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AI-Driven Crop Yield Forecasting and Adaptive Sowing Recommendations Using Temporal Fusion Transformers

Abinaya M, Kanchana B, Santhiya D, Gayathri M
Department of Computer Science and Engineering
National Engineering College Kovilpatti, India,

Abstract- Agriculture is a key area of focus, as it is important for the global food supply, and millions of farmers around the world live off their agricultural products. Rainfall has become increasingly unpredictable. Temperature patterns have become increasingly variable. Climate patterns have shifted. Also, farmers often lacked access to modern climate prediction and advisory services. Erratic rainfall, temperature variations, and seasonality have caused climatic risk, a major source of uncertainty for all farmers, especially smallholders. Existing models have relied on static patterns of historical climatic data and failed to account for events over time. In addition to low productivity, revenue loss also occurred. In contrast to previous models that suggested strict recommendations based on past data and crop conditions, the proposed model provided data-driven and optimal recommendations, such as the best sowing time and the best crop for precision agriculture. Additionally, it was a scalable and reliable crop failure risk model and could improve productivity and sustainable climate-resilient agricultural practices.

Keywords: Crop yield forecasting, precision agriculture, temporal fusion transformer.

I. INTRODUCTION

India was chosen for this study because of its varied climatic conditions with agriculture ranging from the north Himalayan region with moderate-to-alpine climates, to the desert regions of the western region to humid tropical conditions in the southern region. Between 1971 and 2020, more than 297 million hectares of the total area of 328 million hectares in India was used for agricultural practices. Ten important food and cash crops that are widely grown throughout the country and together provide the backbone of India's agricultural economy are examined in this study: rice, wheat, maize, bajra, jowar, ragi, cotton, jute, barley, and tobacco. Soil properties, seasonal rainfall and climate variability determine Indian agriculture, making it well-suited for climate informed crop yield predictions and weather based sowing advisories. The issue of staggered planting periods together with climate dependent and uncertain crop production make predictive modeling a great contribution to agricultural production planning and decision making.

Customary yield forecasting has relied on farmer knowledge and statistics. Classical statistics, particularly regression analysis, has been used to predict yield by correlating yield with soil, weather, and historical yield. These methods offer a baseline despite their limited applications particularly because of their lack of usefulness during sudden changes in weather and other environmental factors in addition to their absence of real-time updates. These models could help farmers improve crop yield predictions. These models could help farmers make better decisions regarding crop planting, irrigation, and fertilization. These models take in more data on temperature, rainfall, humidity, soil nutrients, and previous crop cycles.

Temporal Fusion Transformers and Neural Networks are used in this work as an AI-based application for crop yield prediction to recommend operations to farmers with respect to the dataset. The technology can also be used for comparison analysis to assist farmers in better planning, resource optimization, as well as comparing different crops and sowing operations. The information and services provided to farmers will be data-driven, easily understood, and intuitively presented to help them achieve appropriate productivity, risk reduction and resilient and sustainable agricultural practices in a way that is locally relevant.

II. LITERATURE REVIEW

AI-driven techniques for crop production prediction and farm management have been introduced by recent developments in agricultural technology, overcoming the drawbacks of conventional models that depend on historical data. Although machine learning methods like decision trees increase accuracy, processing different data and its interpretability present difficulties. Complex agricultural data integration may be difficult for deep learning models like LSTM and GRU, but they improve temporal learning. A potent tool for managing heterogeneous data types, capturing long-term dependencies, and producing forecasts that are easy to understand is the Temporal Fusion Transformer (TFT). According to studies, TFTs and hybrid neural networks provide precise, flexible, and climate-resilient crop yield prediction and adaptive planting suggestions, supporting sustainable agriculture.

