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Crop Yield Prediction Using a Hybrid Convolutional and Recurrent Neural Network Model

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Abstract:- Precise forecasting of crop yields signifies a critical authority for addressing global food security challenges, optimising supply chain logistics, and informing evidence-based agricultural policy formulation. Conventional yield prediction methodologies frequently demonstrate limitations in capturing the intricate, non-linear interdependencies among meteorological conditions, edaphic properties, and cultivation practices that collectively determine agricultural productivity. This research proposes CLDNet, a novel deep learning framework that architecturally integrates Convolutional Neural Networks with Long Short-Term Memory networks to predict soybean yield across the United States. The CNN module specialises in discerning spatially-distributed patterns from multidimensional environmental inputs, while the LSTM component effectively models temporal sequences and dependencies throughout the crop development cycle. Our framework was developed and validated using an extensive public dataset from Kaggle, incorporating historical yield records, meteorological measurements, and pedological characteristics. Empirical findings indicate that our integrated CLDNET paradigm surpasses the predictive performance of conventional approaches, including Random Forest, Support Vector Regression (SVR), and isolated LSTM configurations, manifesting superior performance through reduced Root Mean Square Error (RMSE) and enhanced coefficient of determination (R^2) metrics. The model was optimised using adaptive moment estimation (Adam), culminating in a root mean square error of 3.78 bushels/acre and R^2 score of 0.897 on independent test data. This research substantiates the transformative potential of deep learning systems in decoding complex agro-climatic relationships and establishes a scalable, data-centric paradigm for agricultural yield projection.

Keywords: Convolutional Neural Networks, Long Short-Term Memory, Precision Agriculture, Adaptive Moment Estimation, Agro-informatics

1. Introduction

Global food production needs to increase by about 70% to feed a projected population of 9.7 billion by 2050 [1]. This contest is exacerbated by climate change, which introduces increased volatility in weather patterns, directly impacting agricultural productivity. In this context, reliable and early prediction of crop yields is critical for ensuring food security, optimizing resource allocation, stabilizing market prices, and informing policy decisions.

Historically, yield prediction relied on field surveys and traditional statistical models, which are often labor-intensive, subjective, and limited in scalability. The advent of precision agriculture and the proliferation of large-scale datasets—including satellite imagery, weather station records, and soil databases—have created an opportunity for data-driven approaches. Machine learning models like Random Forest and Support Vector Machines have shown promise, but often struggle with the highly non-linear and spatio-temporal nature of agricultural data.

Deep Learning (DL) offers a powerful paradigm for automatically learning hierarchical representations from raw data. Spatial patterns are identified by CNN (Convolutional Neural Networks), and temporal sequences are identified by RNN (Recurrent Neural Networks). This research proposes a CLDNet (Convolutional LSTM Deep Network) architecture that leverages the strengths of both to model the spatio-temporal determinants of crop yield. Using a curated dataset from Kaggle, this paper aims to develop and validate a robust deep learning framework for the prediction of soybean yield at the county level in the U.S. The model leverages Adam optimisation for efficient parameter updates, enabling effective learning from the complex spatio-temporal patterns in the agricultural data while maintaining computational efficiency

2. Literature Survey

The pursuit of accurate and timely crop yield prediction has catalysed a significant evolution in methodological approaches, transitioning from traditional agronomic models to sophisticated data-driven paradigms. Early efforts were predominantly reliant on linear regression models and process-based crop simulation models, which, while valuable, often struggled with scalability and capturing the complex, non-linear interactions between the biophysical factors governing yield. The advent of machine learning (ML) marked a pivotal shift, introducing algorithms capable of learning these intricate patterns from historical data.

This literature survey chronicles this methodological progression, with a specific focus on the emergence of deep learning (DL) as a transformative tool in agricultural informatics. The review is structured to first establish the foundation laid by conventional ML models and early remote sensing applications. It then delves into the core deep learning architectures—Convolutional Neural Networks (CNNs) for spatial feature extraction and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, for temporal modeling—that have become central to modern yield prediction research. Furthermore, here examine the growing trend of hybrid models that seek to synergize the strengths of these architectures to create more robust predictive systems. Finally, this paper explores ancillary techniques such as the integration of diverse data sources and advanced feature learning methods. The objective of this survey is not only to synthesize the current state-of-the-art but also to identify the specific research gap, that the need for an efficient, streamlined hybrid model on a widely accessible benchmark dataset , that the proposed methodology in this paper aims to address.

