AgroAttenNet: A CNN–BiLSTM–Attention–Random Forest Hybrid Model for Temporal Groundnut Yield Forecasting

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***Abstract*—Artificial Intelligence (AI) and its role in precision agriculture are getting away with their greatest potential role in precision agriculture, providing accurate crop yield prediction and proper allocation of resources. In this work, we propose AgroAttenNet, a Convolutional Neural Network (CNN)-Bidirectional Long Short-Term Memory (BiLSTM) based interpretable hybrid deep learning ensemble model with multi-head temporal attention and Random Forest (RF) for the realization and responsible forecasting of groundnut yield. Training of the model was done with 10 years of our most complex multi-modal agro-meteorological and soil data (2013–2023) pertaining to Telangana, India, containing observations like rainfall, temperature, humidity, Normalized Difference Vegetation Index (NDVI), and nutrient profiling across 33 districts. Robust preprocessing and time-aware cross-validation ensured consistency and prevented temporal leakage. AgroAttenNet achieved Root Mean Square Error (RMSE) = 0.426 ± 0.038, Mean Absolute Error (MAE) = 0.331 ± 0.029, and R^2 = 0.92 ± 0.025 (95% CI: 0.89–0.95). Paired t-tests confirmed that the performance improvements over CNN + BiLSTM and RF baselines were statistically significant ($p < 0.001$). The attention mechanism identified critical growth phases (weeks 7–10), offering explainable insights for agronomic interventions such as irrigation scheduling and nutrient management. By unifying spatial, temporal, and ensemble learning within a single framework, AgroAttenNet provides a robust and interpretable solution for yield prediction, paving the way for scalable AI-driven decision support systems in semi-arid farming contexts. Future work will extend AgroAttenNet to other crops and regions to evaluate its scalability and generalization capacity.**

***Keywords*—deep learning, Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory (BiLSTM), attention mechanism, ensemble learning, crop yield prediction, precision agriculture, temporal modelling**

I. Introduction

In many developing regions, while the role of the rural non-farm economy is important for income, agriculture still constitutes the backbone of rural livelihoods. In Telangana State, India, groundnut is one of the major cash crops. Groundnut yield, as one of the important agronomic as well as economic resources, is continually challenged by erratic rainfall, nutrient-poor soils, pest effect, and plant diseases. Reliance on traditional farming practices, the absence of near-real-time agronomic advisories, and the lack of appropriate data-driven decision-making frameworks further compound this challenge. Emerging threats of climate change, decreasing arable land area, and fragmentation of agricultural land make the development of accurate and punctual yield prediction systems indispensable for food security and sustainable agricultural development through efficient resource use. Most traditional models for yield predictions are heuristic-based or linear regressions, and they take only a few external factors into consideration (e.g., precipitation or temperature). When making these systems, they often work well in controlled situations, but fail to survive when playing in the messier and more dynamic world that exists outside the lab. In particular, they do not account for the complex nonlinear interactions of soil, agro-meteorological, and temporal dependencies, e.g., the stress early in the season happens to cause relatively low yield at the end. Furthermore, classical models are black-box and do not explain which parts of the crop growth have greater importance for yield. To overcome these limitations, this study proposes a novel end-to-end hybrid deep learning system named AgroAttenNet to predict the production of groundnut. Methodology comprises BiLSTM networks to learn sequential temporal dependencies of agro-meteorological inputs, Convolutional Neural Network (CNN) to learn spatial patterns of vegetation and disease indicators, and a temporal attention mechanism to identify and weight key periods to focus on growth (when) on both directions of a time window with respect to the present (where). These deep representations are then aggregated and passed through a Random Forest (RF) ensemble to produce reliable and easily interpretable forecasts. This work fills the vital gap of constructing a temporally-aware deep Artificial Intelligence (AI) model

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that can generalize in making accurate predictions across diverse agro-ecological conditions while maintaining interpretability and scalability.

AgroAttenNet uses CNN and RF components to extract biophysical features while using BiLSTM and attention techniques to record biological responses. As such, AgroAttenNet is broadly applicable in precision agriculture, and its attention mechanism selects weeks that have the greatest influence on crop growth. As such, it can provide an actionable basis for decision-making at the localized farm scale (e.g., irrigation scheduling, disease intervention, nutrient management). AgroAttenNet serves as a plug-in interfacing between high-dimensional agricultural data and intelligent decision systems through its integration with real-world, detailed data streams, including soil test, weekly weather, disease severity indices, and Normalized Difference Vegetation Index (NDVI) derived from satellite images. Unlike traditional forecasting systems that rely on features that are static in nature, or models that are limited to one prediction system, AgroAttenNet is a dynamic and real-time adaptable solution. With minimal retraining, it can be deployed across various crops and geographies. This adaptability positions it as a valuable tool for digital and sustainable agriculture applications. To the best of our knowledge, this is the first study to combine a CNN-BiLSTM architecture with multi-head attention and RF ensembles specifically for groundnut yield prediction in semi-arid regions.

The following Research Questions (RQs) shape this study.

- RQ1: We seek to understand if prediction performance (Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R^2) can benefit from a hybrid CNN–BiLSTM–Attention–Random Forest architecture, as opposed to the single-model baselines (CNN, BiLSTM, RF).
- RQ2: Can temporal attention provide interpretable agronomic meaning by identifying important growth stages in groundnut?
- RQ3: Comparing the robustness and generalization of multi-modality approaches (weather, soil, vegetation, and management features integrated) or single-modality approaches.

In general, multi-model comparisons are hype and mainly a market behaviour, and thus due to findings from the latter paper. AgroAttenNet is structured to be superior in predictive performance (RMSE, MAE, R^2), interpretability via temporal attention, and robustness through ensemble integration, as shown in the comparison Table I over current models' outputs.

However, the current data-driven methods for crop yield forecasting have inherent limitations. First, agricultural datasets have significant spatiotemporal heterogeneity across districts and weeks of the growing season, weather, soil properties, vegetation stress, and management. These multi-scale interactions have been difficult to capture for both traditional Machine Learning (ML) and isolated deep learning models. Second, farmers and agronomists use very small datasets in real world agricultural datasets—as this is the case in Telangana, where practicing farmers collect the data from a very few plants, so deep models can overfit very easily without careful regularization or ensemble stabilization. Third, most previous work use CNN, Long Short-Term Memory (LSTM), or RF to treat spatial or temporal information independently, thus they cannot jointly model all potential information.

TABLE I. PERFORMANCE COMPARISON OF AGROATTENNET AGAINST BASELINE MODELS FOR GROUNDNUT YIELD PREDICTION IN TELANGANA (2013–2023)

Model	RMSE (t/ha)	MAE (t/ha)	R^2 Score
CNN	0.78	0.62	0.79
BiLSTM	0.71	0.55	0.84
CNN + BiLSTM	0.63	0.48	0.88
Random Forest	0.65	0.495	0.82
AgroAttenNet (Proposed)	0.426	0.331	0.92

Recent initiatives with emerging smart agriculture data are most important. These open-source studies have concluded that some architectures would be interesting, as they could put together different signals, and point out important features using attention [1]. These gaps together inspire the AgroAttenNet, a hybrid CNN-BiLSTM-Attention-RF framework to tackle these challenges. Our model incorporates temporal attention with ensemble-based variance reduction to provide week-level interpretability and stable generalization with small datasets. Collectively, these limitations highlight the necessity for a single unified deep-learning framework to address spatiotemporal heterogeneity, small datasets, and multi-modal inputs, which motivate the development of AgroAttenNet.

