A Novel Blended Machine Learning Approach with TempoQA-Net for Crop Yield Prediction

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ABSTRACT

Accurate crop yield prediction remains a significant challenge due to the complexity, non-linearity, and variability inherent in agricultural data, which are influenced by diverse climatic, geographic, and management factors. To address this, the present study introduces TempoQA-Net, a hybrid model integrating Long Short-Term Memory (LSTM) networks with Quantile Random Forest (QRF). Utilizing a comprehensive dataset of 12,834 records from the Special Data Dissemination Standard (SDDS) Division of the Indian Ministry of Agriculture, the model incorporates variables such as year, location, cultivated area, and climatic conditions. TempoQA-Net outperformed existing approaches, achieving a Mean Absolute Error (MAE) of 0.11995 kg/ha, a Mean Squared Error (MSE) of 0.02215 kg^2/ha^2, an R-squared value of 0.743, and an overall accuracy of 98.87%. These results demonstrate the model's robustness and predictive accuracy, providing a valuable tool for enhancing agricultural planning and policy development.

Keywords-crop yield; accuracy; prediction; long short-term memory; agriculture

I. INTRODUCTION

In real-world agricultural settings, crop yields are shaped by a complex interplay of dynamic factors, including unpredictable weather patterns, heterogeneous soil fertility, fluctuating irrigation availability, and evolving farming practices. These factors vary significantly across regions and seasons, introducing substantial variability that makes crop yield prediction a challenging task. In India, agriculture remains a cornerstone of the national economy, employing approximately 58% of the workforce and contributing significantly to the Gross Domestic Product (GDP) [1–3]. Accurate crop yield forecasting is therefore crucial, given the country's diverse agroclimatic zones, soil types, and irrigation practices [4–6]. Moreover, reliable predictions help mitigate risk, support farmer incomes, and enhance the stability of agricultural supply chains [7].

Recent advances in predictive analytics and Machine Learning (ML) offer new opportunities to improve the accuracy of crop yield forecasts [8-11]. While traditional statistical approaches are useful, they often fall short when dealing with the high dimensionality and intricate interdependencies characteristic of agricultural datasets [12-13]. In contrast, ML models leverage large-scale, heterogeneous data, including historical yields, weather patterns, soil characteristics, and crop management practices, to uncover hidden patterns and relationships, thereby improving predictive performance.

This study presents a novel hybrid modeling approach that integrates Long Short-Term Memory (LSTM) networks with Quantile Random Forests (QRF) to achieve both accurate and probabilistic crop yield prediction. The proposed model is developed and evaluated using a comprehensive dataset obtained from the Indian Ministry of Agriculture, encompassing temporal, spatial, climatic, and economic variables for the years 2022 and 2023. Within the hybrid architecture, the LSTM component effectively captures sequential climatic patterns, while the QRF component generates quantile-based yield estimates, thereby enabling both point prediction and uncertainty quantification essential for risk assessment in agricultural forecasting.

