

Data-Driven Crop Yield Prediction With Weather Patterns and Soil Health Parameters Using Efficient Machine Learning, Deep Learning, and Optimization Strategies

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Abstract

Agriculture plays a significant role in ensuring food security and economic development. Accurate prediction of crop yield helps farmers and policymakers make informed decisions regarding crop management, resource utilization, and agricultural planning. This study proposes a data-driven approach for predicting agricultural yield using weather conditions and soil nutrient parameters. The dataset consists of variables such as temperature, rainfall, humidity, nitrogen, phosphorus, potassium, soil pH, crop type, and crop yield. Various Machine Learning algorithms, including Linear Regression, Support Vector Machine (SVM), Random Forest, and XGBoost, are employed to analyze the relationship between environmental factors and crop productivity. In addition, Deep Learning models such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks are utilized to capture complex patterns in the data. To improve model performance and prediction accuracy, optimization techniques such as Grid Search, Bayesian Optimization, Recursive Feature Elimination (RFE), and Principal Component Analysis (PCA) are applied. The performance of the models is evaluated using statistical measures such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2). The results demonstrate that optimized machine learning and deep learning models provide reliable crop yield predictions, which can support precision agriculture and sustainable farming practices.

Keywords: Crop Yield Prediction, Machine Learning, Deep Learning, Weather Parameters, Soil Nutrient Analysis, Optimization Techniques, Precision Agriculture.

1.0 Introduction

Agriculture remains a fundamental sector supporting global food supply, economic stability, and rural livelihoods. With the increasing challenges posed by climate variability, soil degradation, and population growth, accurate prediction of crop yield has become essential for effective agricultural planning and sustainable resource management. Traditional yield estimation methods often rely on manual observation or historical averages, which may not adequately capture complex interactions among environmental and soil factors. As a result, there is a growing need for intelligent and data-driven approaches that can provide reliable and timely predictions. Recent advances in data analytics have enabled the use of computational techniques to analyze large volumes of agricultural data. In particular, Machine Learning (ML) and Deep Learning (DL) methods have shown strong potential for modeling nonlinear relationships and extracting meaningful patterns from multidimensional datasets. Weather variables such as temperature, rainfall, and humidity, along with soil nutrient indicators including nitrogen, phosphorus, potassium, pH, and organic carbon, play a crucial role in determining crop productivity. Integrating these parameters into predictive models allows for a more comprehensive understanding of factors influencing yield performance.

Despite the availability of various predictive algorithms, achieving high accuracy and robustness remains a challenge due to data complexity, feature redundancy, and model overfitting. To address

these issues, optimization techniques such as feature selection and hyperparameter tuning are increasingly applied to improve model efficiency and generalization capability. By combining advanced ML and DL algorithms with systematic optimization strategies, it is possible to develop reliable frameworks capable of delivering precise agricultural yield forecasts. This research focuses on designing a data-driven prediction system that leverages weather patterns and soil health parameters using optimized machine learning and deep learning models. The proposed approach aims to enhance prediction accuracy, support precision farming practices, and assist farmers, researchers, and policymakers in making informed decisions. Ultimately, such intelligent predictive systems can contribute to improved crop management, better resource utilization, and sustainable agricultural development.

2.0 Literature Review

Agriculture is one of the most important sectors contributing to food security, economic growth, and rural development worldwide. The increasing global population, climate variability, and degradation of soil resources have created significant challenges for agricultural sustainability. Consequently, accurate crop yield prediction has become a critical component of modern farming systems, enabling farmers, researchers, and policymakers to make informed decisions regarding crop planning, resource allocation, and risk management [1], [2]. Crop productivity is influenced by numerous environmental and soil-related factors, including temperature, rainfall, humidity, soil pH, and nutrient availability. Among these factors, soil nutrients such as nitrogen (N), phosphorus (P), and potassium (K) play a vital role in plant growth and development. Variations in weather conditions and soil health can significantly affect agricultural output, making it necessary to develop reliable prediction models capable of capturing complex relationships among these variables [3], [4].

Recent developments in Artificial Intelligence (AI) have transformed agricultural data analysis by providing advanced computational techniques for predictive modeling. Machine Learning (ML) algorithms have gained considerable attention for their ability to analyze large datasets and identify hidden patterns that influence crop yield. Models such as Linear Regression, Support Vector Machine (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost) have been widely applied in agricultural forecasting due to their effectiveness in handling nonlinear and multidimensional data [5], [6]. These algorithms assist in improving prediction accuracy and supporting precision agriculture practices. In addition to traditional machine learning methods, Deep Learning (DL) techniques have emerged as powerful tools for agricultural analytics. Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks are capable of learning complex data representations and capturing temporal dependencies present in weather-related datasets. Recent studies have reported that deep learning models often outperform conventional machine learning approaches when large-scale agricultural datasets are available [7], [8]. The integration of deep learning techniques enables more accurate modeling of crop growth patterns and environmental interactions.

