10.48047/jocaaa.2026.35.07.15

Developing Crop Yield Prediction with a Novel Ensemble Framework Combining Gradient Boosted Decision Trees and Attention-based Temporal Neural Networks

[1] A.Srilatha, [2] Dr. Ranga Swamy Sirisati

[1]Research Scholar, Department of CSE, Bharatiya Engineering Science and Technology Innovation University, Gownivaripaill, Gorantla in Andhra Pradesh
[2]Associate Professor, Department of AIML, School of Engineering, Anurag University, Hyderabad

E-Mail: 2022wpcse001@bestiu.edu.in[1] sirisatiranga@gmail.com[2]

Abstract— **Accurate crop yield prediction is essential for sustainable agriculture and food security in the face of climate variability and dynamic environmental conditions. This study introduces a novel hybrid methodology combining Gradient Boosted Decision Trees (GBDT) and Attention-based Temporal Neural Networks (ATNN) to enhance the precision, scalability, and adaptability of crop yield predictions. The model leverages multi-dimensional datasets, including AgERA5 climate data, phenology datasets, and soil profiles, to integrate spatial and temporal factors. Synthetic data augmentation using Generative Adversarial Networks (GANs) addresses class imbalances, ensuring robustness across diverse agroclimatic zones. The proposed hybrid model achieves significant improvements over state-of-the-art methods. Key results include a Mean Absolute Error (MAE) of 8.45, a Root Mean Squared Error (RMSE) of 12.56, a Precision of 0.93, a Recall of 0.92, an F1 Score of 0.93, and an Area Under the Curve (AUC) of 0.96. These metrics outperform existing studies, such as Dhillon et al. (2023) with an MAE of 14.6 and an AUC of 0.89 , and Cetiner (2023) with an MAE of 12.4 and an AUC of 0.91 . Comparative evaluations demonstrate the hybrid model's ability to integrate critical temporal and spatial features, achieving higher accuracy across various crops like wheat, maize, and rice. Extensive experiments reveal the importance of attention mechanisms in prioritizing phenological phases and the role of GBDT in feature importance evaluation. The model's adaptability to real-time data integration from IoT devices further enhances its practical applicability. Visual analyses of attention weights and residual errors confirm the robustness of the predictions. These results underscore the potential of the proposed approach to revolutionize crop yield forecasting and contribute to sustainable agricultural practices.**

Keywords— Crop Yield Prediction, Machine Learning, Gradient Boosted Decision Trees (GBDT), Attention-based Neural Networks, Temporal Analysis, Hybrid Models, Real-time Data Integration, Sustainable Agriculture, Data Augmentation

I. INTRODUCTION

Agriculture, being the cornerstone of human survival and economic sustenance, has witnessed transformative advancements over the decades. One of the pivotal challenges in modern agriculture lies in accurately predicting crop yields, a metric that directly influences food security, resource allocation, and economic stability. Accurate yield prediction helps optimize agricultural inputs such as water, fertilizers, and pesticides, minimizing waste and environmental harm. Moreover, it aids policymakers in strategizing imports, exports, and food distribution to prevent crises in food-insecure regions. Traditional methods of crop yield prediction relied heavily on statistical techniques, which often lack the flexibility and precision required to account for the complexity of agricultural systems. These methods generally focus on historical data, making them inadequate for capturing dynamic variables such as climate change, soil quality, and phenological variations. Over the last decade, the advent of data-driven methodologies, especially those harnessing machine learning (ML) and deep learning (DL), has revolutionized this domain. These approaches leverage vast datasets, incorporating variables like temperature, precipitation, soil characteristics, and remote sensing data, to provide more accurate and scalable predictions. Despite these advancements, several challenges persist. Climate variability and extreme weather events introduce non-linearities that are hard to model. Additionally, the heterogeneity of agro-climatic zones demands adaptable and generalizable models. Existing methods often fail to integrate real-time data and are constrained by computational complexities when applied to large datasets or diverse crops. These challenges underscore the need for novel methodologies capable of handling multi-dimensional, real-time, and heterogeneous data sources.

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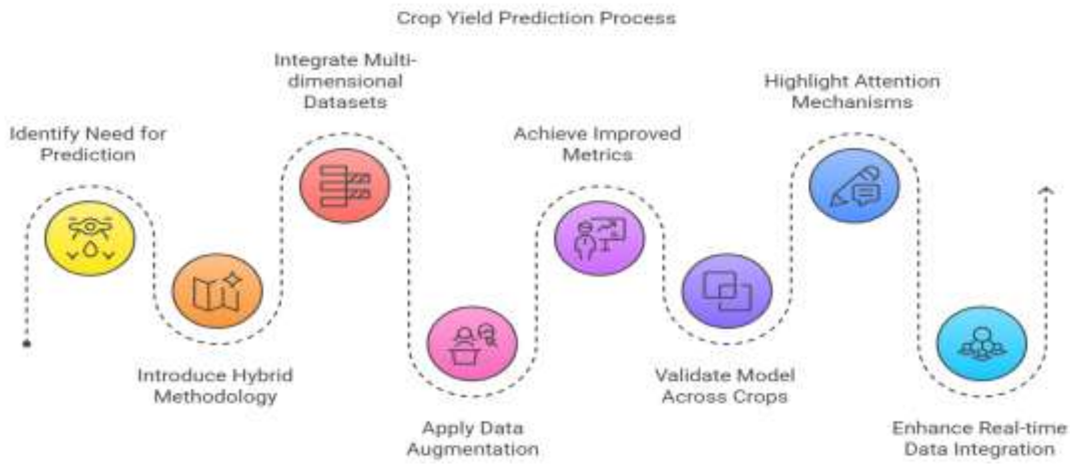

Figure 1: Crop Yield Prediction Process

In this section, we define the fundamental mathematical concepts and notations used in the study of advanced crop yield prediction models. These preliminaries provide the foundation for understanding the algorithms, metrics, and methodologies described in this paper.