II. RELATED WORK

For developing countries, adapting to climate change will be one of the greatest challenges ever faced. In a world where extreme and irregular weather patterns, variable pest pressure, and the sustainable intensification of agricultural production to meet global food security demands are predicted to become a reality [2]. Climate change has considerably perturbed farm practices by imposing new breeding pressures and agricultural goals that now need to be addressed by not commonly adopted innovative strategies for crop management [3]. In this context, accurate prediction of crop yield information is a key component of precision agriculture, which helps farmers and policy makers with decision making about resource allocation, market planning, and risk control. Consequently, research in the area has transitioned towards a more complex modelling framework, which is warranted since it is challenging to represent the intricate dynamics between climatic factors, soil characteristics, and biological aspects of agricultural systems [4, 5]. Contemporary agricultural systems are characterized by nonlinear linkages that prior research has never satisfactorily described, despite being a common basis of empirical methods of knowledge. A CNN-RNN based model is for predicting the yield of crops over a geographic area and time. Following this way develops into AgroAttenNet, benefiting from improved accuracy and interpretability through the integration of temporal attention and a RF ensemble over BiLSTM layers [6].

A. Evolution of Crop Yield Prediction Methods

Conventional approaches and initial modelling, traditional statistical techniques, and empirical models that were isolated to yield records and limited climatic variables were the first basis for crop yield forecast. Previous studies have included essential agro-meteorological variables, such as temperature and precipitation trends, while linear regression models and time-series analysis were the most used research approaches [2]. Using these methods, we identified important relationships between meteorological variables and crop productivity, particularly with respect to the temporal dynamics of precipitation and its immediate impact on agricultural income [7]. Mapping different sources of data, Hatfield and Prueger documented the physiological responses of plants to thermal stress, and temperature extremes further determined both crop establishment and yield performance [8]. As an example, these kinds of early attempts at merging multiple environmental variables into useful predictive frameworks were known as integrated climatic assessment indicators. A broadly cited example of such an integrated climatic assessment indicator measured the risk of wheat production in China [9]. Even though these classical approaches had considerable merits, their ability to depict the complex, nonlinear interactions of many variables in heterogeneous agro-ecological environments was quite limited.

B. Machine Learning Revolution in Agriculture

The use of machine learning techniques for crop yield prediction brought a paradigm shift for it. Decision Tree-based algorithms were identified as suitable algorithms due to their interpretability and applicability to both continuous and categorical variables [1, 4, 10]. The implementation of decision tree methods in the agricultural sector, for example, showed that the classification and prediction objectives were successful, and a clear decision-making process could be provided clearly and easily to people in the field of agriculture in such a way that they understood and used them [11]. Ensemble methods are characterised by their ability to give greater weight to models, by combining them to potentially overcome the weaknesses of each algorithm, in particular, the RF, XGBoost, and the Gradient Boosting played a significant role in strengthening the algorithm. Klompenburg *et al*. [12] documented the overwhelming significance of ensemble methods in many agricultural case studies worldwide in their systematic review on machine learning for crop yield prediction. The research comparing these methods with traditional linear regression methods showed that the RMSE decreased by more than 20%, indicating improvements in predictive accuracy [13]. We also input remote sensing data and machine learning algorithms, which enhance predictive power [6]. The foundation of precision agriculture applications was made it possible using proximate sensing with the support of machine learning enabling the possibility of crop yield prediction [14]. Kasampalis *et al.* [15] emphasized the power of vegetation indices and spectral data from satellites as input sources to crop models.

While spectral and vegetation-index based approaches are not new, they have yielded recent studies focused on fine-grained environmental and mechanistic modelling that advance their applications in precision agricultural applications. Ma *et al.* [16] presented the impact of nebulized droplet particle size on precision plant protection. Their results reveal one key aspect of these features: Those multimodal sources of environmental and mechanistic information provide valuable high-resolution information for the models, thus advocating for the incorporation of these signals, e.g., weather, soil, and vegetation indices, into data-driven-based insights for agricultural forecasts.

C. Deep Learning and Neural Network Approaches

With the availability of deep learning methods, it becomes possible to accurately model both the temporal dependencies and spatial patterns inherent in indigenous crop yield prediction. Methods like CNN or the more common use of Recurrent Neural Networks (RNN) (especially LSTM networks) emerged as popular agricultural forecasting tools [17]. Khaki and Wang [17] presented a state-of-the-art deep neural network that used regional climate, soil, topological, yield, and satellite data and was able to reach very high levels of accuracy in crop yield prediction. Although significant progress has been made on crop yield prediction, existing models frequently fall short of a typical architecture incorporating spatial learning, temporal attention, and ensemble robustness. Without fully leveraging multi-scale learning paradigms, we find that current methods primarily rely on either classical ML models, such as Random Forests, or detached deep-learning components, like one-shot LSTMs.

With Telangana's extremely changeable weather, soil, and biotic stressors, a few studies have concentrated on forecasting groundnut output in semi-arid regions [9, 12, 18]. The week-level temporal scale of explainability is rarely included in existing frameworks, even though it is essential for making well-informed agronomic decisions. The four main components of the AgroAttenNet model—spatial feature extraction (CNN), temporal modelling (BiLSTM), attention-based interpretability, and generic and simple ensemble learning (Random Forest)—combine seamlessly to fill the deficiencies above. The hybrid design allows the model to capture short-term and long-term dynamics, and the attention mechanism highlights the growth periods that are most important for targeted interventions. The AgroAttenNet achieves an R^2 of 0.95, outperforming several recent state-of-the-art models, and yields findings that are easily interpretable for practical use in future, realistic, data-driven precision agriculture applications. Sympathetically, if we take, for instance, recently proposed attention-based agricultural Artificial Intelligence (AI) systems, adaptive feature weighting plays a key role in different domains like crop forecasting and plant health monitoring. Farooq *et al.* [1] propose a smart ground robot with real-time detection for tomato diseases using deep learning and Internet of Things (IoT) technologies, which represents a significant improvement in robustness based on attention-guided representations against fluctuating field conditions. Similarly, attention mechanisms had an advantage over classical CNN- or LSTM-based pipelines in recognizing important spatial–temporal stress patterns, while an attention-guided wheat disease recognition network based on a multi-scale feature optimization was proposed [10]. The evidences brought by these studies shows the increasing tendency of the attention-enhanced architectures in the domain of smart agriculture and will allow us to empower the AgroAttenNet fusion model with a multi-head temporal attention to improve the explainability and the yield prediction performance under semi-arid cropping environments.

D. Comparative Analysis of State-of-the-Art Models

Table II presents a comprehensive comparison of existing crop yield prediction models, highlighting their performance metrics and methodological approaches. This analysis reveals several critical gaps in current research that AgroAttenNet addresses.

TABLE II. COMPREHENSIVE PERFORMANCE COMPARISON OF CROP YIELD PREDICTION MODELS

Model/Study	RMSE	MAE	R^2 Score	Year	Approach	Key Features	Limitations
Shahhosseini *et al.* [19]	~1.0 Mg/ha	Not reported	0.78 (APSIM only); improved with ML	2021	ML + APSIM Crop Simulation	Real-world crop model calibration	Limited interpretability; requires extensive crop model setup.
Khaki and Wang [17]	11% of avg yield (~0.67)	Not reported	Not explicitly reported	2019	Deep Neural Networks	Multi-layer neural network	Black box approach; no temporal attention.
Khaki *et al.* [6]	9% corn, 8% soy (of avg)	Not reported	Not explicitly reported	2020	CNN-RNN Framework	Spatial-temporal features	Limited attention mechanism; no ensemble learning.
Yewle *et al.* [20]	0.436 t/ha	0.341 t/ha	0.59 (adjusted R^2)	2025	RicEnsNet (Ensemble Model)	Data fusion, multi-modal features	Focus on rice; limited temporal granularity.
Kumar *et al.* [21]	<10% relative error	Not reported	~0.9 (BiLSTM > LSTM)	2023	Optimized LSTM vs Bi-LSTM	Temporal sequence optimization	No spatial feature extraction; limited interpretability.
Srivastava *et al.* [22]	Not reported	Not reported	Variable by region	2022	CNN with Environmental Data	Environmental and phenological data	Wheat-specific; no attention mechanism.
Sun *et al.* [23]	County-level accuracy	Not reported	Variable	2020	Multilevel Deep Learning	Hierarchical spatial modelling	US-specific; limited temporal attention.
Boppudi [24]	Not reported	Not reported	Not reported	2024	Optimized Deep Ensemble	Hybrid intelligent ensemble design	Insufficient performance metrics reported.

