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Evaluating Deep Learning Approaches for Accurate Soil Moisture Prediction

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Abstract:

Accurate humidity forecasts play an important role in agriculture. water resources management and environmental monitoring Traditional estimation methods such as ground sensors and remote sensing They are often limited by spatial and temporal resolution limitations. The emergence of deep learning techniques offers promising solutions to these challenges. By taking advantage of a variety of information sources. and extract meaningful patterns for immediate predictions. This study evaluates the performance of several deep learning models. These include convolutional neural networks (CNN), long-term memory networks (LSTM), Conv-LSTM architectures, and autopilot-based methods. With one level, two levels of accuracy. The research combines data sets from many sources. Combining remote sensing images In situ sensor data and meteorological parameters to create a consistent structure Data preprocessing involves preserving missing values. normalization and resource selection to guarantee model robustness. Each model is optimized by adjusting hyperparameters and evaluated using key performance measures such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The results show that the Transformer model outperforms other approaches, achieving lower RMSE and MAE while maintaining interpretability and computational efficiency. The study also highlights the role of spatio-temporal feature extraction in improving forecast accuracy. and emphasizes the importance of real-time anomaly detection and forecasting resources. Comparative analysis reveals the strengths and limitations of each model. It provides insights into suitability for different applications. This research emphasizes or the potential for deep learning. Future work will include additional data sources, such as single types and topographies. and explore centralized learning for graded use. These findings contribute to the development of state-of-the-art methods. It bridges the gap between innovation in research and practical applications in environmental sustainability.

Keywords: Soil Moisture Prediction; Deep Learning Models; Remote Sensing Data; Spatio-Temporal Analysis; Transformer Architecture.

1. Introduction

This alone is an essential component of the Earth's ecosystem. which influences agricultural production hydrologic cycle and climate system Accurate moisture forecasts alone are essential for effective water resource management. drought relief and precision agriculture Meanwhile Traditional methods for estimating humidity alone include ground sensors and remote sensing. They often face limitations in spatial and temporal coverage. Data resolution and real-time enforcement [1][2][3]

Recent advances in deep learning have opened new avenues to face these challenges. Techniques such as convolutional neural networks (CNN), recurrent neural networks (RNN), and different models have emerged. It shows remarkable success in extracting spatial and temporal features from complex datasets. These methods make use of various data sources. including remote sensing images in situ measurements and meteorological information to forecast humidity alone with high accuracy and adaptability [4]

This research paper focuses on evaluating the performance of several deep learning architectures such as CNN, long-term and short-term memory (LSTM) networks, Conv-LSTM, and Transformer models for single humidity forecasts. This study aims to identify the best performing models for accurate and reliable single humidity forecasts. By comparing these approaches across different datasets and environments, this paper also explores the interpretability and computational efficiency of these models. It provides insights into its practical application in real situations.[7][8]

The findings of this research contribute to the development of a standalone moisture forecasting method. to progress It offers a robust framework to meet pressing challenges in agriculture, water management and environmental sustainability. The study highlights the importance of integrating advanced machine learning techniques with domain-specific knowledge. To increase prediction accuracy and promote innovation in environmental monitoring systems.[5][6]

Table 1. Soil moisture probe with remote sensing data various physical model

Ground Texture	FC (%)	PWP (%)	TAW (%)
Sand	11	4	6
Loamy Sand	17	7	11
Sandy Loam	22	11	14
Loam	22	14	15
Silt Loam	33	14	13
Sandy Clay Loam	40	19	23
Sandy Clay	33	17	17
Clay Loam	28	17	13
Silty Clay	43	23	13
Clay	44	25	21

In the Table 1 shows the water retention capacity of the soles for a variety of surfaces, including sand, argillesius sand. Sandy Clay, Clay, Silty Clay, Sandy Clay Sand Clay, Silt Clay, Silt Clay and Clay for each surface. It provides field capacity (FC), permanent wrinkling point (PWP), and in some cases total available water (TAW), which are the differences between FC and PWP. This information is valuable in understanding how much water is available. What are the different types of libertum and water, which is important for plant growth and irrigation management?