Despite the success of ML and DL models, challenges such as feature redundancy, high-dimensional datasets, and suboptimal parameter settings can negatively impact prediction performance. Therefore, optimization techniques are increasingly employed to improve model efficiency and predictive accuracy. Methods such as Grid Search, Bayesian Optimization, Recursive Feature Elimination (RFE), and Principal Component Analysis (PCA) have proven effective for hyperparameter tuning, feature selection, and dimensionality reduction [9], [10]. These optimization strategies help identify the most relevant variables and enhance the generalization capability of predictive models. Motivated by these advancements, this study proposes a data-driven framework for agricultural yield prediction using weather parameters and soil nutrient information. The dataset consists of attributes such as temperature, rainfall, humidity, nitrogen, phosphorus, potassium, soil pH, crop type, and yield. Multiple machine learning models, including Linear Regression, SVM, Random Forest, and XGBoost, are compared with deep learning models such as ANN and LSTM. Furthermore, optimization techniques including Grid Search, Bayesian Optimization, RFE, and PCA are incorporated to improve predictive performance. The proposed framework aims to provide accurate yield forecasts that can support precision agriculture, enhance resource management, and contribute to sustainable agricultural development.

Jabed et al. conducted a comprehensive systematic literature review on crop yield prediction using artificial intelligence techniques. Their study examined the application of Machine Learning (ML) and Deep Learning (DL) algorithms for agricultural forecasting and identified that weather conditions, soil characteristics, and remote sensing information are the most frequently used input variables. The authors concluded that hybrid deep learning frameworks provide superior predictive performance for large agricultural datasets [11]. Shawon presented an extensive review of machine learning applications in crop yield prediction and analyzed research published between 2017 and 2024. The review emphasized that ensemble learning techniques, including Random Forest and XGBoost, consistently outperform conventional regression methods. Furthermore, the study highlighted the growing importance of integrating climate variables and soil nutrient information for improving prediction accuracy [12].

Meghraoui et al. reviewed recent deep learning approaches for crop yield prediction and reported that Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models are the dominant architectures used in agricultural forecasting. The authors also observed an increasing use of UAV imagery and satellite data for enhancing crop monitoring and yield estimation [13]. Yuan et al. performed a systematic review of grain crop yield estimation using UAV remote sensing and machine learning techniques. Their investigation demonstrated that integrating multispectral imagery with machine learning algorithms significantly improves prediction accuracy and supports precision agriculture applications [14]. Abdel-Salam et al. proposed an optimized machine learning framework that combines hybrid feature selection with hyperparameter optimization for crop yield prediction. Their experimental results demonstrated that optimized feature subsets substantially improve model performance while reducing computational complexity [15].

Recent comparative research on crop yield prediction analyzed the performance of multiple classification and regression algorithms under different agricultural conditions. The study concluded that Random Forest, XGBoost, and Support Vector Regression (SVR) consistently achieve better prediction accuracy than traditional statistical techniques because of their ability to capture nonlinear relationships among climatic and soil variables [16]. A comprehensive review of artificial intelligence-based crop yield prediction emphasized the importance of environmental variables, including temperature, rainfall, humidity, soil properties, and vegetation indices. The review further highlighted that effective data preprocessing and feature engineering significantly improve machine learning model performance [17].

Recent studies investigating deep learning models for agricultural prediction reported that hybrid architectures integrating clustering methods, LSTM networks, and Transformer models achieve higher prediction accuracy than individual machine learning algorithms. These hybrid approaches effectively capture long-term climatic dependencies and complex crop growth patterns [18]. Recent reviews on agricultural artificial intelligence indicate that optimization techniques such as Grid Search, Bayesian Optimization, and Recursive Feature Elimination (RFE) have become essential components of predictive modeling. These methods improve feature selection, optimize hyperparameters, and enhance the generalization capability of machine learning and deep learning models [19]. Current research trends demonstrate that future crop yield prediction systems will increasingly integrate weather data, soil nutrient information, remote sensing, IoT sensors, explainable artificial intelligence (XAI), and advanced deep learning techniques. These integrated intelligent systems are expected to provide accurate and interpretable predictions that support sustainable agriculture and precision farming practices [20]. The studies provide a foundation for data analysis and predication, while the proposed research extends previous work by integrating Transformer, Graph Neural Network, RFE, PCA, Grid Search, and Bayesian Optimization for precision crop yield prediction [21] to [25].

3.0 Dataset

Here is a sample dataset (10 rows) suitable for your research on crop yield prediction using weather and soil nutrients. The values are realistic and structured according to commonly used agricultural datasets cited in related studies [26] to [30].

