



# Optimization of Irrigation Through Data-Driven Approaches in Precision Agriculture Utilizing Deep Neural Networks

Dr. Nikhat Akhtar<sup>1</sup>, Sarita Maurya<sup>2</sup>, Sunny Kumar<sup>3</sup>,  
Neha Anand<sup>4</sup>, Dr. Yusuf Perwej<sup>5</sup>

<sup>1,2</sup>Department of Computer Science & Engineering, Goel Institute of Technology & Management, Lucknow

<sup>3,4,5</sup>Department of Computer Science & Engineering, Shri Ramswaroop Memorial University, Deva Road, Lucknow

<sup>1</sup>dr.nikhatakhtar@gmail.com, <sup>2</sup>sarita.maurya@goel.edu.in, <sup>3</sup>sunnykumar.cs24@gmail.com,  
<sup>4</sup>nehaanandmails@gmail.com, <sup>5</sup>yusufperwej@gmail.com

## KEYWORDS

*Agriculture Data, Feature Selection, Long Short-Term Memory, Crop Selection, Pre-Process, Crop Yield Prediction.*

## ABSTRACT

*Agriculture is an essential vocation worldwide, dependent on climate conditions and rainfall. This article aims to use climatic, soil, and temperature data to forecast crop yield in advance. This research presents a classification-oriented methodology for forecasting agricultural output using Long Short-Term Memory (LSTM) integrated with an Attention Mechanism. The Government of Karnataka's Economics and Statistics department gather manual data. This method used data from the Department of Economics and Statistics about three crops: jowar, rice, and ragi. The linear interpolation method is used to address the missing and null values in the dataset. The feature selection process is advantageous for the Correlation-based Feature Selection Algorithm (CBFA) and the Variance Inflation Factor Algorithm (VIF) since it facilitates the identification and elimination of correlated feature groups. We use Accuracy, R2, Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to evaluate the model's performance. The proposed LSTM model yields assessment metrics with accuracy, R2, MAE, MSE, and RMSE values of around 99.10%, 0.44, 0.132, and 0.233, respectively.*

## 1. Introduction

Agriculture is the most prominent sector of the Indian economy. Numerous countries globally continue to struggle with the management of their food supply systems due to rapid population growth. Agriculture has emerged as a crucial component in the cultivation of essential food crops in our age. Jowar, paddy, and ragi are the primary food crops and rank second in production significance. Jowar is a significant component of the Indian economy and is cultivated throughout both the monsoon and post-monsoon seasons. Agriculturists may enhance their decision-making on optimal planting times by considering environmental factors that maximize productivity. The factors influencing crop production include climate, soil, temperature, biological elements, geographical aspects, and other variables [3]. At all levels, from local to global, agricultural decision-makers have significant challenges in predicting crop yields. Agronomists, merchants, farmers, and policy makers find it advantageous to anticipate crop yields. Achieving the objective is challenging when crop output is extensive on a limited amount of land. Agriculturalists are evaluating optimal methods to achieve substantial yields based on the data they collect, devising strategies to predict crop outputs that enhance their understanding of rural life and agriculture. The crop yield prediction model assists farmers in identifying the ideal time and types of crops to cultivate, taking into account environmental conditions to optimize output. In contrast to conventional farming techniques, precision agriculture is an innovative approach that conserves both time and financial resources for farmers. Machine Learning (ML) autonomously acquires knowledge from prior experiences via continuous training, resulting in enhanced prediction and classification outcomes [7]. Over the last decade, recent data-driven modelling

**Corresponding Author: Dr. Nikhat Akhtar, Department of Computer Science & Engineering, Goel Institute of Technology & Management, Lucknow**

**Email: [2004aryanrai@gmail.com](mailto:2004aryanrai@gmail.com)**

techniques have been used in several agricultural domains to enhance forecasting accuracy, increase efficiency, and include beneficial characteristics [8]. Machine learning image classifiers are used to distinguish between healthy and diseased crops. The predictive model is developed by using many attributes, namely model parameters identified from historical data during the training phase [9]. The machine learning methods, such as Naïve Bayes (NB), Decision Tree (DT), and Random Forest (RF), demonstrate both parametric and non-parametric traits, substantially impacting agricultural output forecasting [10]. In some instances, an Artificial Neural Network (ANN) is used to address crop production forecast challenges by analysing factors such as CO<sub>2</sub> fixation, solar radiation, and water content. This study introduces Long Short-Term Memory (LSTM) for the early forecasting of agricultural production [12].