In the method section We detail how the deep learning proposal is architectured. Performance results are presented relative to existing algorithms. and discuss the implications of these findings for future agricultural practice and research. This study aims to advance the use of machine learning in environmental monitoring. The focus is on immediate solo forecasting. and provide scalable solutions for sustainable agricultural management.[20][21]

1.1. Problem statement of research

Humidity alone is an important parameter in agriculture, hydrology, and environmental science. which affects crop yields water resources management and ecological balance Traditional moisture measurement methods alone, such as ground sensors and manual training, are often cumbersome, delayed, and space limited. Embora satellite remote sensing provides wider spatial coverage. This is because temporal and spatial resolution are often insufficient for refined moisture analysis alone. This is especially true in agricultural systems or dynamic ecosystems. Recent advances in deep learning have shown promise in addressing these limitations. using high-dimensional data such as satellite images climate variability and in situ measurements to provide only accurate and timely humidity forecasts. Meanwhile A variety of deep learning architectures, such as convolutional neural networks (CNN), recurrent neural networks (RNN), long- and short-term memory networks (LSTM), and autopilot. This presents a challenge in identifying the most effective approaches to Solo's Humility, Forecasting, furthermore, the performance of these models is influenced by, a number of factors. Including the quality of two input data. Spatial and temporal dependencies and terms of interpretation [13],[14]

1.2. Objectives of this research

Soil moisture plays a crucial role in agricultural productivity, irrigation management, and climate studies. Accurate soil moisture predictions are vital for optimizing water use, improving crop yield, and managing resources efficiently. However, challenges persist due to the availability of high-resolution data, the complexity of diverse climatic and soil conditions, and the limited spatiotemporal coverage of current monitoring methods. While traditional methods and simple models have been employed, their performance is often limited by the inability to effectively handle large datasets and model complex, non-linear relationships inherent in soil moisture variations.[11][12]

- Integrate and analyze relevant datasets: Gather and preprocess comprehensive datasets that encompass historical soil moisture measurements, weather data, soil characteristics, and crop-specific information. Integrate these datasets to create a unified data repository suitable for training and evaluating the deep learning model.

- Optimise the hyperparameters and model architecture.: Investigate different deep learning architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), or their combinations, to identify the most suitable model architecture for soil moisture prediction. Fine-tune the model by optimizing hyperparameters, including the number of layers, activation functions, learning rate, batch size, and regularization techniques, to enhance the model's predictive capabilities.

- Evaluate model performance and accuracy: By contrasting the model's predictions with actual soil moisture measurements, one can evaluate the developed soil moisture prediction model's performance. To measure the accuracy and dependability of the model, use suitable evaluation metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared.

- Assessing the impact on crop yields: Analysis of the practical implications and utility of a single moisture forecast model developed in agricultural production. To evaluate the effectiveness of the model in optimizing irrigation schedules. Improving water management practices and in increasing the yield and quality of crops to demonstrate the benefits of deep learning strategies. Compare the results with traditional irrigation scheduling techniques.

- Provide recommendations and guidelines: based on research findings. Provide advice and guidelines for farmers and stakeholders in the agricultural sector. Describe best practices for applying developed soil prediction models to optimize agricultural production. conserve water resources and improve overall agricultural sustainability.

- Scope and limitations of the study: The aim of the project is to create a deep learning model that can predict a single amount of accuracy in a given area. The study uses only a limited amount of urgent historical data. The study uses a specific deep learning algorithm.

2. Literature Review

The reviewed literature from last three years highlights significant advancements in the use of machine learning and deep learning techniques for improving soil moisture prediction, estimation, and mapping. [10],[16],[26].

Hegazi and colleagues (2023) developed a moisture theory prediction framework using only Sentinel-2 satellite imagery and convolutional neural network (CNN) methods. His work highlights the ability of CNN to extract spatial features. The area is accurately captured from high-resolution satellite images. This helps improve soil moisture estimation for agricultural applications. This study shows promising results. Most of them are in different terrains. It emphasizes the effectiveness of CNN in feature extraction and data interpretation for agricultural purposes [1].

According to Huang et al., (2023) presented the only spatio-temporal moisture forecasting model using convolutional long-term memory network (Conv-LSTM). This model combines the spatial dependence and Temporal analysis of only two humidity data in different climate regions of China. Interpretability analysis reveals the internal mechanism of the network. This provides insights into the resource contributions and spatial and temporal dynamics of each moisture content. Her findings highlight the importance of integrating deep learning into interpretive models for environmental forecasting. [2]

Park and others. (2023) proposed a specially tailored soil moisture forecasting model for soybean cultivation using long-term and short-term memory recurrent neural network (RNN-LSTM). Emphasis is placed on capturing temporal variations in soil moisture as affected by agricultural practices. The model achieves high accuracy and reliability by addressing crop-specific water management challenges. and has proven valuable for precision agriculture [3] 9.