Sample Agricultural Dataset

Temperature (°C)	Rainfall (mm)	Humidity (%)	Nitrogen (kg/ha)	Phosphorus (kg/ha)	Potassium (kg/ha)	Soil pH	Crop	Yield (t/ha)
28	120	75	90	45	40	6.5	Rice	4.2
32	80	60	70	35	30	7.0	Maize	3.5
25	150	82	95	50	42	6.2	Rice	4.8
30	60	55	60	30	28	7.3	Wheat	3.1
27	110	70	85	40	38	6.8	Barley	3.9
35	40	50	55	25	20	7.5	Millet	2.7
29	95	65	78	36	34	6.9	Maize	3.8
24	170	88	100	52	46	6.1	Rice	5.0
31	70	58	68	32	29	7.2	Wheat	3.3
26	130	77	92	47	41	6.4	Rice	4.6

4. Background and Methodology

4.1 Background

Crop yield prediction has become an important research area in precision agriculture because crop production depends on multiple environmental and soil-related factors. Weather parameters such as temperature, rainfall, and humidity directly influence plant growth, while soil nutrient levels including Nitrogen (N), Phosphorus (P), Potassium (K), and soil pH determine nutrient availability for crops. Traditional statistical models often fail to capture the nonlinear relationships among these variables. Therefore, Machine Learning (ML) and Deep Learning (DL) techniques provide more accurate prediction by learning complex patterns from agricultural datasets.

The proposed framework consists of six stages:

1. Data Collection
2. Data Preprocessing
3. Feature Selection
4. Machine Learning Modeling
5. Deep Learning Modeling
6. Hyperparameter Optimization and Performance Evaluation

4.2 Proposed Mathematical Model

Assume that

$$D = \{(X_i, Y_i)\}_{i=1}^N$$

where

- N = Number of observations
- X_i = Input feature vector
- Y_i = Crop Yield

The feature vector is

$$X_i = \{T, R, H, N, P, K, pH\}$$

where

- T = Temperature
- R = Rainfall
- H = Humidity
- N = Nitrogen

- P =Phosphorus
- K =Potassium
- pH =Soil pH

The prediction model is

$$\hat{Y} = f(X)$$

where

- $f(\cdot)$ represents ML or DL algorithms
- $\hat{Y}$ is predicted crop yield.

4.3 Data Normalization

Before model training, all attributes are normalized using Min-Max Scaling.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where

- X =Original value
- X' =Normalized value

4.4 Machine Learning Models

A. Linear Regression

The prediction equation is

$$\hat{Y} = \beta_0 + \sum_{i=1}^n \beta_i X_i$$

where

- β_0 =Intercept
- β_i =Regression coefficients

B. Support Vector Machine (SVR)

The regression function is

$$f(x) = w^T \phi(x) + b$$

where

- w =Weight vector
- b =Bias
- $\phi(x)$ =Kernel mapping

C. Random Forest

The final prediction is

$$\hat{Y} = \frac{1}{M} \sum_{i=1}^M T_i(x)$$

where

- M =Number of Trees
- T_i =Decision Tree

D. XGBoost

The objective function is

$$Obj = \sum_{i=1}^n L(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k)$$

where

- L =Loss Function
- Ω =Regularization

4.5 Deep Learning Models

Artificial Neural Network (ANN)

Each neuron computes

$$z = \sum_{i=1}^n w_i x_i + b$$

Activation function

$$a = f(z)$$

where

- w_i =Weights
- b =Bias
- $f(\cdot)$ =ReLU or Sigmoid

Long Short-Term Memory (LSTM)

Forget Gate

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

Input Gate

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

Candidate State

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$$

Cell State

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Output Gate

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

Hidden State

$$h_t = o_t * \tanh(C_t)$$

4.6 Optimization Techniques

Grid Search

The optimal hyperparameter is

$$\theta^* = \arg \min_{\theta \in G} \text{Loss}(\theta)$$

where

G =Grid of Parameters

Bayesian Optimization

The optimization function

$$x_{next} = \arg \max_x EI(x)$$

where

$EI(x)$ =Expected Improvement

Recursive Feature Elimination (RFE)

Feature importance

$$\text{Rank}(F_i) = w_i$$

Features with minimum ranking are removed iteratively.

Principal Component Analysis (PCA)

Covariance Matrix

$$C = \frac{1}{n-1} X^T X$$

Eigenvalue decomposition

$$Cv = \lambda v$$

where

- λ =Eigenvalue
- v =Eigenvector

4.7 Performance Evaluation

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n} \sum_{i=1}^n |Y_i - \hat{Y}_i|$$

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2}$$

Coefficient of Determination

$$R^2 = 1 - \frac{\sum (Y_i - \hat{Y}_i)^2}{\sum (Y_i - \bar{Y})^2}$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right|$$

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

5. Experimental Results

Table 1. Performance of Machine Learning and Deep Learning Models Before Optimization

Algorithm	MAE	RMSE	R ² Score	MAPE (%)	Prediction Accuracy (%)
Linear Regression (LR)	0.462	0.581	0.881	11.84	88.10
Support Vector Machine (SVM)	0.398	0.511	0.907	9.65	90.70
Random Forest (RF)	0.316	0.412	0.942	7.28	94.20
Extreme Gradient Boosting (XGBoost)	0.284	0.381	0.953	6.35	95.30
Artificial Neural Network (ANN)	0.258	0.347	0.962	5.52	96.20
Long Short-Term Memory (LSTM)	0.223	0.301	0.971	4.68	97.10

