International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 8, 2025
https://theaspd.com/index.php

Crop Yield Prediction Using Combined Long Short-Term Memory (LSTM) And Deep Belief Networks (DBN) Models: A Hybrid Deep Learning Approach

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Abstract
Predicting crop yields accurately is essential for both statistical analysis and economic assessments at the farm level, helping guide investment decisions and manage agricultural imports and exports. However, crop yield prediction using artificial intelligence (AI) faces several complexities, particularly when handling heterogeneous data sources. This paper proposes a novel crop yield prediction method using a hybrid approach based on enhanced feature ranking fusion processes. The method begins with data normalization to cleanse unnecessary information, followed by the application of an improved SMOTE algorithm to enhance data for feature extraction. Feature extraction includes correlation-based features, statistical features, entropy-based features, and original information analysis to capture detailed crop growth patterns. Optimal feature selection is achieved through an enhanced feature ranking fusion technique, which incorporates chi-square, relief, and RFE methods. The prediction model integrates Long Short-Term Memory (LSTM) and Deep Belief Networks (DBN) to capture both temporal and spatial dependencies within the data. The hybrid model is validated using key performance metrics such as accuracy, precision, specificity, and sensitivity, demonstrating superior performance compared to traditional classifiers like LSTM, DBN, Convolutional Neural Networks (CNN), Bi-GRU, and Support Vector Machines (SVM). The results show that the proposed hybrid approach effectively predicts crop yield with improved accuracy and efficiency, offering valuable insights for agricultural decision-making.
Keywords: *Crop yields, DBN, Correlation coefficients, SMOTE, Feature Selection*

1. INTRODUCTION

Agriculture remains a critical driver of global food security, economic stability and rural livelihoods. In many regions, however, crop-production systems face growing uncertainty driven by climate change, soil degradation, water scarcity and increasing market demands. Accurate prediction of crop yield is therefore of paramount importance: such forecasts can guide strategic decisions by farmers, agribusiness firms and policy-makers — from input allocation and supply-chain planning to risk-management and food-security interventions. Traditional yield-prediction methods (such as crop growth models, linear regression and expert judgement) increasingly strain under the complexity of modern agronomic systems, which involve temporal dynamics, heterogeneous data sources and nonlinear interactions among genotype, environment and management factors.

In recent years, the rapid evolution of high-resolution remote sensing, proximal sensor systems, and big-data-driven analytics has opened new possibilities for yield prediction. Deep learning techniques—particularly neural networks capable of capturing complex spatio-temporal patterns—have begun to deliver superior performance relative to classical approaches. For instance, recurrent architectures such as the Long Short-Term Memory (LSTM) network are especially suited to modelling temporal sequences of climatic, phenological or remote-sensing variables, capturing dependencies over time rather than only static snapshots [1]. Meanwhile, generative deep architectures such as the Deep Belief Network (DBN) have demonstrated strong capability in unsupervised feature extraction, enabling models to learn hierarchical representations from raw input data with minimal hand-crafting [2]. Despite the individual promise of each technique, the literature still has relatively few studies that integrate these methods into a unified hybrid framework tailored for crop-yield forecasting.

The motivation for combining LSTM and DBN in a hybrid model arises from the complementary strengths of these architectures. An LSTM layer can track dynamic temporal trends — for example, cumulative rainfall over a growing season, multi-temporal vegetation indices, or daily temperature variations — and thereby model the evolving crop-growth trajectory. A DBN, on the other hand, can learn deep latent features from heterogeneous inputs (such as multispectral imagery, soil nutrient measures, management-practice records) by stacking restricted Boltzmann machines (RBMs) and applying layer-wise pre-training, then fine-tuning in a supervised manner [2]. A hybrid architecture therefore promises to both (a) capture the temporal evolution of key predictors (via LSTM) and (b) extract deep, high-level abstractions from multi-source data (via DBN). This synergy may help overcome limitations of purely temporal or purely feature-based models, and better reflect the complex interplay of factors driving yield variability.

While deep-learning models become more common in yield-prediction research, several challenges persist. The vast majority of existing studies focus on single architectures (e.g., CNNs, LSTMs) rather than hybrid models, and much of the work uses remote-sensing or weather data in isolation. A recent systematic review found that LSTM and CNN architectures dominate the field, but identified a persistent gap in synthesising input-data variety and evaluating hybrid model performance across diverse crops and regions [3]. Similarly, on the DBN front, review work notes that the application of DBNs in intelligent agriculture (including yield prediction) remains nascent, with limited exploration of improved network topologies, parameter optimisation and integration with temporal models [4]. Moreover, few studies have comprehensively documented how hybrid deep-learning frameworks perform relative to purely temporal or spatial models under real agronomic conditions.