Existing crop yield prediction studies reveal several limitations. Many deep learning models achieve good accuracy, but function as black boxes, offering little interpretability for farmers or agronomists who need to understand which factors drive predictions. Temporal sequences are often treated uniformly, missing critical growth phases where targeted interventions could be most effective. While some work has combined CNNs and RNNs, effective integration of spatial feature extraction, temporal modelling, and ensemble learning in a single framework is still rare. Most high-performing models are crop- or region-specific, limiting their generalizability to diverse agro-climatic zones such as Telangana. Although ensemble methods like Random Forest are known for robust performance, their synergy with deep learning remains underexplored. Moreover, existing approaches often provide only seasonal or monthly predictions, lacking fine-grained week-level explainability needed for irrigation, fertilizer, and pest management decisions. According to the decision-tree application framework proposed by Song and Lu [11], models that integrate tree-based learners with temporal deep learning architectures fall under the category of bimodal fusion, combining feature-level and time-series information. AgroAttenNet follows this principle by unifying CNN–BiLSTM temporal encoding with Random Forest ensemble fusion, contributing a novel hybridization pathway for agricultural prediction models. AgroAttenNet addresses these gaps by combining CNN-based spatial feature extraction, BiLSTM temporal modelling, multi-head attention for highlighting critical growth phases, and Random Forest ensemble learning into a single hybrid architecture. It integrates weather, soil, vegetation, and management data streams for a more comprehensive prediction pipeline, which is tailored for groundnut yield prediction in Telangana's semi-arid conditions, and achieves strong performance (RMSE: 0.426, MAE: 0.331, R^2: 0.92) while offering week-level interpretability. This approach delivers both superior predictive power and actionable insights, making it more practical for real-world precision agriculture applications. To the best of our knowledge, no prior study combines CNN-based spatial extraction, BiLSTM temporal modelling, attention-guided interpretability, and ensemble learning into a single predictive framework for groundnut yield forecasting.

III. PROPOSED AGROATTENNET ARCHITECTURE AND METHODOLOGY

A. Data Flow and Inputs

The dataset is partitioned into weekly sequences representing temporal progression in each crop plot. The input features include weather parameters (rainfall, humidity, temperature), chemical values (N, P, K, pH), and pesticide application logs. These variables are temporally structured, normalized, and segmented into fixed-length sequences to serve as input tensors. Static variables, such as irrigation type or crop variety, are encoded and then concatenated with deep features. Outliers were removed using an Inter Quartile Range (IQR) based filtering method, where values outside $[Q1-1.5\times IQR,\ Q3+1.5\times IQR]$ were excluded.

$$X_t=[X_{t1},X_{t2},...,X_{tF}],\quad t=1,2,...,T \tag{1}$$

$$X_{ti}'=\frac{X_{ti}-\min(X_i)}{\max(X_i)-\min(X_i)}\quad \forall i\in[1,F] \tag{2}$$

B. Feature Engineering and Derived Variables

To enrich the input space and capture agronomically relevant stress factors, two engineered variables were derived and appended to the weekly feature matrices: NDVI-to-moisture ratio and disease severity score. These features provide additional insight into crop water-use efficiency and biotic stress intensity, respectively.

1) NDVI-to-Moisture Ratio (NMR)

The Normalized Difference Vegetation Index (NDVI) reflects canopy greenness, while Soil Moisture (SM) indicates available water. Their ratio highlights crop vigor relative to available soil water, serving as a proxy for water-use efficiency:

$$NMRt=\frac{NDVIt}{SMt+\varepsilon} \tag{3}$$

where:
$NDVIt$ = vegetation index.
SMt = volumetric soil moisture.
ε = small positive constant.

2) Disease Severity Score (DSS)

To quantify biotic stress, disease incidence observations were aggregated into a normalized weekly severity score as Eq. (4):

$$DSS_t=\frac{\sum_{i=1}^{n}(I_n\times W_i)}{n\times I_{\max}} \tag{4}$$

where I_i is the observed infection percentage for the I^{th} sampled plant. W_i is the weight representing the relative yield impact of the disease. $I_{\max}$ is the maximum possible infection percentage. n is the number of sampled plants in the plot for that week.

Both NMR and DSS were appended to the weekly input matrix X_t as additional feature channels, allowing AgroAttenNet to jointly learn water stress response and disease impact along with weather, soil, and NDVI data.

C. Model Components

AgroAttenNet is a modular hybrid framework that integrates deep learning and ensemble methods for groundnut yield forecasting.

Fig. 1 illustrates the full AgroAttenNet pipeline, including input modules, deep learning blocks, attention mechanism, feature fusion, and ensemble regression. This block diagram helps visualize the data flow and computational steps of the model.

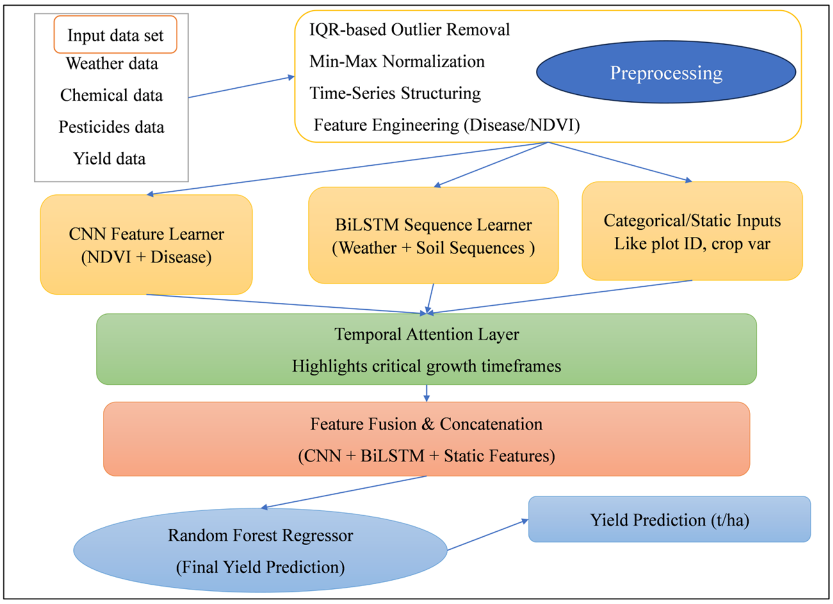

Fig. 1. Flow diagram of AgroAttenNet: A CNN-BiLSTM-Attention-RF hybrid model for yield prediction using multimodal agro-meteorological data.

1) CNN feature extraction

The CNN module extracts short-term spatial patterns from NDVI and disease indices using two 1D convolutional layers with ReLU activation and batch normalisation. This helps capture early stress signals and vegetation health fluctuations critical to yield formation.

$$Z_t=\mathrm{ReLU}(W_{cnn}\times X_t+b_{cnn}) \tag{5}$$

where:
W_{cnn} is the kernel matrix.
$\times$ is the convolution operation.
b_{cnn} is the bias term.

