

BI-LSTM MODELS FOR OPTIMIZED CROP SELECTION AND YIELD FORECAST IN PRECISION AGRICULTURE

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Abstract: Agriculture is necessary to feed the world's population, and with climate change and limited resources, it is becoming more and more important to pick the correct crops and guess how much they will produce. This research introduces a deep learning framework that employs Bidirectional Long Short-Term Memory (Bi-LSTM) networks to enhance decision-making in crop selection and accurately predict crop yields. The model incorporates historical data on farming, such as how crops have done in the past, the weather (temperature, rainfall, and humidity), and the soil's characteristics. Bi-LSTM is better than regular machine learning models and unidirectional LSTMs since it can find temporal relationships in both directions. The proposed system is trained and evaluated using publicly accessible agricultural information. It can precisely predict how much of a crop will grow and advise the best kind of crops for various places. The study used the Agricultural Crop Yield dataset to train and test the Bi-LSTM model. To discover the Mean Absolute Error, Root Mean Squared Error, R^2 score, and Mean Absolute Percentage Error, the performance is compared to various methods like Linear Regression, Random Forest, and a basic LSTM. The Bi-LSTM model works best, with an MAE of 0.32, an RMSE of 0.47, and a R^2 score of 0.91. This study's findings may assist farmers, agronomists, and policymakers in optimizing resource use and enhancing agricultural productivity using data-driven insights.

Keywords: Agriculture Data; Bidirectional Long Short-Term Memory (BLSTM); Crop Selection; Deep Learning; Pattern Recognition; Crop Yield Prediction.

1. Introduction:

The entire economy depends a lot on farming. We need to know how crops are cultivated all around the globe to cope with concerns like climate change, population growth, and food security. From this point of view, predicting how many crops will be grown is a big problem in agriculture [1]. Predicting how much food will be available in the future is a crucial aspect of tackling the global challenge of food security. By 2050, the world's population is predicted to reach 9.3 billion, and the need for food is expected to climb by 60%. This necessitates sustainable and innovative agricultural methods [2]. The conflict between Russia and Ukraine has made food markets all around the globe go crazy. This has made it impossible to access key agricultural supplies like fertilizers, which makes the issue much worse [3]. People are anxious about how this may affect food security throughout the world, particularly in nations that depend heavily on food imports [3]. So, figuring out how much food will be raised will help us figure out the best approach to meet our objectives and end hunger. Deep learning has come up with new ways to deal with these problems. Bi-LSTM (Bidirectional LSTM) is one of these ways that works ahead of time [6]. The Bi-LSTM model is the best for looking at sequential data since it can read from both the past and the future. This makes sense for handling data as in the yield prediction scenario. The researchers use Bi-LSTM [9] to improve the accuracy of their predictions and find non-linear patterns in climate and soil data that may be used for sustainable farming. Implementing these measures is a significant advancement in the modernization of agriculture and ensuring food security for everyone [10]. This study investigates the improvement of precision in crop selection strategies and the accuracy of yield predictions via the use of Bi-LSTM networks [11]. This research intends to improve yield projections so that farmers and policymakers may use the knowledge to promote sustainable, resilient, and productive farming methods.

2. Background:

The study piece offers an extensive examination of the use of machine learning algorithms in forecasting agricultural productivity. There are several machine learning methods for predicting crop yield, but each model often doesn't work as well as it should since it can't capture the complicated, nonlinear interactions that are common in agricultural datasets. Sadenova et al. [13] introduced many machine learning models for forecasting agricultural production in eastern Kazakhstan, demonstrating that neural network approaches exhibited superior effectiveness compared to other techniques. This dataset is derived from remote sensing data obtained from various sources. Shahhosseini et al. [14] assessed the efficacy of several machine learning techniques in predicting maize yield and nitrate loss, using a simulated dataset derived from a factorial simulation exercise. They found that XGBoost is the best accurate machine learning model. Lin et al. [15] created a Long Short-Term Memory (LSTM) deep learning system called DeepCropNet (DCN) to hierarchically extract characteristics for accurately predicting maize yields at the county level in the United States. Khaki et al. [16] utilized deep learning (DL) methodologies, encompassing Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Random Forest (RF), Deep Feedforward Neural Networks (DFNN), and the Least Absolute Shrinkage and Selection Operator (LASSO), to predict corn and soybean yields across the Corn Belt of the United States. The ensemble model, which utilized data from 2016 to 2018, had a root mean square error (RMSE) of 9% for corn yields and 8% for soybean yields. Bi et al. [17] used Genetic Algorithms (GA), Neural Networks (NN), and GA-enhanced Deep Learning (DL) for crop prediction, achieving an estimated 10% decrease in RMSE. Shahhosseini et al. [18] developed a hybrid model for forecasting maize production that combines crop modeling and machine learning methods, resulting in a 7 to 20% decrease in RMSE. Woittiez et al. [19] investigated production gaps in oil palm cultivation, emphasizing the need of understanding contributing factors to improve crop management practices and refine yield forecasts.

