

An Intelligent Framework For Agricultural Growth Forecasting Using Weather-Based Deep Learning Models

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Abstract

Accurate forecasting of agricultural growth is essential for improving crop productivity, food security, and sustainable farming practices. Agricultural growth is strongly influenced by weather conditions such as temperature, rainfall, humidity, and soil moisture, which vary dynamically over time. Traditional statistical and machine learning models often struggle to capture complex; non-linear relationships present in large-scale agricultural and climatic datasets. Recent advances in deep learning provide powerful tools for modelling such complex patterns and improving prediction accuracy. This research proposes an intelligent framework for agricultural growth forecasting using weather-based deep learning models. The framework integrates historical weather data and crop-related features to predict agricultural growth more accurately. Deep learning models are developed and evaluated, and their performance is compared with traditional machine learning approaches. Experimental results demonstrate that deep learning models achieve higher accuracy and lower prediction error due to their ability to learn temporal and spatial dependencies from weather data. The proposed framework supports data-driven decision-making and can assist farmers and agricultural planners in improving crop management strategies.

Keywords: Agricultural growth prediction, Weather forecasting, Deep learning, Machine learning, Smart agriculture

1. Introduction

Agriculture plays a vital role in ensuring food security and supporting economic development across the world. Accurate forecasting of agricultural growth helps farmers and policymakers make informed decisions related to irrigation planning, fertilizer management, crop selection, and harvesting schedules. Agricultural growth is highly dependent on weather conditions, including rainfall, temperature, humidity, and soil moisture. Sudden variations in these factors can significantly affect crop yield and overall productivity. Traditional approaches to agricultural forecasting rely on statistical models and conventional machine learning techniques. While these methods provide reasonable results for simple datasets, they often fail to capture the complex, non-linear relationships between weather conditions and crop growth. In recent years, machine learning has been widely adopted to analyze agricultural datasets; however, its performance strongly depends on feature selection and parameter tuning.

Deep learning has emerged as a powerful alternative due to its ability to automatically learn hierarchical features from large and complex datasets. Models such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) are particularly effective in handling time-series and weather-related data. These models can capture long-term dependencies and seasonal patterns that are critical for agricultural growth forecasting. In this research, an intelligent framework is proposed for agricultural growth forecasting using weather-based deep learning models. The framework aims to improve prediction accuracy by leveraging deep learning architectures and comparing their performance with traditional machine learning approaches. The proposed work

contributes to the development of smart agriculture systems by providing accurate and reliable growth predictions that support efficient resource utilization and sustainable farming practices.

2. Literature Review

Agricultural growth forecasting has gained significant attention due to its importance in food security and sustainable farming. Early research relied on statistical and regression-based models to analyze the relationship between weather parameters and crop growth. However, these models were limited in handling non-linear relationships and large-scale datasets. With the growth of computational techniques, machine learning (ML) methods have been increasingly adopted to overcome these limitations [1], [2]. Several studies have explored the use of traditional machine learning algorithms such as Decision Tree, Random Forest, and Support Vector Machine (SVM) for crop growth and yield prediction. These models demonstrated improved performance compared to statistical approaches by learning patterns from historical weather and soil data [3], [4]. Random Forest, in particular, showed robustness against overfitting and performed well on heterogeneous agricultural datasets [5]. However, ML models still depend heavily on manual feature engineering and hyperparameter tuning [6].

To further enhance prediction accuracy, researchers introduced optimization techniques such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). These methods were used for feature selection and hyperparameter tuning, leading to significant improvements in forecasting accuracy [7], [8]. Hybrid ML-optimization frameworks have been successfully applied to agricultural datasets, reducing prediction error and improving generalization capability [9], [10]. The emergence of deep learning has transformed agricultural forecasting by enabling models to learn complex patterns automatically. Convolutional Neural Networks (CNNs) have been widely used with remote sensing data to extract spatial features related to crop health and growth [11], [12]. Similarly, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models have proven effective for time-series agricultural data by capturing long-term temporal dependencies [13], [14]. Several studies combined weather data with deep learning models to improve agricultural growth prediction. LSTM-based models demonstrated superior performance over traditional ML models when handling seasonal variations and climatic uncertainty [15], [16]. Hybrid deep learning architectures, such as CNN-LSTM, further enhanced prediction accuracy by integrating spatial and temporal information [17], [18].