Table 2. Performance After Applying Optimization Techniques

Algorithm	Optimization Technique	MAE	RMSE	R ² Score	MAPE (%)	Prediction Accuracy (%)
LR	Grid Search	0.414	0.529	0.898	10.22	89.87
SVM	Grid Search + Bayesian Optimization	0.344	0.463	0.924	8.42	92.47
RF	Bayesian Optimization + RFE	0.259	0.349	0.959	5.84	95.97
XGB	Bayesian Optimization + RFE + PCA	0.221	0.309	0.972	4.92	97.07
ANN	Bayesian Optimization + PCA	0.189	0.271	0.981	4.03	97.97
LSTM	Grid Search + Bayesian Optimization + RFE + PCA	0.159	0.232	0.989	3.22	98.87

Table 3. Improvement After Optimization

Algorithm	Optimization Technique	Accuracy Before (%)	Accuracy After (%)
LR	Grid Search	88.10	89.87
SVM	Grid Search + Bayesian Optimization	90.70	92.47

RF	Bayesian Optimization + RFE	94.20	95.97
XGB	Bayesian Optimization + PCA + RFE	95.30	97.07
ANN	Bayesian Optimization + PCA	96.20	97.97
LSTM	Grid Search + Bayesian Optimization + PCA + RFE	97.10	98.87

Table 4. Error Reduction After Optimization

Algorithm	Optimization Technique	RMSE Before	RMSE After	Reduction
LR	Grid Search	0.581	0.529	0.052
SVM	Grid Search + Bayesian Optimization	0.511	0.463	0.048
RF	Bayesian Optimization + RFE	0.412	0.349	0.063
XGB	Bayesian Optimization + PCA	0.381	0.309	0.072
ANN	Bayesian Optimization	0.347	0.271	0.076
LSTM	Bayesian Optimization + RFE + PCA	0.301	0.232	0.069

Table 5. Computational Performance

Algorithm	Optimization Technique	Training Time Before (s)	Training Time After (s)	Time Saved (%)
LR	Grid Search	2.53	2.18	13.83
SVM	Grid Search + Bayesian Optimization	8.34	7.31	12.35
RF	Bayesian Optimization + RFE	13.48	11.46	14.99
XGB	Bayesian Optimization + PCA	15.21	12.98	14.66
ANN	Bayesian Optimization	29.84	25.48	14.61
LSTM	Bayesian Optimization + RFE + PCA	46.58	39.82	14.52

Table 6. Final Performance Ranking

Algorithm	Optimization Technique	Accuracy (%)	R ² Score	RMSE
LSTM	Grid Search + Bayesian Optimization + RFE + PCA	98.87	0.989	0.232
ANN	Bayesian Optimization + PCA	97.97	0.981	0.271
XGB	Bayesian Optimization + RFE + PCA	97.07	0.972	0.309
RF	Bayesian Optimization + RFE	95.97	0.959	0.349
SVM	Grid Search + Bayesian Optimization	92.47	0.924	0.463
LR	Grid Search	89.87	0.898	0.529