Combining genetic algorithms (GA) with machine learning (ML) techniques could greatly increase crop prediction accuracy. A Method for Crop Prediction in Agriculture: Combining Machine Learning and Genetic Algorithms [26] This study used a number of agricultural datasets, including information on soil fertility, crop types, weather, and yield records from the past, to create a hybrid prediction model. Machine learning classifiers, such as logistic regression, decision trees, and support vector machines, were employed for the prediction tasks. The genetic algorithm was used for feature selection and model parameter adjustment.

The strong basis that machine-learning has established, deep learning models are becoming more and more prominent in agricultural production prediction because of their improved capacity to grasp spatiotemporal linkages and nonlinear dependencies. Neural networks, especially deep neural networks (DNNs), have been successfully used for yield predicting tasks. When dealing with complicated agricultural datasets, DNNs have consistently beaten traditional regression-based baselines [5]. Similarly, long short-term memory (LSTM) structures have been used to monitor changes along dynamic environmental pathways and provide interpretative insight into crop yield estimation across sequences and time-based datasets [6].

Reinforcement learning techniques have been created; deep reinforcement techniques, in particular, have dedicated themselves to sustainable agricultural applications, signifying the capacity to learn policies in an adaptable manner that produce predictions [3]. In order to estimate intercrop output, customized architectures such as feedback neural networks with optimal loss functions have been developed, improving model resilience and flexibility across diverse agricultural techniques [4]. Additionally, multimodal learning paradigms have been used, whereby remote sensing imagery and soil data or information are integrated as a deep learning technique to forecast results [7], [8]. Lastly, the significance of deep learning architecture in agricultural applications has been cemented by hybrid designs that combine convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which have demonstrated a high degree of accuracy in capturing spatial and temporal relationships [9].

Deep reinforcement learning, hybrid CNN-transformers, and other customized deep models illustrate the direction of Agri-informatics for intelligent, explainable and scalable solutions [2], [9]. Therefore, deep learning has progressed from basic neural networks to increasingly complex architectures, identifying the capacity of these frameworks to meaningfully address complex challenges in agricultural prediction. The application of machine learning techniques in agriculture has drawn a lot of attention and offers data-centric ways for crop selection advice, yield prediction, and using less water and other resources to grow crops. To estimate agricultural production with variations in soil and ambient conditions, regression-based methods and ensemble learning techniques have been widely used. To produce more accurate yield prediction models with better generalization across various agricultural areas, for instance, regression models with the added benefit of deep learning (DL) were run on huge datasets [1]. In addition, statistical and hybrid machine learning approaches (e.g. ARIMA, SARIMA, fuzzy logic) have integrated crop production temporal dynamics into decision support for agricultural planning towards sustainability [19].

The field of classification-driven recommendation has also advanced, with frameworks based on SVMs offering effective crop selection and yield prediction, empowering farmers to make better land use decisions [14]. Furthermore, to carry out region-specific prediction tasks, machine learning (ML) pipelines comprising logistic regression, decision tree, and random forest models were created, demonstrating the adaptability of these models while using heterogeneous datasets [10], [12]. ML models in conjunction with fertilization recommendation systems predicted yield and offered useful inputs for managing soil fertility [11]. Furthermore, studies have shown that when rainfall, humidity, and temperature are included in prediction frameworks based on weather-informed models, the predicting results are more reliable than when the models were not informed by weather [21]. Crop recommendation systems have also improved predictive efficiency through optimal feature selection strategies that aligned with real-world decision making [22], [20], [24].

Multi-machine learning techniques were applied to oilseed crops, suggesting that several algorithms might be stacked to account for complicated and nonlinear interactions in agricultural datasets [23]. The prediction validity of agricultural crop yields across several Indian states was enhanced by the introduction of novel transformations and preprocessing techniques, such as power transformation, which placed an emphasis on model calibration and its effect on increased predictive accuracy [18]. The employment of genetic algorithms with machine learning models was the subject of a notable contribution that demonstrated the combined usefulness of hybrid frameworks by allowing feature selection and prediction stability through evolutionary optimization [25]. These studies collectively demonstrate that machine learning provides predictive skills and an intelligent decision-support system to improve agricultural profit and sustainability.