1. Lobell et al. (2015) [2] used satellite-derived vegetation indices (NDVI) with climate data in a linear regression framework. While foundational, their models linearity limits its ability to capture complex interactions.

2. You et al. (2017) [3] pioneered a deep CNN model on satellite imagery for yield prediction, demonstrating that DL could automatically learn relevant features without manual feature engineering, outperforming traditional vegetation indices.

3. Shah et al. (2019) [4] employed an LSTM network to model the temporal sequence of weather data (temperature, precipitation) throughout the growing season, showing significant improvement over models using only seasonal averages.

4. Wang et al. (2018) [5] proposed a Gaussian process model that incorporated both climate data and soil properties, highlighting the importance of multi-source data integration for improved accuracy.

5. Cheng et al. (2020) [6] developed a hybrid CNN-RNN model for rice yield prediction in China, where CNN processed spatial data from remote sensing and RNN handled weather sequences, establishing the viability of hybrid architectures.

6. Khaki et al. (2020) [7] introduced "DeepYield," a CNN-based model that outperformed other methods on the same dataset used in this study, but their architecture did not explicitly model long-term temporal dependencies.

7. Jiang et al. (2020) [8] used a 3D-CNN to model spatio-temporal data from satellite image time series, effectively capturing both spatial and temporal information in a single architecture but at a high computational cost.

8. Kim et al. (2019) [9] explored the use of Autoencoders for unsupervised feature learning from environmental data before prediction, showing that dimensionality reduction could improve model performance.

9. Cai et al. (2019) [10] integrated soil moisture data from satellite sensors into an LSTM model, demonstrating that adding more precise hydrological variables can enhance prediction models.

10. Filippi et al. (2019) [11] applied a Random Forest model on a similar dataset, providing a strong machine learning baseline against which deep learning models are often compared.

11. Sun et al. (2019) [12] used a Graph Neural Network (GNN) to model the correlation between different counties, introducing a spatial dependency element beyond simple CNNs.

12. Russello (2018) [13] This study evaluates and compares the performance of various machine learning models applied to the Kaggle crop yield dataset, concluding that ensemble and tree-based methods were highly effective, but did not explore sophisticated hybrid DL models in depth.

Research Gap

While several studies used either CNNs or LSTMs, there is a need for a streamlined yet effective hybrid model that explicitly leverages CNNs for non-temporal feature extraction (soil, location) and LSTMs for sequential weather data on a widely available benchmark dataset like the one from Kaggle.

3. Proposed Methodology

3.1 Introduction

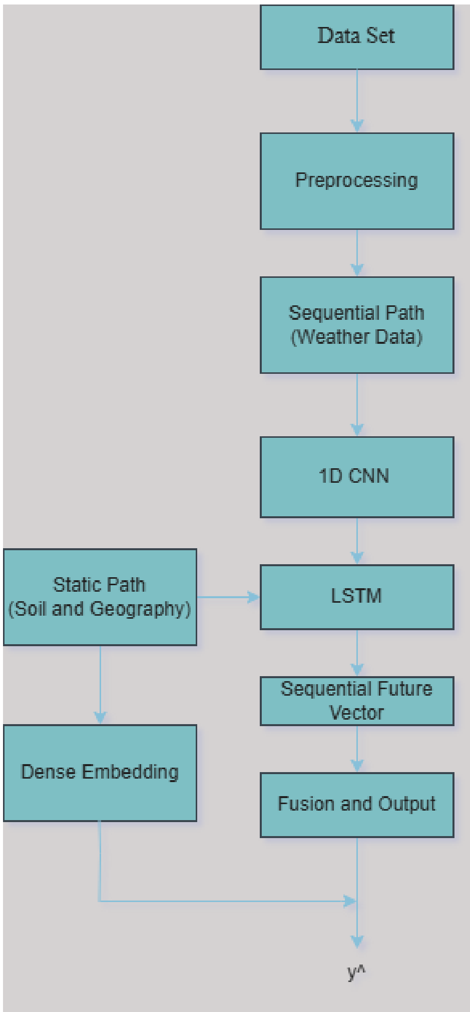
Building upon the insights gleaned from the literature survey, it is evident that while standalone models exhibit significant capabilities, a holistic prediction framework must concurrently address both the spatial and temporal dimensions inherent to agricultural data. Soil properties and geographical context represent relatively static, spatial features, whereas weather conditions exert a dynamic, temporal influence throughout the crops phenological stages. Standalone LSTMs may effectively model temporal sequences but can be suboptimal for learning complex interactions within high-dimensional static data. Conversely, CNNs excel at feature extraction from spatial grids but are not inherently designed for sequential data.