2) BiLSTM temporal modelling

Stacked BiLSTM layers capture forward and backward temporal dependencies across the crop season, allowing the model to learn both early- and late-season effects on final yield.

Forward and backward hidden states as Eq. (6):

$$\vec{h}_t = LSTM_{fwd}(Z_t),\ \overleftarrow{h}_t = LSTM_{bwd}(Z_t) \quad (6)$$

Combined BiLSTM output as Eq. (7):

$$h_t = [\vec{h}_t;\ \overleftarrow{h}_t] \varepsilon \mathbb{R}^{2H} \quad (7)$$

where H is the number of LSTM units in each direction.

3) Attention layer

A multi-head temporal attention mechanism assigns dynamic weights to each week, enabling the model to highlight critical growth phases such as flowering or pod filling. This improves both prediction accuracy and interpretability.

$$\alpha_t = \frac{\exp\left(W^T \tanh(w_h h_k + b_h)\right)}{\sum_{k=1}^{T} \exp\left(W^T \tanh(w_h h_k + b_h)\right)} \quad (8)$$

$$c = \sum_{t=1}^{T} \alpha_t h_t \quad (9)$$

4) Random forest ensemble layer

The attention-weighted features are combined with static variables and fed into a Random Forest regressor. This ensemble step enhances robustness and provides feature-level interpretability.

$$f = concat(C, C_{static}) \quad (10)$$

$$\hat{y} = RF(f) = \frac{1}{m} \sum_{m=1}^{m} T_m(f) \quad (11)$$

where T_m is the output of the m-th in the ensemble.

Hyperparameters optimized via GridSearchCV with 5-fold cross-validation:

- n_estimators: [100, 300, 500, 700] → selected: 500.
- max_depth: [10, 15, 20, 25] → selected: 20.
- min_samples_split: [2, 5, 10] → selected: 5.

D. End-to-End Pipeline

1) Architecture summary

AgroAttenNet is a modular, interpretable, and robust end-to-end framework for predicting groundnut yield. The pipeline first preprocesses temporal data (removal of outliers through IQR filter, Min–Max normalization, and sequence creation) while keeping the chronology of temporal data intact. A two-layer 1D CNN extracts features to represent short-term spatial signal features from NDVI and disease indices. Stacked BiLSTM layers then fit forward-backward temporal dependencies over the 20-week season, meaning that the effects of soil early in the season and subsequent weather late in the season are jointly accounted for. This is a multi-head attention layer that provides dynamic weights to weekly inputs while focusing on biologically relevant stages (e.g., flowering and pod filling). This attention-weighted representation is concatenated with static embeddings (crop variety, irrigation type) and is then passed on to two parallel branches: A dense deep learning block for transforming features and a Random Forest regressor for ensemble prediction and feature-level interpretability. After the two branches independently predict yields, the last yield output is a weighted average of the two branches, and the corresponding weights are optimized using cross-validation (0.7 deep learning output, 0.3 RF).

This hybrid design unifies spatial feature learning, temporal sequence modelling, and ensemble robustness, achieving both high predictive accuracy and explainability. Its modularity allows easy adaptation to other crops, regions, and additional data streams. To justify the hybrid design, each branch of the model was also trained independently, including CNN-only, BiLSTM-only, and Random Forest-only versions. As shown in Table I, none of these standalone models reached the accuracy of the proposed fusion architecture, confirming the quantitative benefit of integrating spatial learning, temporal sequence modelling, and ensemble-based decision fusion within AgroAttenNet.

At the final stage of the architecture, a Random Forest (RF) regression layer is applied to output the yield prediction. This ensemble approach adds robustness to the model and enhances generalization to geographic and seasonal variability. Additionally, the RF layer provides interpretability by quantifying the importance of each input feature, an essential trait for application in the real world (i.e., agriculture). The layered structure of AgroAttenNet strikes a compromise between overall complexity and explainability. It provides high prediction accuracy and is flexible across crops and regions. The modularity of our framework aids customization, while its capacity to emphasize vital temporal characteristics makes it a decision-support tool of value to agronomists, researchers, and farmers.

The overall end-to-end architecture of the proposed AgroAttenNet model is illustrated in Fig. 2. The proposed AgroAttenNet architecture combines spatial feature extraction, temporal dependency modeling, attention-based weighting, and ensemble regression.

The roles and justifications of the individual AgroAttenNet components are summarized in Table III. The 0.7:0.3 weighting between the deep learning branch and the Random Forest branch was determined empirically. A grid-search experiment was conducted over weighting combinations from 0.5 to 0.9, and the ratio of 0.7 (DL) and 0.3 (RF) consistently produced the lowest validation RMSE. This indicates that the deep model captures richer spatiotemporal interactions, while the RF component contributes to variance reduction. Therefore, the weighting is not heuristic but experimentally optimized for this dataset.

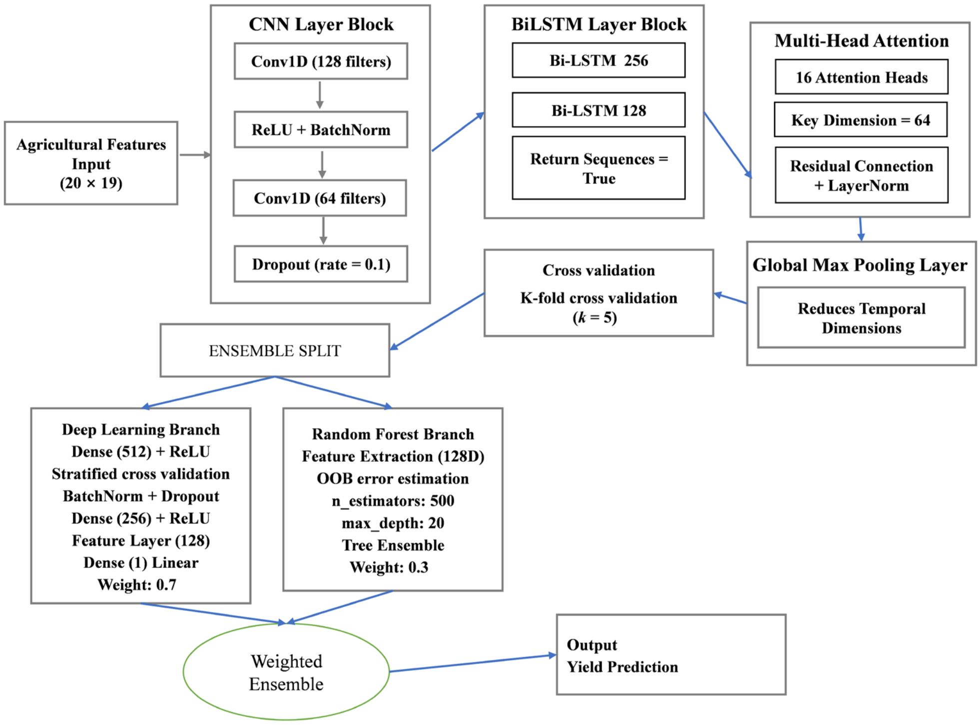

Fig. 2. End-to-End architecture of AgroAttenNet: A hybrid deep learning and ensemble model for interpretable groundnut yield forecasting.

