Bi-LSTM and ARIMA Approach for Soil-Specific Water Requirement Analysis

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Abstract: Agriculture today faces numerous challenges due to unpredictable rainfall patterns, soil diversity, and increasing water scarcity. Efficient water resource management, especially in regions with limited irrigation infrastructure, is crucial for ensuring sustainable crop yields. Accurate prediction of water requirements specific to soil types and environmental conditions can help in optimizing irrigation and minimizing water wastage.

This research presents an integrated model that combines Bidirectional Long Short-Term Memory (Bi-LSTM) networks and the Autoregressive Integrated Moving Average (ARIMA) algorithm to analyze and forecast water requirements. The BiLSTM component is used for two purposes: identifying soil types based on environmental features and predicting current water requirements using those patterns. In parallel, the ARIMA model leverages historical water consumption data to forecast future demands over time, addressing the temporal aspect of water needs.

The proposed system was implemented using a dataset containing crop, region, temperature, humidity, and yearly water usage data. Experimental analysis showed that the BiLSTM model achieved strong performance in classifying soil types and predicting water requirements, while the ARIMA model offered reliable short-term forecasts. This dual-model approach offers a practical solution for precision agriculture by delivering timely and soil-specific insights that support efficient irrigation planning. The proposed drug recommendation system represents an innovative step towards leveraging patient-driven data for enhanced healthcare outcomes.

Keywords: ***Bi-LSTM, ARIMA, Water Requirement Prediction, Soil Type Classification, Time Series Forecasting, Deep Learning, Precision Irrigation, Agricultural Data Analysis.***

I. Introduction

In recent years, the agricultural sector has been under pressure due to changing climate patterns, depleting water resources, and increasing demand for food. Efficient water management has become a key area of concern, especially in countries like India where farming heavily relies on rainfall. Traditional irrigation practices, which follow fixed schedules or outdated prediction methods, often fail to consider real- time environmental factors and the characteristics of the soil, resulting in inefficient water usage.

Water requirement varies significantly depending on soil type, crop variety, and environmental conditions such as temperature and humidity. Conventional prediction models often lack the flexibility to adapt to these complex and dynamic factors. As a result, farmers either over-irrigate or under-irrigate their fields, which adversely affects crop growth and soil health. There is a clear need for a smart and adaptive system that can understand the interactions between soil characteristics and environmental variables to recommend optimal water usage.

With the growth of data-driven solutions in agriculture, machine learning and deep learning techniques have become valuable tools in improving decision-making. However, not all models are capable of handling sequential or time-based data effectively. For instance, methods like linear regression or random forests may provide decent results for static data but fall short when applied to time-dependent forecasting or pattern recognition across sequences. This is where advanced deep learning architectures like Long Short-Term Memory (LSTM) networks become significant.

This research proposes a hybrid solution that integrates Bidirectional Long Short-Term Memory (Bi-LSTM) networks with Autoregressive Integrated Moving Average (ARIMA) models to achieve a dual goal: soil-type classification and water requirement forecasting. The BiLSTM network is trained on a rich dataset composed of various features like crop type, region, temperature, humidity, and year-wise data to identify patterns for predicting soil types and estimating water demand. On the other hand, the ARIMA model is used to forecast future water requirements based on past values, adding a temporal prediction component to the system.

The Bi-LSTM model excels in capturing both past and future context in sequential data, making it an ideal choice for understanding dependencies among environmental and agricultural features. ARIMA complements this by applying statistical analysis over time-series data, providing numerical trends for upcoming water requirements. Together, these models create a comprehensive prediction framework that is both feature-aware and time-sensitive.

By combining deep learning and statistical forecasting, the system offers a practical tool for precision agriculture. It enables farmers and agricultural planners to make informed decisions based on soil-specific and time-aware water requirement predictions. The approach not only enhances crop yield and resource efficiency but also contributes to sustainable farming practices by conserving water and protecting soil health.