## 2. Background

Occasionally, conventional agricultural techniques lack precision and efficacy, resulting in the squandering of time and resources. For example, consistently applying pesticides and fertilizers throughout an expansive field may result in excessive or insufficient use of these inputs, adversely affecting the environment, increasing costs, and yielding suboptimal results [13]. Agriculturalists struggle to make informed decisions because of the difficulty in obtaining accurate and current information on weather conditions, soil health, and consumer demand. Moreover, insufficient financial resources and infrastructure, especially in rural areas, exacerbate these challenges. This renders it unfeasible for farmers to use optimal approaches and the latest technologies [15]. Khaki et al. [16] used deep learning (DL) techniques to forecast maize and soybean yields in the maize Belt of the United States. The approaches included 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). The ensemble model, using data from 2016 to 2018, exhibited 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-augmented Deep Learning (DL) for crop forecasting, resulting in an approximate 10% decrease in RMSE. Shahhosseini et al. [18] created a hybrid model for predicting maize production that integrates crop modeling and machine learning approaches, achieving a decrease in RMSE by 7 to 20%. Woittiez et al. [19] investigated output discrepancies in oil palm farming, highlighting the need of comprehending relevant aspects to enhance crop management tactics and refine yield predictions.

The study results clarify the many machine learning techniques used to forecast agricultural production. This will facilitate continuing research aimed at enhancing the accuracy of predictions via the use of ensemble learning methodologies. Oikonomidis et al. [20] established a deep learning model to evaluate the efficacy of machine learning algorithms according to certain criteria. Their study concentrated on the XGBoost algorithm and other hybrid models using a CNN with other methodologies, such as DNN, RNN, and LSTM. The models were applied to a publicly accessible soybean dataset including 25,345 samples and 395 attributes pertaining to meteorological and edaphic conditions. Their results indicate that future developments may integrate XGBoost with deep learning techniques, such as LSTMs or RNNs, especially for jobs requiring sequential data, such as predicting agricultural yield. The [22] demonstrated the efficacy of random forest models by rapidly and accurately assessing large datasets of agricultural production. This is especially vital for estimating food production, which requires extensive data [23]. Random forests exemplify a data mining approach capable of uncovering concealed patterns and trends across large datasets [24]. Data mining reveals insights that enable firms to make educated judgments on forthcoming agricultural trends and circumstances [25]. Hasan et al. (2023) presented the K-nearest Neighbour Random Forest Ridge Regression (KRR) model in this study. The objective is to formulate precise predictions for food production, concentrating on primary crops such as rice, wheat, and potatoes. This model has outperformed conventional machine learning methods. It also enables the use of a recommender system to identify the most suitable crops for enhanced agricultural planning and production [26]. Boppudi (2024) presents the Deep Ensemble Classifier Integrated Bird Swarm Butterfly Optimization Algorithm (DEC-IBSBOA) model for forecasting agricultural yield. This model employs the IBS-BOA methodology for sophisticated data pre-processing, feature extraction, and optimal feature selection. The DEC-IBSBOA model has high accuracy, with a low Mean Absolute Error (MAE) of around 1.0, surpassing all other methods [27].

Various research initiatives have used Time Series Forecasting techniques, such as ARIMA models, to identify seasonal and temporal trends in yield data [28]. These models use past trends and their temporal variations to predict future yields. However, certain models have specific issues. Firstly, they depend on stable assumptions; secondly, they fail to account for several aspects simultaneously [29]. Nonetheless, the efficacy of these models may vary significantly across different crops and contexts [30]. Research using UAV-based multispectral data and several machine learning algorithms for yield prediction demonstrates that Random Forest is the most

effective model for forecasting maize yields, but Gaussian Process regression is the preeminent approach for predicting wheat and soybean yields. Support Vector Machines (SVM) have shown remarkable efficacy in predicting broad bean yields, whereas Convolutional Neural Networks (CNN) have exhibited impressive precision in forecasting rice yields. These inconsistencies indicate that comprehensive framework approaches may be used to tackle yield prediction issues across diverse crops and environmental situations. Ensemble learning (EL) improves prediction accuracy by integrating many core models using methods like as bagging, boosting, and stacking to use their own strengths. In several instances [36], these strategies have consistently outperformed individual models in terms of generalization performance.