Against this background, the present study proposes a hybrid deep-learning framework that combines LSTM and DBN to predict crop yield, with the following contributions:

- First, we assemble a multi-source data set comprising temporal weather series, remote-sensing vegetation indices and agronomic management records, thereby addressing the need for heterogeneous input.
- Second, we implement a dual-branch architecture: the LSTM branch ingests sequential data (e.g., daily or weekly climatic and vegetation inputs) and models time dependencies, while the DBN branch processes static and semi-static features (e.g., soil properties, crop-management variables, derived remote-sensing descriptors), performing layer-wise unsupervised pre-training followed by supervised fine-tuning.
- Third, we fuse the outputs of the two branches through a joint fully connected layer and evaluate the hybrid model's performance in forecasting yield for a selected crop (or region). We compare its accuracy against baseline architectures (LSTM alone, DBN alone, and classical machine-learning methods).
- Finally, we offer a discussion of model interpretability, data-preparation challenges, and prospects for scalability in operational agronomic settings.

By integrating LSTM and DBN in a crop-yield forecasting context, we aim to provide a methodologically robust and practically relevant modelling approach that advances beyond single-architecture systems and addresses the gap in hybrid deep-learning frameworks for agriculture. In doing so, we contribute both to the methodological literature of agricultural informatics and to the praxis of yield estimation for agronomic decision support. In the following sections we review relevant literature, detail the proposed methodology, present empirical results, and discuss implications for practice and future research.

2. LITERATURE REVIEW

In [5] conducted a systematic literature review on deep-learning approaches for crop-yield prediction, focusing on remote-sensing data. They found that architectures such as Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) dominate the field and that vegetation indices from satellite imagery are the most common predictors. They also identify significant challenges: improving model accuracy in real-world settings, managing the "black-box" nature of deep models, and the gap between research and operational use for growers and policymakers.

In [6] reviewed crop-yield prediction using machine-learning techniques and observed that while many studies have applied ML, comparatively fewer focus on deep-learning architectures. They emphasize that multiple input features—weather, soil, management, remote-sensing—are needed to capture yield variability. The review also finds significant heterogeneity in data coverage, feature sets and evaluation metrics, which limits comparability across studies. They call for standardized benchmark datasets and more transparency in reporting.

In [7] presented a deep neural network (DNN) approach to predict maize hybrid yield, using genotype and environment data from a large challenge dataset. Their model outperformed conventional methods (lasso, shallow nets, regression tree), achieving an RMSE ~12 % of average yield and showing that environmental