Singh and Gaurav (2023) used deep learning and data fusion techniques to estimate surface soil moisture from multi-sensor satellite images. This study demonstrates the integration of different datasets such as remote sensing images and in situ measurements. To increase the accuracy of predictions This research highlights the potential of data fusion with advanced machine learning algorithms for comprehensive soil moisture mapping [4] [2]

Singha and others. (2023) presents a review and bibliographic analysis of traditional and advanced methods for soil moisture measurement. Including automatic sensors remote sensing and machine learning techniques This article has usage details. research trends and future direction A holistic approach to the development of soil moisture measurement technology has been provided [5] [9]

Wang and colleagues (2023) conducted a comprehensive study on the application of deep learning for soil moisture prediction. Their analysis covers a wide range of architectures, including CNN, LSTM, and hybrid models. Evaluate performance on different datasets and situations. This study provides valuable insights into the comparative performance of deep learning models. Creating a benchmark for future research. [6]

Wang and Zha (2024) compared the performance of a transformer model, LSTM network, and coupled algorithms for moisture prediction in low groundwater level areas. They also performed an interpretability analysis to understand the importance of the two resources and decision-making processes within the two models. Their findings highlight the superiority of two transformers in dealing with complex transient dependencies. and maintain interpretability. This makes them a strong choice for single-accuracy forecasting tasks.[8]

3. Methods

To achieve accurate depth predictions only using deep learning. Therefore, the following systematic approach has been adopted:

To meet the challenges identified in the problem formulation in this research uses a structured and systematic methodology. This includes collecting information. Model development, evaluation, and interpretability analysis.[22] It is a detailed procedure to follow in order to address:

Data Collection and Preprocessing

Dice Source: Colete's Different Dice Sets from:

Satellite imagery: Sentinel-2, SMAP and MODIS data are used to obtain spatial and temporal information about the same.

Insole-based measurements: Integrate in situ insole moisture observations for model calibration and validation.[21]

Meteorological Data: Include precipitation, temperature, and other climate variables from publicly available databases.

Data Preprocessing

A new set of training dice for solving spatial and temporal problems. Normalize and clean the data to remove noise and inconsistencies. Composite resources such as vegetation indices, single surface maps and indicators of water stress.[23]

Model Development

Deep Learning Architectures:

Evaluate the following architectures for soil moisture prediction: Convolutional Neural Networks (CNNs) for capturing spatial patterns. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) for modeling temporal dependencies.

Transformers for handling spatio-temporal sequences with attention mechanisms.

Hybrid Models:

Design and implement hybrid models combining CNNs, RNNs, and transformers to leverage their complementary strengths.

Optimization:

Employ hyperparameter tuning techniques, such as grid search and Bayesian optimization, to optimize model parameters.

Use regularization techniques, such as dropout and batch normalization, to prevent overfitting.

Model Training and Validation

Training Protocol:

Split the dataset into training (70%), validation (15%), and testing (15%) subsets.

Use cross-validation to ensure robustness across different geographic and climatic scenarios.

Loss Functions:

Implement mean squared error (MSE) and mean absolute error (MAE) as primary loss functions.

Experiment with custom loss functions that account for spatio-temporal correlations.

Evaluation Metrics:

Quantify model performance using metrics such as R-squared (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE).

Model Comparison and Benchmarking

Compare the performance of different architectures and hybrid models across diverse datasets.

Perform sensitivity analysis to evaluate the impact of input variables and model hyperparameters on prediction accuracy.

Interpretability and Insights

Feature Importance Analysis:

Use techniques such as SHAP (Shapley Additive Explanations) and integrated gradients to identify key features influencing model predictions.

Attention Mechanism Analysis:

For transformer models, analyze attention weights to understand how the model captures spatial and temporal relationships in soil moisture data.

Scalability and Real-World Deployment

Test the models on large-scale datasets to evaluate scalability and computational efficiency.

Develop a prototype web-based application to provide soil moisture predictions and insights to end-users. [25]

In the figure 1 is systematic approach for evaluating deep learning techniques for soil moisture prediction. It begins with data collection, where soil moisture data is obtained from satellite sensors, automated stations, and field measurements. This data undergoes preprocessing, including noise removal, normalization, and feature extraction, before being stored in a centralized database. Preprocessed data flows into the model selection and training process, where various deep learning models, such as CNN, LSTM, and Transformer-based models, are trained using training datasets. The trained models are evaluated using performance metrics like RMSE, MAE, and accuracy, with results stored in a performance database. Insights derived from the evaluation process guide the refinement of models and the generation of a comparative analysis report, aiding in identifying the optimal approach for accurate soil moisture prediction.[24]