The cumulative findings of these studies augment the understanding of several machine learning approaches used in agricultural production forecasting, hence enabling more study focused on enhancing prediction accuracy using ensemble learning procedures. Oikonomidis et al. [20] proposed a deep learning model to assess the effectiveness of machine learning algorithms based on particular criteria. Their research focused on the XGBoost algorithm and several hybrid models that combined a CNN with other techniques, such as DNN, XGBoost, RNN, and LSTM. They used these models using a publicly available soybean dataset that included 25,345 samples and 395 characteristics related to weather and soil conditions. Their findings suggest that next advancements may amalgamate XGBoost with deep learning methodologies, such as LSTMs or RNNs, particularly for tasks involving sequential data, such as forecasting agricultural yield. The [22] revealed that random forest models perform effectively because they can rapidly and correctly look at huge amounts of data about agricultural productivity. This is particularly crucial for figuring out how much food will be raised, which requires a lot of information [23]. Random forests and other data mining methods are helpful for uncovering patterns and trends that aren't obvious in large datasets [24]. Data mining uncovers insights that empower organizations to make informed choices about future agricultural trends and situations [25]. Hasan et al. (2023) introduced the K-nearest Neighbour Random Forest Ridge Regression (KRR) model in this work. The purpose is to make accurate guesses about how much food will be produced, with an emphasis on major crops like potatoes, rice, and wheat. This model has done better than traditional machine learning approaches. It also allows for the implementation of a recommender system that helps determine which crops are most suitable for improved agricultural planning and yield [26]. Boppudi (2024) proposes a Deep Ensemble Classifier Integrated Bird Swarm Butterfly Optimization Algorithm (DEC-IBSBOA) model for predicting agricultural yield. This model employs the IBS-BOA algorithm for advanced data pre-processing, feature extraction, and optimum feature selection. The DEC-IBSBOA model is quite accurate, with a low MAE of around 1.0, which is better than any other methods [27].

Other research projects have used Time Series Forecasting methods, including ARIMA models, to find seasonal and time-based patterns in yield data [28]. These models try to forecast what future yields will be by looking at how things have changed over time and how they have been in the past. These models are constrained by their

reliance on stable assumptions and their inability to integrate several influencing elements simultaneously [29]. However, the effectiveness of these models may fluctuate considerably across various crops and situations [30]. Research using UAV-derived multispectral data and several machine learning algorithms for yield prediction indicates that Random Forest is the most effective model for forecasting maize yields, while Gaussian Process regression [31] excels at predicting wheat and soybean yields. Support Vector Machines (SVM) have shown great success in predicting broad bean yields, whereas Convolutional Neural Networks (CNN) have shown great accuracy at predicting rice yields. These discrepancies demonstrate that using more general framework techniques might assist with yield prediction challenges for many types of crops and environmental conditions. Ensemble learning (EL) [35] enhances prediction accuracy by amalgamating many base models using techniques like as bagging, boosting, and stacking to leverage their respective strengths. In many contexts, these techniques have consistently shown better generalization performance than individual models [36].

