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Employing Artificial Intelligence for Optimizing Crop Yield Forecasting in Bundelkhand Region

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Abstract:- Due to significant challenges in agriculture arising from climate variability, population growth, and resource limitations, precise crop yield prediction is essential to safeguard food security and promote sustainable agricultural practices. Therefore, accurate evaluation of crop production levels is crucial for effective agricultural resource management. The direct impact of variables such as temperature, soil moisture, and weather conditions on crop yields underscores the critical importance of precise forecasting in agricultural production. This paper presents a composite model that integrates a CNN (Convolutional Neural Network) with an LSTM (Long Short-Term Memory) network to improve the accuracy of agricultural output projections. The model is specifically applied to rice and wheat, two of the most essential crops in India. The proposed hybrid framework improves prediction accuracy using multi-head attention and multiplicative skip connections. Compared to more conventional methods, such as the Support Vector Regressor along with the Random Forest Regressor, the proposed hybrid model demonstrates significantly enhanced performance features. The Root Mean Square Error (RMSE) of 0.018 indicates negligible prediction error. Additionally, the Mean Absolute Error (MAE) is 0.08, and the R^2 value is 0.97, demonstrating a strong correlation between the predicted yields and the actual yields.

Keywords: *CNN, Crop Yield Prediction, Deep Learning, LSTM Network, RMSE, MAE, AI.*

1. Introduction

Global agricultural output must increase by 60% by 2050 to support the global population approaching nine and a half billion; yet, crop yields are threatened by rising temperatures and soil degradation [1]. Conventional statistical methods, such as regression analysis, are inadequate for capturing nonlinear relationships in varied datasets, including environmental data, soil nutrients, and satellite imaging. Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), offers disruptive potential by analyzing large datasets for precise predictions [2]. Historically, assessments of agricultural production have depended on observations by experts, impacting decision-making and the lives of the communities involved. However, inaccuracies in such forecasts may result in food scarcity [3]. Contemporary precision agriculture has difficulties in accurately measuring crop yield, despite the existence of multiple excellent models. Overcoming these issues requires the use of comprehensive datasets and an ongoing commitment to enhancing precision [4].

A subset of Artificial Intelligence, known as Machine Learning, allows computers to recognize patterns and extract insights through data without the need for explicit programming.

Model performance improves incrementally as the system is exposed to more data. Deep Learning is a distinct subset of Machine learning that focuses on the training of Neural Networks to comprehend intricate data representations. This learning method is used in several applications, including image identification, recommendation systems, processing of natural languages, and predictive analytics. Recent improvements include LSTM models powered by feature engineering, which improve agricultural harvest predictions by extracting new features from existing data. These models are based on the notion of feature engineering. Machine Learning techniques are progressively used in agriculture to monitor and predict environmental variables [5]. These approaches include the creation of prediction models via data application and have ramifications across several fields. Due to the many variables affecting agricultural output, creating models that are both precise and comprehensible remains a challenge [6]. Various approaches have been utilized to properly anticipate agricultural yields, including field surveys, mathematical models for crop growth models, including remote sensing. Accurate crop production estimates at both national as well as regional levels are crucial, since they enable farmers to make educated choices based on dependable data [7]. Although several approaches enable forecasting agricultural yields, the complex interplay of climatic and soil conditions requires extensive data, the intricate nature of agricultural production impacted by climatic and soil conditions require large information. When choosing between descriptive versus predictive Machine Learning models, it is essential to consider the context of the research [8].