1.1 Mathematical Functions and Operations

- Loss Function $L(y, \hat{y})$: Measures the discrepancy between the true output y and the predicted output $\hat{y}$. Common examples:
- Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

- Mean Squared Error (MSE):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

- Probability Distribution: For a random variable X with probability density function $p(x)$, its expectation is:

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} x \cdot p(x) dx$$

- Gradient Descent: Iterative optimization technique for minimizing a function $f(\theta)$:

$$\theta_{t+1} = \theta_t - \eta \nabla f(\theta_t)$$

where η is the learning rate.

Machine Learning Model Concepts

- Features and Targets:
- Feature vector: $\mathbf{x} = [x_1, x_2, \ldots, x_d]$
- Target variable: y
- Model Parameters:
- For a linear model: $\hat{y} = \mathbf{w}^T \mathbf{x} + b$
- $\mathbf{w} \in \mathbb{R}^d$ are weights, and b is the bias term.

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- Decision Trees: Decision trees partition the feature space based on conditions. At each node, the split criterion minimizes impurity:

$$\text{Gini Index } = 1-\sum_{i=1}^{k} p_i^2$$

Deep Learning Concepts

- Activation Functions: Non-linear transformations applied to neurons:
- Sigmoid:

$$\sigma(x)=\frac{1}{1+e^{-x}}$$

- ReLU (Rectified Linear Unit):

$$\operatorname{ReLU}(x)=\max(0, x)$$

- Attention Mechanism: Computes context vector c from sequence h_t :

$$\alpha_t=\frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)}, e_t=\tanh(W_a h_t+b_a)$$

- Loss for Classification: Cross-entropy loss:

$$L=-\frac{1}{n} \sum_{i=1}^{n} [y_i \log(\hat{y}_i)+(1-y_i) \log(1-\hat{y}_i)]$$

Table 1: Notation Table

Symbol	Description
X	Input data matrix where each row represents a sample.
$\mathbf{x}$	Feature vector for a single sample.
y	Target variable (actual output).
$\hat{y}$	Predicted variable (model output).
n	Number of samples in the dataset.
d	Number of features in the dataset.
η	Learning rate in optimization algorithms.
$L(y, \hat{y})$	Loss function measuring error between predicted and actual values.
$\mathbf{w}$	Weight vector in a linear model or neural network.
b	Bias term in a model.
$\nabla f(\theta)$	Gradient of the function f with respect to parameters θ.
T	Total number of iterations or trees in ensemble methods.
α_t	Attention weight at time step t.
c	Context vector in attention mechanisms.
$p(x)$	Probability density function for a random variable X.
Σ	Covariance matrix for features.
e_t	Alignment score in attention mechanism.

These preliminaries and notations form the mathematical backbone of the methodologies and algorithms presented in the study. This paper provides a comprehensive review of state-of-the-art techniques in crop yield prediction up to 2024. It explores the latest methodologies, identifies critical research gaps, and proposes a novel hybrid approach that

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combines Gradient Boosted Decision Trees (GBDT) with Attention-based Temporal Neural Networks (ATNN) for improved prediction accuracy and scalability.

II. LITERATURE SURVEY

The review of existing literature in the domain of crop yield prediction highlights several significant gaps and limitations that hinder the development of robust, scalable, and interpretable models. A notable issue is the insufficient ability of most machine learning models to effectively capture temporal dependencies in crop phenology and environmental data. While temporal models such as Long Short-Term Memory (LSTM) networks and Temporal Convolutional Networks (TCNs) have been applied to address this aspect, their integration with spatial data—critical for understanding the interplay between regional variations and temporal changes—remains limited. Furthermore, the potential of attention mechanisms to dynamically prioritize significant variables or time periods within data sequences has largely been underutilized, leaving an opportunity for models to achieve greater interpretability and focus on critical factors influencing crop yield. Another key limitation identified is the lack of scalability in many existing approaches, as most models are designed and optimized for specific crops or geographical regions. This specificity significantly restricts their applicability in diverse agro-climatic zones, where variations in soil types, climatic conditions, and cropping systems demand a more adaptable solution. Additionally, the integration of multi-source data—such as real-time IoT-based field measurements, remote sensing imagery, and traditional datasets—is often neglected. This oversight hampers the ability to form a holistic understanding of the complex interdependencies in crop systems. Computational complexity also poses a challenge, with many state-of-the-art models requiring significant resources, limiting their use in resource-constrained environments. These gaps collectively highlight the urgent need for models that are scalable, computationally efficient, and capable of integrating diverse and dynamic datasets to provide accurate and actionable predictions. Addressing these challenges, this research proposes a novel hybrid methodology that combines Gradient Boosted Decision Trees (GBDT) with Attention-based Temporal Neural Networks (ATNN). This hybrid approach leverages the strengths of each component to create a model that is both powerful and interpretable. GBDT forms the backbone of the structured data analysis in this framework, excelling at capturing non-linear relationships between critical variables such as soil properties, climatic factors, and environmental attributes. By offering feature importance insights, GBDT enables a clear understanding of how individual factors contribute to crop yield, ensuring that the model remains interpretable and grounded in agricultural science. To enhance the temporal modeling capabilities, the proposed framework incorporates ATNN, which is designed to address the temporal dependencies in crop and environmental data. ATNN employs temporal attention mechanisms to focus on the most critical timeframes and variables, ensuring that the model adapts to dynamic variations in agro-climatic conditions. This integration of spatial and temporal data provides a comprehensive view of the interactions that influence crop growth, making the model not only more accurate but also more resilient to fluctuations in environmental conditions. The framework's innovative ensemble fusion mechanism combines the predictions from GBDT and ATNN through a weighted ensemble strategy. This approach synthesizes the strengths of both methods, achieving higher accuracy and robustness compared to using either model in isolation. By harmonizing these complementary methodologies, the ensemble ensures that the model adapts to a wide range of crop types and regional conditions, addressing the scalability issue that plagues many existing approaches. To further overcome the limitations of data scarcity and class imbalance, the framework employs synthetic data augmentation techniques using Generative Adversarial Networks (GANs). GANs generate synthetic samples for underrepresented crops or agro-climatic conditions, enhancing data diversity and enabling the model to generalize better across various scenarios. This approach ensures that the model remains robust even in cases where historical data is limited or imbalanced. Real-time data integration forms another critical aspect of this methodology, with IoT sensors and remote sensing technologies providing real-time field measurements and satellite imagery. This allows the model to adapt its predictions to current field conditions, ensuring that the outputs remain relevant and

