Abhishek Sharma, 2026, 14:4
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Yield Enhancement and Prediction of Crops Using Deep Learning

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Abstract- Agriculture all over the globe is becoming more challenging due to increasing populations, erratic climate conditions, and a scarcity of cultivable land. The ability to predict crop yields accurately is crucial for the development of management strategies for agriculture and for the guarantee of food security. Traditional statistical models oftentimes do not reflect the complex, nonlinear interactions among the factors of crop, soil, and environment. A very effective approach for precision agriculture is deep learning (DL), a branch of artificial intelligence that can model high-dimensional and unstructured data. A comprehensive review of the application of DL models in agriculture as a tool for the prediction and enhancement of production is the focus of this paper. The research indicates improved accuracy of forecasts for multiple crops by evaluation of various architectures, such as CNN, LSTM, and hybrid CNN-LSTM models with attention mechanisms. Moreover, the integration of climate factors, soil properties, and remote sensing data gives valuable insights into the application of yield improvement strategies. There is also discussion of future prospects and challenges, such as transparency, data limitation, and scalable implementation.

Keywords: Crop yield prediction, deep learning, precision agriculture.

I. INTRODUCTION

Agriculture is the foundation of both economic stability and global food. Crop productivity must expand rapidly while limiting the restrictions of water, land, and climate unpredictability as population of the world is anticipated to approach 10 billion by 2050 [1]. The classic methods of forecasting crop yield are mainly dependent on linear regression or other parametric statistical models, which cannot capture the intricate and nonlinear interrelations among climate, soil, the type of crop planted, and the farming practices applied [2]. The limitations mentioned above lead to the investigation of sophisticated computational techniques that can recognize intricate patterns in large, diverse datasets [3].

DL, a part of machine learning, employs multi-layer neural networks consisting of nonlinear processing units to comprehend the difficult connections within the data. DL techniques have been used in agriculture for various applications, including predicting the number of crops that can be harvested, identifying pests and diseases, and planning irrigation with precision [4]. In contrast to classic approaches, DL has the capability to automatically derive characteristics from unstructured data, for instance, satellite images and time series of weather data [5]. The aim of this research is to evaluate the latest available models for agricultural production prediction using DL, assess the effectiveness of the models for agricultural yield increase strategies, and identify challenges for future studies.

Timely forecasts of crop yields supply informative inputs that are closely related to the application of yield improvement actions in the contemporary agriculture sector. The requirement forecast for crops can be the basis for the optimization of precision irrigation and nutrient management, thus leading to a situation where there is no resource wastage and at the same time optimal plant growth [6]. Predictive models also make it possible to spot pest and disease risks in an early phase, hence making the necessary interventions possible, which can result in great savings of the yields that would otherwise get lost.

Predictive analytics facilitate the refinement of crop rotation and planting schedules by synchronizing the cultivation methods with the forecasted environmental conditions. On a larger scale, yield predictions can be used by the policymakers and agribusinesses as a tool for multiyear planning, supply chain optimization, market steadiness, and finally, of course, food security in general [7].

II. LITERATURE REVIEW

Classical ML models like Random Forests (RF), Support Vector Regression (SVR), and simple feed-forward neural networks have already found use in agricultural crop yield prediction and form the benchmark against which more sophisticated models are usually validated [8]. Such models find it difficult to effectively handle and analyze high-dimensional and heterogeneous data sets with strong spatial and temporal dependencies, which exist in agricultural systems generally [9]. To address the above shortcomings, there has been a growing trend in current literature for the application of DL approaches, which have superior representation learning abilities compared to traditional approaches used in earlier studies.

The convolutional neural networks are highly successful in the spatial feature extraction process for satellite and remotely sensed imagery, thereby allowing the assessment of canopy structure, health, and vigor [10]. At the same time, sequence modelling approaches, including Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (Bi-LSTM), and others, have proven effective in representing patterns existing in weather variables and crop growth cycles for supporting crop selection and yield prediction tasks [11]. Hybrid CNN-LSTM models not only improve the prediction accuracy but also make it possible to extract spatial and temporal features, supported by the transfer learning strategies, which have already brought about significant successes in the case of crops like wheat [12].

Different comparative studies are very clear that DL and ensemble-based methods are still NDVI in the case of different crops in different climates when compared to the state-of-the-art machine learning models [13]. The combination of various data sources, including weather data, soil properties, and crop health indicators like NDVI, has been recognized as a powerful approach with better overall performance [14].