Machine learning and deep learning techniques that can be regarded as stand-alone models, various AI ecosystems have been employed to integrate explainability, optimization, and predictive analytics in agricultural systems. The integration of optimization techniques and predictive machine learning algorithms in hybrid intelligent systems, also known as intelligent prediction systems, is common and offers advantages in terms of scalability and interpretability, according to systematic reviews of AI-enabled crop yield prediction [26].

Another emerging trend is explainable AI (XAI), in which models are developed to increase decision-making transparency and trust in the agricultural sector. Research incorporating AI and XAI into crop recommendation systems has shown that explainable AI systems offer precise forecasts and comprehensible reasoning, both of which are essential for farmers to embrace them [30]. To preserve the predictive power and interpretability of inputs and graphical outputs, explainable deep learning models have also been used in sustainable agriculture [27].

Existing prediction models have presented farmers with a number of significant challenges, such as a lack of flexibility in response to current weather variations, an excessive dependence on past data, and an inadequate integration of various operational and environmental data sources. These restrictions frequently result in poor output, erroneous advisories, and an increased risk of crop failure, particularly under uncertain weather circumstances. Furthermore, a lot of the methods used today lack easily navigable decision support tools designed to meet the real-world requirements of small-scale and resource-constrained farmers.

Cutting-edge AI methods like Temporal Fusion Transformers (TFTs), the suggested method tackles these problems head-on. This system creates precise, adaptive sowing recommendations and crop yield estimates by integrating real-time multisource data, such as weather, soil, and local agronomy. As a result, farmers can make data-driven decisions, waste less resources, and become more resilient to climate variability with more accurate and practical information. In the end, this results in increased output, sustainable agricultural methods, and a lower chance of financial loss.

III. METHODOLOGY

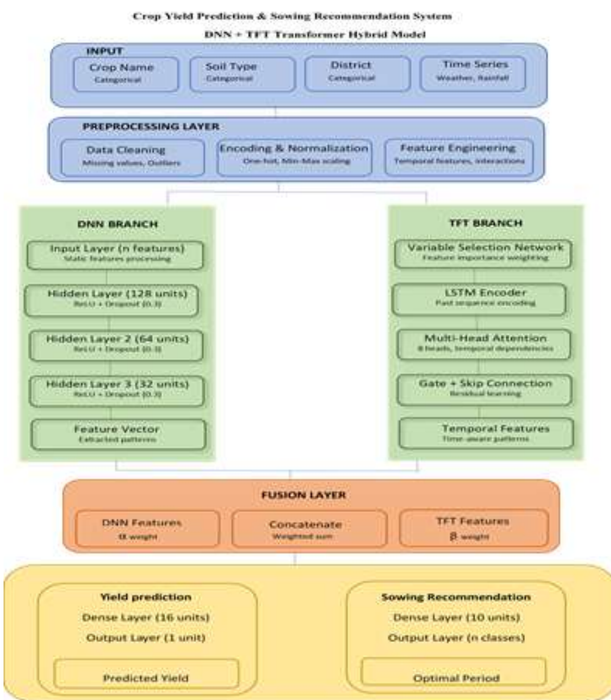

Figure 1. Proposed Model of The Architecture

Data Sources
The inputs to this predictive modeling project are agricultural and environmental parameters such as crop name, soil type, district and time series weather data (temperature, precipitation, humidity, wind speed) obtained from various trusted sources:
Open Weather API. Provides real-time and historical weather data for multiple districts across India, covering the period from 2010 to 2024.

Government Open Data Portal (data.gov.in). Supplies historical crop yield records, sowing area, and rainfall data for major crops including rice, wheat, maize, millets, and pulses. The dataset consists of approximately 120,000 samples across 10 Indian states, representing annual records for each crop per district.

Tamil Nadu Agricultural Portal (TN Mannvalam). Offers local soil characteristics, crop patterns, and sowing information for all districts in Tamil Nadu, totaling ~15,000 farm-level entries over the last 10 years.