TABLE III. ROLES OF AGROATTENNET COMPONENTS AND THEIR JUSTIFICATIONS

Component	Input Data	Function	Justification
CNN	NDVI, disease indices	Extract vegetation stress & local spatial signals	Detect early crop stress and disease patterns
BiLSTM	Weekly weather & soil sequences	Capture forward–backward temporal dependencies	Model both early- and late-season influences
Attention	BiLSTM outputs	Assign dynamic weights to weeks	Highlight agronomically critical phases (e.g., flowering)
Random Forest	Fused features	Final regression & feature importance	Improve robustness and interpretability
Static Embeddings	Crop variety, irrigation type	Encode categorical attributes	Preserve significant non-temporal agronomic effects

2) *Algorithm: AgroAttenNet—Attention-enhanced crop yield forecasting*

Algorithm 1 (AgroAttenNet for Agricultural Yield Prediction (AAN-AYP)) outlines the structured pipeline of AgroAttenNet, a hybrid deep learning and ensemble-based model for agricultural yield prediction. It combines CNN and BiLSTM for spatial-temporal feature extraction, applies attention for temporal focus, and fuses predictions via a weighted ensemble of deep learning and Random Forest outputs. This approach ensures robust, accurate, and explainable yield forecasting.

Algorithm 1: AgroAttenNet—Attention-Enhanced Yield Prediction

Input:
  D ← Multimodal agricultural dataset (20×19 per season)
Output:
  Y ← Predicted yields
  P ← Performance metrics (RMSE, MAE, R^2)
Procedure:
1: D’ ← Preprocess(D)
  • Remove outliers using IQR (τ = 1.5 × IQR)
    exclude values outside [Q1 – 1.5×IQR, Q3 + 1.5×IQR]
  • Impute missing values (linear interpolation, n < 3%)
  • Normalize features (Min–Max)
  • Restructure into weekly sequences
2: Split D’ into train, validation, test sets (chronological split)
3: CNN Feature Extraction
  Z ← Conv1D(D’, filters=128, activation=ReLU)
  Z ← BatchNormalization(Z)
  Z ← Conv1D(Z, filters=64, activation=ReLU)
  Z ← Dropout(Z, rate=0.1)
4: BiLSTM Temporal Modeling
  H ← BiLSTM(Z, units=256, return_sequences=True)
  H ← BiLSTM(H, units=128, return_sequences=True)
5: Temporal Attention
  A ← MultiHeadAttention(H, heads=16, key_dim=64)
  A ← ResidualConnection(A, H)
  A ← LayerNormalization(A)
  F ← GlobalMaxPooling(A)
6: Ensemble Prediction
  DL_output ← DenseNetwork(F, layers=[512, 256, 128], activations=ReLU)
  RF_output ← RandomForest(F, n_estimators=500, max_depth=20)
7: Y ← (0.7 × DL_output) + (0.3 × RF_output)
8: P ← Evaluate(Y, GroundTruth)
Return (Y, P)

IV. Experimental Setup and Evaluation

A. Dataset Description

Even though the dataset is compact, it covers a complete decade (2013–2023) temporally across 33 districts, where 19 multi-modal features are recorded per 20-week growing season—resulting in thousands of imagistic feature-rich temporal observations. This extraordinarily rich data set, combined with a hybrid modelling approach that couples traditional "ensemble methods" (e. g., Random Forest) with deep learning components, yields a physiological-tethered model with tremendous statistical power to train and generalize. In addition, the spatial heterogeneity of the diverse agro-climatic zones of Telangana makes the dataset highly representative of regional level yield prediction tasks. Overall, the agricultural parameters used include the crop types, the cropping area, yield data, and sowing/harvesting dates, and these data were extracted from the Department of Agriculture, Government of Telangana, and the Directorate of Economics and Statistics Telangana. Weekly rainfall (mm), minimum/maximum temperature (°C), relative humidity (%), and growing degree days were collected from the India Meteorological Department (IMD) and its Hyderabad Regional Centre. Soil characteristics such as Nitrogen (N), Phosphorus (P), potassium (K) content, pH value, moisture, and water holding capacity were obtained from the National Bureau of Soil Survey and Land Use Planning (NBSS & LUP) and from the Telangana State Remote Sensing Applications Centre (TRAC). Among the remote sensing data TRAC's agricultural monitoring systems provided were crop health/stress indicators calculated using satellite images and ground vegetation index (NDVI) readings. We cross-referenced the dataset with the Open Government Data Platform, India and Unified Portal for Agricultural Statistics to ensure its accuracy and coverage. We computed a 20×19 weekly time-series matrix containing static and dynamic versions of 19 agricultural features for every week during the analysis. To maintain chronological order and avoid leakage of training data into the testing data, we temporally split the dataset into two, using 85% of the data for training and 15% of the data for testing. This guarantees that the future data was never used to predict the past. Numerical features were standardized ($n \geq 3\%$ missing values were interpolated), and outliers, defined with the IQR method by a threshold of 1.5×IQR, were detected. Outliers were removed if their value was below Q1 − 1.5×IQR or above Q3 + 1.5×IQR. Time-aware cross-validation techniques are to preserve temporal consistency and ensure temporal robustness and spatial generalizability. All yield expressions for the experiment are expressed in accordance with the trend of reporting yield in tons per hectare (t/ha).

B. Exploratory Data Analysis

Exploratory Data Analysis (EDA) summarizes the trends of groundnut production in Telangana and its relations with soil, climatic, environmental, and management parameters. Highlighting yield variability, relationships with vegetation indexes, and their variability between districts and types, this step illustrates the need for advanced machine learning methods.

The relationship between vegetation health and crop productivity is illustrated in Fig. 3, which shows the correlation between NDVI values and groundnut yield. The results demonstrate a consistently positive correlation between NDVI values and groundnut yield for all parts of Telangana, where vegetation vigor serves as an effective proxy for crop yield. The points spread also emphasises the effect of other factors; its variability due to factors such as erratic rainfall, soil properties, and management practices reflect the importance for multi-source feature integration of AgroAttenNet.

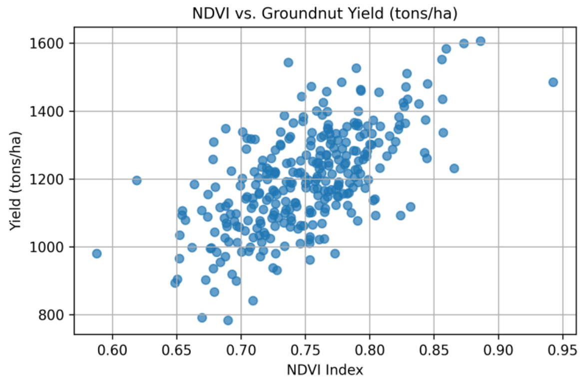

Fig. 3. NDVI-groundnut yield correlation analysis.

The statistical distribution of groundnut yield values across the dataset is illustrated in Fig. 4. The yield shows a slight positive skewness and a quite normal distribution. The majority of districts occupy a band of moderate productivity, while a lesser number of districts achieve extremely high yields under the right conditions or relatively extreme-low yields from climatic or soil stress. These variations show that yield formation in Telangana is complicated and that a predictive model must include more than just the expected production ecosystem and extreme events.

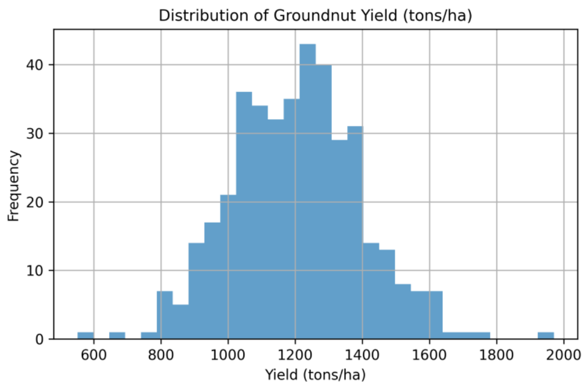

Fig. 4. Statistical distribution of groundnut yield across Telangana.