However, several complex factors make it hard to predict agricultural yield. Soil quality, pests, genotypes, weather, seasonal timing, and several other variables influence crop production. Secondly, the methodologies and procedures used to predict yield fluctuations over time are not always linear [38]. A significant aspect of agricultural systems sometimes escapes representation by simple stepwise computations, especially in cases when datasets are intricate, partial, or ambiguous. Common techniques used by computers to generate predictions include decision trees, linear regression, and ensemble learning. Linear regression is a fundamental and widely used machine learning technique that employs a linear model to forecast the correlation between crop output and other influencing variables. Deep learning is extensively used in agriculture because to its effectiveness in handling spatiotemporal data dependencies and extracting relevant features without necessitating human feature building. Deep learning use multi-layer neural networks to derive abstract characteristics from extensive datasets. These datasets may be categorized as organized, semi-structured, or unstructured. This technique emphasizes on the relationship between functional qualities and interaction aspects, which is crucial for generating precise predictions about crop output [45].

### **3. Things influencing Crop Yield Prediction**

Multiple variables, including weather conditions, soil type, crop variety, and farm management practices, influence the accuracy of crop production estimations. Weather significantly influences crop growth. Precipitation, temperature, and humidity are all crucial for plant growth. However, one of the most challenging aspects is our inability to do long-term weather forecasts. Migdall says that inclement weather may hinder harvesting if the fields are too saturated for machinery. She suggests enhancing long-term estimates by using seasonal forecasts that include many scenarios [47]. The quality and fertility of the soil are crucial since they directly influence the health and growth of plants. The kind of crop influences production predictions, since different crops exhibit varying levels of resistance to pests and diseases. Migdall said that although individual farmers are aware of their specific plantings, obtaining comprehensive information on crop types and growth patterns on a larger scale, such as across whole countries or continents, is very challenging. The management of your farm may influence the performance of your crops. These include crop rotation, irrigation systems, fertilization protocols, and pest management, all of which significantly influence food production levels.

#### **3.1 Kaggle Datasets**

Agriculture is a crucial component of the global economy. The growing global population need a comprehensive understanding of agricultural production to address food security challenges and mitigate the impacts of climate change. Estimating crop output is a significant agricultural issue. The primary factors influencing agricultural productivity are climatic conditions (such as precipitation and temperature), pesticide use, and the accessibility of precise historical crop yield data [50]. This data is crucial for informed decision-making regarding agricultural risk management and future predictions, as seen in figure 1.

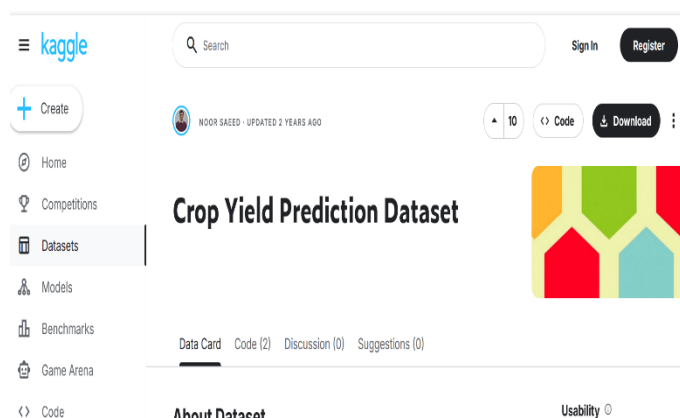


Figure 2. Kaggle Datasets for Crop Yield Prediction

#### 4. The Suggested Model

The proposed method entails collecting data from the yield outputs of three principal crops: jowar, rice, and ragi. Subsequently, evaluate the three crops to determine which has the most favorable production forecast. The primary components of this system are the dataset, pre-processing, feature selection, and LSTM [51]. The attention mechanism facilitates the prediction of enhanced crop yields via classification. Figure 2 illustrates the flowchart for the proposed crop production projection. The primary crops cultivated in Karnataka are jowar, paddy, and ragi. The dataset originates from Kaggle datasets.