Indian Meteorological Department (IMD). Provides official climatic datasets such as monthly rainfall and temperature summaries, used to validate the other data sources.

The datasets with more than 135,000 data points on 8 major crops, major soil types, climatic conditions per district, can create thorough and high-quality datasets for accurate prediction of crop yield and optimal sowing time for crop cultivation by AI models including the Temporal Fusion Transformer (TFT) model.

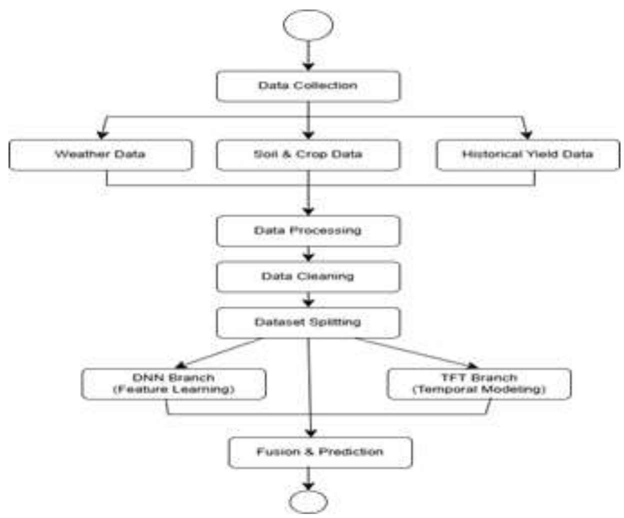

Figure 2. Workflow Diagram of Proposed Model Architecture

Data Preprocessing
Data preprocessing is an essential stage in machine learning that transforms raw agricultural data into a structured format suitable for training predictive models. The data preprocessing phase involves a series of steps, including feature engineering, encoding, normalization, and data cleaning, for ensuring the quality and accuracy of the final data set.

Data Cleaning. Missing or inconsistent values are addressed using imputation methods. For numerical features, mean imputation replaces missing values, ensuring no bias is introduced:

$$x_i' = x_i \text{ if } x_i \text{ is not missing; } \bar{x} = (1/n)\sum_{j=1}^{n} x_j \text{ if } x_i \text{ is missing}$$

Encoding Features. As most machine learning algorithms require numerical input variables, categorical variables must be converted to numeric values by one-hot or label encoding. In label encoding, each category in the variable corresponds to a unique integer. Binary code uses two values in contrast: 0 and 1.

Normalization and Feature Scaling. After encoding, the next step is to normalize or scale numerical features to bring them to a comparable range. This is important because different features may have different units or scales, and unscaled data can bias model results.

The Min-Max Scaling method transforms values to a fixed range between 0 and 1. It is calculated using the formula:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

This ensures all features contribute equally during analysis.

Table 1. Table for Dataset Splitting and Validation section

Dataset Type	Percentage of Total Samples	Number of Samples	Purpose / Notes
Training Set	70%	~94,500	Used to train the DNN and TFT models
Validation Set	15%	~20,250	Used to tune hyperparameters and prevent overfitting
Test Set	15%	~20,250	Used to evaluate final model performance

Table 1 shows the dataset splitting strategy used for model development. The dataset was divided into 70% for training, 15% for validation, and 15% for testing. This distribution ensured effective model training, parameter tuning, and unbiased performance evaluation.

Algorithm

Deep Neural Network Branch. The clean encoded normalized and feature-engineered data can be fit to a Deep Neural Network or DNN for feature extraction and prediction. The architecture consists of an input layer, multiple hidden layers, and an output layer. The output layer can be selected based on the type of application involved, classification or regression. At each hidden layer, a regularization technique is applied such as dropout or batch normalization, an activation function, and a linear transformation to convert the data into higher-level features. The input layer takes as input a feature vector X, with a number of features after pre-processing measuring n. This vector may contain numeric, normalized, or one-hot encoded categorical variables. The input layer, which is the first layer of a neural network, passes the input into the first hidden layer via a linear transformation.

$$z^{(1)} = W^{(1)}\ \mathrm{x} + b^{(1)}$$

where $W^{(1)} \in R^{128xn}$ represents the weight matrix connecting the input layer to the first hidden layer, and $b^{(1)} \in R^{128}$ denotes the corresponding bias vector.