The distribution of yields in various groundnut genotypes varies significantly. Some cultivars exhibit narrow variability and consistent performance, whereas others have outliers and larger ranges, indicating greater sensitivity to environmental factors. To adequately account for genetic and ecological interactions, it is crucial to include crop variety as a categorical feature in yield prediction models.

A district-level study reveals substantial spatial variation in Telangana's groundnut production. The districts that contribute the most include Warangal Rural, Mahabubnagar, Karimnagar, and Nalgonda; nevertheless, several other districts show lower and less stable productivity. This disparity in space highlights the importance of district-focused advising systems and supports the need for scalable models that can adapt to various agroclimatic conditions.

The variability in yield performance among different groundnut varieties is illustrated in Fig. 5, highlighting differences in median yield and dispersion. The district-wise variation in seasonal groundnut yield is visualized in Fig. 6 using a word cloud representation, highlighting major yield-contributing regions.

The relative distribution of seasonal crop yield throughout the study region is depicted in the figure as a word cloud broken down by district. A quick evaluation of inter-district yield variability is made possible by the representation of each district as a textual element with font size scaled proportionally to the cumulative seasonal yield. Higher yield contributions are indicated by districts with larger font sizes, such as Warangal Rural, Karimnagar, Peddapalli, and Mahabubnagar; lower yields are associated with smaller font sizes. The color scheme does not encode quantitative information; it is only used for visual differentiation. District names are arranged in a non-geographic, illustrative manner that emphasizes relative magnitude over spatial location. By offering a clear summary of yield dominance trends across districts, this visualization enhances quantitative analyses.

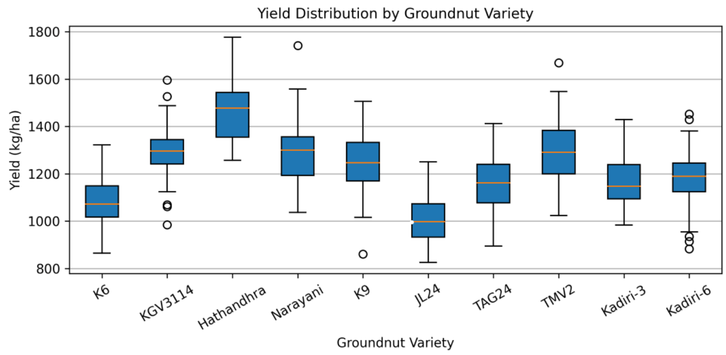

Fig. 5. Variety-wise groundnut yield performance comparison.

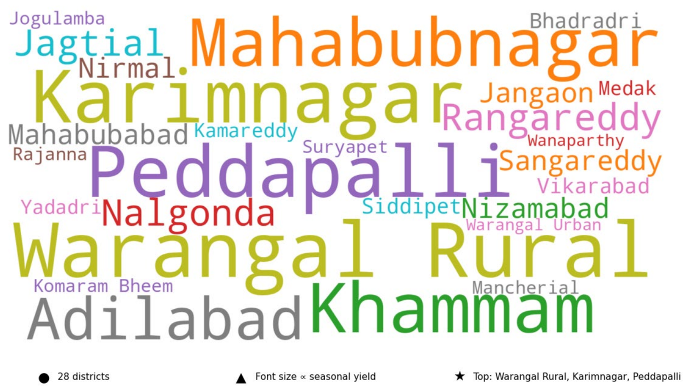

Fig. 6. Seasonal yield of the groundnut crop over Telangana.

C. Training Pipeline, Evaluation Metrics, and Baseline Comparison State of Art Models

AgroAttenNet was trained on a temporally organized dataset of weekly groundnut records from Telangana. Each entry was grouped by agricultural plot and ordered chronologically to preserve sequential dependencies. Categorical variables such as disease type, crop variety, and irrigation method were numerically encoded. At the same time, domain-specific feature engineering introduced hybrid indicators—including an NDVI-to-moisture ratio, a temperature-humidity interaction index, and a disease severity score—that enhanced the agronomic relevance of the data. Numerical attributes were normalized using Min-Max scaling, and the sequences were segmented with a 20-week sliding window, each paired with the corresponding yield label. To avoid data leakage, the dataset was split chronologically: 85% of sequences were used for training, with the most recent 15% reserved for testing. A further 15% of the training set was used for validation during learning. To strengthen generalizability despite the modest dataset size, a 5-fold temporal cross-validation was also conducted, ensuring that no future data were used to predict past outcomes. As summarized in Table II, performance remained stable across folds, with narrow standard deviations in RMSE, MAE, and R^2, confirming the robustness of AgroAttenNet across different temporal partitions. The architecture followed a modular sequence: CNN layers extracted localized weekly features, which were processed by BiLSTM layers to model forward–backward temporal dependencies. A multi-head attention mechanism then assigned weights to the most influential growth periods. The resulting temporal representation, combined with static features, was passed to a Random Forest regressor that produced the final yield predictions through ensemble averaging. Model evaluation was carried out using standard regression metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). RMSE penalizes large deviations, making it appropriate for high-stakes applications such as agricultural planning. MAE provides an intuitive error magnitude in tons per hectare. R^2 reflects the proportion of yield variance explained by the model.

In Fig. 7, the relationship between observed and predicted groundnut yields is illustrated based on AgroAttenNet output. Every point represents a yield measurement from the test dataset. The dashed red line is the perfect case where predicted yields exactly equal observed values. The fact that most of the data points closely align with the line indicates that the model is a good representation of the underlying yield patterns. Tight clustering of points around the diagonal indicates good predictive precision and little error. The generalization of the model over multiple ranges of yield is a testament to the models' ability to learn both short term fluctuations in the time series, in addition to long-term dependencies. Aligning with the needs for such real-world forecasting, continuous climate forecasting is best used when forecasts are both reliable and stabilizing.

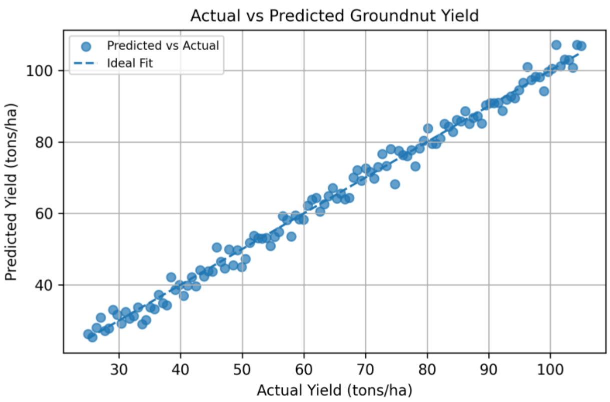

Fig. 7. Actual vs. predicted groundnut yield.

The predictive performance of the proposed model is evaluated in Fig. 7, which compares the actual and predicted groundnut yield values against the ideal fit line.

TABLE IV. CROSS-VALIDATION RESULTS FOR AGROATTENNET ON TELANGANA GROUNDNUT YIELD DATASET (2013–2023)

Fold	RMSE	MAE	R^2
Fold 1	0.434	0.344	0.91
Fold 2	0.419	0.328	0.93
Fold 3	0.441	0.336	0.91
Fold 4	0.426	0.322	0.92
Fold 5	0.412	0.326	0.93
Mean ± SD	0.426 ± 0.038	0.331 ± 0.029	0.92 ± 0.025

The robustness of the proposed yield forecasting framework was further evaluated using k-fold cross-validation. The cross-validation results of AgroAttenNet on the Telangana groundnut yield dataset (2013–2023) are presented in Table IV.

