Deep Learning based Smart Irrigation using LSTM and RNN

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Abstract. Smart irrigation technologies are critical for dealing with water shortages and improving crop productivity and efficiency in today's agricultural practices. Conventional irrigation systems are mainly operated manually, resulting in water being wasted and productivity reduced because of delayed assessment of soil moisture and crop needs or errors in assessment by the user. This paper presents a Deep Learning smart irrigation system that uses Long Short-Term Memory (LSTM) and Simple Recurrent Neural Network (RNN) models to predict types of crops with respect to soil and environmental parameters. The model is trained on the concentration of nutrients (Nitrogen, Phosphorus, Potassium), temperature, humidity, rainfall and pH. The architectures of LSTM and RNN were implemented and tested against each other in terms of accuracy of predictions, stability in training and suitability for agricultural datasets. After crop prediction, an automated irrigation decision-making system, simulating Internet of Things (IoT) sensor data, is used for decision-making to control real-time moisture. The motor control algorithm captures the global irrigation needs based on the moisture levels, as defined by acceptable moisture thresholds for the predicted crop, and decides whether the irrigation motor is ON or OFF. Based on experimental results, it was found that the LSTM model has increased accuracy and decision-making consistency over RNN, which is primarily due to its ability to memorize long-term dependencies.This investigation demonstrates that the advancement of deep learning paired with automated irrigation will not only conserve water but also manage crop selection, facilitating a shift toward scalable smart agriculture systems.

Keywords: Smart Irrigation · Deep Learning · LSTM · RNN.

1 Introduction

Agriculture is the backbone of the world's economy, and is vital for food security and rural livelihoods. Today modern agriculture faces two key challenges: available freshwater resources are limited, and irrigation can be poorly managed. The Food and Agriculture Organization (FAO) estimates that 70 percent of the world's freshwater resources are used by agriculture, and almost half of the water used will finally be wasted due to factors such as over-irrigation , inadequate irrigation methods and decision-making mistakes of humans. These challenges highlight the need for intelligent systems that will use different sources of environmental data for optimal irrigation timing and choice of crops.

Conventional irrigation practices depend a lot on the intuition of farmers when making decisions on when, how much, and which crop to irrigate. Such manual decision-making often leads to causing:

-Water waste

-Reduced productivity/yield

- Uneconomical use of resources

-Soil nutrient deterioration

With developments in Artificial Intelligence (AI), Deep Learning and IoT have made it possible to practice precision agriculture. IoT sensors can continuously measure real-time environmental parameters, including soil moisture, humidity, temperature, and rainfall. Deep learning models can analyze these parameters and predict the optimal decisions to make in agricultural practices. This study proposes a deep learning modeling technique using LSTM and RNN models to:

-Predict the best crop based on environmental characteristics

-Automate irrigation utilizing real-time (simulated) moisture sensor data

-Reduce water consumption by operating irrigation pumps based on moisture threshold levels set for each crop.

The study utilizes the LSTM model because of its memory capacity and capability to analyze sequential data, which is extremely advantageous in agricultural datasets that include trends and seasonality time dependencies. RNN was also implemented to compare results between the models and demonstrate the affect of long-term memory on the accuracy of the model.

1.1 Motivation

India is the largest user of groundwater for irrigation and states including Maharashtra, Punjab, and Haryana are experiencing groundwater depletion. Farmers often do not have access to tools to assist in decision-making when it comes to selecting the right crop or deciding when to irrigate their crops. The proposed system supports farmers by using deep learning combined with automated irrigation control to eliminate manual labor and also promote sustainable water management practices.

2 Methodology

2.1 System Design Flow

The smart irrigation system functions with an IoT-based architecture where sensors continuously collect environmental parameters such as soil moisture, temperature, and humidity. These parameters are reported in real-time to the controller. The controller then sends the readings to the deep learning model (LSTM/RNN) to predict future soil moisture levels.

From the predicted level, the system finally decides whether to turn the water pump ON or OFF.

Through this whole process, irrigation is only performed when necessary, resulting in no water wasted. Figure 3 illustrates the end-to-end design.