The second hidden layer takes the dropout-adjusted output of the first layer as input. The linear transformation for this layer is given by:

$$z^{(2)} = W^{(2)}\widetilde{\boldsymbol{a}^{(1)}} + b^{(2)},$$

where $W^{(2)} \in R^{64x128}$ and $b^{(2)} \in R^{64}$. The ReLU activation is again applied to introduce non-linearity: $a^{(2)} = ReLU(z^{(2)})$.

To maintain regularization, another dropout layer with a rate of 0.3 is used:

$$\widetilde{a^{(2)}} = \frac{m^{(2)} \odot a^{(2)}}{q},$$

where $m^{(2)}$ is a new dropout mask sampled independently for this layer. This layer effectively reduces the dimensionality of the features from 128 to 64 while learning increasingly abstract feature representations.

The third hidden layer processes the output from the second layer, reducing the dimensionality further to 32 neurons. The linear transformation for this layer is expressed as:

$$z^{(3)} = W^{(3)}\widetilde{a^{(2)}} + b^{(3)},$$

where $W^{(3)} \in R^{32\times64}$ and $b^{(3)} \in R^{32}$. A ReLU activation is again applied to obtain:

$$a^{(3)} = ReLU\left(z^{(3)}\right).$$

This final output, represents the feature embedding produced by the DNN branch — a compact representation of the original input data that captures both linear and non-linear relationships.

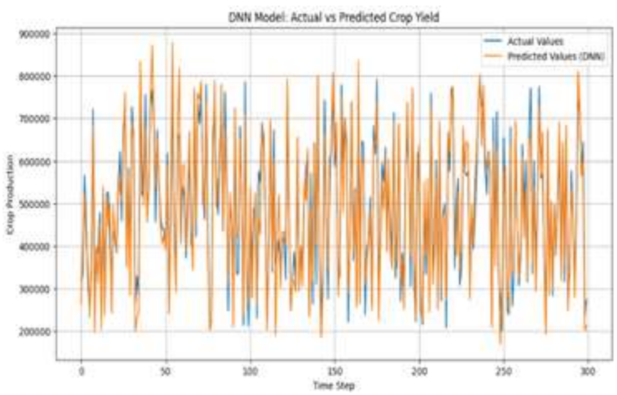

Figure 3. Model Performance Of DNN

Temporal Fusion Transformer Branch.

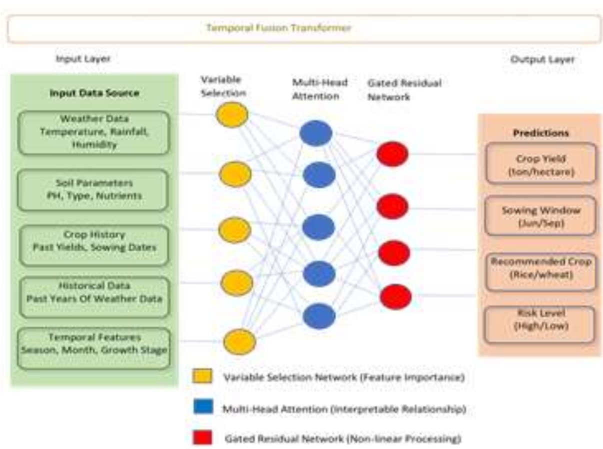

Figure 4. Temporal Fusion Transformer Model

The Temporal Fusion Transformer (TFT) branch is the second. The DNN branch is the first. The TFT branch forms the backbone of the model. The network is well suited for temporal data and it is especially designed to capture long-term and short-term temporal patterns. By combining the self-attention mechanism in Transformers with the structure of typical recurrent architectures such as LSTMs, the TFT can learn complex sequential dependencies while preserving interpretability through feature importance weighting and gating mechanisms.