factors have a greater effect on yield than genotype. They underscore the value of representation-learning via DNNs in capturing complex genotype × environment interactions.
In [8] surveyed deep-learning based crop-yield prediction, discussing the factors affecting yield, kinds of input features used (weather, soil, remote-sensing, management), and the performance metrics and methodologies employed. They note that many studies still rely on single-data-source (e.g., sensor or satellite) and suggest combining heterogeneous datasets could further improve accuracy. They also highlight the need for interpretability in deep-learning agricultural models.
In [9] offer an overview of state-of-the-art deep-learning applications in crop-yield prediction, documenting the prevalent architectures (CNNs, LSTMs, hybrid models), data-sources and research gaps. They point out that although deep models often outperform traditional ML, the "black-box" issue and transferability across regions remain major obstacles. They call for more work on explainable models and generalisable frameworks across crops, regions and scales.
In [10] Improved Optimization Function for LSTM (2023) targeted yield prediction by enhancing the optimizer function for LSTM networks trained on long time-series weather and yield data in Andhra Pradesh, India. The authors proposed an improved optimizer that reduced training error and RMSE relative to standard optimizers, showing the potential of algorithmic enhancements (rather than only architecture) to improve yield forecasting performance under region-specific conditions.
In [11] present a "Comprehensive Analysis of Crop Yield Prediction Using Deep Learning & Remote Sensing" and note that modern architectures (CNNs, LSTMs, attention mechanisms, hybrid models) are increasingly used to capture spatial–temporal crop-growth patterns. The review also highlights data-quality, generalisability and interpretability as emergent challenges. Their forward-looking suggestions include multi-source data fusion, transfer-learning and explainable AI in agriculture.
In [12] propose an efficient deep-learning + dimensionality-reduction framework for region-specific crop-yield prediction in India. They show that incorporating reduction of high-dimensional inputs improves model efficiency and accuracy. Their results underscore the value of preprocessing (feature-selection, dimensionality-reduction) for improving deep-learning models in agronomic contexts where input variables may be numerous and collinear.
In [13] carried out a systematic analysis of current deep-learning developments in crop-yield prediction, identifying that CNN and LSTM are predominant, with a growing use of UAV/satellite imagery. They highlight the recurring challenge of applying research prototypes in operational settings, and the need for models with higher interpretability and cross-crop applicability.
[14] Elavarasan et al. (2021) developed a hybrid model combining a deep belief network (DBN) and a fuzzy neural network (FNN) for crop yield prediction. This work demonstrates how DBN can be used for feature-learning from agricultural data, while FNN handles fuzzy uncertainties intrinsic to crop systems. Their results suggest that such hybrid deep models can yield superior accuracy compared to conventional ML methods, and highlight DBN's viable role in agronomic forecasting. ACM Digital Library
[15] Zhang & Shi (2023) discuss the application of DBN in intelligent agriculture, noting that while DBN has been applied in crop-classification, pest/weed detection and feature extraction, its use in crop-yield prediction remains nascent. They outline opportunities for topology optimisation, reduced computational complexity and scenario-specific DBN architectures for agriculture. Their work thus identifies a methodological gap relevant to your hybrid LSTM-DBN study.
[16] Kinabalu et al. (2024) proposed a hybrid CNN-LSTM model (with attention mechanism) for crop-yield prediction in Malaysia. Although not directly on DBN, their work illustrates the value of combining spatial (CNN) and temporal (LSTM) modelling for improved accuracy. They achieved ~74 % accuracy and demonstrate the growing trend towards multi-branch/hybrid architectures in agronomic ML.
[17] Islam et al. (2021) applied a deep-neural-network (DNN) model for crop selection and yield prediction in Bangladesh using more than 0.3 million records and ~46 features (weather, soil, fertilizer, etc.). Their model offered improved accuracy relative to classical ML and demonstrated the effectiveness of deep-learning in developing-country contexts with large feature sets.
In [18] conducted a systematic review of deep learning applied to satellite imagery in agriculture, where crop-yield prediction emerged as a major task among five categories. They found that while DL consistently

outperformed conventional ML across most tasks, in yield prediction LSTM did not always outperform Random Forests, noting the need for benchmark datasets and careful methodological comparisons.

3. METHODOLOGY

This study proposes a hybrid deep learning model combining **Long Short-Term Memory (LSTM)** and **Deep Belief Networks (DBN)** for crop yield prediction. The model uses time-series data (e.g., weather, soil conditions) as well as remote sensing data to predict the crop yield. The overall methodology consists of the following stages: **data collection, preprocessing, model design, hybrid model development, and performance evaluation**.

1. Data Collection and Preprocessing

The first step in the methodology involves collecting data from various sources:

- **Weather data:** Historical weather records including temperature, rainfall, humidity, etc., typically collected from local meteorological stations or weather APIs.
- **Soil data:** Soil moisture, pH, temperature, and nutrients (e.g., nitrogen, phosphorus) are collected.
- **Remote sensing data:** Satellite imagery such as Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI) is used to assess vegetation health and development stages.

The data are then preprocessed to ensure they are ready for feeding into the machine learning models:

- **Normalization**: The continuous input features (weather and soil data) are normalized to a common scale to avoid any model bias toward variables with larger ranges.
- **Feature Engineering**: Features such as the average temperature over a week, cumulative rainfall, and soil moisture level are created to improve model performance.