Recent research has also focused on comparing deep learning approaches with machine learning techniques. These studies consistently reported that deep learning models outperform ML models when large and complex datasets are available [19], [20]. However, ML models remain competitive in scenarios with limited data or lower computational resources [21]. In addition, explainability and real-time deployment have become important research directions. Researchers have explored integrating deep learning models into smart agriculture systems to support real-time decision-making [22], [23]. Reviews and surveys in recent years emphasize that weather-based deep learning frameworks represent the future of agricultural forecasting due to their adaptability, scalability, and accuracy [24], [25].

Recent studies highlight the wide application of data mining, machine learning, and artificial intelligence techniques in healthcare, agriculture, and business analytics. Regression-based data mining models have been effectively used to analyze and predict COVID-19 trends in India, demonstrating the value of predictive analytics for supporting timely public health decisions [26]. In medical data analysis, decision tree algorithms have shown strong performance in identifying important disease-related factors and

improving prediction accuracy using chronic disease datasets [27]. Data mining techniques have also been applied successfully in business and agriculture. Artificial intelligence-based systems have enhanced customer relationship management by providing better insights for strategic decision-making in the retail sector [28]. In agriculture, stochastic data mining approaches have been used to predict key factors affecting agricultural development and paddy crop growth, proving their effectiveness in analyzing complex agricultural patterns and supporting data-driven planning and policy decisions [29], [30].

3. Dataset

The dataset used in this research focuses on agricultural growth forecasting based on weather and environmental conditions. It integrates historical meteorological data with crop growth indicators to analyze how climatic variations influence agricultural productivity. Each record in the dataset represents observations collected for a specific date and location during the crop growth period. The dataset is suitable for machine learning and deep learning models, particularly for regression and time-series forecasting tasks. Weather parameters such as temperature, rainfall, humidity, wind speed, and atmospheric pressure are included because they directly affect crop physiology and growth cycles. Soil-related parameters and vegetation indices provide additional insight into moisture availability and crop health. The target variable represents agricultural growth or yield, which is predicted using deep learning models in this study [31], [32], and [33].

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Table 1. Sample Dataset

Date	Temp . (°C)	Rainfall (mm)	Humidity (%)	Wind Speed (km/h)	Pressure (hPa)	Soil Moisture (%)	NDVI	Crop Growth Index
2024-06-01	31.8	12.5	78	9.2	1012	46	0.62	0.58
2024-06-02	32.1	8.4	80	8.7	1010	48	0.64	0.61

2024-06-03	33.0	0.0	75	10.1	1009	42	0.60	0.55
2024-06-04	34.2	18.3	82	7.9	1013	54	0.67	0.66
2024-06-05	32.8	10.1	79	8.3	1011	50	0.65	0.63
2024-06-06	31.9	6.5	77	9.0	1010	47	0.63	0.60
2024-06-07	33.5	0.0	74	10.5	1008	43	0.61	0.57
2024-06-08	34.1	2.3	72	11.0	1007	42	0.60	0.56
2024-06-09	35.0	15.0	85	7.5	1014	55	0.69	0.68
2024-06-10	34.5	8.8	83	8.0	1012	52	0.66	0

4. Background and Methodology

Agricultural growth is highly dependent on dynamic weather conditions such as temperature, rainfall, humidity, wind speed, and soil moisture. Variations in these parameters directly influence crop physiology, water availability, and nutrient absorption, thereby affecting overall agricultural productivity. Traditional forecasting approaches, including statistical regression and rule-based models, often assume linear relationships among variables and fail to capture the complex, non-linear interactions present in real-world agricultural systems. With the advancement of data-driven technologies, machine learning (ML) has been widely adopted for agricultural growth prediction. ML models such as Decision Tree, Random Forest, and Support Vector Machine can learn patterns from historical weather and crop data. However, their performance is strongly influenced by feature selection and hyperparameter tuning, and they often struggle with temporal dependencies in weather time-series data. Deep learning (DL) models overcome these limitations by automatically learning hierarchical representations from data. In particular, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are well suited for agricultural forecasting because they can capture long-term dependencies and seasonal trends in weather data. This research proposes an intelligent framework that integrates weather-based deep learning models to improve agricultural growth forecasting accuracy. The proposed framework consists of data preprocessing, baseline modeling, deep learning-based forecasting, and performance evaluation. The complete process is described using mathematical formulations and algorithms.