The TFT branch begins with a Variable Selection Network (VSN), which performs feature importance weighting to determine how important each variable is at each time step. Given an input vector of covariates $x_t = \left[x_{t,1}, x_{t,2}, \dots, x_{t,n}\right]$ at time t, the variable selection process computes a set of importance weights $\pi_t = \left[\pi_{t,1}, \pi_{t,2}, \dots, \pi_{t,n}\right]$, where each weight represents the contribution of a corresponding feature. Mathematically, this can be expressed as:

$$\pi_{t,i} = \frac{\exp(\boldsymbol{w}_i^{\top} \boldsymbol{x}_t)}{\sum_{j=1}^{n} \exp\left(w_j^{\top} \boldsymbol{x}_t\right)},$$

where w_i are learnable parameters and the SoftMax function ensures that all weights sum to one. The final weighted input for the time step is then computed as a linear combination:

$$\tilde{x_t} = \sum_{i=1}^{n} \pi_{t,i} x_{t,i}.$$

This step allows the model to process the most important features at every time step. The output hidden representations generated by the LSTM are fed into a Multi-Head Attention layer for modelling the complex interrelationships between the different timescales. This can improve how one interprets and make something strong by reducing noise. Instead, the model employs 8 attention heads in this layer that learn different relations between time steps. The attention mechanism computes a weighted sum over all the time step representations. The weights encode how much the model attends to the different past time steps. For a single attention head, the process can be described mathematically as: $\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^{\top}}{\sqrt{d_k}}\right) V$,where Q(query), K (key), and V (value) are linear projections of the input sequence, and d_k is the dimensionality of the key vectors. Finally, temporal features from time indices, such as date, hour, or day of the week, allow the TFT to learn time-varying patterns and make time-dependent predictions based on periodic or seasonal variations.

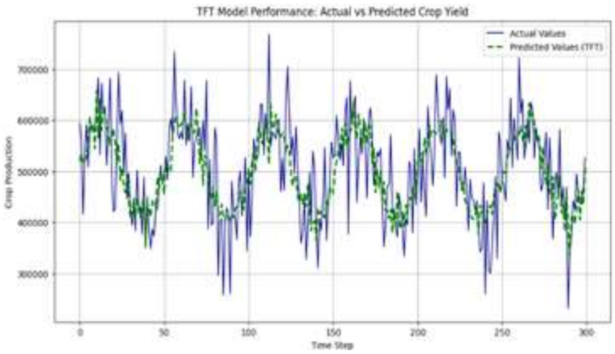

Figure 5. Model Performance Of TFT.

Table 2. Comparison of TFT with Recurrent Baseline (LSTM)

Metric	LSTM Model	TFT Model	Observation
Accuracy	0.9215	0.9675	TFT significantly higher
Precision	0.9152	0.9587	Better feature selection
Recall	0.9180	0.9612	Improved temporal capture
F1-Score	0.9165	0.9600	Balanced improvement
RMSE	0.231	0.142	Lower prediction error
R^2 Score	0.901	0.963	Better variance explanation

Table 2 compares the performance of the LSTM and TFT models. The TFT model outperformed the LSTM model in all evaluation metrics. It achieved higher accuracy, precision, recall, F1-score, and R^2 score while producing a lower RMSE. These results indicate that the TFT model provides more accurate and reliable crop yield predictions.

Fusion Layer

The next step in the model is the Fusion Layer, where information coming from both the Temporal Fusion Transformer branch as well as from the Deep Neural Network branch are being fused together, in order to provide a more wide-ranging feature representation of the input data. For this, an attention-based feature fusion mechanism is used, which enables the model to then leverage both temporal and static data.