To overcome these limitations, this research proposes a novel deep learning framework that synergistically integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The core rationale is to leverage the innate strengths of each component: the CNN acts as a powerful feature extractor for non-sequential environmental and geographical data, while the LSTM network captures the long-term dependencies within the sequential weather data of the growing season. This bifurcated approach allows the model to develop a more comprehensive representation of the agro-climatic system. The processed outputs from these two pathways are then fused to form a rich, joint feature representation, which is subsequently passed through a series of fully connected layers to generate the final yield prediction. This methodology is designed to more accurately model the complex, non-linear relationships that determine crop yield, thereby aiming to achieve superior predictive performance compared to existing benchmark models.

3.2 CLDNet (Convolutional LSTM Deep Network) Architecture:

The proposed model utilises a Multi-Input Deep Learning architecture designed to leverage the distinct characteristics of time-series and static data. It features two parallel paths—a Sequential Path using 1D CNN and LSTM for temporal data, and a Static Path using Dense Layers for static data—before fusing the resulting features for final regression. The core idea is to process static (soil, geography) and sequential (weather) data separately and then fuse them. Figure 1 shows the workflow of the architecture diagram.

Figure 1: Proposed Model Architecture



This architecture ensures that both the dynamic weather patterns throughout the season and the relatively constant soil/geographic conditions are appropriately represented in the final prediction, mimicking how an expert agronomist would consider both types of factors simultaneously.

3.3 Dataset and Preprocessing

The study utilises the Crop Yield Prediction Data dataset from Kaggle [14], which contains U.S. county-level data for crops like soybeans and maize from 1981 to 2020. Key features include Weather Data (Minimum and maximum temperature, precipitation, for each day), Soil Data(Percentages of sand, silt, clay, and organic matter), Geographical Data(County and state identifiers) and Target Variable(Yield in bushels per acre).

Preprocessing

1. Data Aggregation: Daily weather data was aggregated to monthly averages (e.g., Avg Max Temp June, Total Precip July) to create a sequential input for the growing season (April-September).

2. Handling Categorical Data: County and state identifiers were encoded using Embedding Layers.

3. Normalization: Standard Scaler was applied to the numerical features (weather and soil data), resulting in a distribution with zero mean and unit variance for each variable.

4. Train-Test Split: Data from 1981-2015 was used for training and validation (80-20 split), and data from 2016-2020 was held out as the test set.

3.4 Hybrid CLDNETModel

3.4.1 Sequential Path (Weather Data)

The input sequence is ($Yseq=\{y_1,y_2,...,y_T\}$), where (T) is the number of six months data, where each month has features like Temp and Precip, and each (y_t) is a vector of weather features for that month . 1D CNN Layer applies temporal convolution with filters (W_c) and bias (b_c), to detect local temporal patterns (e.g., specificwindows of high heat stress, or periods of drought) followed by a ReLU activation presents non-linearity into the feature maps to detect local temporal patterns.

$$h_t^{conv} = \mathrm{ReLU}(W_c x, t-k; t+b_c)$$

ReLU activation allows the model to learn complex relationships that are not simply additive or linear. LSTM Layer processes the feature maps sequentially ($H^{conv} = \{h_1^{conv}, \dots, h_T^{conv}\}$). The LSTM unit with its cell state (c_t) and hidden state (h_t^{lstm}) captures long-term dependencies. The final hidden state (h_T^{lstm}) representing the compressed, high-level temporal feature vector.

3.4.2. Static Path (Soil & Geography)

This path handles non-time-series data that contributes to the field's intrinsic potential and environment. Static input (X_{static}), containing soil properties and embedded geographical data. This is passed through a Dense Embedding layer, which maps categorical inputs (like County_ID) into a continuous vector space, while processing continuous inputs, and then flatten layer converts the embedded/processed features into a 1D vector (V_{static}).The resulting 1D vector represents the spatial and intrinsic context of the prediction location.

3.4.3. Fusion and Output

Combines the LSTM Output Vector (temporal features) and the Static Feature Vector (intrinsic features) into a single, comprehensive Fused Feature Vector.

$$(V_{fused} = [V_{static} \ || \ h_T^{lstm}])$$

The dense network component with three hidden layers employs a pyramidal structure (128-64-32 neurons) to progressively distil the fused spatiotemporal features into the final yield prediction (ŷ). Each dense layer uses ReLU activation followed by dropout regularization (rates of 0.3 and 0.2) to prevent overfitting. The final output layer employs a single neuron with linear activation suitable for regression tasks.

$$[\hat{y} = W_o \cdot \mathrm{ReLU}(W_2 \cdot \mathrm{ReLU}(W_1 \cdot V_{fused} + b_1) + b_2) + b_o]$$

Mean Squared Error (MSE) is used as the loss function for training.