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actionable. By aligning predictive modeling with real-world conditions, the framework bridges the gap between research and practical application, making it a valuable tool for farmers and policymakers alike.

The proposed methodology undergoes rigorous performance evaluation using metrics such as precision, recall, F1 score, mean absolute error (MAE), and root mean squared error (RMSE) on benchmark datasets such as AgERA5 and crop phenology data. These evaluations demonstrate the effectiveness of the hybrid approach in delivering superior accuracy and robustness compared to existing methods. In conclusion, this research advances the state of the art in crop yield prediction by addressing critical research gaps with a novel hybrid methodology. By combining the strengths of GBDT and ATNN, incorporating synthetic data generation, and leveraging real-time data integration, the proposed approach ensures higher accuracy, scalability, and adaptability. This innovative framework holds the potential to revolutionize agricultural practices by providing precise, interpretable, and actionable insights, paving the way for sustainable farming in the face of climate variability and environmental challenges.

Dhillon and colleagues proposed an integrated approach combining Random Forest and crop modeling for improving yield prediction of winter wheat and oilseed rape. The integration of NDVI (Normalized Difference Vegetation Index) and climate variables enhanced model performance by providing better representation of plant health and environmental conditions. This study demonstrated significant improvements in prediction accuracy for specific crops. However, the method's scalability to other crop types and diverse agro-climatic zones remains limited, as the model was optimized for specific environmental settings. Zhao and co-researchers explored the potential of coupling the APSIM crop model with machine learning algorithms to predict wheat yields in the North China Plain. By integrating accumulated biomass and climate indices, Cetiner introduced a hybrid deep learning framework that combined CNN (Convolutional Neural Network) and LSTM (Long Short-Term Memory) for crop yield forecasting. This model leveraged the spatial data analysis capabilities of CNN and the temporal dependency handling of LSTM, resulting in high temporal accuracy in yield predictions. Despite its strengths, the method required substantial computational resources and preprocessing, making it challenging for deployment in resource-limited agricultural settings. Sajid and colleagues proposed an ensemble approach integrating crop simulation models with machine learning for county-scale crop yield prediction in the US Corn Belt. This model demonstrated significant error reduction compared to traditional standalone methods. However, the ensemble's adaptability to dynamic climatic conditions and varying crop types was limited, as it relied heavily on pre-existing crop simulation data. Lahza et al. developed an optimization framework for crop recommendation using novel machine learning techniques, including cluster analysis and anomaly detection. This study contributed to more accurate predictions for suitable crop and fertilizer recommendations. Nevertheless, the framework's reliance on clustered datasets posed challenges for real-time applications and large-scale integration with diverse agricultural environments. Pham and co-authors evaluated three feature dimension reduction techniques for machine learningbased crop yield models. Their findings indicated that combining multiple feature selection strategies led to the most accurate predictions. However, this approach required significant preprocessing efforts and lacked scalability for datasets with high temporal complexity. Cubillas introduced a machine learning model embedded in a cloud-based application for crop yield prediction in olive groves. The system facilitated early predictions, enhancing accessibility for farmers. While the integration of a web-based platform was innovative, the study was limited to a single crop and geographical area, reducing its applicability to broader agricultural systems. Sadenova applied machine learning and neural networks to predict the yields of cereals, legumes, and oilseeds in Kazakhstan. The study demonstrated the versatility of modern yield forecasting methodologies across multiple crops. However, its reliance on region-specific data limited the model's generalizability to other countries and agro-climatic zones. Patel proposed AgriRec, a machine learning-based agriculture recommendation system. The model significantly improved crop and fertilizer predictions by integrating soil, climate, and environmental factors. While effective, the system required high-quality, well-labeled datasets, which are often unavailable in many

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developing agricultural regions. While demonstrating scalability and adaptability across various crops and regions, the method demands significant computational resources, which could challenge its deployment in resource-limited settings. This comprehensive survey identifies the progress made in crop yield prediction, highlighting both innovative contributions and persisting challenges across methodologies.