II. RELATED WORKS

In 2024, authors in [14] introduced the Crayfish Optimization Algorithm (COA), which is specifically designed for predicting crop yields. While COA is capable of handling complex agricultural data, it has inherent limitations in achieving higher R-squared values, indicating potential areas for improving its predictive capability through algorithmic adjustments or additional data inputs. In the same year, authors in [15] used the Random Forest (RF) algorithm, achieving an overall accuracy of 85%. Although this model is well-known for its resistance to overfitting, particularly in scenarios involving large datasets, its performance can be hampered by biases inherent in the training data, which may limit the model's generalizability to other datasets or real-world conditions. Authors in [16] investigated the capabilities of Graphical Neural Networks (GNNs) and obtained a Mean Squared Error (MSE) of 0.02363 kg^2/ha^2, a R-squared of 0.51719, and a Mean Absolute Error (MAE) of 0.12004 kg/ha. GNNs excel at capturing complex patterns in graph-structured data, but their effectiveness is limited by the computational complexity and scale of graph data, which may necessitate significant computational resources for larger datasets. Authors in [17] utilized the Extra Trees Regressor (ETR), a method that effectively reduces variance and enhances prediction accuracy. Nonetheless, the algorithm's reliance on random split selection can lead to inconsistent performance across datasets due to variability in tree construction. In [18], a voting classifier was implemented, which achieved an accuracy of 92%. By leveraging ensemble learning, this approach benefits from the complementary strengths of multiple base models. However, its overall effectiveness is contingent upon the careful selection and tuning of these constituent classifiers, which can be both time-consuming and sensitive to configuration. Lastly, authors in [19] proposed an LSTM model augmented with an attention mechanism, which attained strong performance metrics, including 98.23% accuracy, an R-squared of 0.43, MAE of 0.131 kg/ha, MSE of 0.054 kg^2/ha^2, and Root Mean Squared Error (RMSE) of 0.232 kg/ha. Despite its temporal modeling capabilities, the LSTM-attention model is computationally intensive, particularly when processing long input sequences, requiring efficient training strategies or high-performance hardware to ensure scalability.

III. PROPOSED SYSTEM

A. *Proposed Hybrid Model*

The TempoQA-Net architecture, illustrated in Figure 1, integrates LSTM networks with QRF, forming a hybrid model specifically tailored for crop yield prediction. The LSTM component is designed to capture temporal dependencies and patterns in sequential data, including weather trends, soil moisture fluctuations, and crop phenological stages. This addresses a key limitation of traditional RF models, which are inherently static and incapable of modeling temporal sequences [20]. By sequentially processing input features and maintaining contextual information through memory cells regulated by input, forget, and output gates, the LSTM effectively models how past climatic conditions and agronomic interventions influence present yield outcomes.

The output of the LSTM module serves as an enriched feature set for the subsequent QRF component. Unlike standard RF models that generate point estimates based on the mean of individual tree predictions, QRF is capable of estimating conditional quantiles of the response variable. This enables the generation of prediction intervals, rather than single-value forecasts, allowing for a more comprehensive characterization of yield variability. This is particularly useful in the agricultural domain, where decision-making often depends on the understanding of uncertainty and risk [21].

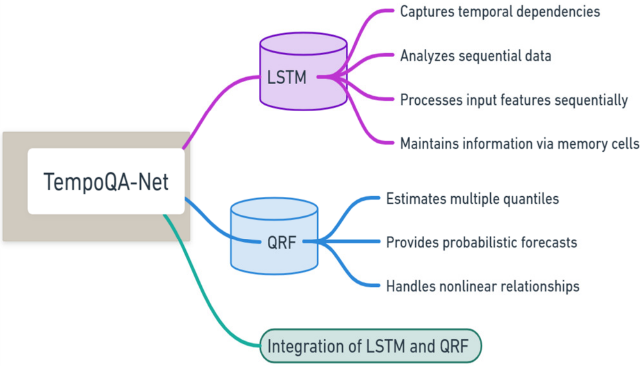


Fig. 1. Proposed TempoQA-Net model.

B. *Pseudocode Algorithm of the Proposed Model*

The pseudocode below outlines the process of loading and preprocessing data, extracting features via an LSTM model, using these features to train a QRF, and subsequently evaluating the model.

Algorithm: TempQA-Net Model

```
Start
Step 1: Data Preprocessing
Step 2: Feature Extraction using LSTM
Step 3: Quantile Random Forest for Predictive
Modeling
Step 4: Model Evaluation
         Input: Predictions, ActualCropYield
         Metrics = evaluate(Predictions,
ActualCropYield)
             Optimize(LSTM, QRF, Metrics)
Final Output
Output: Median Yield Prediction, Confidence
Intervals (25th–75th Percentiles)
return Predictions
End
```