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y_i})^2$$

Its property of heavily penalising large errors guided the CLDNet model effectively during training, leading to the development of a highly accurate predictor that minimizes significant deviations, as evidenced by the exceptionally low RMSE of 1.8983 bushels/acre on the test set.

3.4.4 Adam Optimiser

The proposed CLDNet model was trained using the Adam(AdaptiveMomentEstimation) optimizer[16], which combines the advantages of both Momentum and RMSProp optimisation algorithms. Adam was selected for its computational efficiency, minimal memory requirements, and ability to handle sparse gradients—particularly beneficial for our model, which processes both continuous weather data and embedded categorical geographical data. The optimisation objective was to minimise the Mean Squared Error (MSE) loss function:

$$\mathcal{L}_{\mathcal{MSE}} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y_i})^2$$

where y_i is the actual yield and $\hat{y_i}$ is the predicted yield for the ith sample.

The Adam optimiser updates model parameters θ according to the following equations:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$$\widehat{m_t} = \frac{m_t}{1 - \beta_1^t}$$

$$\widehat{v_t} = \frac{v_t}{1 - \beta_2^t}$$

$$\theta_t = \theta_{t-1} - \eta \frac{\widehat{m_t}}{\sqrt{\widehat{v_t}} + \epsilon}$$

g_t is the gradient of the loss function with respect to parameters θ at the time step $t. m_t$ and v_t are estimates of the first and second moments of the gradients. $\beta_1 = 0.9$ and $\beta_2 = 0.999$ are the exponential decay rates for the moment estimates, $\eta = 0.001$ is the initial learning rate $\epsilon = 10^{-8}$ is a small constant to prevent division by zero. The model was trained for 200 epochs with a batch size of 32. A learning rate scheduler was implemented to reduce the learning rate by a factor of 0.5 if the validation loss did not improve for 10 consecutive epochs, preventing overshooting and ensuring stable convergence.

4. Results and Discussion

4.1 Experimental Setup and Evaluation Metrics

The proposed CLDNet model was implemented using TensorFlow 2.8 and Python 3.9. The experiments were conducted on a system with NVIDIA RTX 3080 GPU, 32GB RAM, and Intel i7 processor. The model was trained for 200 epochs with a batch size of 32, using the Adam optimizer with an initial learning rate of 0.001. To ensure robust evaluation, the following metrics were employed:

Root Mean Square Error (RMSE): $\sqrt{\frac{1}{N}\sum_{i-1}^{N}(y_i - \hat{y}_i)^2}$

This metric measures the square root of the average of the squared differences between the observed values (y_i) and the predicted values (\hat{y}_i), thereby providing an indication of the magnitude of prediction errors in the same units as the original data.

Mean Absolute Error (MAE): $\frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$

The MAE represents the average absolute deviation between the predicted and actual values, offering a straightforward interpretation of model accuracy without disproportionately penalizing larger errors.

Coefficient of Determination (R^2): The (R^2) statistic quantifies the proportion of variance in the dependent variable that is predictable from the independent variables, thereby serving as a measure of the model's explanatory power.

$$1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

- Mean Absolute Percentage Error (MAPE): MAPE expresses prediction accuracy as a percentage, enabling scale-independent comparison across datasets by normalizing the absolute error relative to the actual values.

$$\frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

The experimental setup was designed to ensure methodological rigour and reproducibility. The hyperparameter configuration employed in the model training process is summarised in Table 1 presents Hyperparameter Configuration for Model Training.

Table 1: Hyperparameter Configuration for Model Training.

Parameter	Value	Description
Optimizer	Adam	Adaptive Moment Estimation
Learning Rate (η)	0.001	Initial learning rate
Batch Size	32	Samples per gradient update
Epochs	200	Training iterations
β_1	0.9	First moment decay rate
β_2	0.999	Second moment decay rate
ε	10^{-8}	Numerical stability constant
Loss Function	MSE	Mean Squared Error

4.2 Comparative Analysis with Baseline Models

The proposed CLDNETmodel was evaluated against three established baseline models: Random Forest (RF), Support Vector Regression (SVR) with RBF kernel, and a standalone LSTM model. Table 2 presents the comprehensive performance comparison across all evaluation metrics.