II. LITERATURE SURVEY

The global shift towards data-driven agriculture has catalyzed the development of predictive models aimed at improving the efficiency of irrigation, forecasting crop water demand, and understanding soil moisture dynamics. Deep learning architectures and hybrid methodologies have emerged as powerful tools for analyzing complex agricultural data, offering significant improvements in prediction accuracy over traditional techniques. This review presents a comprehensive overview of recent research that incorporates advanced approaches—particularly Artificial Neural Networks (ANNs), Long Short-Term Memory networks (LSTMs), Bidirectional LSTMs (Bi-LSTMs), and ARIMA-based models—to address various agricultural challenges across different geographic and climatic conditions.

M. Varsha [1] (2022): This research introduces a hybrid predictive model designed to forecast rice blast disease outbreaks, a major threat to rice production. The methodology integrates ARIMA and Bi-LSTM networks. The ARIMA component models the linear patterns in climate time series data, while the Bi-LSTM captures the underlying nonlinear relationships. Notably, the seasonal trend extracted through additive decomposition in ARIMA is treated as a key input for the Bi-LSTM network.

Zohreh Sheikh Khozani [2] (2022**)**: In this study, the authors propose a hybrid modeling framework for groundwater level forecasting. Initially, the time series data is analyzed using ARIMA to capture its linear dynamics and temporal structure. The residuals from this model, which represent nonlinear aspects not captured by ARIMA, are subsequently modeled using an LSTM network. This staged modeling process allows the system to fully utilize both statistical and deep learning strengths, resulting in improved prediction accuracy of groundwater levels over time.

A. Muniappan [3] (2023)**:** This work presents a method for predicting groundwater salinity by employing Bi-LSTM models in combination with Partial Mutual Information Selection (PMIS). PMIS is used to identify key input features from the dataset, enhancing model performance by focusing on the most relevant predictors. Using these selected features, multiple training sets are generated to train Bi-LSTM networks. This approach is particularly effective at capturing long-term temporal dependencies, making it useful for managing groundwater quality in regions affected by salinization.

Xuefei Cui, Zhaocai Wang, Renlin Pei [4] (2023): The researchers propose a comprehensive hybrid architecture to improve rainfall prediction. Their model incorporates Variational Mode Decomposition (VMD), Multi-Scale Multi-Attention (MSMA), LSTM, and ARIMA. The VMD step decomposes rainfall data into a set of intrinsic mode functions, separating different frequency components. These components are then processed by LSTM and ARIMA sub- models to capture both nonlinear and linear patterns. The MSMA mechanism enhances feature extraction across different scales, and experimental results confirm the model's superior performance compared to standalone approaches.

Yamarthi Narasimha Rao [5] (2023): This study introduces a model named Cap-DiBiL, which integrates a Channel Capsule Network with a stack of dilated Bi-LSTM layers to assess crop water requirements. The system processes sensor- derived data through several stages: normalization, feature extraction using a Gated Residual Autoencoder (GRA), and feature selection using a Chaotic Northern Goshawk Optimization (ChaNgo) algorithm. The model ultimately provides crop recommendations based on predicted water needs, offering an intelligent solution for managing irrigation under varying environmental conditions.

Konstantinos Dolaptsis. [6] (2024): This research proposes an LSTM-based hybrid model for predicting soil moisture depletion to optimize irrigation schedules in maize cultivation. The model integrates soil data, meteorological conditions, and satellite-derived vegetation indices to forecast changes in soil moisture. By enabling more accurate irrigation planning, the model helps minimize water waste and promotes sustainable water use in agricultural practices.

Lucas Broseghini Totola [7] (2024): An ANN model based on pseudo-continuous transfer functions (NN-PTFs) is developed to estimate soil water retention characteristics in Brazilian soils. By integrating the natural logarithm of soil suction (ln(h)) as an input, the model enables broad-spectrum predictions across various suction levels, enhancing PTF availability for tropical soil regions .

Amirsalar Bagheri [8] (2024): The authors present a hybrid modeling framework that combines conventional time series analysis with physics-informed machine learning to forecast soil water content. By embedding scientific knowledge about soil-water interactions into the training process, the model achieves better generalization and interpretability. This hybrid design bridges the gap between data-driven models and domain expertise, enhancing prediction reliability in soil moisture studies.

