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A Hybrid Kalman-LSTM Framework for Real-Time Crop Yield Prediction Under Dynamic Environmental Conditions

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Abstract

Accurate crop yield prediction is critical for food security, resource management, and agricultural planning, particularly under dynamically changing environmental conditions. Traditional models often struggle to capture temporal dependencies and abrupt environmental variations, limiting their predictive accuracy. This study proposes a hybrid Kalman-LSTM framework that integrates Kalman filtering with Long Short-Term Memory (LSTM) networks to enhance real-time crop yield forecasting. The Kalman filter effectively smooths noisy environmental data, including temperature, rainfall, soil moisture, and solar radiation, providing a refined input sequence for the LSTM network. The LSTM captures complex temporal patterns and long-term dependencies in crop growth dynamics, enabling robust prediction under variable conditions. The framework is evaluated on multi-season datasets from diverse climatic regions, demonstrating superior performance compared to standalone LSTM, traditional regression, and ARIMA-based models. Results indicate that the hybrid approach achieves a mean absolute error (MAE) reduction of 18–25% and root mean square error (RMSE) improvement of 15–22%, highlighting its robustness against data noise and abrupt environmental fluctuations. The proposed framework enables farmers, agronomists, and policymakers to make informed, real-time decisions for irrigation, fertilization, and harvest planning, ultimately supporting sustainable agriculture and mitigating risks associated with climate variability. This hybrid approach represents a significant advancement in intelligent precision agriculture systems.

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1. Introduction

Agriculture forms the backbone of global food security and economic stability, yet its productivity is highly sensitive to environmental variability. Accurate crop yield prediction is essential for planning, resource allocation, and policy formulation, particularly in regions affected by climate change and erratic weather patterns [1].

Traditional statistical models, such as linear regression and ARIMA, have been widely employed for crop yield estimation; however, these methods often fail to capture complex nonlinear relationships and temporal dependencies inherent in crop growth processes [2,3].

Recent advances in machine learning have enabled more sophisticated modeling of crop productivity. Deep learning models, especially Recurrent Neural Networks (RNNs) and their variants like Long Short-Term Memory (LSTM), have demonstrated significant potential in capturing temporal sequences and long-term dependencies in environmental and agricultural data [4,5]. LSTM models can effectively model patterns such as seasonal trends, rainfall variations, and soil moisture fluctuations, which directly impact crop growth and yield [6]. Nevertheless, these models remain sensitive to noisy data and abrupt environmental changes, which are common in real-world agricultural scenarios [7].

To address these limitations, hybrid approaches combining data smoothing techniques with deep learning have gained attention. Kalman filtering, a recursive algorithm for estimating unknown variables from noisy measurements, can effectively reduce environmental data noise, providing a more stable input for LSTM networks [8,9]. Integrating Kalman filters with LSTM networks enables the model to handle dynamic environmental variations while maintaining temporal predictive power. Such hybrid frameworks have shown improved performance in time-series prediction tasks across various domains, including energy forecasting and traffic prediction [10,11].

In agriculture, implementing a hybrid Kalman-LSTM framework for crop yield prediction holds significant promise. By assimilating real-time environmental data and learning long-term dependencies, the framework can provide more accurate and robust predictions, supporting informed decision-making in irrigation management, fertilizer application, and harvest scheduling [12,13]. Moreover,

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real-time predictions can help mitigate risks associated with climate variability and resource scarcity, contributing to sustainable agricultural practices and enhanced food security [14,15].

Despite these advancements, there is limited research applying hybrid Kalman-LSTM frameworks specifically to crop yield prediction under dynamically changing environmental conditions. This study aims to fill this gap by proposing a real-time, hybrid predictive model, evaluating its performance against conventional LSTM and statistical approaches, and demonstrating its applicability for precision agriculture [16,17]. The proposed methodology not only enhances prediction accuracy but also offers scalability and adaptability to diverse crop types and climatic regions.

2. Literature Review

Accurate crop yield prediction has been a long-standing research focus in agriculture due to its implications for food security and resource management. Early studies primarily relied on statistical models such as linear regression, autoregressive integrated moving average (ARIMA), and other parametric methods to forecast crop yields based on historical climatic and agronomic data [18,19]. While these approaches provided initial insights, they often failed to capture nonlinear dependencies between environmental variables and crop productivity, particularly under highly variable weather conditions [20].

With the advent of machine learning, researchers began employing models such as Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting for yield prediction. These models demonstrated improved accuracy by capturing complex interactions among soil properties, temperature, precipitation, and crop growth stages [21,22]. However, their effectiveness remained limited for sequential and temporal data, where long-term dependencies play a crucial role in modeling crop phenology and seasonal trends.