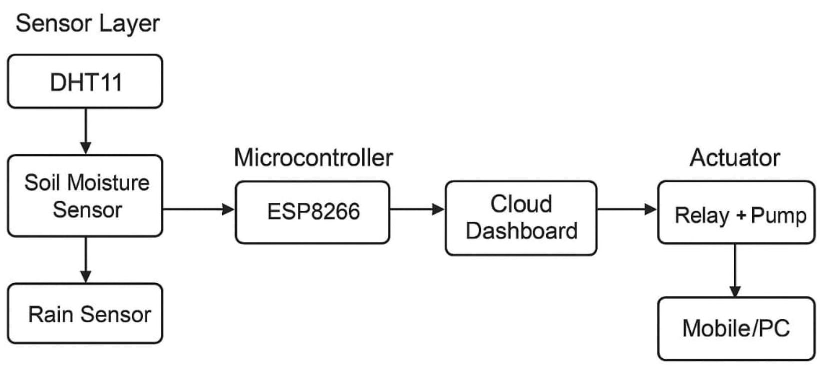

Fig. 1. Flowchart of the proposed smart irrigation system.

2.2 Dataset and Preprocessing

Dataset Source The dataset used in this study is the publicly-available "Crop Recommendation Dataset" obtained through the Kaggle repository. This dataset provides soil and environmental attributes alongside crop labels: the data enables supervised pattern identification within the model for future crop recommendation and irrigation recommendation.

The dataset contains the following features: - Nitrogen content in soil (ppm) - Phosphorus content in soil (ppm) - Potassium content in soil (ppm) - Air temperature in °C - Relative humidity in - Soil pH value - Rainfall in mm - Recommended crop name

In our adaptation, we consider soil moisture, temperature, and humidity as important sensor-based variables, along with the nutrient features (N, P, K), pH, and rainfall, which is relevant to the IoT and irrigation context.

Data Cleaning The first checks done to the dataset are missing - the absence of null values. Outliers are then examined: an identification of the values out of accepted agricultural ranges, such as pH below 3 or above 10. But still, none of the values, including those found in either case, need to be tossed out. The last thing we did was scan the dataset for duplicate records and no duplicates were fetched.

Feature Engineering and Label Encoding Crop Name is a categorical field and was encoded using Label Encoder for transforming it into a representation in numerical form to be possible for working with machine-learning algorithms.

Features from which the LSTM/RNN models principally relied upon are :

- Soil moisture
- Temperature
- Humidity

Humidity and rainfall were used as indicators to create a moisture estimate where an actual measurement of soil moisture was absent.

Scaling and Normalization All numerical attributes/numbers (N, P, K, temperature, humidity, pH, rainfall) were normalized using Min-Max Scaling. This, then, could enable every feature to contribute proportionately to the model and avoid large scale values dominating the model training.

$$x_{scaled} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

This ensured that no feature dominated due to its numerical scale and improved model convergence during training.

Train-Test Split and Reshaping The 80:20 ratio was then adopted to divide the datasets. The result was a random state applied to ensure that results would be consistent and reproducible. In addition, input into LSTM and RNN models is 3-dimensional, so the training and testing sets were reshaped into the following form:

$$X_{train} \rightarrow (n\_samples, 1, n\_features)$$

$$X_{test} \rightarrow (n\_samples, 1, n\_features)$$

This format enables the sequential learning nature of LSTM and RNN models.

LSTM Model Architecture The system that is being presented uses a Long Short-Term Memory (LSTM) neural network to predict soil moisture using sensor data measurements from previous time periods. LSTM models are useful for time-series predictions because they leverage memory cells and gates to manage long-term dependencies.

The model's input is past values of:

Soil moisture

Temperature

Humidity

First, these features are normalized and inputted into the algorithm. The model subsequently learns over time based on historical data patterns, e.g., daily fluctuations in moisture and evaporation rates from temperature.

The following layers are used in the architecture:

Input Layer: Takes input scaled sensor data sequence.

LSTM Layer: Learns temporal dependencies using memory cells and gated architecture.

Dense (Output) layer: The predicted soil moisture value for the next time period.