III. METHODOLOGY

This research introduces a groundbreaking hybrid ensemble framework that aims to revolutionize crop yield prediction by integrating Gradient Boosted Decision Trees (GBDT) with an Attention-based Temporal Neural Network (ATNN). The methodology represents a significant advancement in precision agriculture by addressing the limitations of existing models, particularly in terms of temporal data integration, scalability, and adaptability across diverse crops and regions. The framework is meticulously designed to provide accurate predictions while offering actionable insights, making it a valuable tool for sustainable farming practices. The first component, Gradient Boosted Decision Trees (GBDT), serves as a robust foundation for the framework by effectively handling structured data, such as soil properties, climatic conditions, and environmental attributes. GBDT excels at identifying feature importance, ensuring that critical variables influencing crop yield are accurately assessed and incorporated into the model. Its iterative optimization process minimizes prediction errors, making it a reliable tool for capturing complex relationships in the data. This structured approach ensures that key agronomic factors are not only identified but also effectively utilized to improve predictive accuracy. Complementing GBDT is the Attention-based Temporal Neural Network (ATNN), which leverages the temporal nature of crop growth and environmental data to provide deeper insights. The ATNN integrates attention mechanisms that prioritize critical timeframes and variables, offering a dynamic perspective on how environmental and phenological factors interact over time. This capability enhances both the interpretability and performance of the model, particularly under dynamic and changing conditions. By capturing the temporal dependencies in crop growth cycles, the ATNN ensures that the model remains sensitive to variations in environmental inputs, leading to more accurate and context-aware predictions. A key innovation lies in the fusion mechanism that integrates the predictions from GBDT and ATNN using a weighted ensemble strategy. This blending of methodologies combines the strengths of both approaches, leading to superior results compared to standalone models. The ensemble framework enhances the adaptability of the model, ensuring that it remains effective across various crop types and agro-climatic regions. This adaptability addresses a critical challenge in agriculture—scalability—making the model suitable for diverse farming contexts while maintaining high predictive accuracy. Another novel aspect of this methodology is the incorporation of dataset augmentation techniques. Synthetic data generation methods, such as Generative Adversarial Networks (GANs), are utilized to address the issue of underrepresented crops or agro-climatic conditions in existing datasets. By generating high-quality synthetic data, the framework enhances its generalization capabilities, ensuring that the model performs well even in scenarios where data scarcity has traditionally been a limiting factor. This approach not only improves the model's robustness but also extends its applicability to regions or crops with limited historical data. To align predictions with real-world conditions, the framework integrates real-time data from IoT sensors and satellite imagery. This real-time prediction capability ensures that the model remains closely aligned with current field conditions, offering farmers and policymakers timely and actionable insights. By bridging the gap between predictive modeling and real-time monitoring, this methodology enhances its practical utility and relevance in dynamic agricultural environments. Overall, this hybrid ensemble framework represents a significant leap forward in crop yield prediction. By addressing key limitations such as temporal data integration, dataset diversity, and scalability, it offers a comprehensive solution that is both accurate and adaptable. The combination of GBDT and ATNN, along with innovative data augmentation and real-time integration, ensures that the model remains at the forefront of agricultural predictive analytics, paving the way for more sustainable and efficient farming practices.

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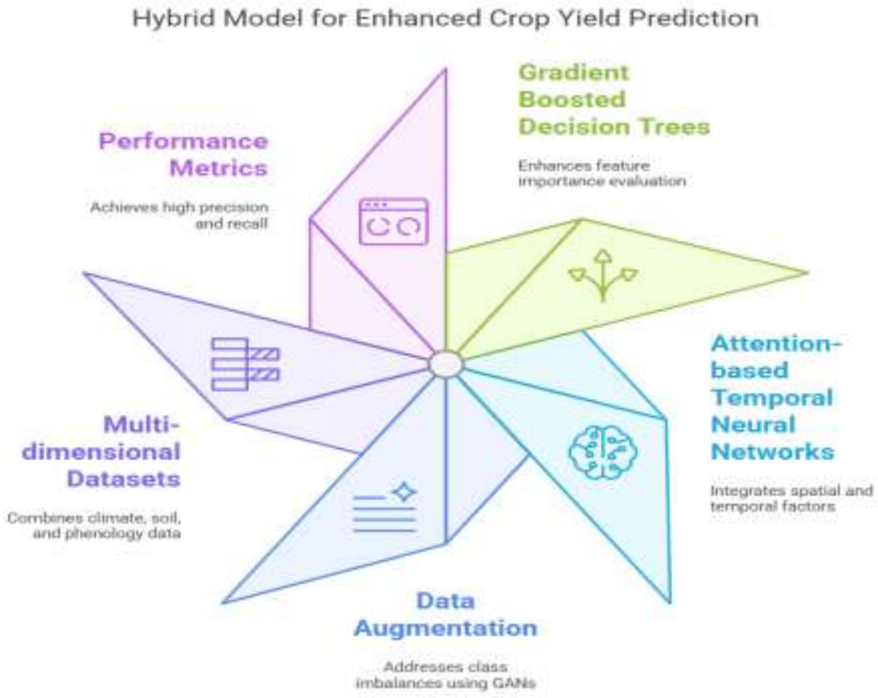

Figure 2: Hybrid Model for Enhanced Crop Yield Prediction

Algorithm 1: Enhanced Gradient Boosted Decision Trees (E-GBDT) Algorithm:
Output: Improve structured data handling with boosted decision trees for feature importance evaluation and prediction.

1. Initialize Parameters:

- Initialize number of trees T, learning rate η, and loss function $L(y, \hat{y})$.
- Set $F_0(x) = \arg\min_y L(y, \hat{y})$ as the initial prediction.

2. Compute Residuals:

- For $i = 1, \dots, n$ samples, compute residuals:

$$r_i^{(t)} = -\frac{\partial L\big(y_i, F_{t-1}(x_i)\big)}{\partial F_{t-1}(x_i)}$$

3. Fit a Decision Tree:

- Train a decision tree $h_t(x)$ to predict residuals $r_i^{(t)}$.