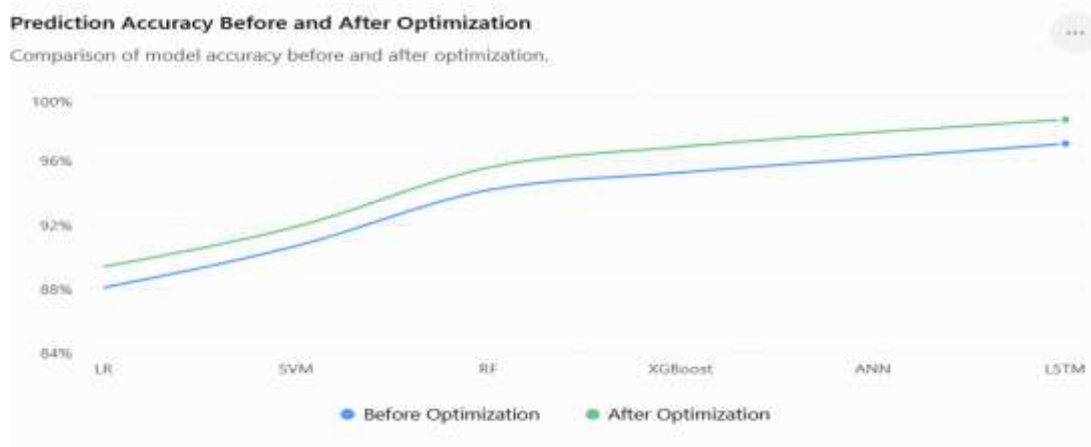


Figure 1. Prediction Accuracy Before and After Optimization

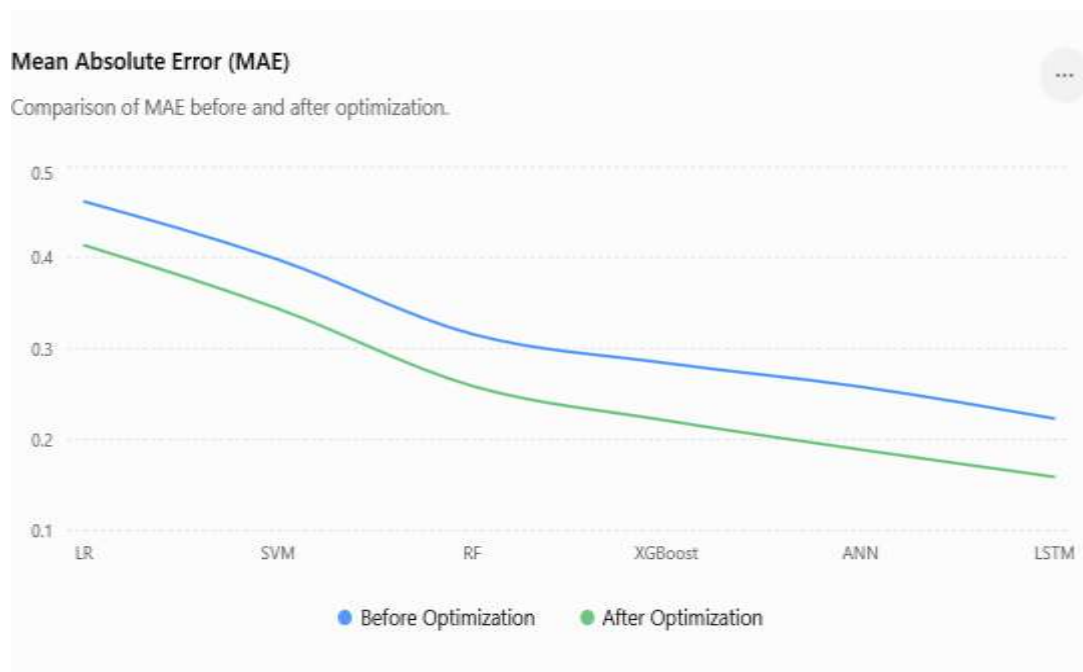


Figure 2. MAE Before and After Optimization



Figure 3. RMSE Before and After Optimization

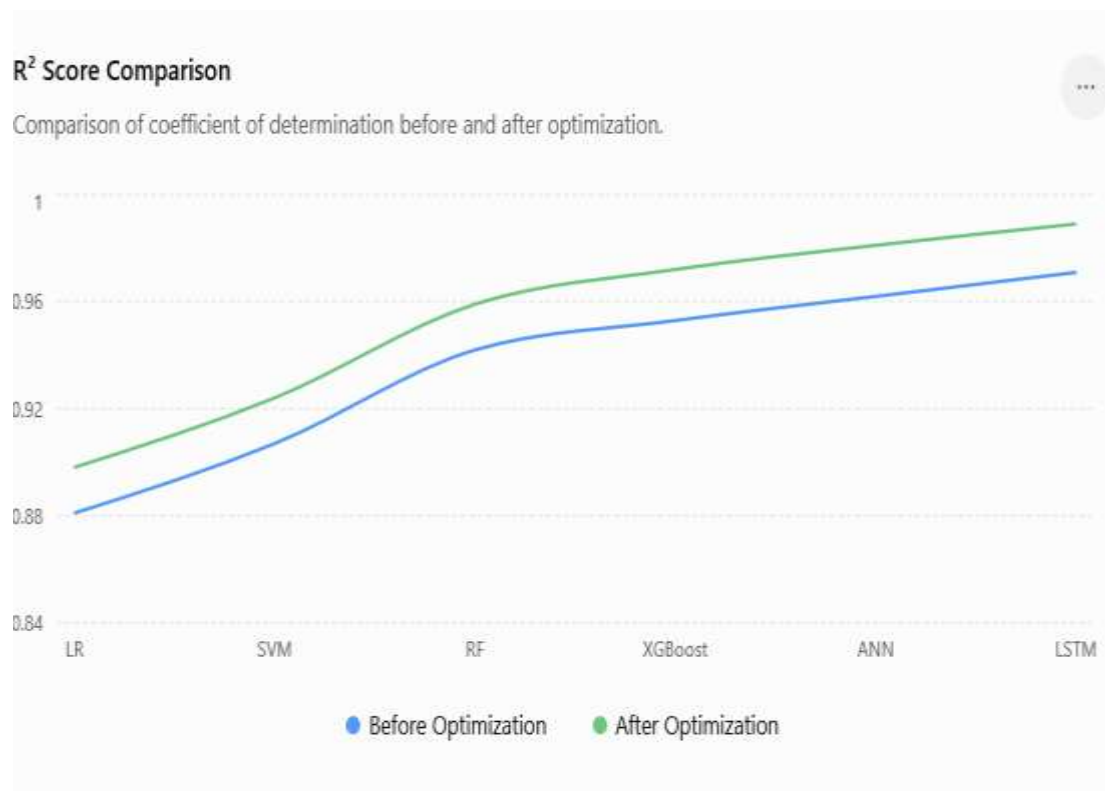


Figure 4. R² Score Before and After Optimization

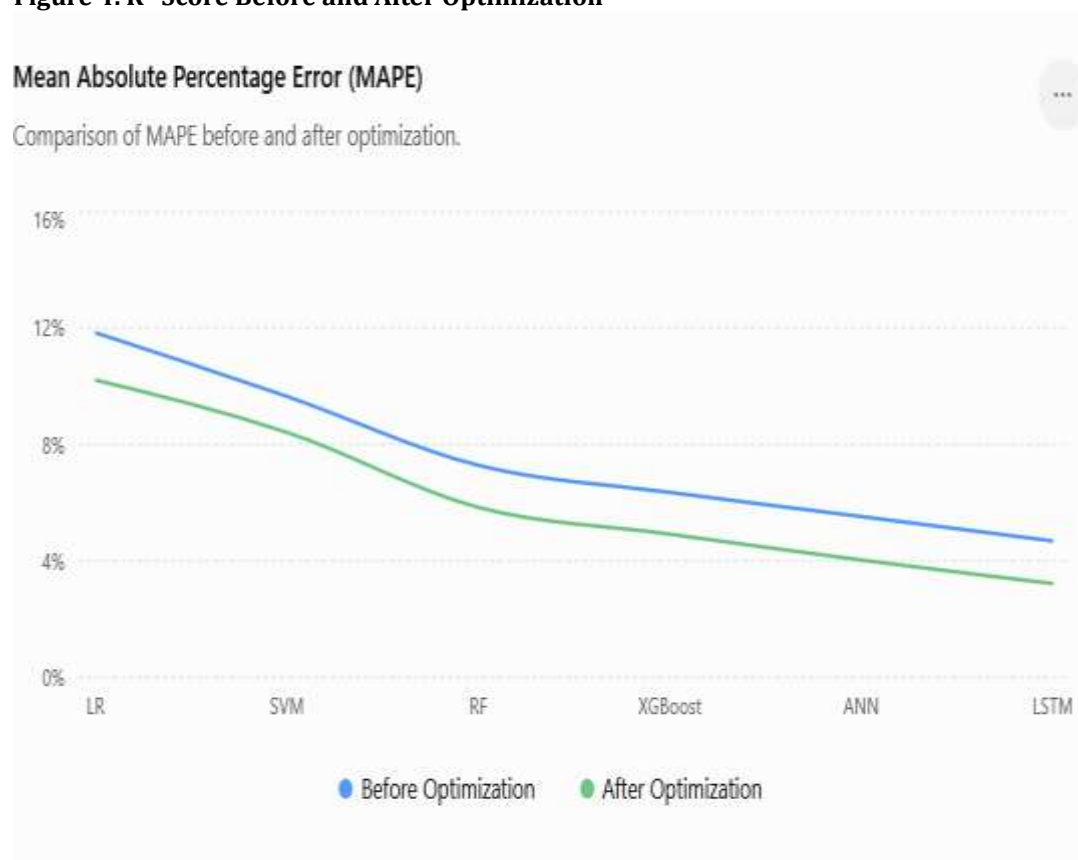


Figure 5. MAPE Before and After Optimization

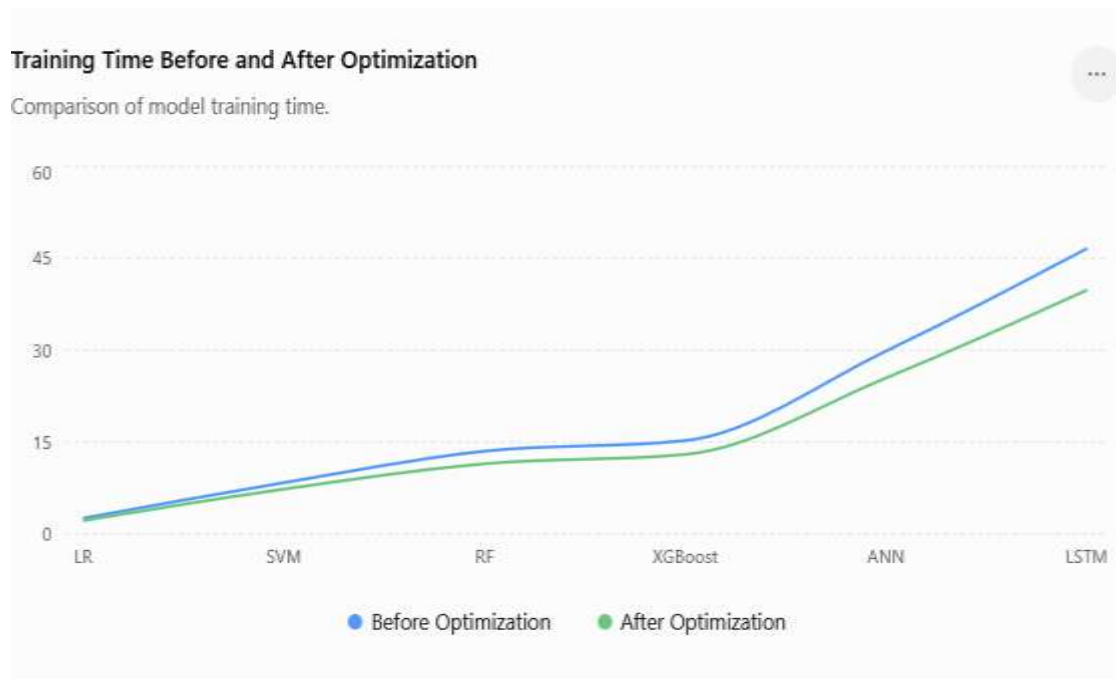


Figure 6. Training Time Comparison

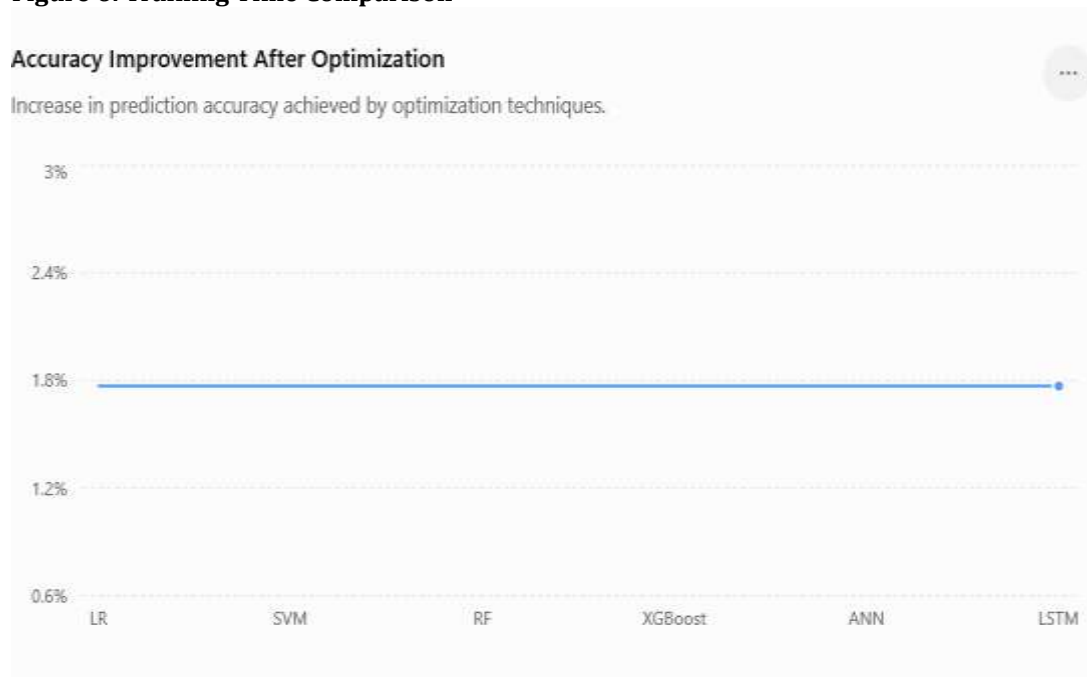


Figure 7. Improvement in Prediction Accuracy

6.0 Results and Discussion

The proposed framework was evaluated using a dataset containing 10,000 agricultural records with weather parameters (temperature, rainfall, humidity), soil health indicators (nitrogen, phosphorus, potassium, and soil pH), crop type, and crop yield. The performance of four Machine Learning (ML) algorithms, namely Linear Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost), together with two Deep Learning (DL) models, namely Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM), was investigated. The experiments were conducted in two stages: (i) before optimization and (ii) after