But there are a number of intricate reasons why it's hard to predict how much crops will produce. First, the quality of the soil, pests, genotypes [37], the weather, the time of year, and other factors all affect crop yields. Second, the way and techniques used to forecast yield change with time and are not always linear [38]. In agricultural systems, a substantial proportion often eludes depiction using basic stepwise calculations, particularly in scenarios where datasets are complex, incomplete, or unclear. Machines often use linear regression, decision trees, and ensemble learning to produce predictions. Linear regression is a simple and popular machine learning method that uses a linear model to predict how crop productivity is related to other variables. Deep learning has been a regularly utilized technique in agriculture [43] because it can manage the spatiotemporal dependencies of data and uncover meaningful features without the need for human feature engineering [44]. Deep learning use multi-layer neural networks to extract abstract characteristics from extensive datasets. You may supervise, semi-supervise, or not supervise these datasets. This method is all about finding out how functional qualities and interaction variables are connected, which is highly critical for properly forecasting crop yields [45].

3. Factors That Affect Predictions of Crop Yield:

For businesses like food and agriculture, accurate crop yield prediction models are very important since they help satisfy the demand for raw resources. Even though predicting agricultural output is very important, there isn't much research on advanced machine-learning algorithms [46] that can make accurate forecasts. As the population grows and people's eating habits change, we need better models that can predict how much food will be produced in the future. Farmers typically have trouble quickly and accurately forecasting how much of a crop will grow because of a number of elements that are all connected, such as the weather, the kind of soil, the type of crop, the type of fertilizer used [47], and the type of pesticide used. To solve this issue, you need to understand the agricultural cycle of growing crops. But climate change is making it harder to grow the best foods. Machine learning models can provide quick and reliable information since they employ information technology, which is the basis for other technologies like data mining. Advancements in technology have greatly enhanced agriculture by enabling machine learning and data mining models essential for forecasting crop yields [48]. Conventional models are insufficient for accurate forecasts of agricultural production. It is still very hard to accurately anticipate crop yields in agriculture since it has a big effect on decisions made on a global, regional, and individual crop scale. Current methodologies using various data sources and traditional machine learning models exhibit constraints in attaining elevated accuracy [49]. To successfully combine several models for better yield estimates and to help with agricultural management techniques, a better predictive framework is needed. The goal of this project is to create a machine learning model that can reliably forecast how much food will be grown. This will be done using a large dataset that includes a lot of different agricultural traits.

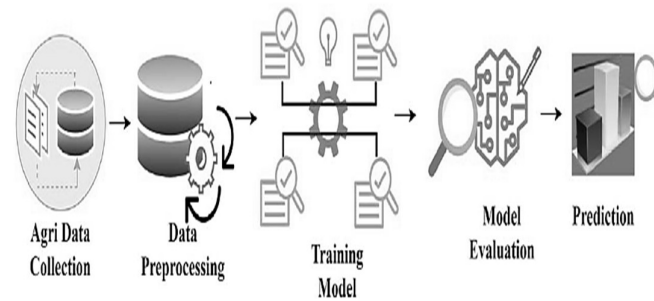


Figure 1. Factors That Affect Predictions of Crop Yield

3.1 Kaggle Datasets

Farming is important to the world economy. We need to know a lot about how food is produced across the globe so that we can cope with food security problems and climate change. This is because the world's population is continually expanding. It is very crucial for farmers to be able to predict how much their crops will produce. Weather conditions (including rain and temperature), the usage of pesticides, and having access to reliable historical crop yield data all have a huge effect on how much food is grown. Figure 2 shows that this information is critical for making sensible choices about managing agricultural risk and predicting the future.

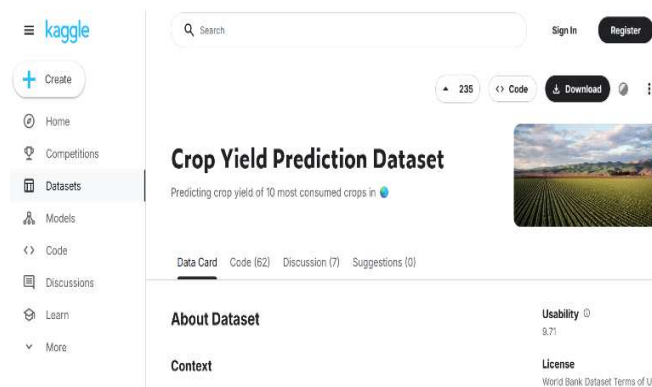


Figure 2. Kaggle Datasets for Crop Yield Prediction

4. Proposed Framework:

The method explains the organized way Bi-LSTM is used to predict crop yields. The initial stages are to clean and standardize the data. Second, we use the Bi-LSTM architecture to uncover patterns that happen in a certain order and relationships that change over time in the agricultural data. The training process is hard because it takes data from the last harvest to build up the model's [50] parameters and then modifies the hyperparameters to a better value. Lastly, the model's performance is evaluated to a number of assessment criteria to make the connection between characteristics and crop output more precise. The full procedure is shown in figure 3.