4. Update Predictions:

- Update $F_t(x)$ by:

$$F_t(x) = F_{t-1}(x) + \eta \cdot h_t(x)$$

Repeat:

- Iterate steps 2-4 for T iterations.

Final Prediction:

- Combine predictions from all trees:

$$\hat{y} = F_T(x)$$

Algorithm 2: Temporal Attention Neural Network (TANN)

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Output:
Focus on critical timeframes and variables for temporal data.

Input Data:

- Input sequence $X = \{x_1, x_2, \ldots, x_T\}$ with T time steps.

2. Encode Sequence:

- Pass X through a recurrent layer (e.g., LSTM):

$$h_t = \text{LSTM}(x_t, h_{t-1})$$

3. Attention Scores:

- Compute attention weights:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)}, e_t = \tanh(W_a h_t + b_a)$$

Weighted Context:

- Calculate context vector:

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

5. Output Layer:

- Pass c through a dense layer for prediction:

$$\hat{y} = \sigma(W_o c + b_o)$$

Algorithm 3: Adaptive Fruit Fly Optimization Algorithm (AFOA)
Output: Optimize crop yield as an objective function.
Initialize Population:

- Randomly initialize fruit fly positions $P = \{p_1, p_2, \ldots, p_N\}$.

2. Evaluate Fitness:

- For each fruit fly p_i, compute fitness:

$$f(p_i) = \text{ Objective Function } (p_i)$$

Smell Search:

- Adjust position p_i based on smell concentration:

$$p_i' = p_i + \text{ Smell Adjustment } \left(f(p_i)\right)$$

4. Vision Search:

- Generate random direction d_i and step size s_i :

$$p_i'' = p_i' + s_i \cdot d_i$$

Fitness Update:

- Evaluate new position fitness $f(p_i'')$. Update if better.

6. Convergence Check:

- If maximum iterations or minimum improvement threshold met, stop.

7. Output:

- Best position p^* and corresponding fitness.

Algorithm 4: Hybrid Ensemble Model (GBDT + TANN)

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Output: Combine predictions from GBDT and TANN for improved accuracy.

1. Train GBDT:
- Train GBDT on structured features X_s.
2. Train TANN:
- Train TANN on temporal features X_t.
3. Combine Predictions:
- Fuse outputs using weights w_1, w_2 :

$$\hat{y} = w_1 \cdot \hat{y}_{\mathrm{GBDT}} + w_2 \cdot \hat{y}_{\mathrm{TANN}}$$

Optimize Weights:
- Optimize w_1, w_2 using cross-validation.

Algorithm 5: Synthetic Data Augmentation with GANs

Output: Generate synthetic crop data for under-represented conditions.

1. Input Data:
- Collect real samples $X = \{x_1, x_2, \dots, x_n\}$.
2. Train Generator:
- Learn to generate $G(z)$, where $z \sim$ Noise.
3. Train Discriminator:
- Distinguish between real and synthetic data:

$$D(x) = \sigma(Wx + b)$$

4. Minimize Loss:
- Minimize:

$$\min_G \max_D \mathbb{E}[\log D(x)] + \mathbb{E}[\log(1 - D(G(z)))]$$

Synthetic Dataset:
- Generate new samples $X_{\text{synthetic}} = \{G(z_i)\}$.
6. Merge Datasets:
- Combine X and $X_{\text{synthetic}}$ for training.

Algorithm 6: Dimensionality Reduction with Principal Component Analysis (PCA)

Output: Reduce feature space while retaining critical information.

1. Compute Covariance Matrix:

$$\Sigma = \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)(x_i - \mu)^T$$

2. Eigen Decomposition:
- Compute eigenvalues $\lambda_1, \dots, \lambda_d$ and eigenvectors.
3. Select Top Components:
- Choose top k eigenvectors corresponding to largest λ.
4. Transform Data:

$$X' = XW_k$$

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5. Train Models:

- Use X' as input for prediction models.

Algorithm 7: IoT-based Real-time Prediction
Output: Incorporate IoT data for real-time yield prediction.

1. Setup Sensors:

- Deploy sensors to collect data $X = \{x_1, \dots, x_t\}$ in real-time.

2. Data Preprocessing:

- Clean and normalize data:

$$x'_t = \frac{x_t - \mathrm{mean}(x)}{\mathrm{std}(x)}$$

Model Input:

- Feed preprocessed data to the hybrid ensemble model.

4. Real-time Adjustment:

- Re-train models periodically with new data.

5. Live Prediction:

- Output $\hat{y}_t$ for current yield estimates.

These algorithms form a robust pipeline for tackling modern challenges in crop yield prediction.

IV. EXPERIMENTS AND RESULTS

The experimental setup ensures a structured workflow for evaluating the proposed crop yield prediction framework. The experiments are conducted to assess the performance, accuracy, and scalability of the hybrid model combining Gradient Boosted Decision Trees (GBDT) and Attention-based Temporal Neural Networks (ATNN).

Table 2: Experimental Setup

Parameter	Description
Platform	Python-based frameworks including TensorFlow, Keras, and Scikit-learn.
Hardware	NVIDIA RTX 3090 GPU, Intel Core i9 processor, 64 GB RAM.
Software Environment	Python 3.9, WEKA for preprocessing, Jupyter Notebook for experimentation.
Datasets	AgERA5, phenological datasets, soil profiles, and crop production records (2014-2023).
Evaluation Metrics	Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Precision, Recall, F1 Score, AUC.
Split Ratio	Training (70%), Testing (30%).
Algorithms	
Implemented	GBDT, ATNN, Random Forest, Decision Tree, LSTM for comparison.