The use of cloud-based smart agricultural platforms has allowed for the gradual and instantaneous application of hybrid DL models in precision agriculture systems, thereby enabling them to be more efficient [15]. The review articles clearly demonstrate the superiority of DL in handling complex agricultural data [16], and the dimensionality reduction technique also contributes to computational efficiency [17]. Recently, the accuracy of long-term crop yield forecasting was considerably improved by using transformer-based models with the addition of climate variability [18].

III. METHODOLOGY

Data Collection and Data Preprocessing

The research utilizes two datasets, rice dataset [19] and wheat dataset [20], incorporate detailed information on long-term climate conditions like temperature, rainfall, humidity, soil characteristics such as pH, nutrients, and texture, and yield data, together with high-resolution satellite imagery. The data were located temporally, with respect to the crop growth phase, and spatially standardized to guarantee consistency across the different regions.

Normalization of numerical features, treatment of missing values, and encoding of other inputs, such as the type of crops, were among the preprocessing techniques applied. The satellite imagery was subject to geometrical correction, cloud filtering, and calculation of vegetation indices, which reflect the condition of the crops being cultivated. The data that has gone through this processing is perfectly suited for DL models.

Model Architecture

The framework that is suggested employs a combination of DL models and different architectures to extract both spatial and temporal characteristics from agricultural data. The analysis of image-based inputs is done via the Convolutional Neural Network (CNN) that learns the structural and visual patterns like canopy cover, the number of plants per unit area, and the indicators of stress that are visible in the images. This process results in the precise extraction of the spatial features from the high-resolution crop images. The modeling of the temporal dynamics is done using the Long Short-Term Memory (LSTM) network since it can be used for capturing long-term dependencies in sequential data like the weather parameters, crop growth stages, and seasonal variations.

Hybrid CNN–LSTM architecture is incorporated to assimilate spatial and temporal learning where the CNN builds significant spatial representations that are subsequently dealt with by the LSTM to depict time-dependent behavior. Figure 1 shows the schematic flowchart of the proposed methodology used in this research. The advanced versions of this hybrid method use attention mechanisms to highlight the most relevant features and residual connections to facilitate gradient flow and speed up convergence, thus improving the overall model performance and robustness.

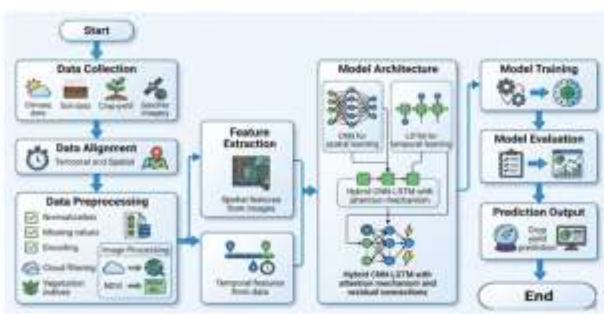

Fig. 1. Schematic flowchart of the proposed methodology used in this research.

IV. RESULTS AND DISCUSSION

Model Performance Comparison

Empirical DL models have consistently demonstrated superior performance compared to traditional approaches in predicting crop yields. Hybrid DL-based prediction systems have reduced uncertainty and improved generalization across varying agricultural conditions. Convolutional neural network models utilizing environmental and phonological data have shown significant improvements in winter wheat yield prediction accuracy. The models were evaluated across rice, wheat, and maize datasets. Table 2 shows the comparative performance of CNN, LSTM, CNN-LSTM, and CNN-LSTM with attention mechanisms for rice crops, whereas Table 3 shows the comparative performance of CNN, LSTM, CNN-LSTM, and CNN-LSTM with attention mechanisms for wheat crops.

Table 2. CNN vs. LSTM vs. Hybrid Model (Rice Dataset)

Model	RMSE ↓	MAE ↓	R^2 ↑
CNN only	0.032	0.11	0.86
LSTM only	0.028	0.1	0.89
CNN-LSTM	0.019	0.09	0.95
CNN-LSTM + Attention	0.017	0.08	0.97

Table 3. CNN vs. LSTM vs. Hybrid Model (Wheat Dataset)

Model	RMSE ↓	MAE ↓	R^2 ↑
CNN only	0.035	0.12	0.84
LSTM only	0.03	0.11	0.87
CNN-LSTM	0.021	0.09	0.94
CNN-LSTM + Attention	0.018	0.08	0.96