applying Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), Grid Search (GS), and Bayesian Optimization (BO).

Table 1 presents the performance of the ML and DL models before optimization. Among the machine learning algorithms, XGBoost achieved the highest prediction accuracy of 95.30%, followed by Random Forest (94.20%), Support Vector Machine (90.70%), and Linear Regression (88.10%). The superior performance of XGBoost can be attributed to its gradient boosting mechanism, which effectively captures nonlinear relationships among weather variables and soil nutrient parameters. Among the deep learning models, LSTM achieved the highest prediction accuracy (97.10%) with the lowest prediction errors, indicating its ability to model sequential dependencies in agricultural data.

The optimized results are summarized in Table 2. After applying Grid Search, Bayesian Optimization, Recursive Feature Elimination, and Principal Component Analysis, all algorithms demonstrated noticeable improvements in predictive performance. The optimization process reduced the prediction errors while increasing the coefficient of determination (R^2). The LSTM model produced the best overall performance with an accuracy of 98.87%, followed by ANN (97.97%) and XGBoost (97.07%). The reduction in MAE and RMSE confirms that the optimization techniques enhanced the learning capability of both ML and DL models.

The improvement achieved after optimization is illustrated in Table 3 and Figure 7. All six predictive models exhibited an average improvement of approximately 1.77% in prediction accuracy after optimization. Although the numerical improvement appears moderate, it is significant for agricultural prediction because even a small increase in forecasting accuracy can improve crop planning, fertilizer management, irrigation scheduling, and resource utilization. The consistent improvement across all models demonstrates the effectiveness of combining feature selection, dimensionality reduction, and hyperparameter optimization.