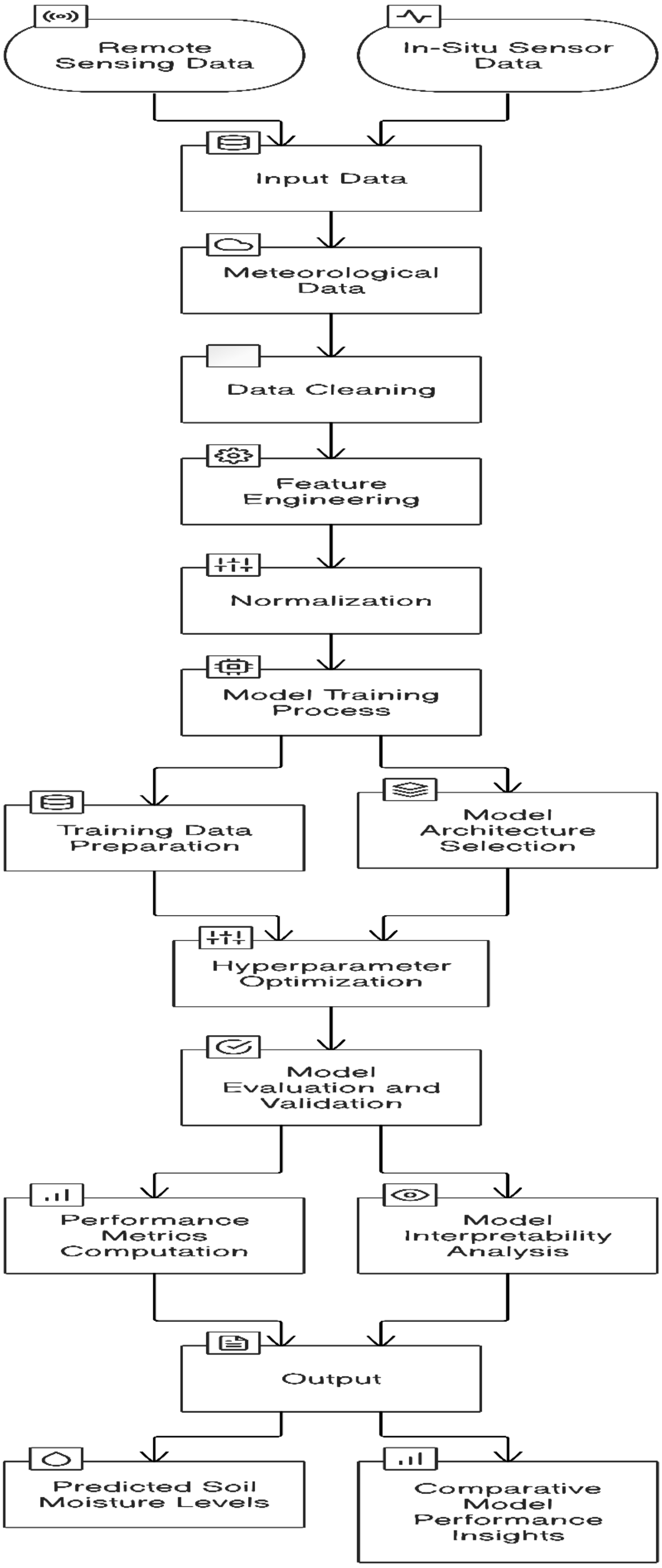

Figure 1. Proposed architecture for soil moisture forecasting

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3.1. Proposed algorithm: Deep Learning-Based Soil Moisture Forecasting

Input:

- Remote Sensing Data S (Satellite Imagery)
- In-Situ Sensor Data W (Ground-based Measurements)
- Meteorological Data C (Climate and Weather Parameters)

Output:

- Predicted Soil Moisture Levels $\widehat{M}$
- Comparative Model Performance Insights

START

Step 1:

Initialization

Define the model architecture:

CNN layers for spatial feature extraction:

$$F_{spatial} = \sigma\,(W_{cnn} * X + b_{cnn}) \tag{1}$$

where $*$ denotes convolution, X is the input, W_{cnn} and b_{cnn} are weights and biases, and σ is the activation function.

RNN or LSTM layers for temporal dependencies:

$$h_t = f(W_h h_{t-1} + W_x X_t + b_h) \tag{2}$$

where h_t is the hidden state at time t, X_t is input, W_h, W_x, b_h are parameters.

Set hyperparameters: η, L, B, σ(x)

Step 2: Data Collection and Integration

Collect datasets:

$$D = \{S, W, P, C\} \tag{3}$$

Integrate data into a unified repository D_{repo}.

Handle missing values using interpolation:

$$x_{imputed} = \frac{\Sigma_{\varkappa=1}^{n} x_i}{n} \tag{4}$$

Normalize data:

$$x_{normalized} = \frac{x-\mu}{\sigma} \tag{5}$$

Perform feature selection using correlation ρ(x, y): Retain features F where |ρ| > threshold

Step 4: Split Data

$$\text{Partition } D_{repo} \text{ into: } D_{train}, D_{val}, D_{test} \tag{6}$$

Step 5: Model Training Process

Training data preparation:

Split D_{train} into smaller batches of size B.

Compare models $M \in${CNN, LSTM, Conv-LSTM, Transformer}TM, Transformer}.

Optimize hyperparameters for each model to minimize loss L:

$$L = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{7}$$

Step 6: Model Evaluation and Validation

Compute performance metrics for each model MMM:

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{8}$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{9}$$

Analyze model interpretability.