C. *Methodology*

The methodology employed in this study is illustrated in Figure 2. The dataset used for model development and evaluation was obtained from the Special Data Dissemination Standard (SDDS) Division [22] of the Government of India and spans the agricultural years 2022 and 2023, comprising a total of 12,834 records. The dataset contains features such as year, location, area cultivated, rainfall, temperature, soil type, type of irrigation, yields, humidity, crop type, market price, and season. Data information was collected from several key agricultural states across India, representing a wide range of agroclimatic zones, including tropical wet and dry (savanna), humid subtropical, and semi-arid regions. Additionally, the soil types present in the dataset include black cotton soil, alluvial soil, red soil, and laterite soil, each influencing crop growth patterns differently due to their different moisture retention and nutrient profiles. The crop types include both staple and commercial varieties, such as rice, wheat, maize, tea, arecanut, and cocoa, thereby offering a comprehensive perspective on India's multi-seasonal and diverse agricultural landscape.

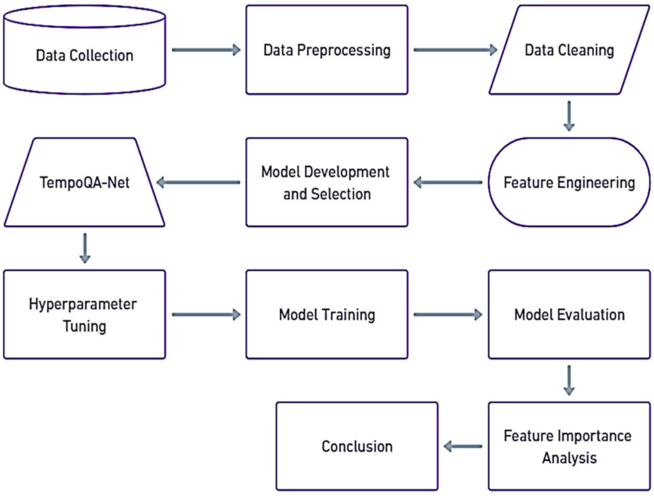


Fig. 2. Proposed system block diagram.

The dataset D used with its several features, denoted as X_i, can be represented as:

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

where Y_i corresponds to the crop yield. The objective is to model the predictive function f that captures the relationship between features and yield, as defined by:

$$Y = f(X) \quad (2)$$

To ensure the dataset's quality and suitability for modeling with TempoQA-Net, extensive preprocessing and feature engineering were performed. Missing values were addressed using statistical imputation, specifically mean imputation:

$$X_{imputed} = \frac{\sum_{i=1}^{N} X_i}{N} \quad (3)$$

Outliers were identified using the Interquartile Range (IQR) method. The bounds for detecting outliers were computed as follows:

$$Lower\ Bound = Q_1 - 1.5 \cdot IQR \quad (4)$$

$$Upper\ Bound = Q_3 + 1.5 \cdot IQR \quad (5)$$

where Q_1 and Q_3 represent the first and third quartiles, respectively. Observations outside these bounds were either capped or removed to prevent skewing the learning process. Categorical variables, such as soil type and season, were encoded using one-hot encoding to convert them into a machine-readable format. Continuous features X_c were standardized using z-score normalization:

$$X_{scaled} = \frac{X_c - \mu}{\sigma} \quad (6)$$

where μ and σ represent the mean and standard deviation, respectively.

The proposed TempoQA-Net model incorporates an LSTM component to learn temporal dependencies from sequential features such as rainfall and temperature. The time series input is defined as:

$$t = \{x_1, x_2, \dots, x_T\} \quad (7)$$

The LSTM processes this sequence to compute hidden and cell states that capture temporal patterns critical for yield prediction. Subsequently, the QRF component estimates conditional quantiles of the yield distribution for a given input feature vector X and quantile level τ, as defined by:

$$Q\tau\,(Y \mid X) = inf\{y: P(Y \le y \mid X) \ge \tau\} \quad (8)$$

Model training was conducted using an 80/20 train-test split to evaluate generalization performance. Hyperparameter tuning was carried out using GridSearchCV to optimize LSTM configurations, ensuring optimal model performance. Following training, the QRF component was utilized to perform feature importance analysis.