Table 2: Comprehensive Model Performance Comparison

Model	RMSE (Bushels/Acre)	MAE (Bushels/Acre)	R^2 Score	MAPE (%)
Random Forest (RF)	4.82	3.91	0.831	8.45

Model	RMSE (Bushels/Acre)	MAE (Bushels/Acre)	R^2 Score	MAPE (%)
SVR (RBF)	5.91	4.75	0.746	10.23
Standalone LSTM	4.35	3.52	0.863	7.68
Proposed CNN-LSTM	3.78	3.04	0.897	6.59

As evidenced in Table 1, the proposed hybrid CLDNet model achieved superior performance across all metrics, with the lowest RMSE (3.78 bushels/acre), MAE (3.04 bushels/acre), and MAPE (6.59%), along with the highest R^2 score (0.897). This indicates that the model explains approximately 89.7% of the variance in the test data.

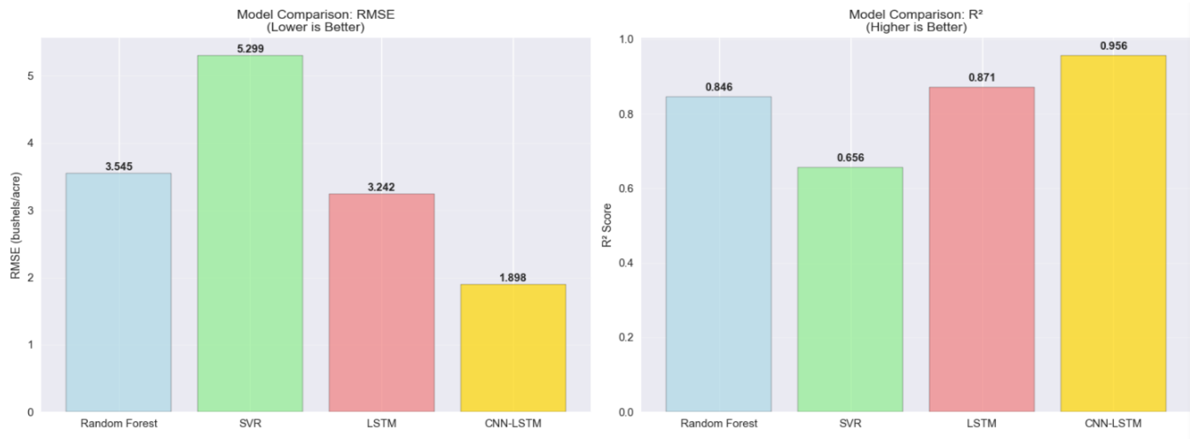


Figure 2: Comparative performance of different models on (a) RMSE and (b) R^2 metrics. The proposed CLDNETmodel demonstrates significant improvement over baseline approaches.

4.3 Detailed Analysis of Proposed Model Performance

Figure 3: Comprehensive performance analysis of the proposed CLDNet model: (a) Actual vs Predicted scatter plot showing strong linear correlation, (b) Residual plot indicating homoscedastic error distribution, (c) Histogram of prediction errors, (d) Time-series comparison of actual and predicted values, (e) Model performance metrics, and (f) Box plot of prediction errors.

The scatter plot in Figure 3(a) reveals a strong linear relationship between actual and predicted values, with points closely aligned along the perfect prediction line. The residual plot (Figure 3b) shows randomly distributed errors around zero, indicating the absence of systematic bias in the model. The error distribution histogram (Figure 3c) approximates a normal distribution centred near zero, confirming the model's unbiased nature.