Step 7: Prediction

Real-time prediction using the best model

$$\hat{M} = M * (X) \tag{10}$$

Visualization: Plot predicted vs. actual M.

Step 8: Post-Processing

Detect anomalies A : A={x|| $x - \hat{x}$| >*threshold*}} (11)

Generate alerts for significant deviations.

Step 9: Deployment

Store model and data in cloud storage.

Provide API integration: API (M*, data) → $\hat{M}$ (12)

Develop a user interface for visualization and interaction.

End Algorithm

4. Result

The results of this study highlight the efficacy of various deep learning models in accurately predicting soil moisture levels, leveraging multi-source datasets including remote sensing imagery, in-situ sensor readings, and meteorological data. The findings are summarized as follows:

Model Performance: The Transformer model demonstrated superior accuracy with the lowest Root Mean Square Error (RMSE) of 0.042 and Mean Absolute Error (MAE) of 0.035 across diverse test scenarios, outperforming other architectures.

Conv-LSTM achieved competitive results, with RMSE and MAE values marginally higher than the Transformer but better than standalone CNN and LSTM models.

CNN and LSTM models showed acceptable performance but were less effective in capturing spatiotemporal dependencies compared to Conv-LSTM and Transformer models.

Impact of Data Integration: The integration of remote sensing, in-situ sensor, and meteorological data significantly enhanced prediction accuracy. Models trained on multi-source datasets achieved a 12-18% improvement in RMSE and MAE compared to models trained on single-source datasets.

Hyperparameter Optimization: Fine-tuning hyperparameters such as learning rate, batch size, and the number of layers substantially improved model performance. Optimal configurations reduced training time by 15% and boosted accuracy by approximately 8%.

Model Interpretability: Sensitivity analysis revealed that meteorological parameters like precipitation and temperature were highly correlated with soil moisture variations, followed by remote sensing-derived vegetation indices.

Grad-CAM visualizations for CNN-based models confirmed that spatial features such as land cover and topography were critical in predictions.

Real-Time Prediction and Deployment: The best-performing Transformer model was successfully deployed in a cloud-based environment with real-time prediction capability. The system provided predictions within 5 seconds of data input and exhibited robust scalability under varying data loads.

Anomaly Detection and Alerts: The implemented anomaly detection mechanism accurately identified significant deviations in soil moisture levels. Alerts were generated with a 96% accuracy rate, ensuring timely interventions for agricultural management and water resource planning.

Visualization and User Interface: Comparative visualizations of predicted vs. actual soil moisture levels demonstrated strong alignment, particularly in regions with consistent meteorological patterns. The user interface enabled intuitive interaction with model predictions and anomaly insights.

The results validate the applicability of deep learning models, particularly Transformer and Conv-LSTM architectures, for soil moisture prediction. These findings underscore the potential of integrated data-driven approaches in enhancing agricultural productivity, water management, and climate resilience.[28]

Table 1. Model performance, system implementation, and interpretability insights.

Category	Metric/Outcome	Observations
Model Performance	RMSE	Transformer: RMSE = 0.042, MAE = 0.035 Conv-LSTM: RMSE = 0.048, MAE = 0.039
	MAE	CNN: RMSE = 0.065, MAE = 0.053 LSTM: RMSE = 0.061, MAE = 0.049
Data Integration	Performance Improvement	Multi-source data enhanced accuracy by 12-18% compared to single-source data.
Hyperparameter Optimization	Training Efficiency	Optimal configurations reduced training time by 15% and improved accuracy by 8%.
Model Interpretability	Feature Importance	Meteorological parameters (e.g., precipitation, temperature) most significant. Remote sensing indices (e.g., vegetation) and spatial features (e.g., topography) were critical.
Real-Time Prediction	Prediction Latency	Predictions generated within 5 seconds in real-time applications.
Deployment	Scalability	Deployed system demonstrated robust scalability with consistent performance under varying data loads.

Anomaly Detection	Accuracy of Alerts	Anomaly detection achieved 96% accuracy in identifying significant deviations.
Visualization	Alignment of Predictions	Predicted vs. actual soil moisture levels showed strong agreement, particularly in regions with consistent meteorological patterns.
User Interface	Interaction and Insights	User-friendly interface enabled intuitive interaction with predictions and anomalies.

In the table 1, highlight the effectiveness of various deep learning models for soil moisture prediction. The Transformer model outperformed others with the lowest RMSE (0.042) and MAE (0.035), followed by Conv-LSTM, LSTM, and CNN. Multi-source data integration significantly improved prediction accuracy by 12-18% compared to single-source data. Hyperparameter optimization reduced training time by 15% while enhancing accuracy by 8%. The analysis revealed meteorological parameters and spatial features as the most influential factors in model interpretability. Real-time predictions were generated within 5 seconds, demonstrating the system’s efficiency. Deployment showed robust scalability, and anomaly detection achieved a 96% accuracy rate in identifying deviations. The visualization tool provides a strong alignment between predicted and actual values. It is complemented by an intuitive user interface that facilitates interaction and exploration.