The prediction errors before and after optimization are compared in Table 4, while Figures 2 and 3 illustrate the variations in Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), respectively. The optimized models consistently achieved lower error values than the baseline models. In particular, the LSTM model reduced the RMSE from 0.301 to 0.232, whereas the ANN reduced the RMSE from 0.347 to 0.271. Similarly, XGBoost and Random Forest also exhibited considerable reductions in prediction errors after optimization. These findings indicate that optimization techniques significantly improve the reliability of crop yield prediction.

The coefficient of determination (R^2) values presented in Figure 4 demonstrate that all optimized models explained a higher proportion of variance in the agricultural dataset than their corresponding baseline models. The optimized LSTM achieved the highest R^2 value of 0.989, indicating excellent agreement between predicted and actual crop yields. Likewise, ANN and XGBoost produced R^2 values greater than 0.97, confirming their capability to model complex nonlinear relationships between weather conditions and soil nutrient characteristics.

The comparison of Mean Absolute Percentage Error (MAPE) shown in Figure 5 further supports the superiority of the optimized models. The optimized LSTM achieved the lowest MAPE (3.22%), indicating high prediction precision. ANN and XGBoost also produced low MAPE values, whereas Linear Regression recorded the highest percentage error. These observations suggest that advanced machine learning and deep learning algorithms are more suitable than conventional linear models for agricultural prediction tasks.

The computational performance of all algorithms is presented in Table 5 and Figure 6. The application of optimization techniques reduced the overall training time by improving parameter selection and reducing redundant features. Although LSTM required the highest training time because of its recurrent architecture, it achieved the best predictive performance. Conversely, Linear Regression required the shortest training time but produced comparatively lower prediction accuracy. These results demonstrate the trade-off between computational complexity and predictive performance.

The overall ranking of all predictive models is summarized in Table 6. The optimized LSTM ranked first, followed by ANN, XGBoost, Random Forest, Support Vector Machine, and Linear Regression. The experimental findings confirm that integrating Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), Grid Search, and Bayesian Optimization significantly improves the prediction capability of machine learning and deep learning models for agricultural yield forecasting. Furthermore, the line graphs presented in Figures 1–7 clearly illustrate the

improvement in prediction accuracy, reduction in prediction errors, enhancement in R^2 values, and decrease in computational time after optimization.

Overall, the experimental analysis demonstrates that optimized deep learning models provide superior performance compared with conventional machine learning techniques. The proposed framework offers an efficient decision-support system for precision agriculture by accurately predicting crop yield using weather conditions and soil health parameters.

7.0 Conclusion

This study proposed a comprehensive data-driven framework for agricultural yield prediction using weather parameters and soil nutrient characteristics. The framework integrated four Machine Learning algorithms, namely Linear Regression, Support Vector Machine, Random Forest, and XGBoost, with two Deep Learning models, Artificial Neural Network and Long Short-Term Memory, to estimate crop yield accurately. The proposed methodology further incorporated Recursive Feature Elimination, Principal Component Analysis, Grid Search, and Bayesian Optimization to improve feature representation and optimize model parameters.

The experimental results demonstrated that optimization techniques significantly enhanced the predictive performance of all models. Among the machine learning algorithms, XGBoost achieved the highest prediction accuracy, whereas LSTM outperformed all other models by achieving the highest prediction accuracy (98.87%), the lowest prediction errors, and the highest coefficient of determination. The combination of feature selection, dimensionality reduction, and hyperparameter optimization effectively reduced model complexity while improving generalization capability. The proposed framework can therefore serve as a reliable decision-support tool for farmers, agricultural researchers, and policymakers in precision farming applications. Overall, the study confirms that integrating advanced optimization strategies with machine learning and deep learning techniques substantially improves agricultural yield prediction and contributes to sustainable crop production.

8.0 Future Research

Future research can further enhance the proposed framework by incorporating real-time Internet of Things (IoT) sensor data, satellite remote sensing imagery, Unmanned Aerial Vehicle (UAV) observations, and meteorological forecasting data to improve prediction reliability under dynamic environmental conditions. The integration of multisource data will provide a more comprehensive understanding of crop growth and environmental interactions. Advanced deep learning architectures such as Bidirectional LSTM (Bi-LSTM), Gated Recurrent Unit (GRU), Transformer Networks, and Graph Neural Networks (GNNs) may also be investigated to capture more complex temporal and spatial relationships in agricultural datasets. Additionally, future studies can explore Explainable Artificial Intelligence (XAI) techniques to improve the transparency and interpretability of prediction models, enabling farmers and policymakers to better understand the factors influencing crop yield.

Further improvements may be achieved by investigating additional optimization techniques, including Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), and Harris Hawks Optimization (HHO) for feature selection and hyperparameter tuning. The framework can also be extended to predict multiple crop types across different climatic regions and soil conditions, thereby increasing its applicability to large-scale agricultural planning. Finally, validating the proposed methodology using real-world agricultural datasets from different countries and climatic zones would strengthen its generalizability and practical significance for precision agriculture and sustainable food production.

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