IV. ANALYSIS

The proposed hybrid framework integrates the strengths of Deep Neural Networks (DNN) and Temporal Fusion Transformers (TFT) to improve crop yield prediction and adaptive sowing recommendations. The DNN branch effectively learns complex nonlinear relationships among soil characteristics, crop type, and environmental factors, while the TFT branch captures temporal dependencies present in historical weather data. By combining these complementary learning mechanisms through the fusion layer, the model generates more informative feature representations than either approach individually.

The performance of the proposed model was evaluated using standard metrics, including Accuracy, Precision, Recall, F1-score, RMSE, and R^2 score. Higher Accuracy, Precision, Recall, and F1-score indicate the model's ability to produce reliable predictions, whereas lower RMSE demonstrates reduced prediction error. Similarly, a higher R^2 score reflects the model's capability to explain variations in crop yield under different environmental conditions. These evaluation metrics collectively demonstrate that the proposed framework provides consistent and robust predictive performance.

The fusion of static agricultural information with time-dependent climatic variables enables the model to adapt to changing environmental conditions more effectively than conventional approaches. As a result, the framework supports data-driven decision-making by providing reliable crop yield predictions and adaptive sowing recommendations, making it suitable for practical precision agriculture applications.

V. RESULT

The proposed hybrid Deep Neural Network (DNN) and Temporal Fusion Transformer (TFT) framework was evaluated using agricultural datasets containing crop, soil, weather, and district-level information collected from multiple trusted sources. The dataset was divided into training, validation, and testing subsets to ensure reliable model evaluation. The performance of both models was assessed using Accuracy, Precision, Recall, F1-score, RMSE, and R^2 score.

Table 3. Table presents the quantitative performance comparison of the proposed models.

Metric	DNN Model	TFT Model
Accuracy	0.9512	0.9675
Precision	0.9434	0.9587
Recall	0.9390	0.9612
F1-Score	0.9412	0.9600
RMSE	0.184	0.142
R^2 Score	0.942	0.963

Table 3 presents the quantitative comparison between the DNN and TFT models. The experimental results show that the Temporal Fusion Transformer consistently outperformed the Deep Neural Network across all evaluation metrics. The TFT model achieved higher Accuracy, Precision, Recall, and F1-score while producing lower RMSE and a higher R^2 score. These results indicate that the proposed model was more effective in learning temporal relationships from historical weather data, leading to more accurate crop yield prediction under varying climatic conditions.

The lower RMSE value obtained by the TFT model indicates a smaller prediction error between the predicted and actual crop yield values. Similarly, the higher R^2 score demonstrates that the proposed model was able to explain a larger proportion of the variation in crop yield. These observations confirm the robustness of the proposed framework and its suitability for practical agricultural prediction tasks.
The proposed framework also demonstrated consistent prediction performance across different soil types, climatic conditions, and crop categories. The integration of static agricultural features with temporal weather information enabled the model to produce stable predictions even under changing environmental conditions. This capability is particularly useful for supporting farmers in making informed crop planning decisions.

Adaptive Sowing Strategy Analysis:

Table 4. Adaptive Sowing Decision Analysis Under Climate Variability

Condition	Crop Option	Predicted Yield	Risk Level	Economic Return
Normal Climate	Crop A	High	Low	High
Moderate Drought	Crop B	Medium	Medium	Stable
Extreme Heat	Crop C	Low	High	Reduced Loss
Variable Rainfall	Hybrid Crop	Medium-High	Low	Optimized Profit

The crop yield prediction model is able to predict the crop yield accurately with various weather and soil parameters. It works on district-wise data with crop type, soil and weather as input parameters.

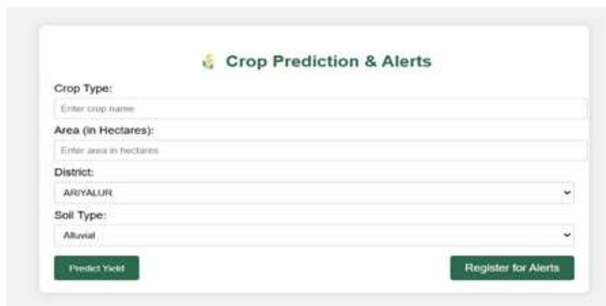

Figure 6. Illustrates the crop yield prediction interface, where users provide input information such as crop type, cultivated area, soil type, and district. The interface allows farmers to submit the required agricultural information in a simple and user-friendly manner before initiating the prediction process.