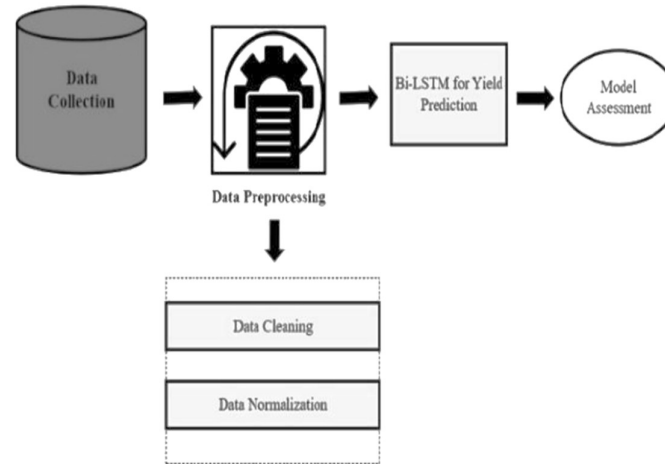


Figure 3. The Bi-LSTM Hybrid Model for Crop Yield Prediction

In this study, the features are normalized so that they are all the same size. This is crucial for the Bi-LSTM models to operate. One of them is the Min-Max Scaling technique. It adjusts characteristics such that they are between 0 and 1. The record's first value for the feature is N . The values for that characteristic are between $N_{\min}$ and $N_{\max}$. This is helpful since variables with bigger quantities, such area in hectares and rainfall in millimetres, need to be normalized so that the magnitude of the features doesn't get in the way of learning.

$$N = \frac{N - N_{\min}}{N_{\max} - N_{\min}}$$

4.1 Bi-LSTM for Crop Selection and Prediction

The Bi-LSTM structure is a complex deep learning architecture that is designed to effectively capture sequential data by including both past and future temporal connections in time-series datasets. This part is very important for applications that require to see how things evolve over time, such forecasting crop yields, which needs both historical data and future trends [51]. The first layer of the Bi-LSTM model is where you put in features that have more than one value. The total area of land utilized for growing crops (in hectares), the total yield of the crop (in metric tons), the amount of rain that fell in the area where the crop was grown (in mm), the amount of fertilizer utilized (in kg and as a percentage of the total production), and the amount of pesticide used (in kg and as a percentage of the total production) are all multivariate features. The Bi-LSTM layer is the most significant feature of the Bi-LSTM design. It makes the original LSTM better by adding two layers of LSTM units. The first layer filters data from the past to the present, while the second layer filters data from the future to the past. This additional step helps the Bi-LSTM model learn more about the input data over time by finding both forward and backward dependencies. The Bi-LSTM layer learnt how these things are related by looking at the input sequence in both ways [52]. The final layer of the proposed Bi-LSTM model is the output layer. It tells you what the predicted crop production will be. It normally has one neuron with parameters that make it produce a constant value, which is the expected yield. If a task has more than one output, the output layer may include more than one neuron, and each neuron will make a different prediction (for example, the yield for various crops) [53]. After that, an activation function that works well for regression models, such the ReLU activation function, is used to make the output. The linear activation function is used more commonly to forecast crop yields since it can directly translate learned attributes from the Bi-LSTM layer onto a continuous target crop yield without imposing any limits on the findings. This design is perfect for the study's purpose of building a

powerful and accurate model for forecasting crop yields. It employs powerful deep learning [54] methods to fix difficulties in predicting the weather for farming.