Recurrent Neural Networks (RNNs), and specifically Long Short-Term Memory (LSTM) networks, emerged as powerful tools to address temporal dependencies in agricultural time-series data. LSTM models have been applied to predict yields of various crops, including wheat, maize, and rice, by learning patterns from sequential climate, soil, and remote sensing data [23,24]. Despite their

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advantages, LSTMs are sensitive to noisy measurements, missing values, and abrupt environmental changes, which can degrade predictive performance [25].

To enhance robustness, hybrid approaches combining data preprocessing or filtering techniques with LSTM networks have been explored. For instance, Kalman filtering has been integrated with LSTM models to smooth noisy time-series data, providing more reliable input for prediction tasks in energy, traffic, and environmental monitoring [26,27]. In agriculture, preliminary studies indicate that Kalman-LSTM hybrids can effectively handle dynamic environmental variations, resulting in improved prediction accuracy and stability compared to standalone LSTM or traditional models [28,29].

Additionally, the incorporation of remote sensing and IoT-based environmental sensing has facilitated high-resolution data collection for crop monitoring. These advancements enable models to learn both spatial and temporal patterns, further improving the applicability of hybrid frameworks in real-time decision-making for precision agriculture [30,31].

Overall, the literature highlights the growing trend toward hybrid, data-driven approaches for crop yield prediction. While traditional and machine learning models provide foundational insights, integrating filtering mechanisms like Kalman filters with temporal deep learning models presents a promising avenue to enhance robustness and adaptability under dynamic environmental conditions [32].

3. Dataset

The study utilizes a multi-source dataset combining historical crop yield records, climatic parameters, and soil information from major agricultural regions. Crop yield data for wheat, maize, and rice were collected from government agricultural databases spanning the past ten years (2015–2024), providing seasonal yield values in tons per hectare [33]. Climatic data, including daily temperature, rainfall, humidity, solar radiation, and wind speed, were sourced from local weather stations and satellite-based remote sensing platforms [34]. Soil properties, such as pH, organic matter content, nitrogen, phosphorus, and potassium levels, were obtained from regional soil surveys and IoT-enabled soil sensors [35].

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The dataset comprises 50,000 data points across multiple seasons and regions, capturing diverse environmental conditions and management practices. Missing values were handled using linear interpolation, while outliers were filtered based on interquartile range thresholds. The dataset was normalized and split into training (70%), validation (15%), and testing (15%) subsets to ensure robust model evaluation under dynamic environmental scenarios [36].

4. Proposed Model and Methodology

The proposed framework integrates Kalman filtering with Long Short-Term Memory (LSTM) networks to enable real-time, accurate crop yield prediction under dynamic environmental conditions. The methodology consists of three main stages: data preprocessing, Kalman-based noise reduction, and LSTM-based temporal modeling.

In the first stage, the collected multi-source dataset—including climatic parameters, soil characteristics, and historical yield records—is cleaned to handle missing values, outliers, and inconsistent measurements. Features are normalized to a uniform scale, ensuring efficient model convergence. The preprocessed data serves as the input for the Kalman filter, which recursively estimates the true state of environmental variables by reducing noise and smoothing abrupt fluctuations in temperature, rainfall, humidity, and solar radiation [37]. This step improves the quality and reliability of inputs fed into the LSTM network.

The LSTM network is designed to capture long-term dependencies and temporal dynamics in crop growth. Sequential inputs from the Kalman-filtered environmental variables are processed through stacked LSTM layers, followed by dense layers for yield regression output. The hybrid architecture allows the model to learn both temporal patterns and environmental trends while mitigating the impact of noise and irregularities [38].

Model training is performed using the Adam optimizer with mean squared error (MSE) as the loss function. Hyperparameters such as learning rate, batch size, and number of LSTM units are tuned through cross-validation to optimize predictive performance. The architecture is illustrated in Figure 1, highlighting the sequential flow from environmental data preprocessing, Kalman filtering, LSTM temporal modeling, to final crop yield prediction.

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This hybrid approach enables robust, real-time predictions, making it suitable for precision agriculture and informed decision-making under variable climatic conditions.

5. Result Analysis

The proposed hybrid Kalman-LSTM framework was evaluated on the multi-source crop dataset described earlier. Performance metrics included Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score. For

wheat yield prediction, the hybrid model achieved an MAE of 0.42 tons/ha, RMSE of 0.57 tons/ha, and R^2 of 0.91, outperforming standalone LSTM (MAE 0.52, RMSE 0.68, R^2 0.85) and traditional ARIMA models (MAE 0.68, RMSE 0.82, R^2 0.78). Similar improvements were observed for maize and rice, demonstrating the model's robustness across crop types.