IV. RESULTS

The scatter plot in Figure 3 illustrates the relationship between cultivated area (in hectares) and crop yield (in kg/ha) across various crops. Notably, cocoa, arecanut, and ginger exhibit the highest yields despite being cultivated over relatively smaller areas.

Figure 4 presents a pie chart showing the distribution of yields (kg/ha) across the various crops in the dataset. This plot includes a Kernel Density Estimate (KDE) to provide a smoother representation of the distribution. Figure 5 displays the boxplots representing the yield distribution before and after outlier removal using the IQR method. Figure 6 shows the average yield for each crop type via a bar plot, aiding in identifying crops with generally higher outputs. Figure 7 compares the average yield of all crop types during the Zaid (March to June period) and Kharif (June to September, monsoon season) cultivation seasons. The plot reveals that Kharif-season crops have a substantially higher average yield (~3000 kg/ha) compared to Zaid-season crops (~500 kg/ha), suggesting more favorable climatic conditions and crop selection during the Kharif season.

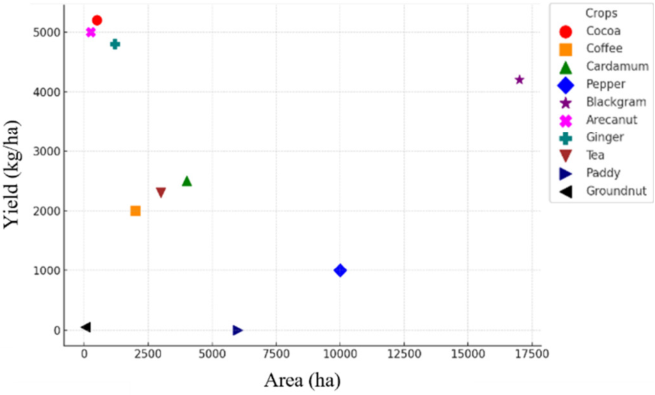


Fig. 3. Area vs yields by crop type.

Figure 8 displays the correlation matrix among key agricultural features, including Price, Humidity, Rainfall, Yield, Area, and Temperature. A strong negative correlation (-0.73) is observed between Rainfall and Price, implying that increased rainfall may lead to oversupply and reduced prices. Yield exhibits moderately positive correlations with both Temperature (0.59) and Humidity (0.59), highlighting the influence of climatic conditions on productivity. A slight positive correlation (0.21) between Area and Yield supports the intuitive relationship that larger cultivation areas typically produce higher yields.

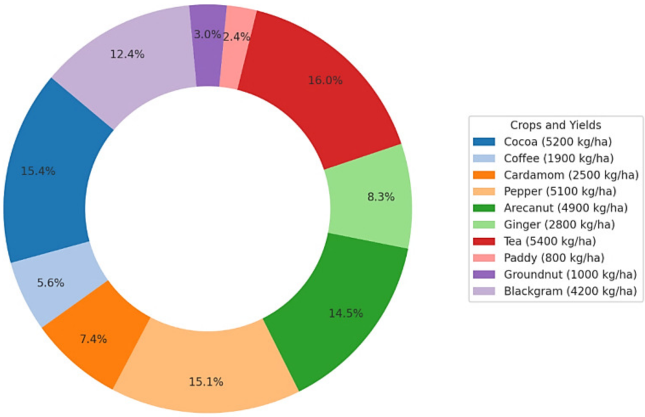


Fig. 4. Distribution of yields.