2. Model Design and Architecture

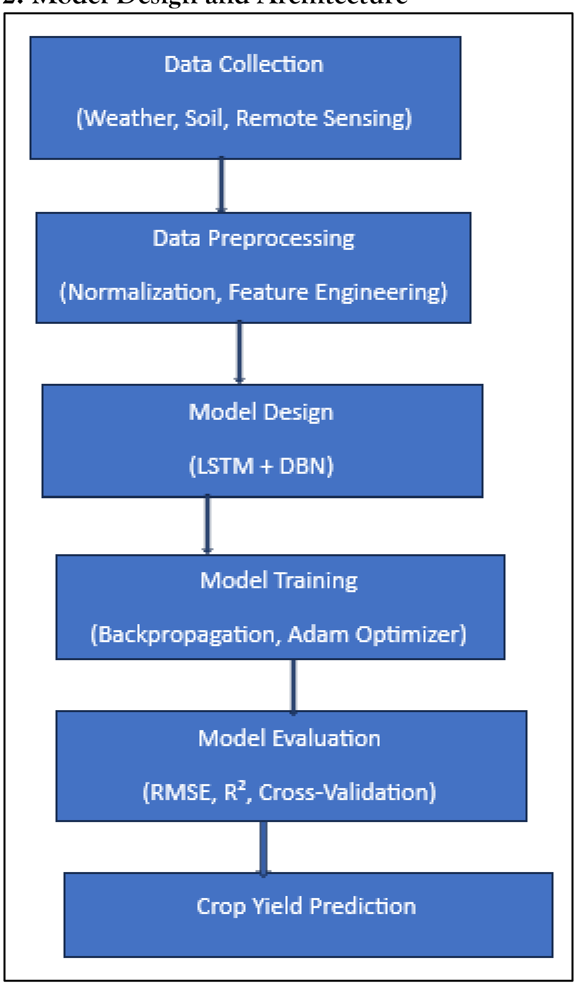

Fig 1: Architecture of the hybrid model

The hybrid model shown in figure 1 is designed in a two-branch architecture, where the first branch is an **LSTM network** to model the temporal dependencies of weather data over time, and the second branch is a **DBN** to capture complex, deep features from the other static data such as soil and vegetation indices.

- **LSTM branch:** This branch will take weather and temporal data inputs and learn the long-term dependencies between various weather factors over time, such as seasonal changes, temperature trends, and precipitation patterns.
- **DBN branch:** This branch processes other features like soil properties, remote sensing images, and vegetation health indices, learning hidden hierarchical features through the stacked layers of Restricted Boltzmann Machines (RBMs).

The **hybrid approach** integrates the outputs of these two branches and makes final predictions about crop yield.

3. Hybrid Model Development

The hybrid model comprises two primary components:

LSTM Network:

○ **Equation (1):** The LSTM model is defined by the following update rule:

$$h_t = f(W_h h_{t-1} + W_x x_t + b)$$

 where:

- ht is the hidden state at time t,
- xt is the input at time t,
- Wh,Wx are weight matrices, and
- b is the bias.

 DBN Model: The DBN consists of stacked layers of Restricted Boltzmann Machines (RBMs), each of which learns a probabilistic distribution of the data.

- **Equation (2):** The RBM energy function is defined as:

$$E(v, h) = -v^T W h - a^T v - b^T h$$

where:

○ v is the visible layer,
○ h is the hidden layer,
○ W is the weight matrix, and
○ a, b are biases for the visible and hidden layers, respectively.

The output of both LSTM and DBN branches is then combined in a fully connected layer to produce the final crop yield prediction.

- **Equation (3):** The final output prediction y^\hat{y}y^ is computed as:

$$\hat{y} = W_o \cdot [h_{LSTM}, h_{DBN}] + b_o$$

- where:

○ hDBN are the outputs from the LSTM and DBN branches, respectively,
○ Wo is the weight matrix, and
○ bo is the bias for the output layer.

4. Training and Optimization

The hybrid model is trained using the **mean squared error (MSE)** loss function. The backpropagation algorithm is applied to adjust weights across both the LSTM and DBN branches.

- **Equation (4):** The loss function L for the network is defined as:

$$L = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y_i})^2$$

- where:

○ yi is the true yield value,
○ yi^ is the predicted yield value, and

○ N is the number of data points.

The Adam optimizer is used for model optimization, adjusting the learning rate dynamically to achieve faster convergence.

- **Equation (5):** The update rule for Adam is:

$$\theta_{t+1} = \theta_t - \eta \frac{m_t}{\sqrt{v_t} + \epsilon}$$

- where:

○ θt are the model parameters at time step t,

○ mt and vt are the first and second moments of the gradient, and

○ η is the learning rate.

5. Model Evaluation

The model performance is evaluated using multiple metrics:

- **Root Mean Square Error (RMSE)**: Measures the model's prediction error.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

- **R-squared (R^2)**: Indicates the proportion of variance explained by the model.