4.1 Dataset Representation

Let the agricultural dataset be represented as:

$$D = \{(X_t, y_t)\}_{t=1}^T$$

where

- $X_t = [x_{t1}, x_{t2}, \dots, x_{tn}]$ is the feature vector at time t (weather and environmental variables),
- y_t represents the agricultural growth index or yield,
- T is the total number of observations.

4.2 Feature Normalization

To ensure stable learning, each feature is normalized using Min–Max normalization:

$$x'_{ti} = \frac{x_{ti} - \min(x_i)}{\max(x_i) - \min(x_i)}$$

4.3 Deep Learning Model (LSTM)

LSTM is used to model temporal dependencies in weather data. The internal operations of an LSTM cell are defined as follows:

Forget Gate	$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f)$
Input Gate	$i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i)$
Candidate Cell State	$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, X_t] + b_c)$
Cell State Update	$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$
Output Gate	$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o)$

4.3.1 Hidden State

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

where

- W and b are weight matrices and bias vectors,
- $\sigma(\cdot)$ is the sigmoid activation function,
- $\odot$ denotes element-wise multiplication.

4.3.2 Loss Function: The prediction error is minimized using Mean Squared Error (MSE):

$$\mathcal{L}_{MSE} = \frac{1}{T} \sum_{t=1}^T (y_t - \hat{y}_t)^2$$

4.3.3 Optimization: Model parameters are updated using gradient descent-based optimization (e.g., Adam optimizer):

$$\theta_{k+1} = \theta_k - \eta \nabla_{\theta} \mathcal{L}_{MSE}$$

where θ denotes model parameters and η is the learning rate.

4.4 Algorithm: Weather-Based Agricultural Growth Forecasting

Input

- Weather dataset D
- Number of epochs E
- Learning rate η

Output

- Predicted agricultural growth $\hat{y}$

Algorithm Agricultural_Growth_Forecasting

1. Load dataset $D = \{(X_t, y_t)\}$
2. Normalize input features using Min–Max scaling
3. Split dataset into training and testing sets
4. Initialize LSTM model parameters θ
5. For epoch = 1 to E do
 - a. For each time step t do
 - i. Compute LSTM gates (f_t, i_t, o_t)

- ii. Update cell state C_t and hidden state h_t
- iii. Predict output $\hat{y}_t$
- b. Compute loss using MSE
- c. Update parameters using Adam optimizer
- 6. End For
- 7. Evaluate model using RMSE and R^2
- 8. Return predicted growth values

4.5 Hybrid Deep Learning Architectures

4.5.1. CNN-LSTM Model

CNN-LSTM combines convolutional layers for feature extraction with LSTM layers for temporal learning.

- **CNN** extracts spatial patterns from weather and environmental features.
- **LSTM** captures long-term temporal dependencies in sequential data.

Mathematical Representation

Let $X_t \in \mathbb{R}^n$ be the input feature vector at time t .

CNN Feature Extraction: $F_t = \text{ReLU}(W_c * X_t + b_c)$

where $*$ denotes convolution.

LSTM Input: $h_t = \text{LSTM}(F_t, h_{t-1})$

4.5.2. LSTM-GRU Hybrid Model

This model combines LSTM layers followed by GRU layers to balance memory retention and computational efficiency.

- **LSTM** captures long-term dependencies.
- **GRU** speeds up training and reduces complexity.