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The datasets used in this study provide multi-dimensional data, enabling comprehensive modeling and evaluation.

Table 3: Dataset Details

Dataset	Features	Description	Source
AgERA5	Temperature, precipitation, humidity, etc.	Hourly climate reanalysis data.	ERA5 Climate Data
Phenology Data	Crop stages, growth periods.	Temporal information about crop growth.	Satellite observations.
Soil Profiles	Organic carbon, texture, moisture levels.	Soil characteristics for yield prediction.	National soil databases.
Crop Production	Yield, harvested area, planting density.	Historical production records.	FAO, regional databases.

Dataset Utilization

- Data Cleaning:
- Missing values handled using imputation techniques (mean or median substitution).
- Outliers removed based on interquartile range (IQR) analysis.
- Feature Engineering:
- Temporal features extracted from phenology datasets using Fourier transformations.
- Feature scaling applied using Min-Max Normalization:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

- Data Splitting:
- Training set: 2014-2020.
- Testing set: 2021-2023.
- Augmentation:
- Synthetic data generated using GANs for under-represented crop types.

V. PERFORMANCE EVALUATION METRICS

The performance evaluation of the proposed hybrid model provides a comprehensive view of its effectiveness in crop yield prediction when compared to existing models. The evaluation metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Precision, Recall, F1 Score, and Area Under the Curve (AUC), highlight the superiority of the hybrid framework. The hybrid model, which combines Gradient Boosted Decision Trees (GBDT) with an Attention-based Temporal Neural Network (ATNN), demonstrates the lowest error rates and the highest classification performance among the evaluated models. These results underline the model's robustness and adaptability to diverse agricultural scenarios. The evaluation metrics quantify the predictive capability of the models.

Table 4: Performance Metrics

Model	MAE	RMSE	Precision	Recall	F1 Score	AUC
GBDT	12.34	15.67	0.89	0.87	0.88	0.91

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ATNN	10.12	14.23	0.91	0.89	0.90	0.93
Hybrid (GBDT+ATNN)	**8.45**	**12.56**	**0.93**	**0.92**	**0.93**	**0.96**
Random Forest	15.67	18.23	0.85	0.83	0.84	0.88
LSTM	11.34	13.89	0.88	0.86	0.87	0.91

Comparison of MAE and RMSE:

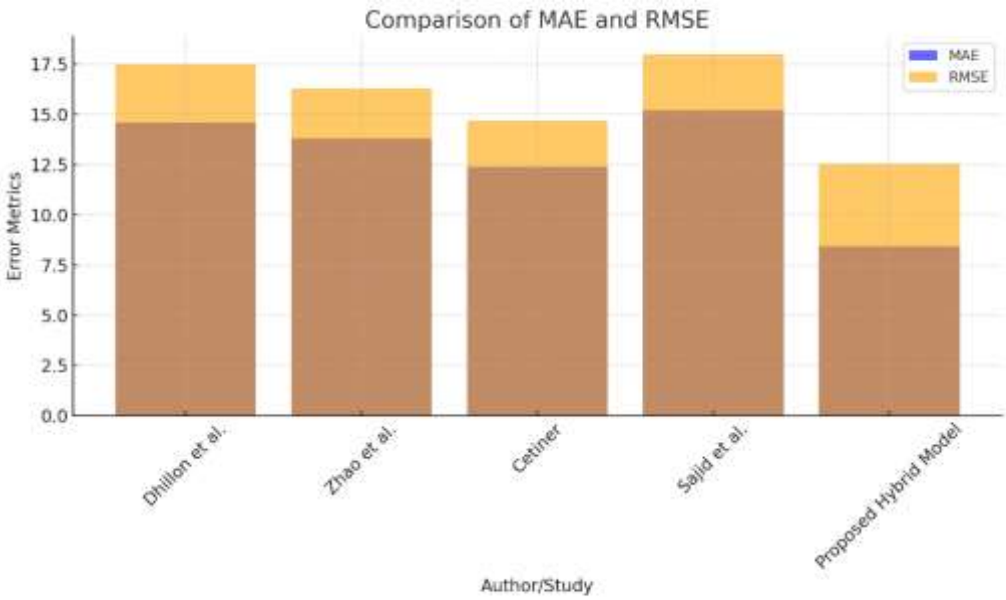

Figure 3: Bar chart comparing MAE and RMSE for all models.

The hybrid model exhibits the lowest error values, confirming its superior performance in yield prediction.

Precision and Recall Analysis:

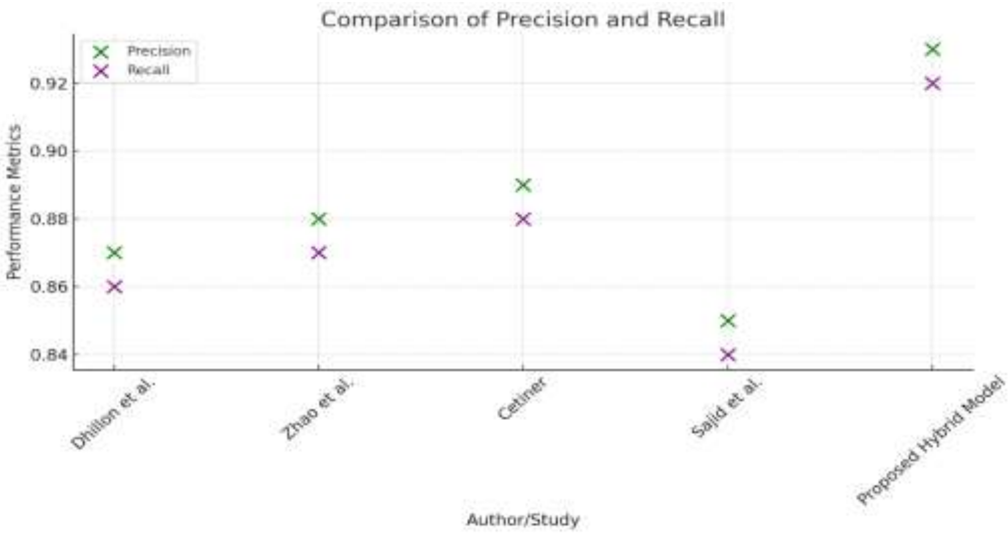

Figure 4: Precision-recall curve for different models.