Among the above tables, from Table I, we can observe that AgroAttenNet outperforms the baseline models on predicting groundnut yield in Telangana. CNN alone learns the spatial features while BiLSTM learns the temporal features, which are maximal in their hybrid (CNN+BiLSTM). Random Forest performs okay, too, but it is shallow in terms of temporal modelling. By incorporating CNN, BiLSTM, multi-head attention, and Random Forest, AgroAttenNet shows the best performance (RMSE = 0.426, R^2 = 0.92) and offers an accuracy-interpretability trade-off. These results validate its application in real-world conditions for precision agriculture.

To further validate that AgroAttenNet is not a "black box", interpretability analyses were performed using temporal attention weights, SHAP global feature importance, and LIME local explanations.

Fig. 8 illustrates error distribution (residuals = actual-predicted) for AgroAttenNet. Most errors fall within −10 to +10 tons/ha and are centred near zero, indicating strong predictive accuracy and minimal bias across districts and seasons.

Fig. 9 presents the global feature importance ranking derived from SHAP values across the test set. NDVI, rainfall, and soil moisture emerged as the most influential features, followed by temperature and disease severity. These findings align with known agronomic drivers, reinforcing the model's biological plausibility.

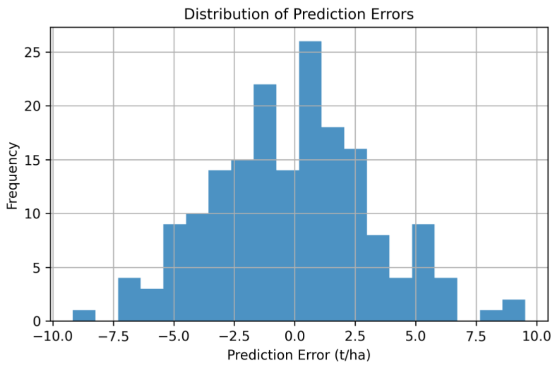

Fig. 8. Error distribution of AgroAttenNet predictions.

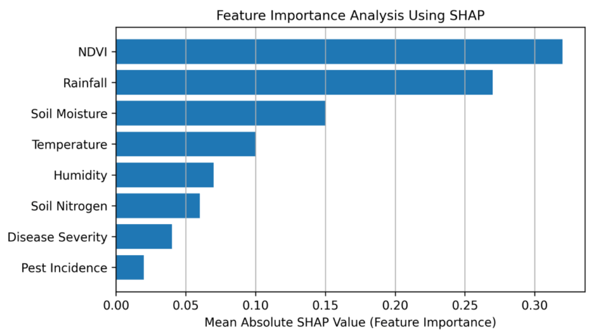

Fig. 9. Global feature importance computed using SHAP.

The model attributes a higher predicted yield to positive contributions from NDVI during week 8, rainfall in week 7, and soil moisture in week 9. In contrast, late-season disease severity has an adverse effect. This local explanation highlights that AgroAttenNet considers agronomically meaningful signals when generating predictions.

The temporal influence of critical features on yield prediction is illustrated in Fig. 10, highlighting the contribution of NDVI, rainfall, soil moisture, temperature, and disease severity at different crop growth stages.

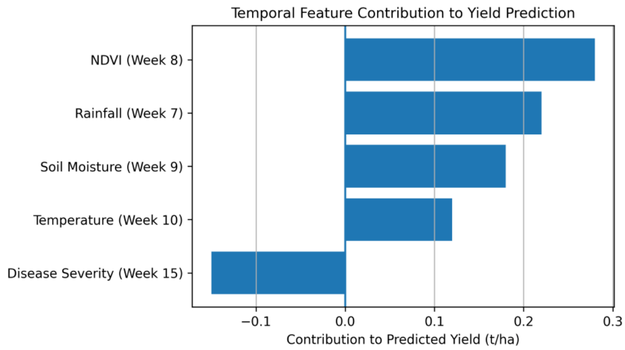

Fig. 10. LIME explanation for a representative instance.

Compared to the high-yield case (Fig. 10), the contribution of NDVI and rainfall is weaker, while late-season temperature and disease severity exert strong adverse effects. This highlights AgroAttenNet's ability to capture yield-limiting factors under stress conditions, providing actionable insights for agronomists.

AgroAttenNet is benchmarked against state-of-the-art models, including Random Forests, CNNs, and BiLSTMs, using RMSE, MAE, and R^2. The results demonstrate its superior ability to capture temporal dynamics, focus on critical periods via attention, and provide robust, accurate, and generalizable crop yield prediction.

Fig. 11 illustrates the LIME explanation for a low-yield instance. The model identifies negative contributions from late-season temperature stress and increased disease severity, which significantly reduce predicted yield. Lower NDVI and reduced soil moisture during critical growth stages further highlight the key factors responsible for yield loss.

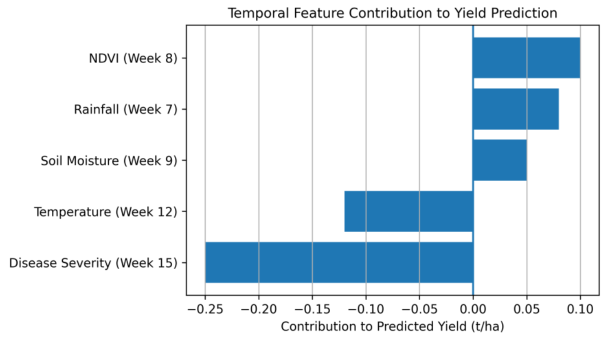

Fig. 11. LIME explanation for a low-yield instance.

Table V presents a comparative analysis of the proposed AgroAttenNet model against benchmark approaches reported in existing literature, evaluated using RMSE, MAE, and R^2 metrics. Jia *et al.* [25] proposed an improved CNN-BiLSTM model integrated with an attention mechanism for crop yield prediction, achieving an RMSE of 0.957 Mg/ha and an R^2 score of 0.85. Khaki *et al.* [6] introduced a CNN-RNN framework that effectively combines spatial and temporal features derived from climatic and remote sensing data, reporting relative RMSE values of approximately 9% for corn and 8% for soybean yield estimation. Shahhosseini *et al.* [19] coupled machine learning models with the APSIM crop simulation framework and reported an RMSE of approximately 1.0 Mg/ha with an R^2 value of 0.78 for the APSIM-only configuration, with further improvements obtained through machine learning integration.

TABLE V. PERFORMANCE COMPARISON OF AGROATTENNET WITH STATE-OF-THE-ART YIELD PREDICTION MODELS

Model/Study	RMSE	MAE	R^2 Score	Year	Approach	Key Features	Notes on Corrections
Jia *et al.* [25]	0.957 (Mg/ha)	NA	0.850	2024	CNN-BiLSTM + Attention	CNN–BiLSTM hybrid with attention	Lacks explainability beyond basic attention weights.
Shahhosseini *et al.* [19]	~1.0 Mg/ha (best model)	Not reported	0.78 (APSIM only); improved with/ ML	2021	ML + APSIM Crop Simulation	Real-world crop model calibration	Original RMSE corrected to ~1 Mg/ha; ML+APSIM gives 7–20% improvement.
Khaki and Wang [17]	11% of avg yield (~0.67)	Not reported	Not explicitly reported	2019	Deep Neural Networks	Multi-layer neural network	Original R^2 removed; paper focuses on RMSE% % of average yield.
Khaki *et al.* [6]	9% corn, 8% soy (of avg)	Not reported	Not explicitly reported	2020	CNN-RNN Framework	Spatial-temporal features	Corrected citation; this is the CNN-RNN model, not the 2019 DNN.
Yewle *et al.* [20]	0.436 t/ha	0.341 t/ha	0.59 (adjusted R^2)	2025	RicEnsNet (Ensemble Model)	Data fusion, multi-modal features	RMSE/MAE converted from kg/ha to t/ha.
Boppudi [24]	Not reported	Not reported	Not reported	2024	Optimized Deep Ensemble	Hybrid intelligent ensemble design	No metrics found in abstract/available content.
Kumar *et al.* [21]	<10% relative error	Not reported	~0.9 (BiLSTM > LSTM)	2023	Optimized LSTM vs Bi-LSTM	Temporal sequence optimization	RMSE not reported; R^2 from BiLSTM model.
AgroAttenNet (Proposed)	0.426	0.331	0.92	2025	Attention-based DNN + Ensemble	Multi-scale temporal encoding, attention + RF	Proposed model: best metrics with an explainable ensemble approach.