2. Literature Review

This section summarizes recent research on crop yield estimation using machine learning and deep learning. To enable efficient decision-making at national and regional levels, it has become essential to define clear priorities for agricultural production growth. Precision agriculture poses a formidable challenge, and various successful approaches have been suggested to tackle this complexity [4]. Various methods may be used to predict agricultural output using precision agriculture. Producers must have a thorough awareness of development patterns in crop production. This review paper analyzes studies on agricultural output prediction using Machine Learning and advanced learning methods as recorded in the literature. A. Chlingaryan et al. [9] studied the use of Machine Learning to estimate nitrogen status in agricultural settings with the goal of improving crop output forecasts. With the rise of hybrid systems based on machine learning techniques, they predict the creation of agricultural solutions that are both cost-effective and efficient. This was being accomplished via advancements in technology for sensing and machine learning. Young [10] investigated key methodologies in government data collection, satellite imagery, and survey techniques for agricultural production forecast. He elucidated the ambiguities intrinsic to forecasting and pinpointed the prevailing research deficiencies. However, it excludes an examination of common Machine Learning methodologies and particular crop yield models for diverse agricultural products, thereby limiting its applicability to specific audiences. In the field of food production and farming, Kamilaris [11] analyzed a comparative review of 40 research initiatives, identifying deep learning as the most effective approach for agricultural tasks.. Their conclusion suggests that neural networks are highly effective, exceeding standard image processing techniques, and have the potential to tackle a wide range of agricultural issues with considerable precision. Elavarasan [12] performed a review of research examining Machine Learning algorithms aimed at forecasting agricultural output by using meteorological indicators. The study suggests that future researches are required to investigate other variables influencing crop output. Mathur [13] conducted a research study on the installation of diverse machine systems, using learning methodologies to forecast agricultural outputs based on five separate crop varieties. The study's results indicate that the Random Forest, SVM, and Lasso Regression models exhibited significantly superior performance. Deep learning algorithms, such as Gradient Descent and LSTM, outperform traditional models in yield prediction. Klompenburg [3] performed a comprehensive assessment of agricultural yield prediction methodologies, primarily emphasizing information extraction over in-depth analysis or suggestions. They found that CNN, LSTM, and DNN are the three most widely endorsed techniques for forecasting agricultural output. They recognized common deep learning algorithms used in the sector based on their results. Hani et al. [14] developed a system using Deep Learning methodologies to detect and measure crops, therefore forecasting the anticipated yield of apples to be gathered. According to their study results, Gaussian Mixture Models (GMM) outperformed deep learning approaches, including U-NET, Fast R-CNN, as well as CNN, in most datasets for yield identification when comparing semi-supervised along with deep learning techniques. Monteiro et al. [15] provide a concise summary of the scientific and technological instruments used in precision agriculture, and the applications of these techniques in grain and animal production. They underscore the significance of resource efficiency and demonstrate how precision agriculture may fulfill food demands while maintaining sustainability. Rashid et al. [16] completed one of the most thorough assessments of Machine Learning-based crude oil output forecasting, highlighting the need for future research to include a diverse array of predictive approaches and characteristics. They reveal that Machine Learning approaches, including Logistic Regression (LR), Random Forests (RF), and Neural Networks (NN), are often used in forecasting agricultural output, alongside particular Deep Learning models. Hasan et al. [17] provide a comprehensive review of Deep Learning techniques for the identification and categorization of vegetation in agriculture. This review covers data gathering, dataset creation, deep learning methodologies, and assessment measures. Singh et al. [20] developed an advanced deep learning model using Mask-RCNN coupled with bidirectional ConvLSTM for object activity detection and people counting. Although the paper primarily addresses human activity monitoring, it’s methodological innovation—integrating convolutional and recurrent layers for spatial-temporal analysis—has strong parallels with crop monitoring systems. This research illustrates how CNN–LSTM architectures can simultaneously process visual and sequential data, a key requirement for precision agriculture systems that integrate satellite imagery, weather sequences, and time-series crop data. Gupta et al. [21] introduced the concept of the Agricultural Internet of Things (AIoT) to facilitate intelligent farming through interconnected sensors, cloud computing, and deep learning analytics. Their framework supports real-time monitoring of soil moisture, temperature, and nutrient conditions, while predictive models such as CNN and LSTM forecast optimal irrigation schedules and crop yields. The study highlights how AIoT bridges data collection and predictive analytics, transforming traditional agriculture into a responsive and adaptive system. This aligns closely with the current paper’s emphasis on leveraging hybrid AI architectures for data-driven agricultural optimization. Nair et al. [22] focused on the combined application of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models to predict wheat yields under varying climatic conditions in India. Their hybrid architecture captured spatial features (via CNN) and temporal dependencies (via LSTM), producing higher accuracy and reduced Root Mean Square Error (RMSE) compared to standalone models. The study validated the superiority of CNN–LSTM networks in addressing agricultural yield prediction problems involving multivariate environmental data. Their findings provide strong empirical support for using deep hybrid learning in the Bundelkhand region’s yield modeling.Gupta and Airen [23] proposed an AIoT-enabled soil irrigation management system integrating smart sensors and automated water distribution algorithms. Their system adapts irrigation scheduling in real-time based on soil moisture data and climatic feedback. Although not directly focused on yield prediction, the paper contributes valuable insights into how AI-based automation can improve resource management efficiency in agriculture. The combination of AI-driven prediction and IoT-based actuation exemplifies a closed-loop approach that can be extended to predictive yield management frameworks.Das et al. [24] examined the role of remote sensing data fused with AI algorithms for agricultural yield prediction. Their study, published in IEEE Transactions on Geoscience and Remote Sensing, integrates satellite imagery with weather and soil data to create a spatio-temporal prediction model using deep learning. The authors demonstrated how convolutional architectures can extract spectral-spatial features from remote sensing data while LSTM modules analyze temporal variations. Their model achieved notable improvements in yield estimation accuracy, highlighting the power of combining multisource datasets for agricultural AI applications.Benos et al. [25] conducted a thorough analysis of the current research on Machine Learning with agriculture, intending to present individuals interested in the prospective benefits of this innovation with pertinent insights. This research emphasizes the use of various sensors on satellites, terrestrial vehicles, and aircraft to provide dependable input data for applications of Machine Learning in the agriculture sector.