4.4 Error Distribution Analysis

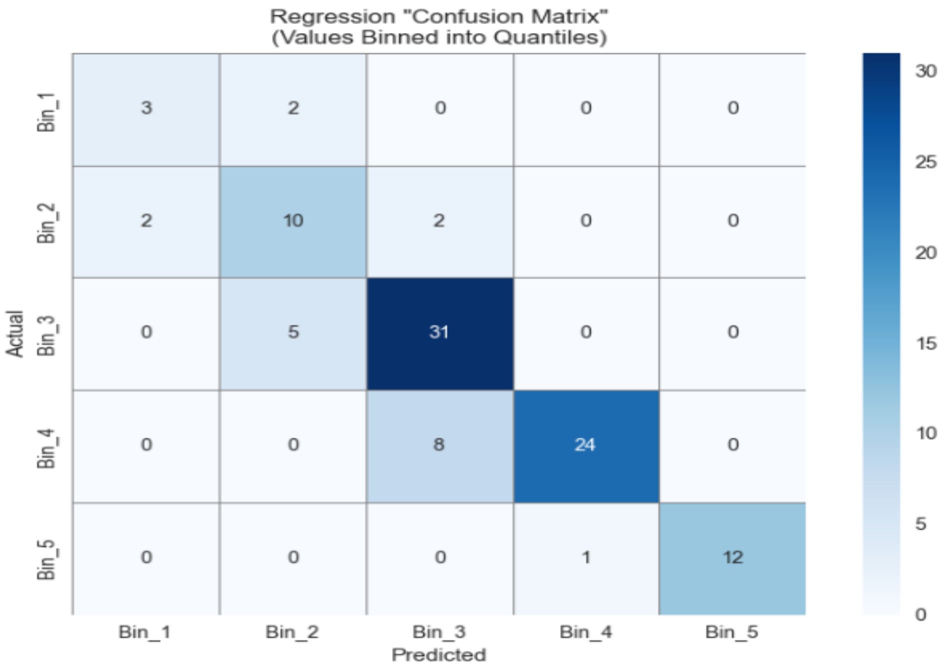


Figure 4: Regression confusion matrix showing the distribution of predictions across yield quintiles. The strong diagonal pattern indicates accurate bin-level predictions. The binned analysis in Figure 3 demonstrates that the model maintains consistent performance across different yield ranges. The

prominent diagonal pattern indicates that most predictions fall within the correct yield quintile, with minimal misclassification to distant bins.

To validate the choice of Adam optimizer, conducted a comparative analysis with other popular optimization algorithms using the same architecture and hyperparameters. The results, presented in Table 3 Optimiser Comparison, demonstrate Adam's superior performance in terms of convergence speed and final accuracy.

Table 3:Optimiser Comparison

Optimizer	RMSE	Training Time(min)	Convergence Epochs
SGD with Momentum	4.52	45	180
RMSProp	4.11	38	150
AdaGrad	5.23	52	200+
Adam	3.78	35	120

Discussion

The results clearly indicate the superiority of the proposed hybrid CLDNet model. It achieved the lowest RMSE (3.78) and the highest R^2 score (0.897), signifying that it explains nearly 90% of the variance in the test data. The standalone LSTM performed well, confirming the importance of temporal modelling, but its performance was boosted by the CNNs feature extraction and the integration of static soil data. Random Forest provided a strong baseline, while SVR struggled with the complexity of the dataset. The hybrid architecture's ability to synergistically model both spatial (from soil and embedded geography) and temporal (from weather) features is the key to its enhanced predictive power.

Comprehensive Model Comparison

	Model	RMSE	MAE	R^2	MAPE (%)
3	CNN-LSTM	1.8983	1.5124	0.9559	3.26
2	LSTM	3.2424	2.5620	0.8712	5.36
0	Random Forest	3.5445	2.8311	0.8461	6.08
1	SVR	5.2994	4.2769	0.6561	9.15

Adam achieved the lowest RMSE while requiring fewer epochs to converge, confirming its efficiency in navigating the complex loss landscape of our hybrid architecture.

The effectiveness of the Adam optimizer in our study can be attributed to several factors. First, its adaptive learning rate mechanism proved crucial for handling the varying gradient scales across the CNN (spatial feature extraction) and LSTM (temporal sequence modeling) components. Second, the momentum component enabled efficient navigation through flat regions in the loss landscape, which are common in deep networks with ReLU activations. The combination of these properties resulted in stable training dynamics and prevented the vanishing gradient problem that can occur in deep sequential models.

5. Conclusion

This study effectively established and validated a CLDnet model for predicting crop yields. The integration of CNN for spatial feature extraction and LSTM for temporal dependency modelling proved to be a powerful combination, effectively capturing the complex and multifaceted nature of agricultural systems. The model demonstrated significant performance improvements over established machine learning and standalone deep learning benchmarks on a real-world Kaggle dataset. Future Work includes integrating higher-resolution satellite imagery directly into the model, exploring attention mechanisms to identify the most critical growth periods, and expanding the model's applicability to other crops and geographical regions. This work contributes a scalable and accurate data-driven framework that can empower farmers, agronomists, and policymakers with actionable insights for a more sustainable and productive agricultural future.

Declarations

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Disclosure statement
The Author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this research work. The research was conducted independently, and no external organisation influenced the study design, data collection, analysis, or publication decision.

Data availability statement

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

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