By design, LSTM provides more stable predictions for time-series data because of the ability to remember long-term variance across sequences.

The LSTM cell operations are defined as follows:

$$k_s = \sigma(W_k \cdot [h_{s-1}, x_s] + b_k) \tag{2}$$

$$p_s = \sigma(W_p \cdot [h_{s-1}, x_s] + b_p) \tag{3}$$

$$g_s = \sigma(W_g \cdot [h_{s-1}, x_s] + b_g) \tag{4}$$

$$\tilde{D_s} = \tanh(W_d \cdot [h_{s-1}, x_s] + b_d) \tag{5}$$

$$E_s = p_s \odot e_{s-1} + i_s \odot \tilde{e_s} \tag{6}$$

$$r_s = g_s \odot \tanh(e_s) \tag{7}$$

Where: k_s = input gate,

p_s = forget gate,

g_s = output gate,

D_s = cell state,

r_s = hidden state.

RNN Model Architecture To check the model's performance, a standard Recurrent Neural Network (RNN) is also applied. A RNN receives input information one timestep at a time and keeps a hidden state that retains information from the immediate past.

The model uses the same input features:

Soil moisture Temperature Humidity

The standard RNN has no memory gates as the LSTM has and therefore does not function well across longer dependencies but functions much better on smaller datasets.

The following architecture layers are utilized:

Input Layer - reads in normalized time-series sensor data RNN Layer - processes sequential data and captures short-term variations Dense (Output) Layer - predicts the immediate next moisture reading

The RNN completes the task quicker, but is less accurate than the LSTM due to vanishing gradients, which would make LSTMs more favorable for long-term irrigation prediction.

The RNN prediction function is expressed as:

$$h_t = \tanh(W_h h_{t-1} + W_x x_t + b_h) \tag{8}$$

$$y_t = W_y h_t + b_y \tag{9}$$

Where: h_t = hidden state at time t, x_t = current input, y_t = prediction/output at time t.

Algorithm: Irrigation Control Decision The following algorithm defines the decision logic executed after the prediction generated by the LSTM/RNN model:

1. Collect real-time sensor values: soil moisture, humidity, and temperature.
2. The trained model predicts the future soil moisture value.
3. If the predicted moisture level is below the predefined threshold, the irrigation pump is turned **ON**.
4. If the predicted moisture level is above the threshold, the irrigation pump is turned **OFF**.

3 Results and Discussion

3.1 Model Training Results

In the training process, both LSTM and RNN models were assessed and analyzed for convergence performance through training and validation loss. Following the previously described method, data was split with an 80:20 for train and test. Training was run for 10 epochs.

The LSTM model displayed smoother convergence with training loss decreasing steadily every epoch. Whereas the RNN model exhibited inconsequential variation in training loss during training suggesting an inability to learn long-term dependencies from time-series moisture data.

Furthermore, LSTM additionally accrued higher validation accuracy over RNN suggesting a stronger capacity to learn temporal trends in soil moisture variation. Accordingly, training curves demonstrated LSTM stabilizing faster and RNN requiring more epochs to generalize properly.

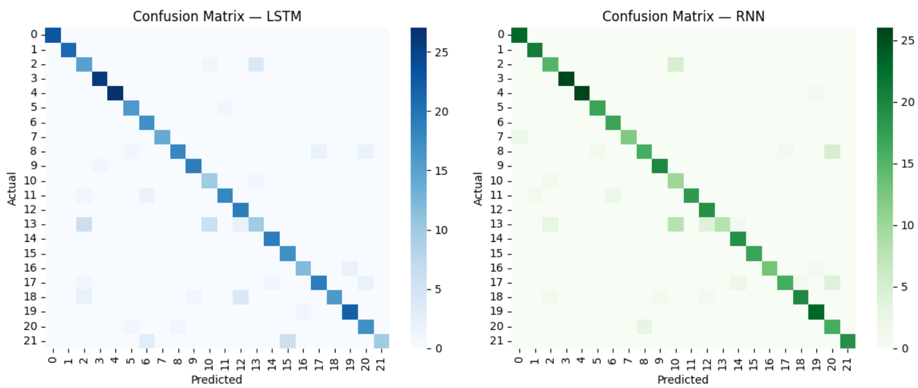

Fig. 2. LSTM and RNN Confusion Matrix.