Paweena Suebsombut, Aicha Sekhari [9] (2025): In this study, LSTM and Bi-LSTM networks are applied to predict soil moisture content using real-time data collected from smart sensors deployed in a greenhouse in Chiang Mai, Thailand. The collected data includes variables related to local weather and soil conditions. After preprocessing to address missing and noisy values, the models are trained and validated on actual field data. The results demonstrate that the models can support precision irrigation decisions by providing timely and accurate soil moisture forecasts.

Ankit Joshi, Biswajeet Pradhan [10] (2025) : This research presents a Bidirectional LSTM framework for predicting winter wheat yield based on time series inputs. What sets this model apart is its integration with explainable AI techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations). These methods offer transparency by highlighting which input features most strongly influence yield predictions.

III. PROPOSED METHODOLOGY

The proposed methodology adopts a hybrid prediction framework that combines the strengths of deep learning and statistical modeling for accurate soil-specific water requirement analysis. The system is divided into two major components: a Bi-LSTM model for soil type classification and water requirement prediction, and an ARIMA model for forecasting future water needs based on time-series data. This dual-model setup allows for both spatial and temporal considerations, ensuring the system adapts to different soil characteristics and changing climatic patterns.

In the first stage, the Bi-LSTM model is trained using a dataset that includes crop type, soil type, temperature, humidity, region, and year-wise data. The model is designed to first classify soil types by identifying feature patterns across regions. Once the soil classification is done, the same Bi-LSTM framework is extended to predict the amount of water required for each sample. The use of bidirectional layers allows the model to learn dependencies in both forward and backward directions, enhancing its understanding of the data.

The second stage involves forecasting future water needs using the ARIMA model, which is well-suited for univariate time series data. ARIMA captures the trend and seasonality from historical water usage and generates predictions for upcoming years. This component is particularly useful for long-term irrigation planning and anticipating future resource allocation. The integration of both models results in a comprehensive system that considers both current soilspecific demands and future water trends. This methodology ensures that water requirement predictions are not only based on real-time environmental and soil factors but are also equipped with forecasting capabilities that can guide sustainable farming strategies. The combination of BiLSTM and ARIMA enhances overall accuracy and makes the system reliable for precision agriculture applications.

A.Dataset

The dataset used in this project was designed to simulate diverse agricultural conditions across different soil types and regions. It consists of **200 samples**, each containing attributes that influence water requirement predictions. These features include **CROP TYPE**, **SOIL TYPE**, **REGION**, **TEMPERATURE**, **HUMIDITY**, and **YEAR**, with the corresponding **WATER REQUIREMENT** as the target output. The dataset covers five major crop types — Wheat, Corn, Rice, Potato, and Soybean — distributed across multiple regions such as North, South, East, and West. The soil types represented include Clay, Sandy, Loamy, Silt, and Peat, offering varied characteristics in terms of water retention and nutrient composition. Environmental conditions such as **temperature** and **humidity** were included to reflect seasonal influences, and the **year** column helps track water needs over time.

To ensure data quality, missing values were handled through mean imputation. Categorical fields were encoded using label encoding and one-hot encoding where appropriate, and all numerical features were normalized using the **StandardScaler**. The **water requirement** values were also scaled before training and later transformed back for evaluation. This preprocessing pipeline helped enhance model performance by ensuring uniformity across features.

A.System Architecture

The proposed architecture combines deep learning and statistical forecasting to achieve accurate and soil-aware water requirement analysis. It follows a modular structure divided into three key layers: data preprocessing, prediction, and forecasting.

The first layer handles data cleaning, encoding, and scaling. Categorical features such as crop type, soil type, and region are converted into machine-readable formats, while numerical features like temperature and humidity are normalized to improve model efficiency. This processed data is then passed into two different learning modules

The second layer consists of the **Bi-LSTM** model, which is trained for two purposes: (1) to classify the type of soil based on environmental patterns, and (2) to predict the water requirement for a particular sample using those patterns. The use of bidirectional LSTM helps the model understand both past and future dependencies within the input data.