3. METHODOLOGY AND DATASET

The crop forecasting algorithm is developed using a dataset that encompasses data on rice and wheat, including variables such as climatic and soil conditions. The dataset includes previous climatic and soil data from various regions of Bundelkhand. This dataset [18] encompasses almost the whole of India. To accurately train and assess the model's effectiveness, to identify which states exhibit higher forecasting precision in forecasting agricultural output based on prevailing data circumstances.

The **R^2 Score measures** how well the predicted values approximate the actual outcomes, representing the proportion of variance in the dependent variable that is explained by the model. A value closer to 1 indicates a stronger model fit [26].

The **Root Mean Square Error** (RMSE) quantifies the standard deviation of prediction errors by calculating the square root of the average squared differences between predicted and observed values, thereby emphasizing larger errors more significantly [27].

The **Mean Absolute Error** (MAE) computes the average magnitude of prediction errors without considering their direction, offering an intuitive measure of the model's overall prediction accuracy in the same units as the target variable [28].

4. Proposed Method with result

Convolutional Neural Networks (CNNs) are an instance of deep neural network that is frequently employed in image as well as signal processing applications. The functions of CNNs include image classification, item identification, and auditory recognition. A specific kind of CNN, referred to as a one-dimensional CNN, is intended for analyzing signals defined by only one dimension, such as audio or data from a time series. It can be viewed as a subclass of two-dimensional CNN models, whereby the input consists of a one-dimensional sequence and the filters that are used are one-dimensional vectors. The primary advantage of CNNs is their ability to effectively extract localized characteristics from input signals, such as sound wave structures or trends in time series data. This capability allows CNNs to do tasks such as voice recognition as well as anomaly detection with efficacy.