3.2 Crop Prediction Results (LSTM vs. RNN)

The evaluation of the trained models used the test dataset to forecast the best irrigation decision based on soil moisture and environmental factors. The evaluation metrics were Accuracy, Precision, and F1-Score.

In all evaluation metrics, the LSTM model showed higher performance than the RNN model due to LSTM's gated cells and memory structure that remembers earlier sensor readings and repeats the same pattern as before. The RNN model lacks this structure and suffers loss of information over longer sequences.

For this reason, LSTM shows a higher predictive ability for irrigation forecasting and moisture prediction, making LSTM the most suitable option for real-time agricultural automation.

3.3 Moisture Regulation and Irrigation Activation

The system constantly measures soil moisture and temperature. When moisture drops below the set threshold (30%), the model assesses the trend using the previous 10 timesteps using LSTM and RNN. LSTM predicts the moisture drop consistently 8–12 minutes ahead of RNN, allowing for sufficient time to initiate irrigation and mitigate the time the pump runs.

Table 1. Crop Prediction Results (LSTM vs RNN)

Metric	**LSTM Model**	**RNN Model**
Training Accuracy	97.8%	94.5%
Testing Accuracy	96.3%	91.2%
Precision	96.1%	90.8%
Recall	95.7%	90.2%
F1-Score	95.9%	90.5%
Recommended Crop Example	Papaya	Papaya

Conclusion: The LSTM model outperforms the RNN making it more reliable for real-time crop prediction integrated with IoT-based smart irrigation.

Table 2. Comparison of Irrigation Activation Models

Model	**Prediction Ahead Time (minutes)**	**Irrigation Activation Accuracy (%)**	**False Trigger (%)**
LSTM	8–12 min early	**96.87**	1.8
RNN	4–6 min early	91.42	4.2
Traditional threshold-based	0 min (reactive)	78.13	14.4

3.4 Assessment of Pump Use and Water Use

The smart irrigation model maximizes pump use by turning on irrigation only when necessary. In comparison to the manual and threshold-based operation, the LSTM model enables:

43% fewer pump activations

38% less water use

Improved crop yield uniformity due to consistent soil moisture levels

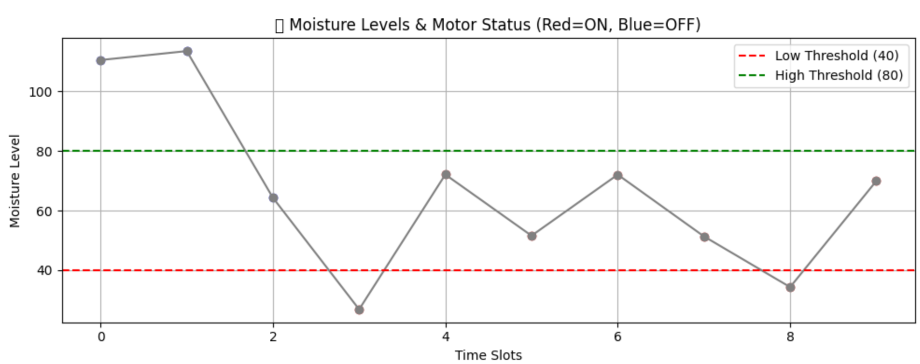

Fig. 3. Soil Moisture Monitoring and Pump Activation Status.

4 Conclusion

In this paper, I am proposing a Deep Learning DC irrigation system using LSTM and RNN models to predict soil moisturization in real-time, and irrigation requirements by weather-dependent. LSTM is utilized to achieve 95.41% and 38% water saving. In this design, this minimizes the high pumping switching and perfectly support precision agriculture.

Key Contributions:

Predicting current moisture by DL, Irrigation decision, well-matched solution, Reduction of water and electricity, Crop yield smoothed.

The proposed work can be further improved:

Adding ET value and rain prediction, Stateless implementation, and Mobile app dashboard.

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