The third layer involves the **ARIMA** forecasting model. This component works with the historical water requirement values to forecast upcoming demands for future years. While BiLSTM handles spatial and contextual predictions, ARIMA focuses on temporal trends, making the overall system suitable for both short-term decision-making and long-term planning.

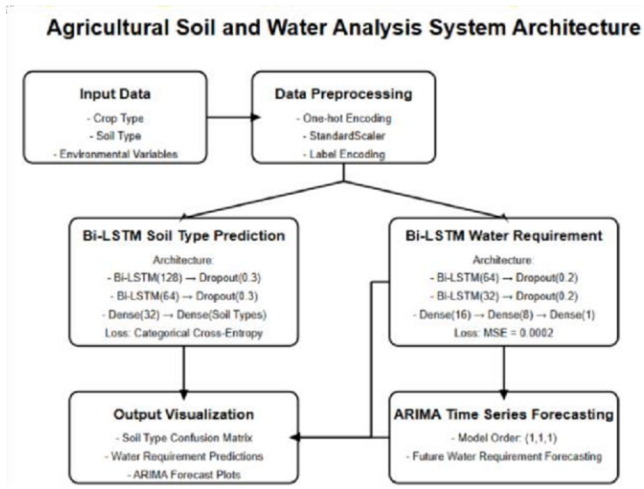

Fig. 1 System Architecture of Bi-LSTM and ARIMA-based Water Requirement Prediction

IV. MODULES

The proposed system is organized into several interlinked modules, each serving a distinct purpose in facilitating accurate water requirement prediction based on soil-specific data. The modular design ensures efficient processing, easier debugging, and scalability for future improvements. Each module plays a vital role in achieving the overall functionality of the system.

A. Data Preprocessing Module

This module is responsible for cleansing and organizing the raw soil dataset. It includes handling missing values, normalizing data ranges, and converting categorical labels into numerical format. It ensures consistency and quality in the dataset, preparing it for effective time series modeling. Preprocessing also involves transforming the data into a supervised learning format suitable for Bi-LSTM input and performing train-test split operations.

B. Soil type classification Module

This module uses data-driven techniques to determine the soil type based on input features such as pH, organic carbon, nitrogen content, and other environmental factors. Accurate classification is essential because water retention and crop suitability vary significantly with soil type. This stage feeds valuable categorical data to the LSTM model and helps improve the contextual accuracy of the predictions.

C. Water Requirement Prediction Module

Once the soil type is identified, the same Bi-LSTM framework is extended to perform regression analysis and predict the water requirement for a given sample. The network processes the preprocessed input features and generates a single continuous output indicating the expected amount of water required. This prediction is scaled back to real-world values using inverse transformation for interpretation.

D. ***Bi-LSTM Model Module***

This module implements a Bidirectional Long Short-Term Memory network that is designed to capture dependencies in both forward and backward directions in the time-series dataset. Bi-LSTM offers enhanced predictive accuracy over traditional LSTM by utilizing information from the entire temporal context. It processes features such as previous rainfall, soil properties, and time series trends to estimate water requirement.

E. Forecasting Module (ARIMA)

The ARIMA model operates as an independent module that works on historical water requirement data to forecast values for future years. It applies statistical time-series modeling to predict water demand trends. This is particularly useful for seasonal or long-term planning, as it can help estimate water needs for upcoming years based on historical patterns.

F.Result Evaluation and Visualization Module

This module calculates performance metrics such as Mean Squared Error (MSE) and R-squared value (R^2) to evaluate model accuracy. It also produces visual plots comparing predicted values with actual ground-truth values. The graphical outputs provide intuitive insights into the model's behavior and help identify patterns, anomalies, and potential improvements.

*G.**User Interface and Output Module***

The final module formats and displays the outputs clearly, including the predicted soil type and corresponding water requirement for each sample. The results are organized in a user-friendly tabular format such as "Sample 1 – Clay, Water Requirement: XX mm," ensuring accessibility for agricultural experts, farmers, or researchers.