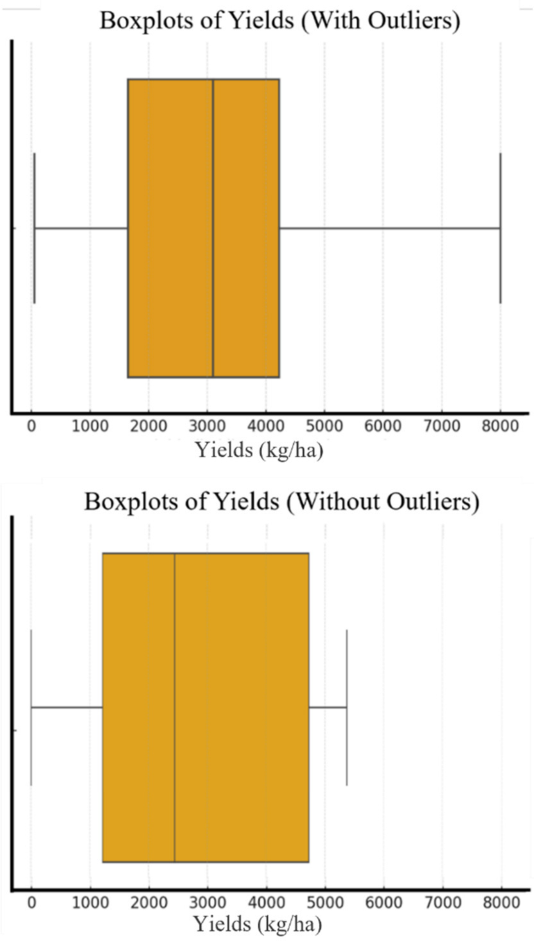


Fig. 5. Boxplot of yields prior and after outlier removal.

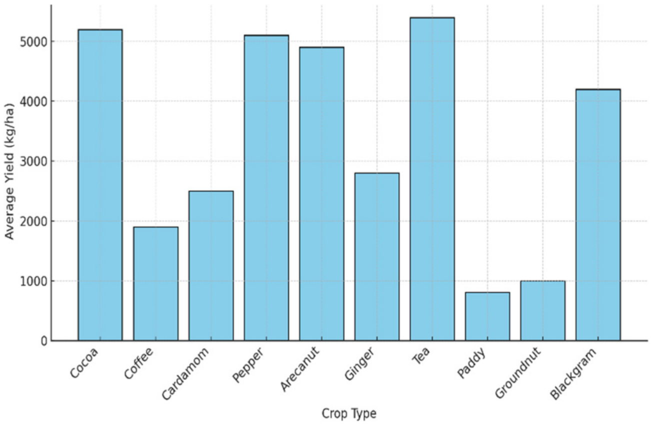


Fig. 6. Average yield by crop type.

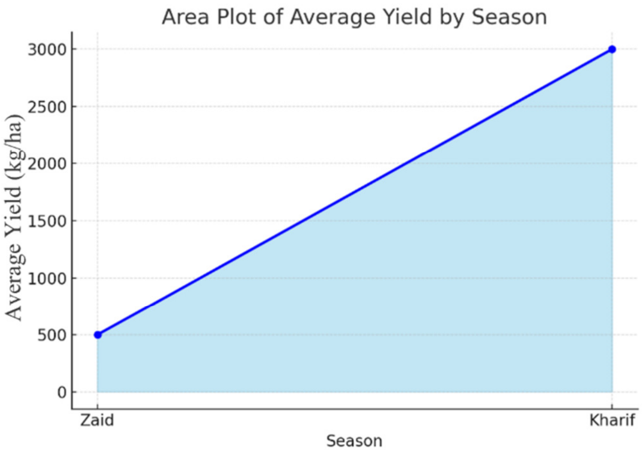
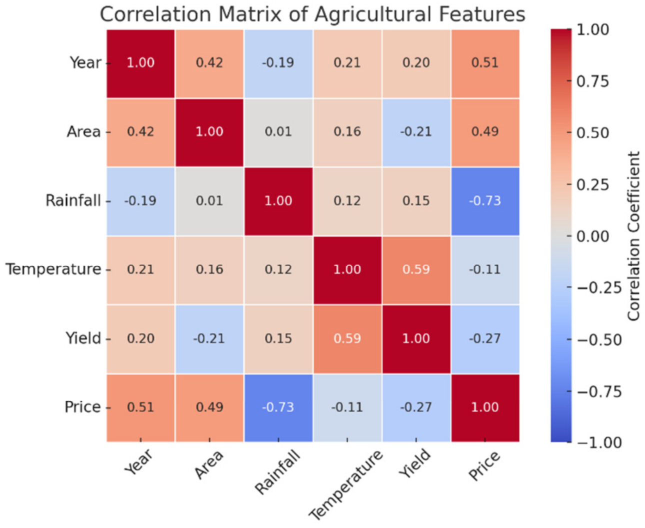


Fig. 7. Area plot of average yield by season.