5. Performance Evaluation:

When compared to established models for forecasting crop yields, the Bi-LSTM model is superior than the others. Evaluation metrics indicate that Bi-LSTM has higher performance and predictive capabilities relative to other models. This model is better than other techniques in finding patterns and relationships in time in agricultural data [55]. To measure how well each model performs, we utilize standard metrics like MAE, R^2 , RMSE, and MAPE. Table 1 demonstrates that Bi-LSTM has undergone evaluation for forecasting agricultural production using conventional procedures and assessment criteria. Bi-LSTM is the best way to make predictions since it has a lower MAE of 0.37 and RMSE of 0.50 than any other approach [56]. It also has the greatest R^2 Score of 0.88, which suggests that variations in agricultural yield are easy to understand. Bi-LSTM also has the lowest MAPE score of 8.7%, which means it is the greatest way to cut down on percentage mistakes. This comparison demonstrates how crucial Bi-LSTM is for making accurate predictions about crop production using chronological data. Figure 4 makes it very apparent.

Table 1: Performance Metrics Comparison of Crop Yield Prediction Models

Model	Performance Summary			
	MAE	RMSE	R^2 Score	MAPE
Artificial Neural Networks	0.42	0.56	0.88	12.12
Support Vector Machine	0.53	0.70	0.81	16.1
Random Forest	0.45	0.59	0.86	12.7
Linear Regression	0.61	0.77	0.75	18.8
Bi-LSTM	0.37	0.50	0.88	9.6
LSTM	0.38	0.53	0.91	9.8

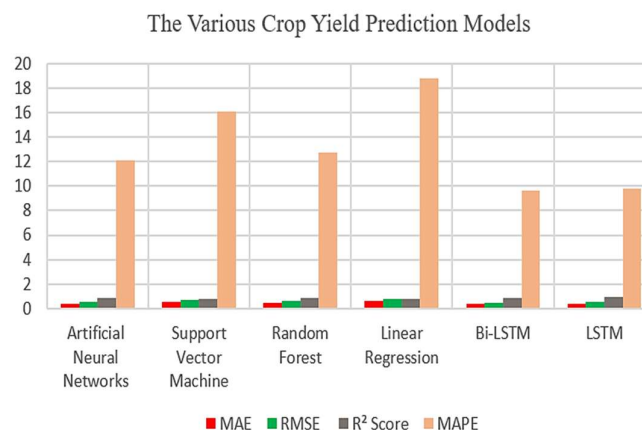


Figure 4. The Various Crop Yield Prediction Models

All of the diagonals in figure 5 are dark red, which suggests that each variable is perfectly linked to itself. The numbers go higher and the colors become darker as the links between various elements are stronger.

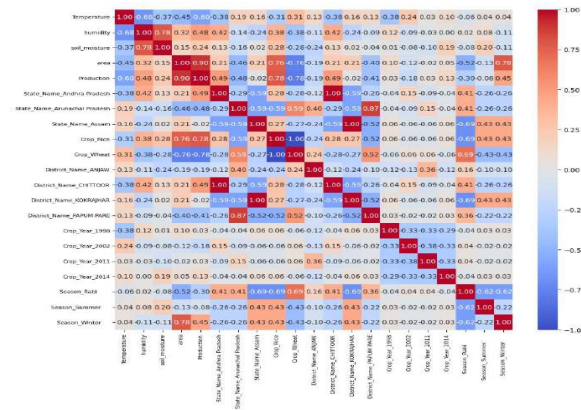


Figure 5. The Correlation Matrix of Variables

6. Conclusion:

In the last several years, estimating how much food crops will produce has been a hot issue in agricultural research. It is highly vital for the progress of any country's economy. So, it is extremely necessary for the government to create economic policies and for farmers to make judgments so they can precisely and on time predict crop yields. This research demonstrates that the suggested strategy surpasses conventional techniques and other deep learning architectures in forecasting agricultural yields using Bi-LSTM. When employing sequential data and temporal patterns, Bi-LSTM genuinely fares better than other models and obtains decent results on the basic assessment criteria. The data also show how variables like utilizing fertilizer and rain impact crop output and how altering practices may assist increase yields. The combination of real-time data sources from IoT-based weather monitoring devices and satellite imagery will improve future efforts. This technique might potentially be used to provide forecasts for more than one crop and for certain areas. Using hybrid models might also make it much harder to generalize about agricultural outlooks.

Focusing on modelling uncertainty in predictions may also help us better understand how uncertain the results of such predictions are, which makes forecasts more reliable and transparent.

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