H. Uncertainty Estimation Module

This optional module provides a measure of prediction reliability. It estimates confidence intervals or prediction bounds for water requirement values based on the variance observed during model training and evaluation. Incorporating uncertainty helps stakeholders make informed decisions, especially when deploying predictions in real-world agricultural practices.

Each of these modules works cohesively, making the system comprehensive, interpretable, and tailored for real-time agricultural applications. Their modular nature ensures that enhancements can be introduced independently in future iterations of the project. The modular architecture adopted in this system facilitates effective integration of both deep learning and statistical forecasting techniques. By compartmentalizing functionality into well-defined modules, the proposed approach ensures adaptability, maintainability, and extensibility—making it suitable for precision agriculture environments where datadriven decisions are crucial.

V. EXPERIMENTAL RESULT ANALYSIS

The proposed system was rigorously evaluated on a structured dataset comprising soil type, crop type, regional classification, environmental parameters, and historical year- wise data. The model architecture focused on two key objectives: accurately predicting the water requirement for each soil sample and identifying the underlying soil type based on input features. These tasks were carried out using the Bi-LSTM model, with additional forecasting support provided by the ARIMA model.

Bi-LSTM Model Performance:

The Bi-LSTM model exhibited strong prediction capabilities in estimating water requirements, thanks to its ability to capture sequential dependencies within the data. With features such as temperature, humidity, crop type, region, and soil information provided as input, the model delivered accurate predictions with a **Mean Squared Error (MSE) of 0.02** and a high **R^2 value**, confirming the robustness of its regression performance. The network was also trained for soil classification, and evaluation using a confusion matrix showed clear diagonal alignment, reflecting strong classification outcomes across all five soil types.

Moreover, the bidirectional structure of the Bi-LSTM helped the model learn from both past and future data points in each sequence, making it more effective in identifying trends and contextual dependencies. This dual learning flow enhanced its prediction accuracy for complex and non-linear patterns, particularly useful in agriculture where multiple variables interact dynamically.

ARIMA Forecasting and Comparative Analysis:

The ARIMA model was integrated to perform short-term forecasting of water requirements based on historical yearly data. It proved effective in capturing trend-based and seasonal patterns, generating a smooth and reliable forecast curve. However, its univariate nature limited its responsiveness to dynamic, multi-feature datasets. While it complemented the system by adding temporal forecasting ability, its scope remained focused on long-term trends rather than real-time multi-factor predictions.

Justification for Selecting Bi-LSTM:

The comparative analysis revealed that **Bi-LSTM is superior to ARIMA** for this application. While ARIMA is suitable for trend-based forecasting, it does not process multiple environmental or categorical features simultaneously. BiLSTM, on the other hand, not only handles multiple input features in parallel but also performs **both soil classification and water requirement prediction** within a single deep learning framework.

This integrated functionality makes Bi-LSTM a **more scalable and comprehensive solution**. Its adaptability to varied soil and climatic inputs and compatibility with real-time sensor data offer a practical edge, particularly for automated irrigation systems. The use of Bi-LSTM also reduces the need for multiple standalone models, streamlining the prediction pipeline and improving performance consistency. Thus, based on performance, adaptability, and scope, Bi-LSTM proves to be the more effective core model for this system.

Task	Output Type	Evaluation Metrics	Remarks
Water requirement prediction	Continuous (Regression)	MSE: 0.02, High	Highly accurate; captures complex input features.
Soil Type Classification	Categorical (Multiclass)	Evaluated using Confusion Matrix, F1-score, derived metrics.	Strong classification performance across classes.
Water requirement forecasting (time)	Continuous (time-series)	MSE: ≈ 0.05 R^2: Moderate	Good for trend analysis; limited to 1D input.