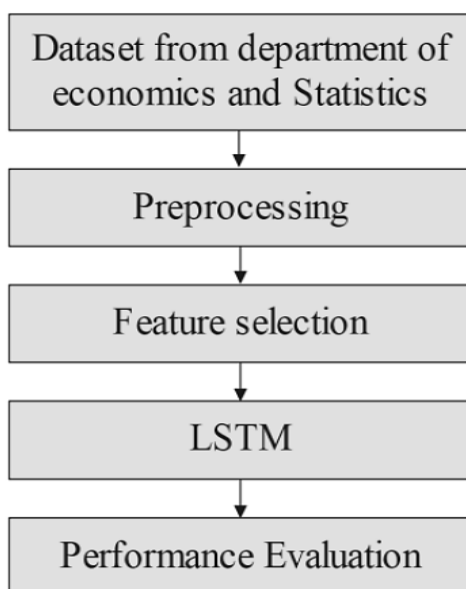


Figure 2. The LSTM Based Model for Crop Yield Prediction

Subsequent to the compilation of the datasets, the following phase involves data cleansing. Deep Learning [19] is ineffective at managing noisy data, such as outliers and errors. Prior to data classification, pre-processing is conducted due to the presence of missing or null values in specific districts of Karnataka. This indicates that the undesired data is eliminated but the appropriate data range is retained in the production row [20]. The mean values may replace the values in that row, and the dataset contains text values that must be converted to numbers to facilitate the division into training and testing groups. We use the Linear Interpolation method to address gaps and absent data. This method uses mathematics to identify new data points by constructing a linear representation of the existing data points in the sequence of the preceding value. Interpolation is a prevalent method for addressing gaps in time-series data with missing values. The linear interpolation equation (1) performs the following function.

$$f(X) = f(x_0) + \frac{f(x_1) - f(x_0)}{x_1 - x_0} (x - x_0)$$

In this scenario,  $x$  represents the independent variable,  $x_0$  and  $x_1$  denote the known values of the independent variable, and  $f(x)$  signifies the dependent variable corresponding to the independent variable value  $x$ . Subsequent to data pre-processing, feature selection is conducted. In datasets with many attributes, high-level feature selection is crucial for achieving optimal predictive accuracy. The primary rationale for use feature selection is that it accelerates training, simplifies the model, and enhances the comprehensibility of the process. This may enhance the model's accuracy by selecting the appropriate subset and preventing overfitting. Attribute selection involves three methodologies for feature selection: wrapper, filter, and embedding. The wrapper and filter procedures are first used to choose the optimal attributes. The wrapper methodology often outperforms the filter method, despite the high operational expenses of the model. The embedded method incorporates both the filter and wrapper techniques, using its unique approach to property selection.