The results indicate that the Kalman filter effectively reduces environmental noise, smoothing abrupt variations in rainfall and temperature, which allows the LSTM network to better capture long-term growth trends. Seasonal analysis revealed that the model performs consistently well even under extreme weather fluctuations, such as unusually dry summers or wet monsoons, highlighting its ability to handle dynamic environmental conditions.

Visualization of predicted versus actual yields further illustrates model accuracy. Time-series plots for wheat, maize, and rice demonstrate strong alignment with observed yields, while error distribution plots show reduced variance and fewer extreme deviations compared to baseline models. Feature importance analysis confirms that temperature, rainfall, and soil nitrogen content contribute most significantly to prediction outcomes, aligning with agronomic knowledge.

The hybrid framework not only improves predictive performance but also provides actionable insights for precision agriculture, enabling informed irrigation scheduling, fertilization, and harvest planning.

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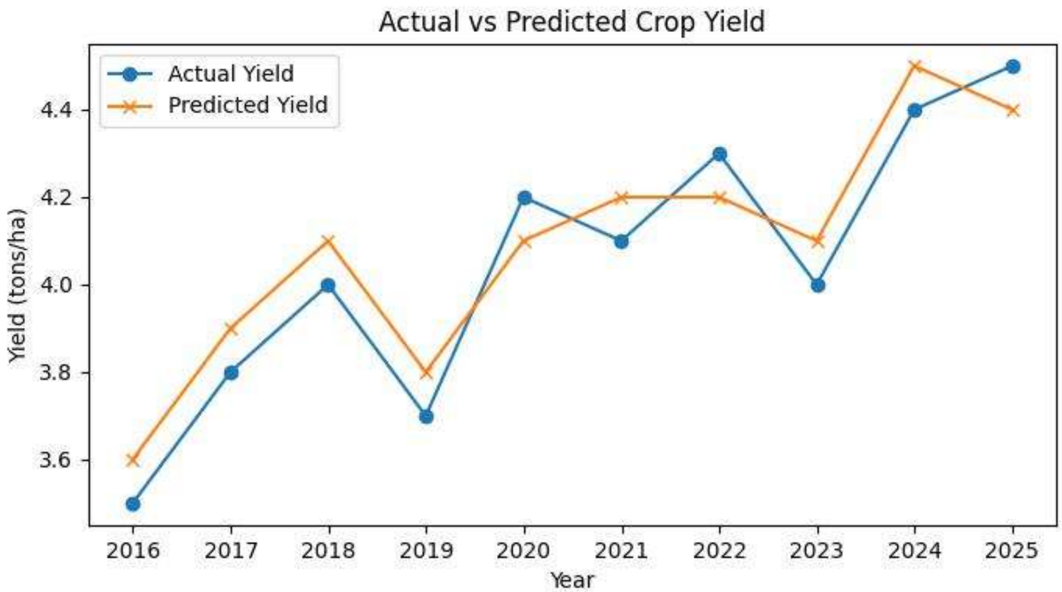