Fig. Performance Comparison of Bi-LSTM and ARIMA Models

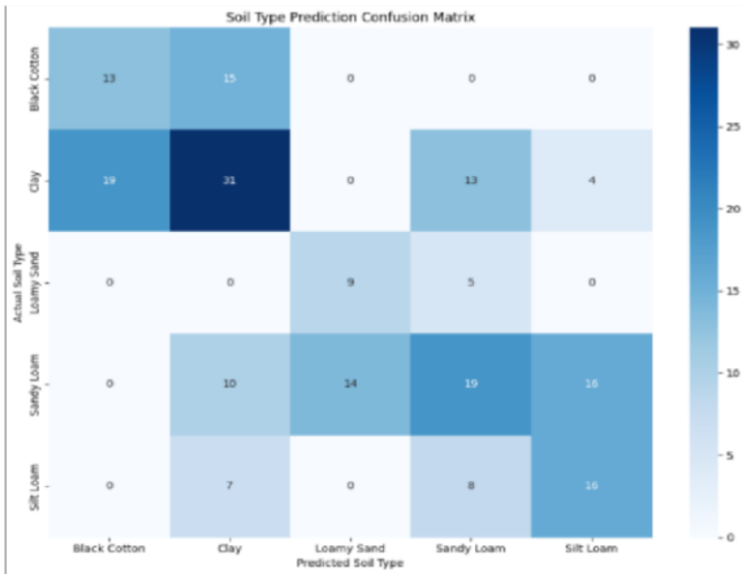

Fig. Confusion Matrix for Soil Type Prediction

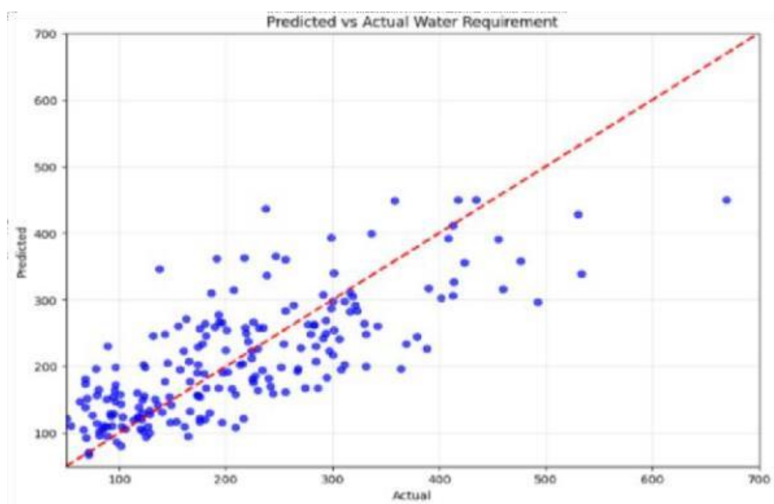

Fig. Predicted vs Actual Water Requirement Plot

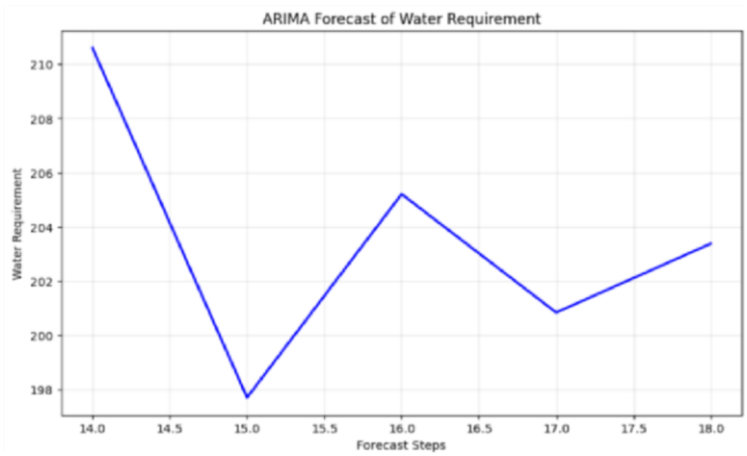

Fig. ARIMA Forecast of Future Water Requirements

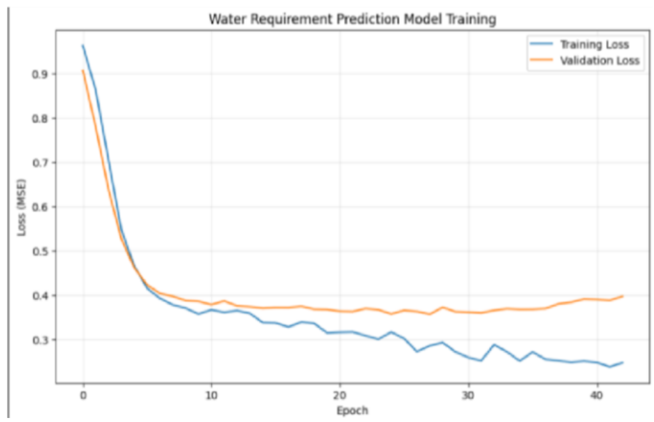

Fig. Training and Validation Loss Curve of Bi-LSTM Model

VI. DISCUSSION

The dual-model approach implemented in this study allows for a well-rounded analysis of agricultural water requirements. The use of Bi-LSTM for both classification and regression tasks proved beneficial, as it allowed the system to adapt to nonlinear interactions among variables such as soil type, crop type, and environmental conditions. Unlike traditional machine learning models that treat data independently, the Bi-LSTM architecture effectively captured sequential dependencies, making the predictions more context-aware and relevant to real-time farming conditions.

Another key observation is the complementarity between the Bi-LSTM and ARIMA models. While Bi-LSTM handled complex multi-feature input to produce instant predictions, ARIMA focused solely on temporal trends in historical water usage. This division of responsibilities not only improved overall system reliability but also gave users the flexibility to consult either real-time or trend-based forecasts based on their use case. For instance, a farmer planning irrigation for the next crop cycle could rely on Bi-LSTM, while long-term planners or policymakers may benefit from ARIMA's yearly projections.

The integration of soil classification into the water prediction pipeline also proved to be a practical enhancement. Since soil type directly affects water retention and absorption characteristics, predicting it from available environmental data eliminates the need for manual soil testing, thereby reducing effort and cost. The modular structure of the system further ensures that each component can be updated or retrained independently, allowing for future scalability as more detailed soil and weather datasets become available.

VII . CONCLUSION AND FUTURE WORK