#### 4.1 Long Short-Term Memory (LSTM)

During the training, there were eleven hidden layers, each containing fifty neurons. Long Short-Term Memory (LSTM) is the optimal model for forecasting time series and determining the most accurate crop output predictions. The LSTM is used to determine which crop will generate the highest output by comparing it with the yield forecasts of the other three crops. Training a model using Deep Learning (DL) algorithms involves consideration of several hyperparameters. This encompasses the quantity of neurons, hidden layers, and learning rate. Manually configuring settings is not always feasible. Hyperparameter optimization is the process of selecting the optimal collection of hyperparameters to enhance model performance. In LSTM, the time steps, the quantity of input and hidden layers, and the number of hidden neurons may all be regarded as variables for hyperparameter optimization. Exercise caution while adjusting the hyperparameters, since this may affect the model's performance. The layers in the deep LSTM model may induce overfitting and prolong convergence. The neurons of the hidden layer operate similarly to the LSTM layer. To forecast time-series data, historical data is essential; yet, a conventional neural network just analyzes the current data it receives. Both RNN and LSTM possess the capability to retain historical data; however, LSTM models exhibit superior long-term memory retention compared to RNN models. LSTM employs two primary concepts to comprehend temporal characteristics in data. The memory notion, which pertains to the cell state, and the cell framework, which effectively trains fully connected layers, are the first two elements. In LSTM, the hidden layer contains specific memory cells designated for reading, writing, and erasing data. These cells are regulated by three gates: the input gate, the output gate, and the forget gate. These three gates determine which data should be preserved in memory. The cell state transmits data between layers. The first component is the forget gate, which permits just the necessary data to pass through the cell state. The sigmoid layer constitutes the first phase of the input gate. It regulates the output value. The Tanh layer constitutes the subsequent phase. It generates the vectors with novel feature values. Both are retained in the cell state. The output gate displays the revised information on the cell. The LSTM examines historical data and current unidentified patterns by regulating them at a fundamental level to identify trends. This enables earlier forecasts on future events. Figure 3 elucidates the functioning of LSTM.

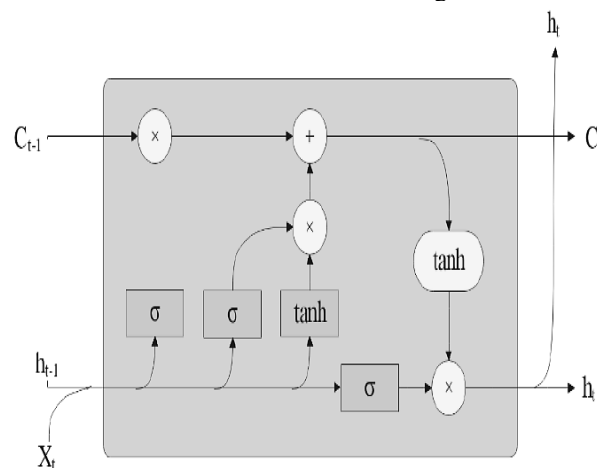


Figure 3. The LSTM Model Functionality

$h_{t-1}$  – previous memory output

$C_t$  – current memory output.

LSTM cell is described in

$$cg_t = \text{Tanh}(wt_{cg} \times [hd_{cg-1}, x_{cg}]) + bs_{cg}$$

where,  $(cg_t)$  – current memory

$(wt_{cg})$  – weight matrix

$(bs_{cg})$  - bias

The input gate controls the current memory input data update to the value of the memory cell and it is calculated

$$ig_t = \sigma(wt_{ig} \times [hd_{ig-1}, x_{ig}]) + bs_{ig}$$

The input gate controls the previous memory data update to the value of the memory cell and it is calculated in

$$fg_t = wt_{fg} \times [hd_{fg-1}, x_{fg}] + bs_{fg} \quad cu_t = fit \times lc_{t-1} + cg_t$$

Where,  $cu_t$  – current memory cell

$lc_{t-1}$  – last LSTM cell value.

LSTM may be used in both stacked and bidirectional configurations. In stacked mode, the LSTM first processes the input and the subsequent LSTM, followed by analysing the outputs derived from the temporal features produced by the preceding models. Stacked LSTM is used in sophisticated temporal learning applications. The bidirectional LSTM trains an additional model, whereas the unidirectional LSTM does not. One LSTM may process the input data sequentially from the beginning of the series to the end ( $t0 \rightarrow tn$ ), while the other can process it in reverse from the end to the beginning ( $tn \rightarrow t0$ ). Subsequently, these two models are integrated to provide the temporal feature output. Bidirectional learns the model attributes from both ends of the input sequences. The LSTM model incorporates the Attention Mechanism to enhance prediction accuracy. The LSTM functions as a mechanism for attention. The decoder reevaluates all of the encoder's states at each step. The last time step's hidden state is used to encode the input sequence during training. The Recurrent Neural Network (RNN) operates as long-term memory, so aiding the attention mechanism and improving the precision of output regression updates. The hidden state has comprehensive information on the input sequence. This classification approach provides effective tools for making accurate forecasts about crop output.

