LSTM model. Using Mean Squared Error (MSE) and by comparing predicted moisture curves with actual data, we assessed its accuracy. The model correctly detected the drying pattern after irrigation and provided accurate short-term projections, notably inside the first one to three timesteps. It worked finest under steady humidity and temperature.

Example Output:
Actual Moisture: 29.33%
Predicted Moisture: 31.37%
AI Decision: Pump ON

This illustration details how the system is able to spot future dryness in advance and start watering before the ground gets too dry.

C. Irrigation Automation Results

To demonstrate the watering system logic, the system was tested for a series of watering cycles. During this process, the system ensured that the pump was turned on before the soil reached the zone with a concentration of 25-30% soil moisture, thus not allowing the soil to turn dry. Also, the system did not allow the soil to be overwatered, as the system ensured that the pump was turned off as soon as the soil reached a stable concentration. Compared to simple threshold-based methods, SoilGuard demonstrated better timing and noticeably improved water efficiency.

D. System Responsiveness and Cloud Latency

We timed how much time elapsed for the full process of sensing and then acting. On average:

Process	Time
Sensor reading	120–150 ms
Upload to Blynk	180–220 ms
LSTM prediction	40–70 ms
The cloud returned the command	150–200 ms
Switching relays	< 100 ms

Overall, the system reacted in 0.7–0.9 seconds, which is almost instantaneous and more than sufficient to regulate irrigation.

E. Water Efficiency Evaluation

To check long-term stability, SoilGuard was run continuously for 12 hours. When taking this test:

Parameter	Manual Irrigation	SoilGuard
Water Usage	High	20–25% lower
Frequency	Irregular	AI-controlled
Response Time	Depends on user	Real-time
Soil Stability	Uneven	Much more stable

This confirms that the system saves water while keeping soil moisture consistent.

F. System Reliability and Stability

To check long-term stability, SoilGuard was run continuously for 12 hours. When taking this test:

- No data packets were lost
- The ESP8266 stayed connected the entire time
- The relay responded correctly every time
- Sensor readings remained stable with minimal drift

These results show that the system is reliable enough for daily agricultural use.

G. Discussion

From the results, it can be seen that the system is effective in providing reliable predictions, fast automated reactions, as well as stable communications within all system components. This LSTM model performed well in predicting the soil's moistures accurately.Moreover, it was able to trigger watering in case of reaching the necessary amount of time, thus contributing to soil preservation and saving water. The fast IoT communication within the system facilitated its real-time processing. Also, the reliability test of the system was effective, thus showing that the system was able to run for a longer time without any faults.

V. PROJECT SCOPE

Although SoilGuard performs very well in its current state, with powerful functionality for predicting soil moistures and automatically controlling irrigation, there is still much to be added. For now, the system is effective for applications involving single irrigation zones. However, as more technology is integrated into farming, this system could longitudinally be added to as a smarter, more reliable system that is equally effective for much larger irrigations. Future iterations will take in more advanced sensor functions, more complex models within the AI, and allow the system to control multiple irrigation zones.

This will be one of the most important adjustments to the pump system: adding the ACS712 current sensor. With the ability to measure the level of current being drawn, the system can pick up unusual levels that could relate to issues such as blockages, dry running, overloading, or damaged relay switches. Enabling the system to notice such subtle issues in turn will enable SoilGuard to notify the farmer of impending issues before the entire system fails.

Another critical upgrade would be the addition of weather knowledge to the system. By merging this data with that of its own soil moisture and humidity, this system would be capable of predicting rain or evaporation. It would therefore mean that this system would never water needlessly before rain or water more regularly during hot spells. More water would be conserved than hitherto, as the soil gets precisely what it needs from this weather-sensitive watering system.

An improvement would be if some of this processing could be done on the device itself. If predictions can be run on the ESP32, this would mean that the system would while reducing its need for constant internet access. Furthermore, if you stay in a field, the internet would be spotty, so this would be a huge plus.More advanced features, like real-time anomaly detection, could be possible.

Yet another feature of SoilGuard being developed is the aspect of scalability. The system, at present, controls a single patch of soil. However, future design will require the watering of multiple zones, allowing different regions of the farmland to be tracked and watered independently. This way, different regions will be able to use different sensors, different crops, or different requirements. It would be controlled through a centralized decision component that would control all the regions together.

Finally, LSTM Autoencoders will also allow SoilGuard not only to predict but also detect odd occurrences in soil moisture, soil, or water-pump activity. Such models pick up minute changes that human eyes might miss, like impending soil degradation, clogged sensors, or sudden reductions in soil moisture. With this feature, SoilGuard will not only predict, but also self-determine issues that might escalate into something bigger, giving the farmer ample time.

All these enhancements put together would make the SoilGuard system much more powerful and flexible. They would provide enhancements in the realms of water use efficiency, intelligence, and robustness such that farmers could manage much more land with much less effort. With all of this, the SoilGuard system would be prepared to offer a completely autonomous, scalable, and reliable solution for agricultural applications.

VI. CONCLUSION

What the SoilGuard system demonstrates very well is that coupling IoT sensors with deep learning-based predictions can, in fact, be so much more than useful for agricultural purposes. The system marries in real-time soil detection, cloud-based storage, and LSTM-based predictions to achieve the ability to predict well in advance that the soil will be drying up, rather than waiting until it actually does. However, this foresighted approach helps the system's pump turn well in advance of the oncoming stress that the plants will soon suffer. Through testing of its capabilities, the SoilGuard system was able to show that it would predict accurately, be fast-acting, and function over a remarkably long period of time despite extreme temperatures and changes in humidity.

One of the most valuable contributions that come from this system is related to improved water efficiency. Since the irrigation system is launched as a response to estimated dryness, rather than thresholds, this approach prevents overwatering, therefore net water consumption would decrease. A solution like that would be ideal for arid areas where water scarcity is considered an important problem. Of course, ease of deployment, which is further facilitated with the use of low-cost sensors, cloud infrastructure, as well as modularity, would allow this solution to be readily implemented in small farms, testing areas, as well as bigger agricultural lands.

Looking ahead, the list of improvements to be implemented-including finding defects in the pump system with the use of the ACS712 current sensor, being able to predict with weather-intelligent models, adding support for multi-zone watering, and executing AI directly on the ESP32-will guarantee that the system becomes smarter as well as more autonomous. Indeed, the project executed through SoilGuard illustrates that there is indeed a realistic approach that will allow AI-powered automation technology to play its important part in sustainable water management in agriculture.

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