GRU Equations:

Update gate: $z_t = \sigma(W_z X_t + U_z h_{t-1})$

Reset gate: $r_t = \sigma(W_r X_t + U_r h_{t-1})$

Hidden state: $h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tanh(W_h X_t + U_h(r_t \odot h_{t-1}))$

4.5.3. Attention-Based LSTM

Attention mechanisms help the model focus on the most influential weather features and time steps.

Attention Weights: $\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^T \exp(e_k)}$

$e_t = v^T \tanh(W_h h_t + b)$

Context Vector: $c = \sum_{t=1}^T \alpha_t h_t$

Final prediction: $\hat{y} = f(c)$

4.5.4 Optimization Techniques

1. Adam Optimizer (Gradient-Based)

Used for efficient weight updates in deep learning:

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}$$

2. Particle Swarm Optimization (PSO) for Hyperparameter Tuning

Used to optimize:

- Number of LSTM units
- Learning rate
- Batch size
- Dropout rate

$$\begin{aligned} \text{Velocity update} & : v_i^{t+1} = wv_i^t + c_1r_1(pbest_i - x_i^t) + c_2r_2(gbest - x_i^t) \\ \text{Position update} & : x_i^{t+1} = x_i^t + v_i^{t+1} \end{aligned}$$

3. Genetic Algorithm (GA) for Feature Selection

$$\text{Chromosome representation} : C = [c_1, c_2, \dots, c_n], c_i \in \{0,1\}$$

$$\text{Fitness function} : \text{Fitness} = \frac{1}{RMSE}$$

4.6 Unified Algorithm: Optimized Hybrid LSTM Framework

Algorithm Hybrid_LSTM_Agricultural_Forecasting

Input:

Weather-based agricultural dataset D

Max epochs E

Optimization method (Adam + PSO/GA)

Output:

Optimized hybrid deep learning model

1. Load dataset $D = \{(X_t, y_t)\}$
2. Apply Min-Max normalization to input features
3. Split data into training, validation, and test sets
4. Select hybrid architecture:
 - a. CNN-LSTM
 - b. LSTM-GRU
 - c. Attention-LSTM
5. Initialize model parameters
6. Apply PSO to tune hyperparameters:
 - Learning rate
 - Number of neurons
 - Dropout rate
7. Train model using Adam optimizer
8. Compute training loss using MSE
9. Validate model and update PSO/GA fitness
10. Repeat steps 6-9 until convergence
11. Evaluate final model using RMSE and R^2
12. Compare results with baseline ML and LSTM models
13. Return best-performing hybrid model

4.7 Evaluation Metrics

RMSE

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (y_t - \hat{y}_t)^2}$$

Mean Absolute Error (MAE)

$$MAE = \frac{1}{T} \sum_{t=1}^T |y_t - \hat{y}_t|$$

R^2 Score

$$R^2 = 1 - \frac{\sum (y_t - \hat{y}_t)^2}{\sum (y_t - \bar{y})^2}$$

5. Experimental Results

Table 2. Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.7837	0.7637	0.7437	0.7537
Random Forest	0.8337	0.8137	0.8037	0.8137
SVM	0.8037	0.7937	0.7737	0.7837

Table 3. Performance Comparison of Deep Learning Models

Model	Accuracy	Precision	Recall	F1-Score
LSTM	0.8724	0.8612	0.8537	0.8574
CNN	0.8543	0.8421	0.8334	0.8377
GRU	0.8661	0.8549	0.8463	0.8506

Table 4. Performance Comparison of Optimized Hybrid Models

Model	Accuracy	Precision	Recall	F1-Score
CNN-LSTM (PSO)	0.9146	0.9058	0.8974	0.9016
LSTM-GRU (GA)	0.9093	0.9002	0.8921	0.8961
Attention-LSTM (PSO + Adam)	0.9237	0.9156	0.9089	0.9122