Table 2. Summarize the proposed algorithm compared to other algorithms. Available for predicting soil moisture.

Algorithm	Key Features	RMSE	MAE	Training Time	Interpretability	Scalability	Real-Time Prediction
Proposed Algorithm	CNN for spatial, LSTM for temporal, multi-source data, Transformer prediction	0.042	0.035	Optimized (15% faster)	High	Excellent	Yes (5 seconds)
Conv-LSTM	Spatio-temporal modeling with Conv-LSTM layers	0.049	0.041	Moderate	Moderate	Good	Partial (7 seconds)
RNN-LSTM	Temporal modeling using LSTM layers (agriculture)	0.056	0.047	Longer	Low	Moderate	No
CNN-Based	Spatial modeling	0.062	0.053	Faster	Low	Good	Yes

	using convolution al layers						
Transformer	Sequential modeling with attention mechanisms	0.044	0.037	Moderate	High	Excellent	Yes (6 seconds)
SMAP Downscaling	Deep belief networks for downscaling SMAP data	0.071	0.059	Moderate	Low	Limited	No

Comparison Table 2 highlights the superior performance of the proposed algorithm in single humidity forecasts. It shows the lowest RMSE (0.042) and MAE (0.035) among all compared methods. This success is due to the innovative combination of CNN for spatial feature extraction, LSTM for temporal dependencies, and Transformer for sequence modeling. Together with integrating multiple data sources, the Transformer-based model also has good performance and the proposed algorithm has the ability to fast scale and reduce training time using optimized hyperparameters. This is different from two conventional methods, such as RNN-LSTM or Conv-LSTM, which offer longer training times and limited interpretability. The above method proposes to balance accuracy and predictability in real time (5 seconds), in addition to novel scalability and high interpretability through resource selection. As a result, they are not ready for practical use in a variety of agricultural and hydrologic contexts.

4.1. Result Analysis

The results highlight the effectiveness of the proposed deep learning algorithm in predicting singleton accuracy with high accuracy. Among the models evaluated The proposed algorithm achieves the lowest RMSE (0.042) and MAE (0.035), indicating superior predictive ability. However, the Transformer-based model demonstrates competitive accuracy (RMSE: 0.048, MAE: 0.040), which requires higher training time. Emphasis is placed on the efficiency of the proposed method in the use of computational resources.[19]

The comparative analysis also shows the limitations of traditional architectures such as RNN-LSTM and Conv-LSTM, which have higher error rates (RMSE: 0.065 and 0.060, respectively) and longer prediction times. The optimized architecture of the proposed algorithm uses CNN for spatial feature extraction, LSTM for temporal dynamics, and Transformer for sequence modeling. Accuracy and interpretability are guaranteed, in addition to the ability to integrate and process diverse data sources. Including satellite images In situ sensor data and meteorological information It also increases durability in various environments.[20]

The new scalability and usability of the proposed model adds significant value. Allowing real-time predictions with low latency (5 seconds), this resource supports practical applications in agriculture and hydrology. It provides additional insights for stakeholders. Analysis of the results confirms that the proposed algorithm is not only a methodological breakthrough. But it is also a practical solution to the challenge of instantaneous forecasting alone.[25][26]

5. Discussion

The results emphasize the superiority of the proposed deep learning algorithm for accurate predictions alone. in terms of accuracy Computational efficiency and scalability By integrating spatial and temporal modeling techniques. The proposed method can effectively capture complex moisture dynamics under various environmental conditions. The combination of CNN for spatial feature extraction and LSTM with Transformer for time series analysis increases the prediction power and capability of nterpretation of the model.[18]

Compared with existing methods such as RNN-LSTM and Conv-LSTM, the proposed algorithm has a significantly lower error rate, with RMSE and MAE values of 0.042 and 0.035, respectively, an improvement. This can be attributed to optimized architecture projects and the use of data from multiple sources. Including satellite images In situ sensor readings and meteorological data, Transformer-based models, which are competitive in accuracy. Shows longer training times It emphasizes the importance of balancing computational complexity and practical performance.[17]

Reduced latency in real-time forecasts Facilitated by new usability and API integration, the proposed model is a viable solution for agricultural and hydrological decision-making processes. Moreover, the integration of anomaly detection mechanisms increases its usefulness. It can provide advance warning about abnormal humidity only. This is necessary for proactive management of both resources.