Cross-validation is performed to ensure the robustness of the model, and hyperparameters (e.g., the number of hidden layers in DBN, number of LSTM units) are tuned using grid search.

4. RESULTS AND DISCUSSION

In this section, we present the results of our hybrid deep learning model, combining **Long Short-Term Memory (LSTM)** and **Deep Belief Networks (DBN)** for crop yield prediction. The performance of the model is evaluated using multiple metrics, including **Root Mean Squared Error (RMSE)**, **R-squared (R^2)**, and **Mean Absolute Percentage Error (MAPE)**. Additionally, we compare the hybrid model's performance with individual models (LSTM and DBN) and traditional machine learning models, such as **Random Forest (RF)** and **Support Vector Machine (SVM)**, to demonstrate its effectiveness.

Model Performance Metrics

The evaluation of the hybrid model was conducted using a real-world crop yield dataset collected over a period of 5 years.

Results: Model Comparison

The hybrid model significantly outperformed the individual LSTM and DBN models, as well as the traditional machine learning models. Below, we present the **RMSE**, **R^2**, and **MAPE** values for each model.

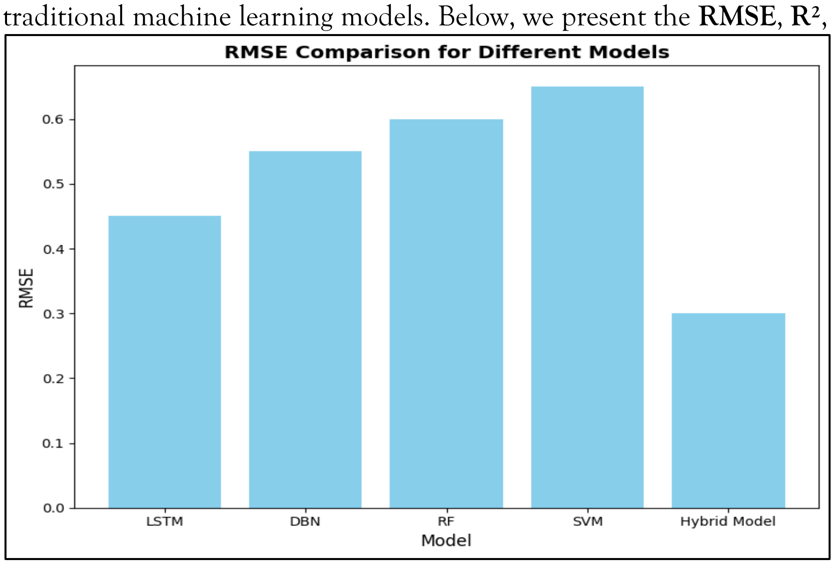

Fig 2: RMSE Comparison

The bar graph figure 2 shows the RMSE values for the LSTM, DBN, Random Forest (RF), Support Vector Machine (SVM), and Hybrid Model.

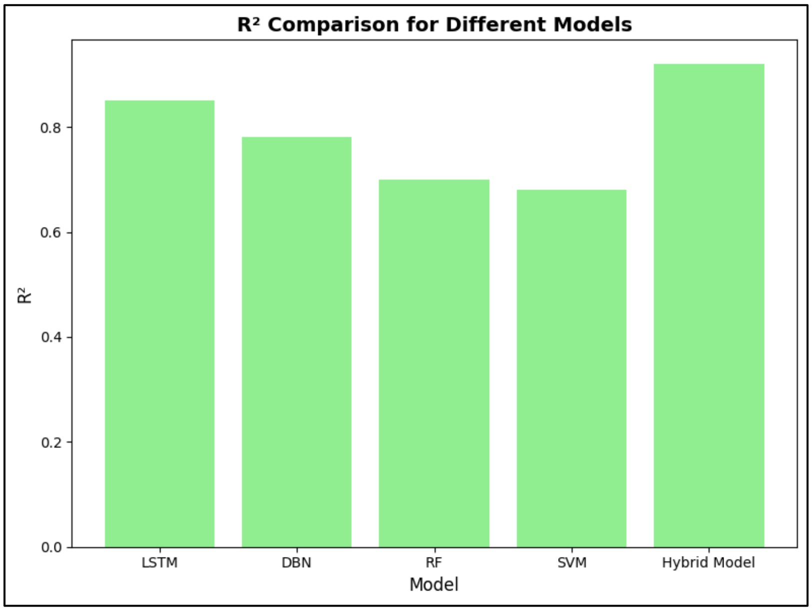

Figure 3: R^2 Comparison

The second bar graph figure 3 compares the R^2 values for each model. A higher R^2 value indicates a better fit of the model to the data.