	Year	Area	Rainfall	Temperature	Yield	Price
Year	1.00	0.42	-0.19	0.21	0.20	0.51
Area	0.42	1.00	0.01	0.16	-0.21	0.49
Rainfall	-0.19	0.01	1.00	0.12	0.15	-0.73
Temperature	0.21	0.16	0.12	1.00	0.59	-0.11
Yield	0.20	-0.21	0.15	0.59	1.00	-0.27
Price	0.51	0.49	-0.73	-0.11	-0.27	1.00

Fig. 8. Correlation matrix.

Among the features analyzed in Figure 10, humidity emerges as the most influential, contributing 30.02% to the model’s predictive importance. This underscores the critical role of climatic factors, as atmospheric moisture directly affects plant growth and productivity. Following humidity, cultivated area contributes 12.63%, highlighting the intuitive relationship between land size and total yield, with larger areas generally supporting higher production. Temperature, accounting for 11.43%, also plays a vital role in regulating crop growth phases such as germination, metabolism, and flowering. Rainfall, with 6.47% importance, significantly influences seasonal success, as both its timing and quantity are crucial for yield outcomes. Price contributes 5.46%, reflecting the economic environment's effect on farming decisions and input investment, which can impact productivity. Among crop types, Tea holds 5.10% of feature importance, indicating its significant influence on model predictions. The Kharif season accounts for 4.71%, reaffirming the substantial effect of monsoonal seasonality on agricultural outputs in India. Irrigation methods also affect yield, particularly drip irrigation (4.14%), which improves efficiency by delivering water directly to roots, especially in low-rainfall areas. Other crop-specific features, such as Arecanut (3.42%) and Cocoa (3.40%), further emphasize the importance of crop diversity in yield modeling.

Figure 11 presents the confusion matrix for the TempoQA-Net model, categorizing yield predictions into five classes: Very Low, Low, Medium, High, and Very High. The matrix demonstrates strong classification performance, with most predictions concentrated along the diagonal, particularly in the Medium and High categories, indicating high agreement between predicted and actual values. Misclassifications mainly occur between adjacent categories, which is expected due to the subtle boundaries in yield class definitions.

Table I lists the optimal hyperparameters for the proposed model. The maximum depth is set to "None", allowing trees to grow without restriction until reaching pure leaves or minimum split criteria, thereby adapting fully to data complexity. A minimum leaf sample size of 1 supports fine-grained pattern recognition, while requiring at least 5 samples for node splitting enhances generalization and reduces overfitting. Using 100 tree estimators strikes a balance between predictive performance and computational efficiency.

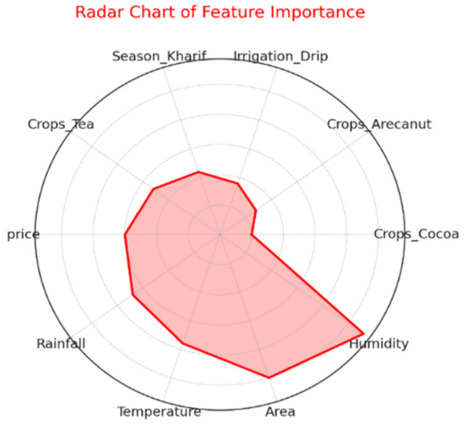


Fig. 9. Feature importances in the proposed model.