Despite the promising results But there are some challenges, such as the potential need for improvements in unique regions or the limited availability of data. Future work may focus on further optimizing the algorithm for these conditions. and explore its adaptability to other domains. Overall, the discussion confirms that the proposed method represents a significant advance in single surface prediction. It addresses the limitations of traditional methods. while providing practical benefits for real-world applications.[15]

6. Conclusion

This research evaluates the performance of deep learning algorithms in accurately predicting two-level humidity alone. using remote sensing data In situ sensor measurement and meteorological information The proposed algorithm combines CNN for spatial feature extraction and LSTM with Transformer for temporal dependency modeling. It shows superior performance compared to existing approaches, with significantly lower RMSE (0.042) and MAE (0.035). The model thus outperforms RNN-LSTM, Conv-LSTM, and the Transformer method alone in prediction accuracy.

The study emphasizes the importance of leveraging various information sources. and advanced deep learning techniques to address the complexities of singleness dynamics. The proposed method also offers real-time prediction capabilities and an efficient anomaly detection mechanism. This makes it very useful for agricultural management. irrigation planning and environmental monitoring. In addition, the use of models on the new platform guarantees scalability and perfect integration with decision support systems.

The results are promising, though. But this study acknowledges the challenges involved in adapting models to specific regional conditions or limited data situations. Future work may involve further generalization of the model. Combining additional data types and extending the approach to other environmental forecasting tasks. Overall, the research contributes to new solutions. Powerful and accurate only for humidity forecasts. It has a significant impact on sustainable resource management and climate resilience.

6.1. Future Research Directions

From the results of this research Some future directions can be pursued to increase the accuracy and applicability of deep learning-only urgent prediction models, firstly by integrating additional data sources such as hyperspectral images and single data types. It can improve the context understanding and, accuracy of the model under various agricultural and environmental, conditions., Second, the development of transfer learning techniques will, allow the proposed model to be adapted to the company, training data region, which faces challenges in the data shortage situation.

Additionally, the inclusion of more explanatory IA techniques can improve model interpretation. Help stakeholders understand the decision-making process and build confidence in automation. Research can also explore hybrid architectures that combine classical statistical methods with deep learning models to balance interpretability and predictive performance. Models to predict relevant parameters such as evapotranspiration and groundwater levels. It could create a more open framework for water resource management.

Ultimately, this research focuses on real-world applications such as precision agriculture and drought relief. It validates the model and reveals potential scalability challenges. These advances will further establish the proposed method as a reliable and adaptable solution for the immediate foresight of individual and large-scale environmental management initiatives.

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Refrences

[1] Hegazi EH, Samak AA, Yang L, Huang R, Huang J. 2023. Prediction of soil moisture content from sentinel-2 images using convolutional neural network (CNN). Agronomy. 13(3):656. doi: 10.3390/agronomy13030656.

[2] Huang F, Zhang Y, Zhang Y, Shangguan W, Li Q, Li L, Jiang S. 2023. Interpreting Conv-LSTM for spatio-temporal soil moisture prediction in China. Agriculture. 13(5):971. doi: 10.3390/agriculture13050971.

[3] Park S-H, Lee B-Y, Kim M-J, Sang W, Seo MC, Baek J-K, Yang JE, Mo C. 2023. Development of a soil moisture prediction model based on recurrent neural network long short-term memory (RNN-LSTM) in soybean cultivation. Sensors. 23(4):1976. doi: 10.3390/s23041976.

[4] Singh A, Gaurav K. 2023. Deep learning and data fusion to estimate surface soil moisture from multi-sensor satellite images. Scientific Reports. 13(1):2251. doi: 10.1038/s41598-023-28939-9.

[5] Singh A, Gaurav K, Sonkar GK, Lee C-C. 2023. Strategies to measure soil moisture using traditional methods, automated sensors, remote sensing, and machine learning techniques: review, bibliometric analysis, applications, research findings, and future directions. IEEE Access. 11:13605–13635. doi: 10.1109/ACCESS.2023.3243635.

[6] Wang Y, Shi L, Hu Y, Hu X, Song W, Wang L. 2023. A comprehensive study of deep learning for soil moisture prediction. Hydrology and Earth System Sciences Discussions. 28:1–38..

[7] Cai, Y. L., P. R. Fan, S. Lang, M. Y. Li, Y. Muhammad, and A. X. Liu, 2022: Downscaling of SMAP soil moisture data by using a deep belief network. Remote Sensing, 14, 5681, https://doi.org/10.3390/rs14225681.

[8] Wang Y, Zha Y. 2024. Comparison of transformer, LSTM and coupled algorithms for soil moisture prediction in shallow-groundwater-level areas with interpretability analysis. Agric Water Manage. 305:109120. doi: 10.1016/j.agwat.2024.109120.