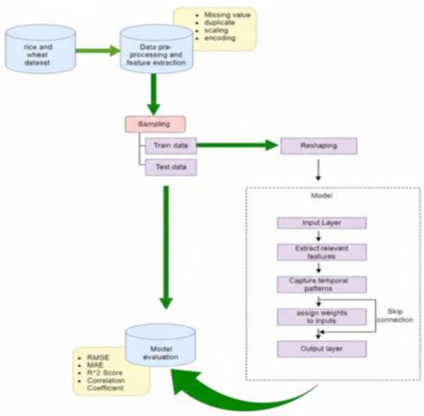

Figure 1: Illustrate how CNN and LSTM techniques are used for crop prediction [19]

The fundamental component of Convolutional Neural Network systems (CNNs) is convolution, which is a mathematical process whereby a filter is methodically traversed over an input signal to generate a collection of feature maps, crucial for identifying key characteristics. We analyzed the projected crop yields using CNN-based modeling.

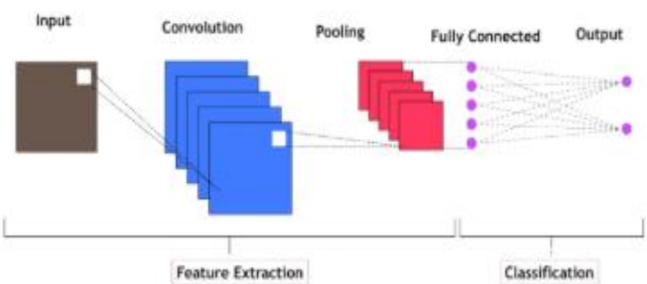

Fig. 2. Core architecture of CNN

LSTM: Gating mechanisms are integrated into this variant of the Recurrent Neural Network (RNN), facilitating the selective retention or discarding of information from prior time steps. Thus, it functions as an exceptional tool for simulating long-term dependencies and managing extensive data sequences. Figure 3 illustrates that the LSTM cell consists of an forgot gate, an input gate, an eligible stimulation, a cell state modification, an output gate, as well as a hidden state output. In an LSTM network, the forget gate regulates the degree to which the prior cell state is retained.

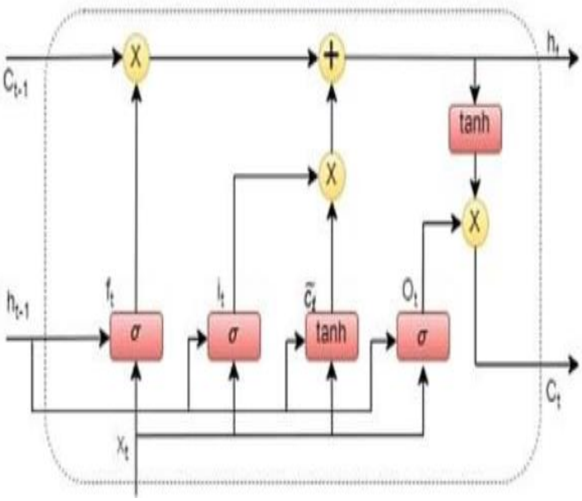

Figure 3: Basic architecture of LSTM

The input gate regulates the degree of candidate activation to be incorporated into the current active cell state. The output gate's function is to ascertain the proportion of the cell state to be conveyed as the state that is concealed.

5. Main Proposed method

This technique aims to include a 1D CNN, LSTM, along with an attention layer within a crop yield forecasting model. The LSTM captures temporal patterns, while the CNN extracts environmental features for feature extraction from environmental input, whereas the attention layer enhances accuracy by prioritizing the most significant elements. LSTM and focused attention outputs are amalgamated via skip connections, hence augmenting pattern recognition skills. This research used a dataset including twelve variables, which was further refined to exclude grains such as wheat and rice, resulting in around five thousand entries. The CNN layer facilitated feature selection, while both the training as well as (and) testing datasets were preserved as separate entities.