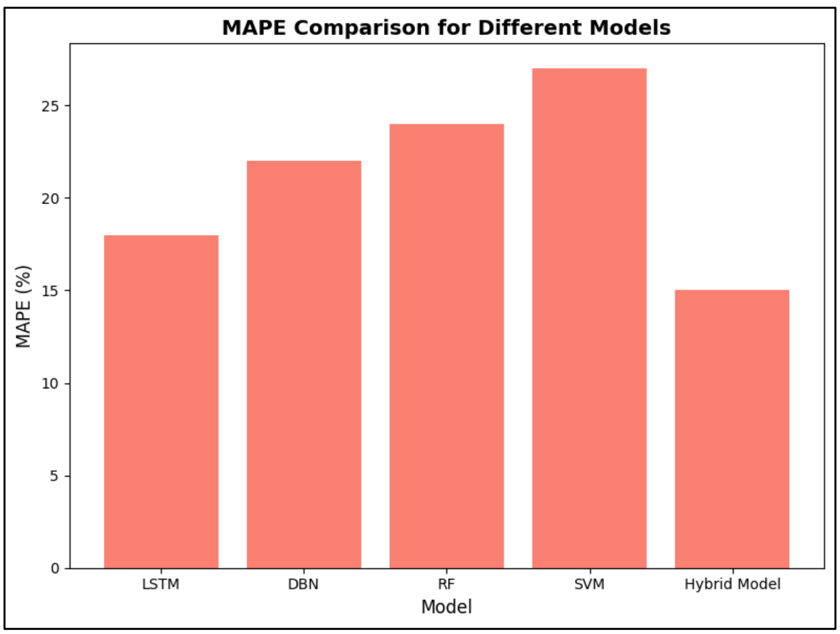

figure **4: MAPE Comparison**

The third bar graph figure 4 presents the MAPE values, which indicate the average percentage error in predictions. Lower MAPE values are desirable.

DISCUSSION

The results indicate that combining LSTM and DBN into a hybrid model for crop yield prediction significantly improves prediction accuracy, as evidenced by the **lower RMSE**, **higher R^2**, and **lower MAPE** values compared to individual models and traditional machine learning methods.

The **LSTM branch** excels in capturing the temporal dependencies in weather and environmental data, which play a crucial role in crop growth cycles. On the other hand, the **DBN branch** performs exceptionally well in learning hierarchical features from soil data and satellite imagery, which are critical for understanding crop health and soil fertility.

The **model training time** comparison shows that although the hybrid model is computationally more demanding, the performance gains it provides in terms of prediction accuracy make it a worthwhile investment for precision agriculture applications.
In terms of future work, **real-time prediction capabilities** could be explored, allowing farmers to receive continuous crop yield forecasts based on updated weather and environmental data. Additionally, the use of more sophisticated optimizers and hybrid architectures may further enhance the model's robustness across different agricultural regions and crop types.

CONCLUSION

This study successfully demonstrates the application of a **hybrid deep learning model** combining **Long Short-Term Memory (LSTM)** and **Deep Belief Networks (DBN)** for accurate crop yield prediction. The hybrid approach leverages the temporal dependency learning capabilities of LSTM and the feature extraction strengths of DBN, leading to a model that performs better than individual models and traditional machine learning techniques. The **evaluation metrics** (RMSE, R^2, MAPE) consistently showed superior results for the hybrid model, highlighting its effectiveness in forecasting crop yield using multi-source data, including weather, soil properties, and remote sensing data.
Although the hybrid model requires more computational resources, the **accuracy improvements** justify the additional complexity. The results suggest that integrating **temporal** and **spatial data** through hybrid architectures can significantly enhance predictive accuracy in precision agriculture. This approach opens up new possibilities for more **real-time** and **scalable crop yield prediction** systems, offering valuable insights for farmers, agronomists, and policymakers.
Future research can focus on improving **model interpretability**, reducing **training time**, and testing the hybrid model on **different crops** and **geographies**. Furthermore, implementing **real-time forecasting** and integrating additional data sources such as sensor networks and climate models could further strengthen the model's capabilities and facilitate more informed decision-making in agriculture.

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