[9] Daw, A., A. Karpatne, W. D. Watkins, J. S. Read, and V. Kumar, 2022: Physics-guided neural networks (PGNN): An application in lake temperature modeling. Knowledge Guided Machine Learning, Chapman and Hall/CRC, 353–372.

[10] Feng, D. P., J. T. Liu, K. Lawson, and C. P. Shen, 2022: Differentiable, learnable, regionalized process-based models with multiphysical outputs can approach state-of-the-art hydrologic prediction accuracy. Water Resour. Res., 58, e2022WR032404, https://doi.org/10.1029/2022WR032404.

[11] Kannan, A., G. Tsagkatakis, R. Akbar, D. Selva, V. Ravindra, R. Levinson, S. Nag, and M. Moghaddam, 2022: Forecasting soil moisture using a deep learning model integrated with passive microwave retrieval. Preprints, IGARSS 2022–2022 IEEE International Geoscience and Remote Sensing Symposium, Kuala Lumpur, Malaysia, IEEE, 6112–6114, https://doi.org/10.1109/IGARSS46834.2022.9883245.

[12] Lee, J., S. Park, J. Im, C. Yoo, and E. Seo, 2022: Improved soil moisture estimation: Synergistic use of satellite observations and land surface models over CONUS based on machine learning. J. Hydrol., 609, 127749, https://doi.org/10.1016/j.jhydrol.2022.127749.

[13] Li, L., Y. J. Dai, W. Shangguan, N. Wei, Z. W. Wei, and S. Gupta, 2022a: Multistep forecasting of soil moisture using spatiotemporal deep encoder-decoder networks. Journal of Hydrometeorology, 23, 337–350, https://doi.org/10.1175/JHM-D-21-0131.1.

[14] Liu, L. C., and Coauthors, 2022: KGML-ag: A modeling framework of knowledge-guided machine learning to simulate agroecosystems: A case study of estimating N2O emission using data from mesocosm experiments. Geoscientific Model Development, 15, 2839–2858, https://doi.org/10.5194/gmd-15-2839-2022..0302

[15] Sabzipour, B.; Arsenault, R.; Troin, M.; Martel, J.-L.; Brissette, F.; Brunet, F.; Mai, J. Comparing a long short-term memory (LSTM) neural network with a physically-based hydrological model for streamflow forecasting over a Canadian catchment. J. Hydrol. 2023, 627, 130380.

[16] Lei, G.; Zeng, W.; Yu, J.; Huang, J. A comparison of physical-based and machine learning modeling for soil salt dynamics in crop fields. Agric. Water Manag. 2023, 277, 108115.

[17] Zhang, G. Synergistic advantages of deep learning and reinforcement learning in economic forecasting. Int. J. Glob. Econ. Manag. 2023, 1, 89–95.

[18] Tesch, T.; Kollet, S.; Garcke, J. Causal deep learning models for studying the Earth system. Geosci. Model Dev. 2023, 16, 2149–2166.

[19] Chen, Z.; Zhang, R.; Song, Y.; Wan, X.; Li, G. Advancing Visual Grounding with Scene Knowledge: Benchmark and Method. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Vancouver, BC, Canada, 17–24 June 2023.

[20] P. K. Verma, P. Pathak, B. Kumar, H. Himani, and P. Preety, "Automatic Optical Imaging System for Mango Fruit using Hyperspectral Camera and Deep Learning Algorithm," International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 5s, pp. 112–117, 2023, doi: 10.17762/ijritcc.v11i5s.6635.

[21] P. K. Verma, V. Sharma, P. Kumar, S. Sharma, S. Chaudhary, and P. Preety,(2023) "IoT Enabled Real-Time Appearance System using AI Camera and Deep Learning for Student Tracking," International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 6s, pp. 249–254, 2023, doi: 10.17762/ijritcc.v11i6s.6885

[22] Li, Q.; Zhang, C.; Shangguan, W.; Li, L.; Dai, Y. A novel local-global dependency deep learning model for soil mapping. Geoderma 2023, 438, 116649.

[23] Lal, P.; Shekhar, A.; Gharun, M.; Das, N.N. Spatiotemporal evolution of global long-term patterns of soil moisture. Sci. Total. Environ. 2023, 867, 161470.

[24] Datta, P.; Faroughi, S.A. A multihead LSTM technique for prognostic prediction of soil moisture. Geoderma 2023, 433, 116452.

[25] Anshuman, A.; Eldho, T. A parallel workflow framework using encoder-decoder LSTMs for uncertainty quantification in contaminant source identification in groundwater. J. Hydrol. 2023, 619, 129296.

[26] Yang, Y.; Gao, P.; Sun, Z.; Wang, H.; Lu, M.; Liu, Y.; Hu, J. Multistep ahead prediction of temperature and humidity in solar greenhouse based on FAM-LSTM model. Comput. Electron. Agric. 2023, 213, 108261.