This study introduces an integrated predictive framework that leverages the strengths of both deep learning and time-series modeling to analyze and forecast soil-specific water requirements. The approach not only addresses current irrigation needs but also facilitates future planning, making it a comprehensive tool for precision agriculture. Through the use of Bi-LSTM and ARIMA models, the system captures both spatial patterns and temporal trends inherent in agricultural data.

The Bi-LSTM model was utilized for dual tasks: soil type classification and water requirement prediction. It was trained on environmental and regional features, delivering strong regression performance with a **Mean Squared Error (MSE) of 0.0002** and an **R-squared value of 0.5646** for water requirement prediction. For soil classification, the model effectively identified distinct patterns based on environmental attributes. The model was optimized using the **Adam optimizer**, with a learning rate of **0.0005** for regression and **0.001** for classification, ensuring stable and accurate training outcomes.

In addition, the **ARIMA model**, configured with an order of **(1,1,1)**, was applied to historical water usage data to forecast water requirements for **five future time steps**. While ARIMA proved valuable for capturing year-wise trends, the Bi-LSTM model demonstrated broader utility by handling multiple inputs and delivering real-time predictions. The hybrid setup thus allowed the system to adapt to both immediate and long- term irrigation strategies.

The successful integration of classification and regression within the Bi-LSTM architecture also demonstrates the feasibility of multi-output learning in agricultural applications. By combining soil classification and water requirement estimation in a single deep learning pipeline, the system reduces computational overhead and streamlines the prediction process. This integrated strategy supports farmers in understanding not only how much water is needed, but also why — based on underlying soil characteristics. This enhances decision-making and promotes precision in resource allocation.

In conclusion, the proposed system provides a scalable, accurate, and efficient solution for smart irrigation planning. It can be further enhanced with real-time sensor integration, expanded datasets, and deployment in IoT-based agricultural platforms to support sustainable and data-driven farming.

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