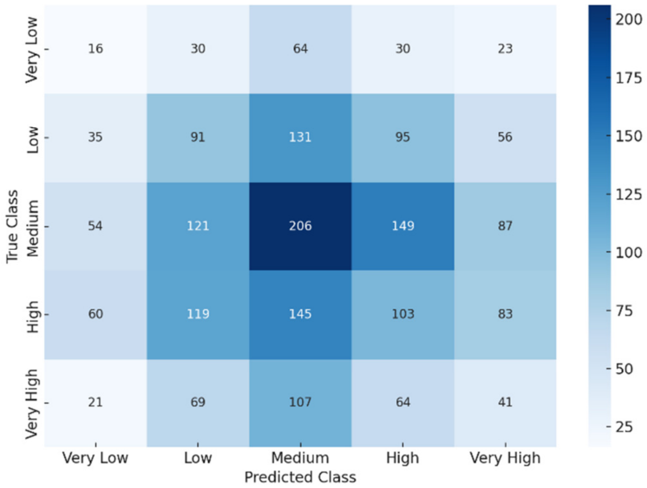


Fig. 10. Confusion matrix.

Table II presents a comparative analysis of MAE values across several models from literature. The COA model achieves an MAE of 0.151 kg/ha, while the GNN and LSTM with Attention models achieve 0.12004 kg/ha and 0.131 kg/ha, respectively. The proposed model marginally outperforms the GNN, attaining the lowest MAE of 0.11995 kg/ha. Table III shows the MSE values, with the COA, GNN, and LSTM with Attention models recording MSE values of 0.062 kg^2/ha^2, 0.02363 kg^2/ha^2, and 0.054 kg^2/ha^2, respectively. The proposed model achieved the lowest MSE of 0.02215 kg^2/ha^2. Table IV reports the R-squared values, showing that the proposed model outperformed the others, achieving a value of 0.743, reflecting its strong explanatory power. Lastly, Table V summarizes the overall classification accuracy of the proposed model and three other models. The COA model achieved an accuracy of 91.98%, the RF model an accuracy of 85%, the voting classifier an accuracy of 92%, the LSTM with Attention an accuracy of 98.23%, and the proposed model achieved the highest accuracy of 98.87%.

TABLE I. HYPERPARAMETER TUNING

Hyperparameter	Optimal Value
Maximum Depth	None
Minimum Samples Leaf	1
Minimum Samples Split	5
Number of Estimators	100

TABLE II. MEAN ABSOLUTE ERROR (MAE)

Model	MAE (kg/ha)
COA [15]	0.151
GNN [17]	0.12004
LSTM with Attention [22]	0.131
Proposed Model	0.11995

TABLE III. MEAN SQUARED ERROR (MSE)

Model	MSE (kg^2/ha^2)
COA [15]	0.062
GNN [17]	0.02363
LSTM with Attention [22]	0.054
Proposed Model	0.02215

TABLE IV. R-SQUARED

Model	R^2
COA [15]	0.572
GNN [17]	0.51719
LSTM with Attention [22]	0.43
Proposed Model	0.743

TABLE V. ACCURACY (%)

Model	Accuracy (%)
COA [15]	91.98
RF [16]	85
Voting Classifier [19]	92
LSTM with Attention [22]	98.23
Proposed Model	98.87

V. CONCLUSION

The research demonstrates that TempoQA-Net is highly effective in predicting crop yields, combining Long Short-Term Memory (LSTM) and Quantile Random Forest (QRF) networks to achieve better accuracy. The model significantly outperforms traditional methods, reducing the Mean Absolute Error (MAE) to 0.11995 kg/ha and the Mean Squared Error (MSE) to 0.02215 kg^2/ha^2, with an accuracy of 98.87% and an R-squared value of 0.743. These strong performance metrics highlight the model's robust predictive ability, which has meaningful implications for agricultural planning and policymaking.

Looking ahead, the promising results of TempoQA-Net establish a solid foundation for its extension into a comprehensive crop recommendation system. Such a system could build upon TempoQA-Net's predictive capabilities to offer tailored guidance on crop selection, fertilization, irrigation, and pest management, informed by real-time data and advanced analytics. These developments could further improve yield outcomes, increase resource efficiency, and reduce the environmental footprint of agricultural practices.

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