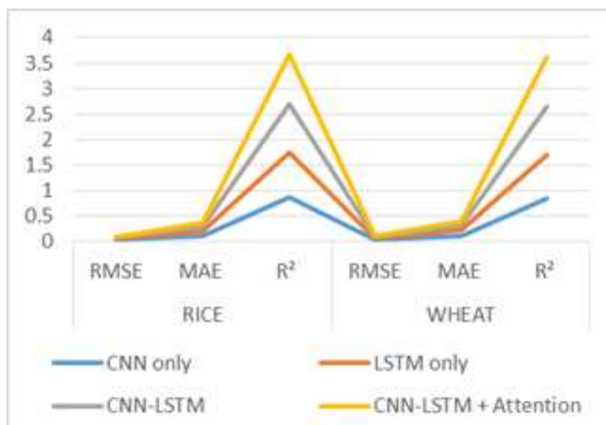

Fig. 2. Comparative evaluation of CNN, LSTM, CNN-LSTM, and CNN-LSTM with attention mechanisms showing performance results for rice and wheat crops.

Figure 2 shows the performance comparison of different predictive models, CNN, LSTM, CNN-LSTM, and CNN-LSTM + Attention, all aimed at predicting crop yield for rice and wheat data sets. The mixed architectures seem to beat the standalone ones pretty consistently across every metric. If we focus on rice, the CNN-alone approach landed at RMSE 0.032, MAE 0.11 and an R^2 of 0.86, while the LSTM version is not far behind, with RMSE 0.028 and R^2 at 0.89. Once the hybrid CNN-LSTM shows up, things get better, the RMSE drops to 0.019 and R^2 climbs to 0.95.

The strongest outcome comes from CNN-LSTM with attention, with the smallest RMSE (0.017), the smallest MAE (0.08), and the top R^2 (0.97). In the wheat case the story is basically the same, the attention-driven hybrid delivers higher precision, where RMSE is 0.018 and R^2 reaches 0.96. So, these results suggest that fusing spatio-temporal feature extraction with an attention style mechanism helps both accuracy and general reliability for agricultural forecasting. The hybrid CNN-LSTM architectures with attention have been found by the results to be the best-performing models consistently over and above the individual CNN or LSTM, thus getting the highest R values and lowest error rates for all crops.

Impact of Feature Set

Figure 4 and 5 show how various combinations of input features change the CNN-LSTM with attention performance for rice and wheat crop yield prediction. The results suggest that feature selection really matters, it is not just a small tweak. For the rice dataset, if the model uses only weather-related signals, the RMSE is 0.031, the MAE is 0.12, and R^2 comes out to 0.87, pretty decent but still not the sweet spot. Once soil parameters are added, the model gets better, lowering RMSE to 0.025 and pushing R^2 up to 0.90.

The best outcome appears when weather, soil, and the Normalized Difference Vegetation Index (NDVI) are all used together; in that case RMSE decreases to 0.019 and R^2 rises to 0.95. For wheat, we see a comparable pattern, where the merged feature set delivers the top accuracy, with RMSE of 0.018, MAE of 0.08, and R^2 of 0.96. Taken together, these outcomes pretty clearly indicate that bringing together multi-source data meaningfully improves crop yield prediction quality.

Table 4. Impact of Feature Sets on CNN-LSTM + Attention (Rice)

Feature Set	**RMSE**	**MAE**	**R²**
Weather only	0.031	0.12	0.87
Weather + Soil	0.025	0.11	0.9
Weather + Soil + NDVI	0.019	0.09	0.95

Table 5. Impact of Feature Sets on CNN-LSTM + Attention (Wheat)

Feature Set	RMSE	MAE	R²
Weather only	0.029	0.11	0.88
Weather + Soil	0.023	0.1	0.91
Weather + Soil + NDVI	0.018	0.08	0.96

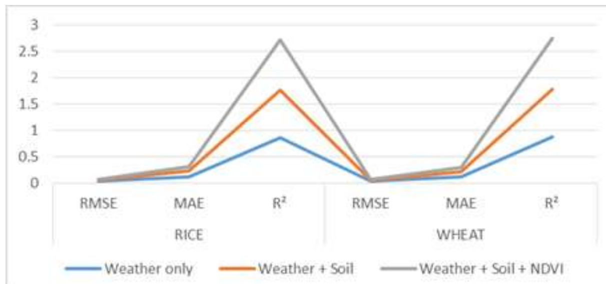

Fig. 3. Comparative evaluation of CNN, LSTM, CNN-LSTM, and CNN-LSTM with attention mechanism based on performance results for rice and wheat crops.