## 5. Performance Evaluation

We ensured that our machine learning models performed well in real-world agricultural conditions by meticulously assessing their performance throughout testing and result assessment. This study replicates the proposed method using LSTM in alignment with the system requirements. We used many measures to assess the experimental results, including Accuracy, Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-Squared (R2). This section illustrates the performance of the LSTM model for the overall rate attained, expressed both numerically and verbally. Table 1 and Figure 4 demonstrate the accuracy of the proposed strategy in comparison to other techniques. The proposed LSTM with an attention mechanism is evaluated against current methodologies, including Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), and Generative Adversarial Networks (GAN). The accuracy statistics indicate that CNN achieved 84.88%, DNN attained 87.49%, RNN reached 90.66%, and GAN secured 92.77%. The proposed LSTM with Attention mechanism achieved a better accuracy score of 99.10% compared to existing methodologies.

Table 1: The Experimental Results of the Proposed Model with Existing Model

Model	Performance Summary for 80% - 20%				
	Accuracy	R2	MAE	MSE	RMSE
DNN	87.49	0.48	0.137	0.060	0.243
CNN	84.88	0.50	0.140	0.063	0.249
RNN	90.66	0.47	0.136	0.059	0.241
LSTM	99.10	0.44	0.132	0.055	0.233
GAN	92.77	0.45	0.133	0.056	0.235

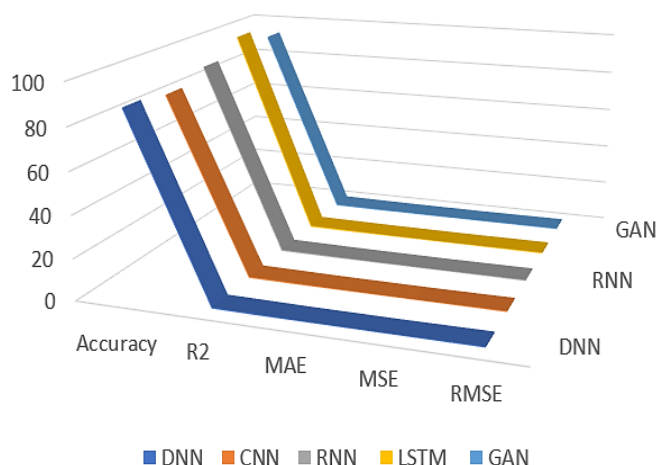


Figure 4. Comparative Graphical Representations of Crop Yields from Experimental Results of Proposed Models vs Existing Models

The findings from the IoT-based soil monitoring system indicate significant potential for enhancing precision agriculture techniques. The technique offers essential information that may enhance crop development and optimize resource use by continuously monitoring crucial soil characteristics. This sensitivity is essential for implementing informed modifications to agricultural practices that might enhance overall yield [60]. It is essential to consider the system's use across various types of farms and its potential modifications to meet their specific requirements. The model has performed well in the examined locations [61], but it requires assessment in additional areas with diverse soil types and climatic conditions [62]. To guarantee the system operates well in diverse agricultural settings.

## 6. Conclusion

Predicting agricultural yield is an essential aspect of global food production. Agricultural yield forecasting significantly benefits farmers, enhancing food value and bolstering the economy. Variations in weather, including precipitation, temperature, and soil conditions, may affect agricultural productivity. This proposed method collects yield data for three significant crops. Subsequently, evaluate the three crop production forecasts to determine which is the most advantageous. The proposed methodology utilizes linear interpolation to address the deficiencies in the Kaggle datasets. The Long Short-Term Memory (LSTM) model, enhanced with an attention mechanism, is used to improve the classification of agricultural output forecasts for three crops: jowar, rice, and ragi. The model's efficacy is assessed using Accuracy, R2, MAE, MSE, RMSE, and MAPE. The proposed strategy produces enhanced results, shown by performance measures including accuracy, R2, MAE, and RMSE values of around 99.10%, 0.44, 0.132, and 0.233, respectively, which are comparatively more advantageous than existing techniques. In future efforts, the proposed approach will be augmented to include more soil variables to improve predicted results.

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