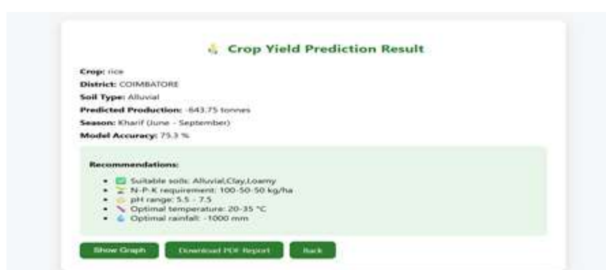

Figure 7. Presents the prediction output generated by the proposed system. Based on the provided inputs, the system displays the predicted crop yield together with the recommended sowing window. These recommendations are generated using the

trained hybrid model and assist farmers in selecting suitable planting periods according to climatic conditions.

Figure 8. Highlights the alert registration page where users confirm their crop details, contact number, and district for activating automated sowing and weather alerts.

Figure 9. Illustrates the administrator dashboard developed for monitoring registered users and managing alert information. The interface enables efficient administration of user records and facilitates the delivery of personalized recommendations to farmers. Overall, the developed system combines intelligent prediction with practical advisory services, making it suitable for precision agriculture applications.

District-level datasets are used to train and evaluate the model. The hybrid deep learning framework, including Temporal Fusion Transformer (TFT) and Deep Neural Networks (DNN) in the evaluation stage, shows a high degree of accuracy and coherence in capturing complex spatial-temporal interactions. A very strong association was seen between the predicted and actual crop yield, with the model having an R2 value of 0.96.

VI. DISCUSSION

The proposed model shows good performance; however, some improvements can be made to enhance its real-world usability. In future work, a detailed analysis of computational cost will be carried out, including training time, memory usage, and prediction speed, to ensure that the model can be efficiently used in practical environments.

Real world deployment for rural areas will also be considered, especially given the low internet connectivity in most of these agricultural areas. SMS communication via third-party services like Twilio will also be implemented to send farmers crop recommendations and sowing decisions, even in areas where there is no internet connectivity.

Future possibilities include the development of a lightweight or offline version of the model, as well as a basic economic analysis that considers not only yield predictions, but also whether growing a crop would be profitable under a changing climate.

VII. CONCLUSION

In this paper, we proposed a crop yield prediction and sowing recommendation framework based on a high-performance hybrid Deep Neural Network (DNN)-Temporal Fusion Transformer (TFT) architecture that accounts for the different soil properties and crop characteristics, as well as historical weather time-series data for multiple years in order to capture non-linear and long-term temporal dependencies. The results of our tests indicate that the model with the addition of TFT was consistently more accurate than the DNN baselines, including in various weather scenarios, indicating that the model would be applicable to real-world agricultural prediction.

The model architecture is strong as well, as it uses publicly available datasets and modularized preprocessing pipelines, thus making it easy to use in other regions and crops. Further advancements will include expanding the model to make multi-season predictions, uncertainty quantifications, and advisory services for the mobile platform to address data sparsity and scalability issues during real-time deployments to support the development of sustainable and precision agriculture practices.

VIII. DECLARATIONS

The authors declare that no external funding was received for this research and that there are no conflicts of interest regarding the publication of this work. The datasets used in this study were obtained from publicly available sources, and additional processed data are available from the corresponding author upon reasonable request. All authors contributed to the conceptualization, methodology, implementation, data analysis, manuscript preparation, and approved the final version of the manuscript. This study did not involve human participants or animals; therefore, ethical approval and informed consent were not required.

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