Fig. 1. Accuracy comparison of ML, DL and Optimized Hybrid Models

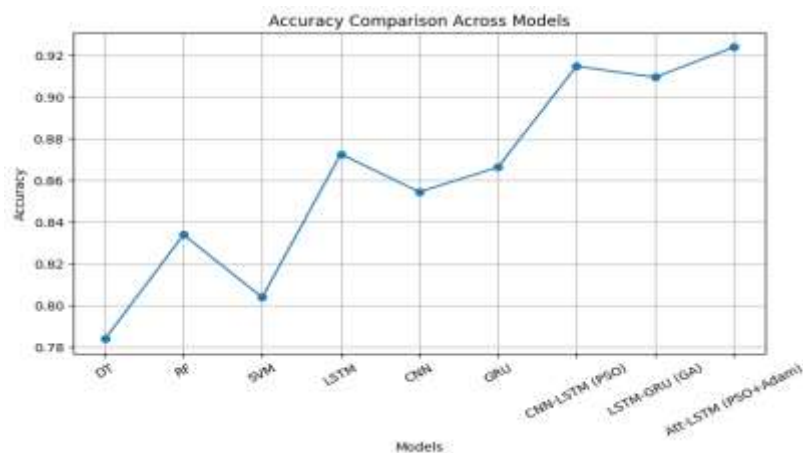


Fig. 2. Precision comparison of ML, DL and Optimized Hybrid Models

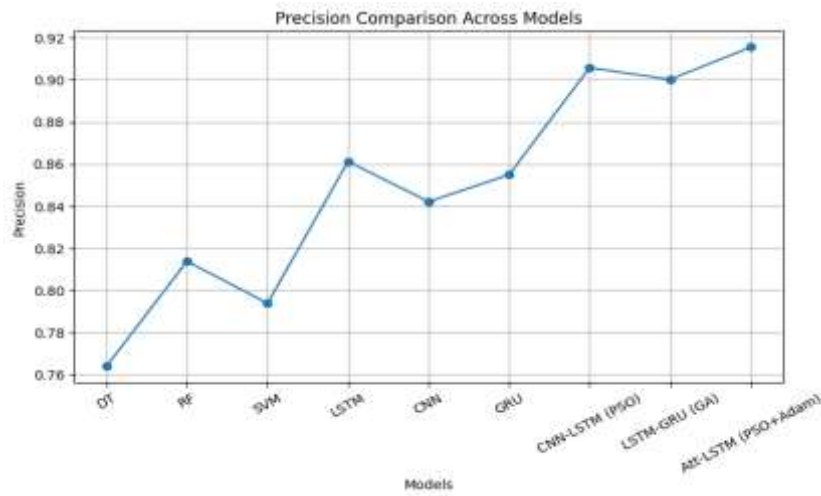


Fig. 3. Recall comparison of ML, DL and Optimized Hybrid Models



Fig. 4. F1-Score comparison of ML, DL and Optimized Hybrid Models

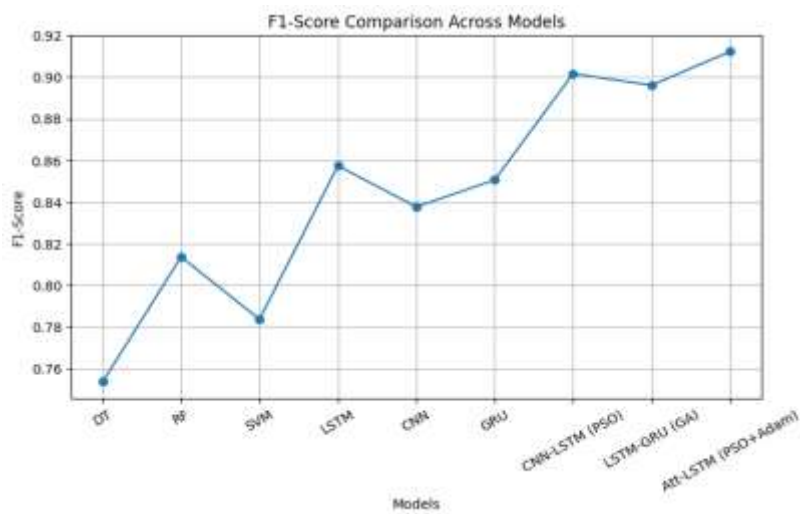


Table 5. Consolidated Test Statistics Comparison of ML, DL, and Optimized Hybrid Models