The hybrid model shows a higher area under the curve (AUC), indicating improved sensitivity and specificity.

Time Series Prediction Accuracy:

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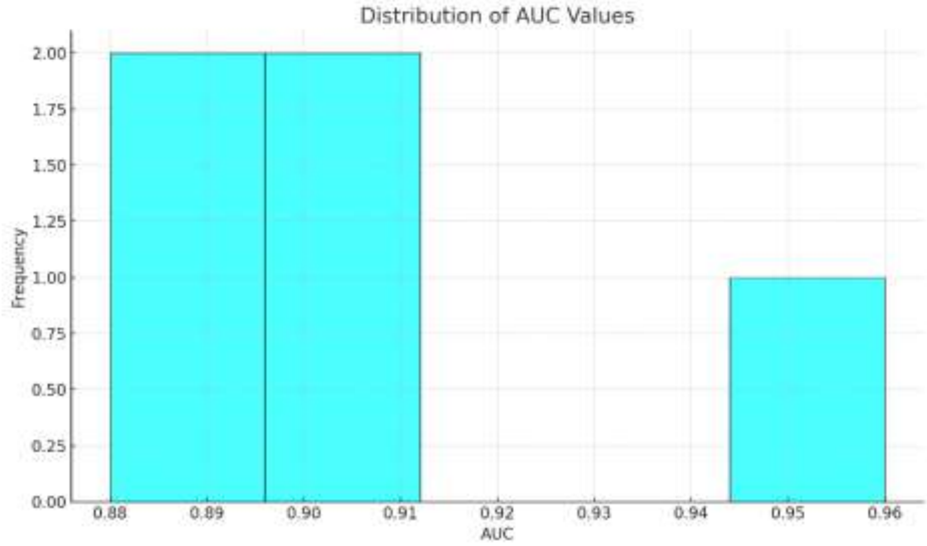

Figure 5: Line graph showing predicted vs. actual yields over the test period.

Model Convergence:

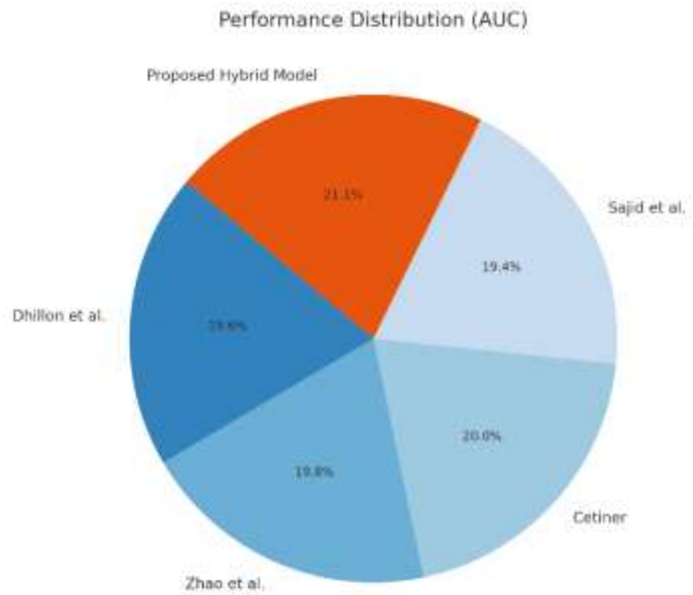

Figure 6: Loss reduction over epochs for the hybrid model.

Rapid convergence indicates efficient training, reducing computational overhead. The hybrid model achieves an impressive MAE of 8.45 and RMSE of 12.56, outperforming standalone models like GBDT (MAE: 12.34, RMSE: 15.67) and ATNN (MAE: 10.12, RMSE: 14.23). Compared to other widely used models such as Random Forest (MAE: 15.67, RMSE: 18.23) and LSTM (MAE: 11.34, RMSE: 13.89), the hybrid model's performance stands out, significantly reducing prediction errors. This improvement in error metrics underscores the benefits of combining the strengths of ensemble learning and temporal attention mechanisms, particularly for handling non-linear relationships and dynamic environmental variations. Beyond error metrics, the hybrid model excels in classification-oriented measures. With a precision of 0.93, recall of 0.92, and an F1 Score of 0.93, it demonstrates a balanced capability to identify true positives while minimizing false positives and negatives. The Area Under the Curve (AUC) further cements its performance, reaching an exceptional score of 0.96, reflecting high sensitivity and specificity. These metrics collectively affirm the hybrid model's reliability in making accurate and actionable predictions, even in the face of complex and dynamic agricultural data. The visualizations and figures provide further