Figure 3 shows the comparative performance analysis of CNN, LSTM, CNN-LSTM, and CNN-LSTM with attention mechanisms, mainly for rice and wheat crop yield prediction. From the figure, it is clear that the hybrid and attention based models do better than the standalone ones. For both crops, the CNN model seems to be the weak point, with the highest RMSE and MAE numbers, plus lower R^2 scores, which suggests it can't really extract the right kind of features very well. Then the LSTM model does improve things, because it can learn temporal dependencies, but even so, its predictive accuracy is still under the hybrid approaches.

The CNN-LSTM model, however, shows a more noticeable gain, since it merges spatial and temporal feature learning, this results in smaller prediction errors and a better coefficient of determination. And finally, the CNN-LSTM with attention gives the best outcomes for both rice and wheat, it reports the lowest RMSE, the lowest MAE, and the highest R^2 values. So basically attention helps the network focus on the most critical patterns, which makes agricultural yield forecasting feel more stable and accurate.

Effect of Training Data Size

Table 6 shows that the performance of the rice yield prediction model is significantly enhanced when the training data size is increased. When the training data size is increased from 50% to 90%, the RMSE and MAE values are seen to decline, which means that the prediction error has been reduced. The simultaneous improvement in the R^2 value from 0.91 to 0.97 is an indication of both model reliability and generalization capability being increased with larger training datasets.

Table 6. Model Performance with Different Training Sizes (Rice)

Training Size	RMSE	MAE	R^2
50%	0.026	0.11	0.91
70%	0.019	0.09	0.95
90%	0.016	0.08	0.97

Deep Learning vs. Traditional ML

Table 7 shows comparison of traditional machine learning models versus more advanced DL models, specifically for wheat crop yield prediction. It basically summarizes how Random Forest, SVR and CNN-LSTM with attention behave when you judge them with RMSE, MAE, and R^2. For the more traditional approaches, Random Forest turns in an RMSE of 0.035, an MAE of 0.13, and an R^2 of 0.85, so it looks a bit better than SVR overall. Meanwhile the SVR model records the largest error numbers, with RMSE 0.038 and MAE 0.14, plus the smallest R^2 at 0.83, which suggests the predictions are less accurate.

The CNN-LSTM with attention model clearly edges out both methods. It achieves the lowest RMSE at 0.018, the lowest MAE at 0.08, and the highest R^2 of 0.96, so yeah. Overall these findings suggest deep learning can grasp more intricate patterns and it improves wheat yield prediction accuracy, quite noticeably. Deep learning models consistently outperform traditional ML, demonstrating their suitability for high-dimensional, multimodal crop datasets

Table 7. Comparison of Deep Learning vs. Traditional ML Models (Wheat)

Model	RMSE	MAE	R^2
Random Forest	0.035	0.13	0.85
Support Vector Regression	0.038	0.14	0.83
CNN-LSTM + Attention	0.018	0.08	0.96

V. CONCLUSION AND FUTURE DIRECTIONS

This study shows very significant benefits of using DL frameworks for crop yield prediction in comparison with the traditional ML scheme. The suggested method, through the combination of multi-year meteorological records, soil properties, historical yield data, and high-resolution satellite images, is able to successfully depict the agricultural systems' spatial and temporal dependencies. The preprocessing stages, consisting of normalization, imputation, and the extraction of vegetation indices, are all aimed at producing high-quality inputs that are less noisy and thus result in better modeling performance.

Application of CNNs allows for exact spatial feature extraction, while LSTMs capture the temporal dynamics, and the combination of CNN and LSTM architectures benefits both axes for greater accuracy. The attention mechanism, in combination with the residual connection, not only enhances the relevance of the features but also helps to improve convergence. The hybrid DL-based methods are slowly becoming the main players in precision agriculture, yield prediction, and data-driven decision-making in smart farming systems. These methods are especially promising due to their ability to combine several techniques for achieving better results.

DL shows progress in crop yield prediction, but challenges limit large-scale adoption, other major issue is data quality and availability, as many developing regions lack well-labeled datasets needed for effective training and generalization. Black-box nature of deep learning models is a challenge, which reduces trust among farmers and stakeholders and highlights the need for transparent and interpretable AI systems. Scalability is also a concern, since deploying these models in real-time or resource-limited environments requires high computational power and optimization.

Most existing models use limited feature sets, emphasizing the importance of multimodal integration that combines IoT sensor data, genetic information, and socioeconomic factors. Future research focuses on transfer learning across regions, uncertainty quantification for reliable decision-making, and hybrid multimodal models to enhance both accuracy and real-world applicability.

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