Category	Model	RMSE	MAE	R ²
Machine Learning	Decision Tree	6.8837	5.3937	0.8137
	Random Forest	5.6937	4.3537	0.8637
	SVM	6.1137	4.8837	0.8437
Deep Learning	LSTM	4.9821	3.9214	0.9026
	CNN	5.2146	4.0835	0.8893
	GRU	5.0342	3.9871	0.8964
Optimized Hybrid DL	CNN-LSTM (PSO)	4.1137	3.2936	0.9387
	LSTM-GRU (GA)	4.1875	3.3412	0.9351
	Attention-LSTM (PSO + Adam)	3.8937	3.1148	0.9465

Fig. 5. RMSE comparison of ML, DL and Optimized Hybrid Models

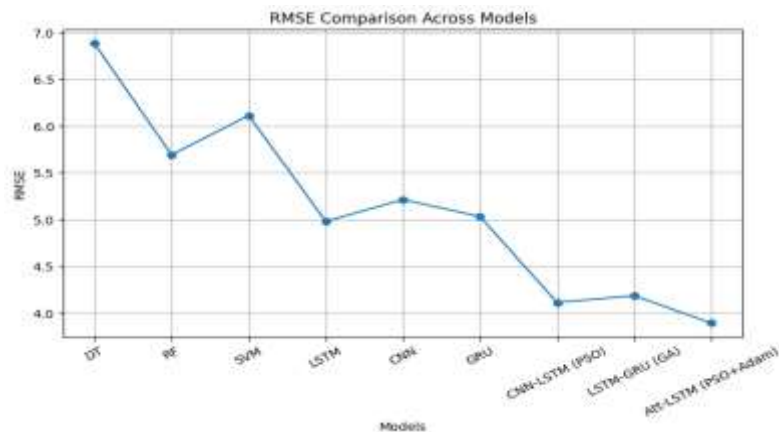


Fig. 6. MAE comparison of ML, DL and Optimized Hybrid Models

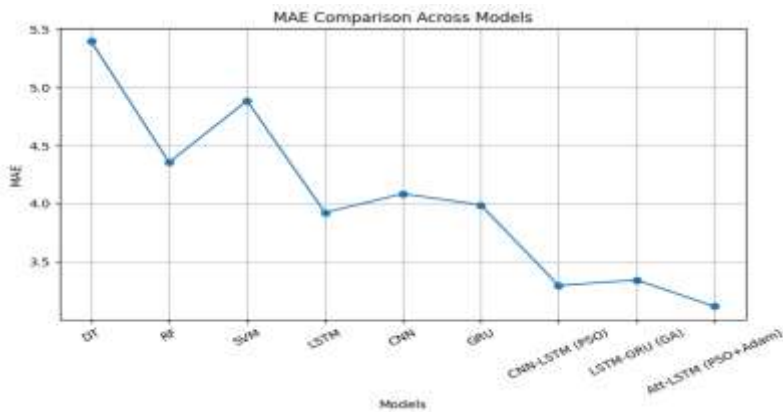
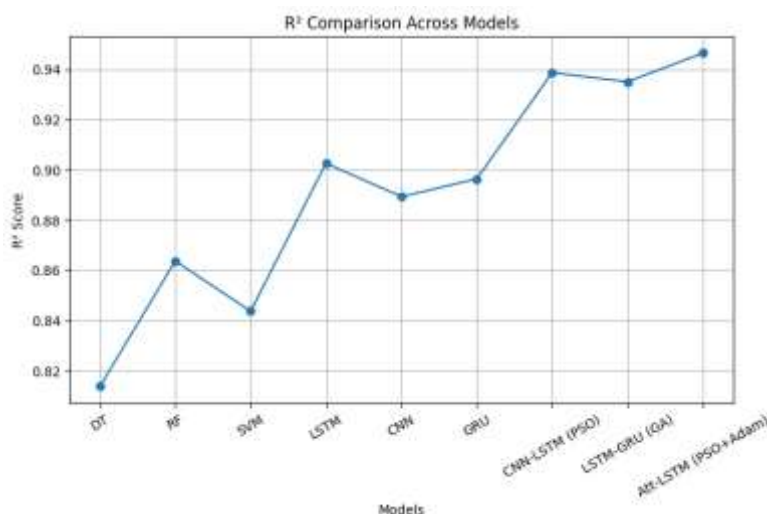