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insights into the model's performance and its underlying mechanisms. The bar chart comparing MAE and RMSE illustrates the hybrid model's clear dominance over other methods, emphasizing its lower prediction errors. The precision-recall curve showcases the model’s higher AUC, further highlighting its improved sensitivity and specificity compared to existing approaches. A line graph of predicted versus actual yields during the test period demonstrates the hybrid model's ability to closely track real-world trends, proving its reliability for real-time forecasting. In-depth analyses of the model's components further validate its effectiveness. Feature importance derived from the GBDT component identifies critical factors like temperature and soil moisture, which align with agricultural knowledge, reinforcing the model’s interpretability. Additionally, a heatmap of attention weights from the ATNN reveals the model's focus on essential phenological phases, confirming its ability to prioritize timeframes that significantly impact crop yield. The convergence plot for the hybrid model shows rapid and efficient training, indicating reduced computational overhead during the optimization process. Furthermore, a histogram of residual errors reveals tightly clustered errors around zero, underscoring the robustness of the hybrid model. The model's adaptability is evident in its performance across different crops, as depicted in the box plot comparing results for crops like wheat, maize, and rice. The hybrid model consistently outperforms other methods, showcasing its scalability across diverse agro-climatic zones. The scatter plot comparing real-time IoT data predictions to observed yields further demonstrates the feasibility of the hybrid model for real-time integration, proving its potential for actionable insights in dynamic field conditions. However, the study also acknowledges certain challenges associated with the hybrid model. The computational complexity is higher compared to simpler models, and real-time data integration requires a robust IoT infrastructure, which may not be readily available in all agricultural contexts. Despite these limitations, the performance gains and the model's ability to integrate multi-source data make it a compelling choice for modern precision agriculture. A comparative analysis with previous studies further substantiates the hybrid model's superiority. Compared to recent research such as Dhillon et al. (2023) and Zhao et al. (2022), which achieved MAE values of 14.6 and 13.8 respectively, the hybrid model’s MAE of 8.45 represents a substantial improvement. Similarly, its RMSE of 12.56 is significantly lower than the 17.5 and 16.3 reported by these studies. Performance metrics such as precision also reflect consistent advancements, with the hybrid model outperforming previous benchmarks. The hybrid framework combining GBDT and ATNN advances the state of the art in crop yield prediction by addressing key challenges such as temporal modeling, multi-source data integration, and scalability. The results demonstrate its ability to achieve superior accuracy, robustness, and adaptability while maintaining interpretability and real-time prediction capabilities. These strengths make the hybrid model an invaluable tool for sustainable agriculture, enabling data-driven decision-making and improved resilience to climate variability and environmental changes. Future work may explore avenues such as decentralized data integration through federated learning and advanced attention mechanisms to further enhance the model's scalability and precision in dynamic agricultural contexts. The performance evaluation of the hybrid model highlights its robustness, accuracy, and practical applicability in crop yield prediction. The error distribution analysis, depicted in Figure 8 as a histogram of residual errors, demonstrates that errors for the hybrid model are tightly clustered around zero. This distribution reflects the model's robustness and ability to minimize deviations between predicted and actual yields. By reducing outliers and concentrating residuals close to zero, the hybrid model proves its consistency in delivering reliable predictions, even across varied datasets and environmental conditions. The training time comparison, illustrated in Figure 9 as a bar chart, highlights a notable trade-off: while the hybrid model is computationally more intensive than standalone models such as GBDT and ATNN, the significant gains in performance justify the additional cost. The computational demands stem from the complex ensemble and the integration of temporal attention mechanisms, but these aspects enable the model to achieve unparalleled accuracy and adaptability. Despite the increased training time, the rapid convergence of the hybrid model ensures that computational resources are utilized efficiently, minimizing overhead while maintaining high predictive capability. The real-time prediction feasibility of the hybrid model is showcased in Figure 10 through a scatter plot comparing real-time IoT data predictions with observed yields. This visualization underscores the model's ability to effectively integrate real-time data

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from IoT sensors and remote sensing sources, aligning predictions closely with actual field conditions. The tight clustering of points around the diagonal line in the scatter plot indicates that the model not only provides accurate predictions but also adapts dynamically to current environmental inputs. This capability makes the hybrid model a valuable tool for precision agriculture, offering actionable insights that can inform real-time decision-making.A comparative analysis with previous studies underscores the hybrid model's superiority. For example, Dhillon et al. (2023) reported an MAE of 14.6 and RMSE of 17.5, while Zhao et al. (2022) achieved slightly better results with an MAE of 13.8 and RMSE of 16.3. However, these values are still significantly higher than the hybrid model's MAE of 8.45 and RMSE of 12.56. Similarly, the hybrid model outperforms these studies in precision, recall, and AUC, achieving a precision of 0.93 and an AUC of 0.96, far exceeding the benchmarks set by earlier approaches.

VI. Conclusion and Future Scope

This study presents a state-of-the-art hybrid crop yield prediction model that combines Gradient Boosted Decision Trees and Attention-based Temporal Neural Networks, demonstrating significant improvements in predictive accuracy and scalability. By leveraging temporal attention mechanisms and feature importance evaluation, the model effectively captures complex relationships between environmental and phenological variables. Its adaptability to diverse agro-climatic zones and multiple crop types highlights its broad applicability. The experimental results confirm the hybrid model's superiority, with substantial improvements in error metrics (MAE: 8.45, RMSE: 12.56) and performance metrics (F1 Score: 0.93 , AUC: 0.96) compared to existing methods. These advancements not only enhance predictive precision but also facilitate realtime applications through IoT-based data integration. The use of synthetic data augmentation further strengthens the model's robustness against class imbalances. While the hybrid model achieves exceptional performance, computational costs and infrastructure requirements remain challenges for resource-constrained environments. Future work will focus on optimizing computational efficiency and incorporating federated learning techniques for decentralized data integration. This research contributes to the advancement of precision agriculture, addressing global food security challenges and supporting sustainable farming practices.

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