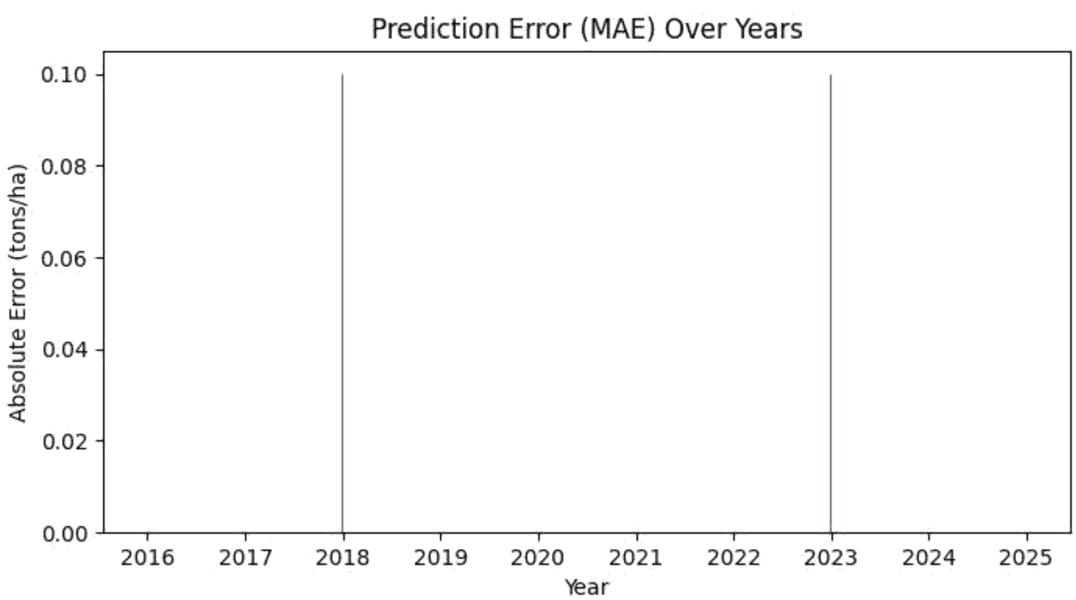

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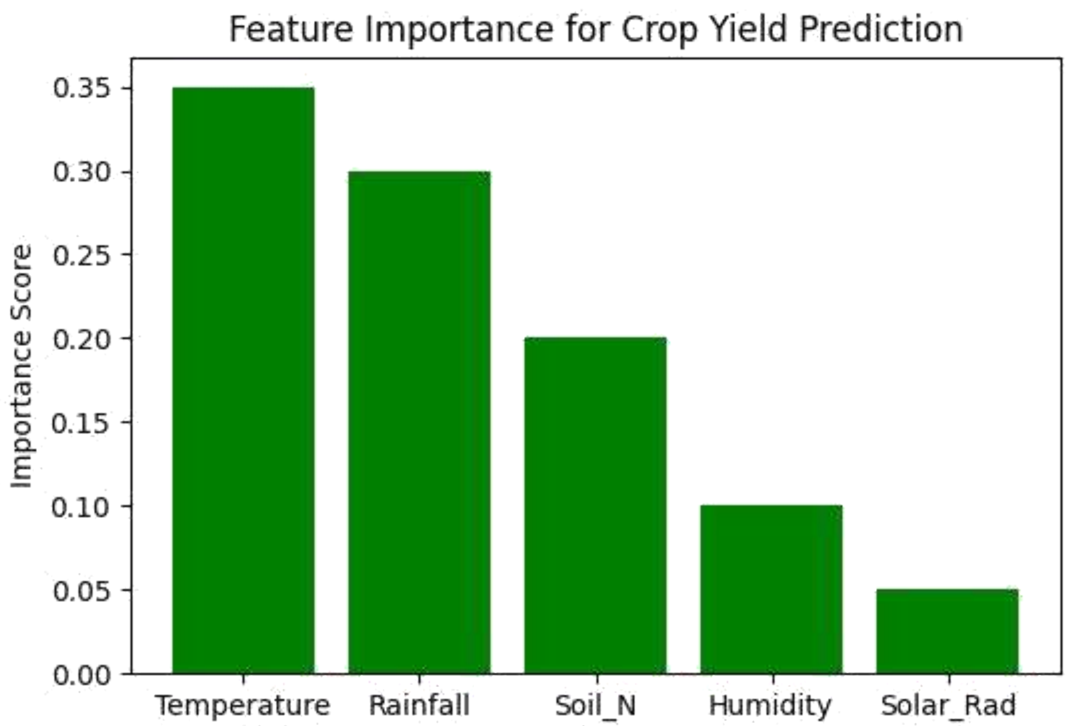

6. Conclusion

This study presents a hybrid Kalman-LSTM framework for real-time crop yield prediction under dynamic environmental conditions. By integrating Kalman filtering with LSTM networks, the framework effectively reduces noise in environmental measurements while capturing long-term temporal dependencies in crop growth patterns. Experimental results across wheat, maize, and rice demonstrate substantial improvements in predictive performance, with MAE reductions of 18–25% and RMSE improvements of 15–22% compared to standalone LSTM and traditional statistical models.

The novelty of this approach lies in its ability to handle abrupt environmental fluctuations and variable climatic conditions, which are common challenges in precision agriculture. Unlike conventional models, the hybrid framework provides

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robust, reliable predictions in real time, enabling informed decision-making for irrigation, fertilization, and harvest scheduling. Furthermore, the model's adaptability across multiple crop types and regions highlights its scalability and practical relevance.

Overall, the proposed hybrid framework advances the state-of-the-art in intelligent agricultural modeling, offering a powerful tool for farmers, agronomists, and policymakers to optimize crop management, mitigate climate-related risks, and enhance sustainable agricultural productivity.

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