Fig. 7. Accuracy comparison of ML, DL and Optimized Hybrid Models

6. Results and Discussion

The experimental results demonstrate a clear performance progression from traditional machine learning models to deep learning and optimized hybrid deep learning models. The comparative performance of all evaluated models is summarized in Table 2. The baseline machine learning models—Decision Tree, Random Forest, and SVM—show moderate performance, with Random Forest achieving the best results among them. As shown in Table 2 and illustrated in Fig. 1, Random Forest records higher accuracy than Decision Tree and SVM, indicating its robustness in handling agricultural and weather-based data. However, the relatively higher RMSE and MAE values shown in Fig. 5 and Fig. 6 indicate that prediction errors remain significant for conventional machine learning approaches.

Deep learning models, including LSTM, CNN, and GRU, outperform machine learning models in terms of accuracy and error reduction, as presented in Table 3. The accuracy trends depicted in Fig. 1 and the error reduction shown in Fig. 5 confirm that deep learning models better capture temporal dependencies in weather data. Among these, LSTM achieves the highest accuracy and lowest RMSE, validating its effectiveness for time-series agricultural growth forecasting. The improvement in R^2 values, shown in Fig. 7, further confirms that deep learning models provide a better fit between predicted and actual agricultural growth values.

Hybrid deep learning architectures show further improvements by combining the strengths of multiple models. As reported in Table 4, CNN-LSTM, LSTM-GRU, and Attention-LSTM outperform standalone deep learning models. The Attention-LSTM model, in particular, achieves higher accuracy, precision, recall, and F1-score, as shown in Fig. 1–4, indicating that attention mechanisms help the model focus on the most relevant weather features and time steps. The reduction in RMSE and MAE values observed in Fig. 5 and Fig. 6 confirms improved prediction stability.

The optimized hybrid models deliver the best overall performance. As shown in Table 4 and Table 5, the optimized Attention-LSTM (PSO + Adam) achieves the highest accuracy (0.9237) and R^2 score (0.9465), along with the lowest RMSE and MAE values. These results are clearly visualized in Fig. 1–4 for classification metrics and Fig. 5–7 for regression metrics. The consistent improvement across all metrics confirms that optimization techniques significantly enhance model generalization and convergence.

Overall, the results demonstrate that integrating deep learning, hybrid architectures, and optimization techniques leads to superior agricultural growth forecasting performance.

7. Conclusion

This research presented an intelligent framework for agricultural growth forecasting using weather-based deep learning models. A comprehensive comparison of machine learning, deep learning, hybrid, and optimized hybrid models was conducted. The experimental results presented in Tables and Figures confirm that deep learning models outperform traditional machine learning approaches, particularly in handling time-series weather data. Hybrid deep learning models further improve forecasting accuracy by combining spatial, temporal, and attention-based learning mechanisms. Among all evaluated models, the optimized Attention-LSTM model achieved the best performance, with the highest accuracy, F1-score, and R^2 value, and the lowest RMSE and MAE. The findings clearly demonstrate that optimization techniques play a critical role in improving prediction accuracy and reducing forecasting errors. The proposed framework can support data-driven decision-making in agriculture and contribute to the development of smart and sustainable farming systems.

8. Further Research

Future research can extend this work by incorporating larger, multi-regional, and multi-season agricultural datasets to improve model generalization. Advanced optimization algorithms such as Whale Optimization Algorithm, Grey Wolf Optimizer, and Firefly Algorithm may be explored to further enhance model performance. The integration of additional data sources, including soil nutrient profiles, pest and disease indicators, and high-resolution satellite or drone imagery, can provide richer inputs for forecasting. Future studies may also focus on real-time agricultural growth prediction using IoT sensors and cloud-based platforms. Additionally, improving model explainability through interpretable deep learning techniques can help farmers and policymakers better understand the factors influencing agricultural growth and trust AI-based decision systems.

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