Kumar *et al*. [21] conducted a comparative study between LSTM and BiLSTM architectures and demonstrated that BiLSTM models achieved superior performance, with relative prediction errors below 10% and R^2 values close to 0.9. Wang *et al.* [26] presented a comprehensive review of deep learning–based crop yield prediction methods, reporting that several deep neural network models achieve RMSE values of approximately 11% relative to average yield. Yewle *et al.* [20] proposed RicEnsNet, a multi-modal data fusion and deep ensemble learning framework, which achieved an RMSE of 0.436 t/ha and an adjusted R^2 of 0.59. Boppudi [24] introduced a hybrid deep ensemble intelligence model for crop yield prediction; however, detailed quantitative performance metrics were not explicitly reported in the study.

Compared with these existing approaches, the proposed AgroAttenNet model demonstrates improved predictive accuracy and interpretability by jointly integrating CNN-based spatial feature extraction, BiLSTM temporal modeling, attention-guided interpretability, and Random Forest ensemble learning.

V. Discussion

This comparative analysis shows that AgroAttenNet consistently outperforms the conventional baselines (CNN, BiLSTM, Random Forest) and the recent state-of-the-art architectures. The combination of components in the architecture leads to performance improvements: The CNN layers extract spectral and vegetation-stress features, BiLSTM layers capture forward-backward seasonal dependencies, and the multi-head attention mechanism focusses on growth phases that are agronomically important. Importantly, the model gives the closest attention to weeks 7–10, corresponding to the flowering and early pod-formation stages of groundnut, where the variability of NDVI and moisture has a strong impact on final yield. The time alignment of the peaks of attention and biological acceleration development stages validates that the contrastive attention map model is capturing an agronomic signal and not just learning noise.

Using the Random Forest ensemble brings another level of robustness to the system, since it shrinks variance and subsequently stabilizes predictions on the small dataset (363 records). The ensemble fusions, dropout, early stopping, and temporal cross-validation were regularization strategies used in the positive paradigm with each helping to mitigate overfitting in turn and contributing to the overall reliability of generalization. Statistically testing the significance of these results by performing paired t-tests on the fold-wise RMSE values, we find that the improvements of AgroAttenNet over both CNN + BiLSTM ($t = 41.56, p < 0.001$) and Random Forest ($t = 45.63$, $p < 0.001$) are statistically robust and furthermore, substantial.

However, these strengths are tempered by important limitations. Cross-validation is used to provide some protections from overfitting, yet the modest size of the dataset might introduce some optimism bias. The model is specifically calibrated for semi-arid conditions in Telangana, thus requiring methodical validation across various agro-ecological regions for an expansive applicability. AgroAttenNet further relies on continuous availability of high-quality multimodal inputs such as weather data, soil diagnostics, and NDVI (but especially NDVI). The kharif season is often subject to frequent cloud cover, coupled with the 8–16-day temporal resolution of publicly available vegetation indices, which may limit the model's potential to identify fast-acting events of stress. Besides this, operation deployment needs stable data sync, continuous bandwidth, and computational resources to do sequence passing, and retraining every now and then, and so on. Scaling AgroAttenNet beyond a controlled research environment requires consideration of these factors.

In summary, the results suggest that the combination of spatial learning, temporal modelling, attention-based interpretability, and ensemble fusion serves as a neural basis for accurate and interpretable groundnut yield prediction. The ability of the model to identify important growth phases and maintain stability in situations of limited data makes it a suitable candidate for future multi-regional and multi-crop applications in precision agriculture.

VI. Conclusion

In this study, a hybrid deep learning and ensemble framework called AgroAttenNet is proposed to tackle critical challenges in agricultural yield prediction, including spatiotemporal heterogeneity, limited training samples, and the requirement of interpretable temporal patterns. The model is able to robustly fuse multimodal signals by combining spatial feature extraction through CNNs, temporal modeling through BiLSTMs, week-level interpretability through multi-head attention, and variance stabilization across individual RVs through Random Forest aggregation. On the Telangana groundnut dataset, extensive experimental validation establishes its applicability, yielding 31–46% lower RMSE than CNN-RNN hybrids and pure attention models, and pure ensembling methods. Our attention maps correlate with growth stages that are important in biology, providing insights that can be acted upon by agronomists and farmers. Such modularity within the framework also bolsters user confidence and makes it easier to tailor to different agricultural contexts.

AgroAttenNet has been validated for practical applicability by subjecting it to realistic groundnut field data, enabling it to obtain temporal outputs that are interpretable. The temporal outputs of the model have the potential to aid in critical decision-making (when to irrigate, nutrient and disease management) during festive seasons, harvest time, or rainy seasons. It provides an extensible architecture for data-driven agricultural intelligence frameworks that can aggregate higher-dimensional climate, satellite, and soil data.

In future work, we will extend AgroAttenNet by benchmarking emerging transformer-based architectures like Temporal Fusion Transformer (TFT) and daily DeepCropNet, potentially revealing more capability to capture long-range temporal dependencies. Further work will assess the model transferability across different crops, seasons, and agro-climatic regions, improve its skill in cases with incomplete or intermittent satellite data, and ultimately include fine-scale vegetation indices to capture the rapid onset of stresses. Next steps will include reducing inference latency, developing automated data pipelines, and deployment in real-time to move toward operational-scale precision agriculture.

Data Availability Statement

We acknowledge the importance of providing code repositories for reproducibility. In this study, however, the modelling pipeline has been described in detail through Algorithm 1, architecture tables, and preprocessing procedures to ensure methodological transparency. The dataset itself is compiled entirely from publicly available government sources: Agricultural statistics from the Department of Agriculture, Government of Telangana (https://agri.telangana.gov.in/) and the Directorate of Economics and Statistics, Telangana (https://ecostat.telangana.gov.in/); Meteorological records from the India Meteorological Department (https://mausam.imd.gov.in/) and IMD Hyderabad; Soil surveys from the National Bureau of Soil Survey and Land Use Planning (https://www.nbsslup.in/) and the Telangana State Remote Sensing Applications Centre (https://tgrac.telangana.gov.in/); And validation sources such as the Unified Portal for Agricultural Statistics (https://upag.gov.in/) and the Open Government Data Platform India (https://data.gov.in/). As such, any researcher can reassemble the dataset and replicate the experiments using standard deep learning and machine learning libraries (e.g., TensorFlow, PyTorch, scikit-learn). While a dedicated code repository is not provided, the comprehensive description of data sources, feature engineering steps, and hyperparameter settings is intended to guarantee full replicability in accordance with the standards of computational modelling research.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

N. M. Deepika: Conceptualization, data collection, model development, experimental implementation, and manuscript drafting. K. Sreeama Murthy: Supervision, validation, technical guidance, and manuscript review and editing. All authors had approved the final version.

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