In evaluating the performance of the different models, measures such as the correlation coefficient, R2 score, Root Mean Square Error, and Mean Absolute Error were used. The CNN-LSTM model was altered in comparison to several attention layers, and the most efficient attention layer was selected for incorporation with skip connections. This conclusion was derived after an assessment of the model. The findings in Table 1 indicate that the CNN-LSTM model with skip connections as well as multi-head attention exhibited markedly enhanced performance relative to the other models. Furthermore, we have used Jupiter to create many other Machine Learning methodologies, such as the Decision-Tree Regressor, the Random Forests Regressor, and the Support Vector Regressor. Since regression models do not rely on accuracy as a performance metric as an evaluative measure; hence, to gauge accuracy, we augmented our correlation coefficients by an extra 100.

$$RMSE = (1/n) * \sqrt{\Sigma (y_i - \hat{y}_i)^2}$$

$$MAE = (1/n) * \Sigma | y_i - \hat{y}_i |$$

$$R^2 = ((1 - SS_{re}) / SS_o)$$

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This study conducted an evaluation of the accuracy of various models and analyzed their individual performance metrics. The proposed CNN-LSTM multiple-head attention model, which incorporates a multiplicative skip connection, demonstrated exceptional performance by achieving an accuracy rate of 98%, thereby surpassing the performance of previous models. A reduction in the root mean square error (RMSE) signifies a more precise model. The RMSE serves as a statistical measure that quantifies the discrepancy between observed and predicted values. Notably, among the models assessed, the support vector regressor exhibited the highest RMSE.

Table 1: Shows a comparisons of various models with respect to accuracy

S. No.	Model	Accuracy
1	Decision tree regressor	95%
2	Support vector regressor	90%
3	Random forest regressor	96%
4	CNN LSTM	97%
5	Since regression models do not relyCNN–LSTM with multi-head attention and multiplicative skip connections on accuracy as a performance metric	98%

Above Table shows a comparisons of different models and gives the accuracy for the crop yield production

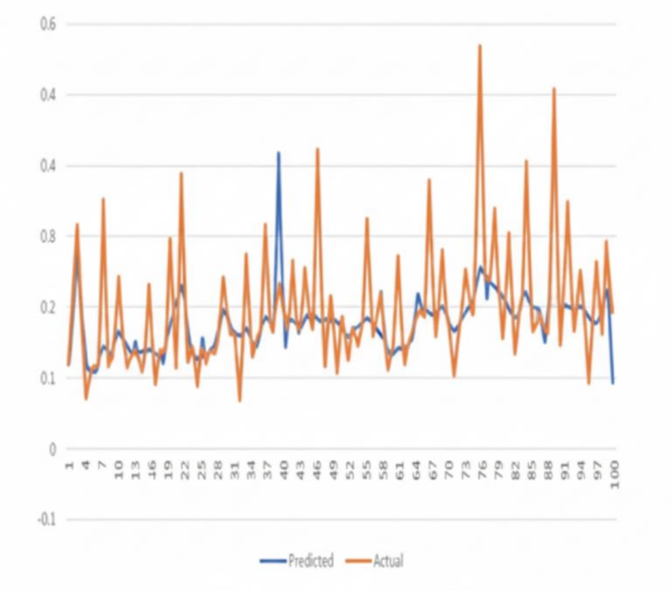

Figure 4: Shows actual and predicted crop yield

6. Conclusion

This study developed an advanced CNN–LSTM model to forecast rice and wheat yields, by leveraging a dataset that includes information on commodities such as soil and climate. We trained and assessed many models, including a Decision-Tree Regressor, Random Forest Regressor, Support Vector Regressor, and various CNN–LSTM architectures such as those with multi-head attention and diverse skip connections. The CNN-LSTM multi-head attention model with multiplied skip connection surpassed the other models based on metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R2 score, as well as correlation coefficient. The limited scope of the dataset used in the study represents a constraint, notwithstanding the promising nature of the results. Future research using larger datasets may yield improved results. According to Table I, the top two models, Hybrid 1D CNN–LSTM without attention and Random Forest, demonstrate the potential for improved performance when integrated into an ensemble.]

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