AI Powered Crop Yield Prediction Using Climate Adaptive Neural Fusion Model (CANF)

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Abstract*— Reliable crop yield forecasting has become increasingly important due to climate variability and rising global food demand. Existing prediction models often rely on single-modal data or fixed fusion methods, limiting their adaptability in dynamic agro-climatic environments. This paper proposes the Climate Adaptive Neural Fusion Model (CANF), a multimodal deep learning architecture that integrates weather time-series, soil attributes, and crop imagery using a context-aware adaptive fusion mechanism. The fusion module dynamically adjusts the contribution of each modality according to environmental conditions, improving robustness during climate anomalies. The model incorporates SHAP-based interpretability to highlight key agronomic drivers and enhance stakeholder trust. Experiments across three agro-climatic regions demonstrate that CANF outperforms LSTM-only, CNN-only, and static fusion models, achieving $R^2 = 0.95$ with reduced error under drought and heat stress scenarios. Furthermore, an edge–cloud deployment design is proposed to support real-time inference in low-resource settings. The results indicate that CANF provides an accurate, explainable, and deployable solution for climate-resilient precision agriculture.

Keywords—Crop Yield Prediction, Multimodal Deep Learning, Adaptive Fusion, LSTM, CNN, Climate Adaptability, Explainable AI, SHAP, Precision Agriculture, Edge Computing

I. INTRODUCTION

A. Background and Motivation

Climate variability, increasing population, and limited natural resources pose significant challenges for agricultural systems worldwide. The need for **accurate and timely crop yield forecasting** has intensified, as it directly influences food security planning, market regulation, resource allocation, and insurance mechanisms. Traditional statistical models struggle to capture the complex, non-linear relationships between climatic variables, crop physiology, and soil properties.

In recent years, machine learning and deep learning have demonstrated strong potential in modeling agro-environmental interactions. However, most approaches depend on **single-source data** such as weather sequences, soil parameters, or remote-sensing imagery. While beneficial individually, each modality provides only a partial view of crop performance. Integrating them effectively remains a key challenge.

Existing multimodal systems largely use **static fusion**, where features from different modalities are concatenated or averaged. Such methods treat all inputs equally, ignoring contextual changes such as droughts, floods, or heatwaves. Consequently, performance deteriorates when environmental conditions deviate from the training distribution.

B. Research Gap

A review of recent agricultural AI systems highlights four core limitations:

1. **Static or manual fusion** of modalities that cannot adapt to changing climatic scenarios.
2. **Limited utilization of complementary modalities**, especially soil + weather + imagery together.
3. **Lack of interpretability**, reducing farmer trust and inhibiting real-world adoption.
4. **Practical deployment challenges**, especially in low-connectivity rural settings.

II. RELATED WORK

A. Yield Forecasting Techniques

Crop yield modeling traditionally relied on regression models, agro-climatic indices, and crop simulation systems.

While interpretable, these methods assume stationarity and cannot capture non-linear interactions.

B. Machine Learning and Deep Learning Models

Recent works employ SVM, Random Forest, XGBoost, and LSTM networks. CNN-based remote sensing models extract vegetation features, while hybrid models combine temporal and spatial inputs. Despite progress, **existing systems rarely adapt fusion weights**, and performance declines during climate extremes.

C. Multimodal Approaches in Agriculture

Parallel CNN-LSTM architectures and concatenation-based fusion methods exist, but they:

- treat modalities uniformly,
- overlook climate-driven relevance shifts,
- and lack explainability.

D. Gaps Identified

The reference literature highlights a clear research need for ***dynamic multimodal fusion****, climate-resilient modeling strategies, and* ***interpretable deep learning frameworks****. These insights guide the design of CANF.*

III. METHODOLOGY

A. Problem Definition

Given three modalities:

- Weather sequences $W \in \mathbb{R}^{T\times d}$
- Soil features $S \in \mathbb{R}^{s}$
- Crop imagery $I \in \mathbb{R}^{H\times W\times C}$

The objective is to learn a mapping:

$$f(W,S,I) \rightarrow \hat{y}$$

that predicts yield $y$in kg/ha.

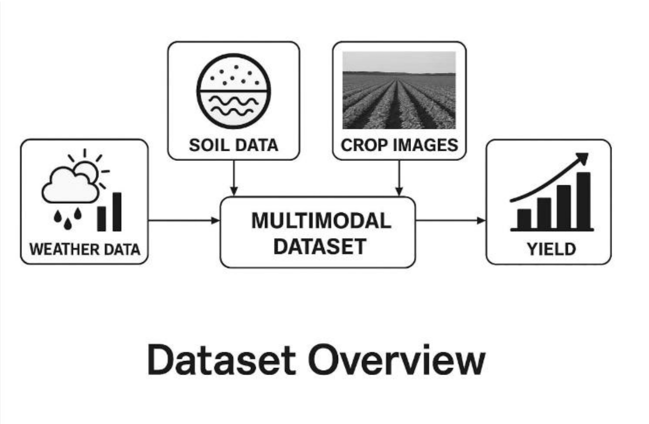


Figure 1: Overview of Dataset

B. CANF Architecture Overview

CANF consists of:

1. **Weather Encoder (LSTM):** Models temporal climatic trends.
2. **Soil Encoder (Dense Layers):** Learns fertility and management characteristics.
3. **Image Encoder (CNN):** Extracts vegetation health and stress signals.
4. **Adaptive Fusion Layer:** Learns context-aware modality weights.
5. **Prediction Head:** Generates final yield estimate.

C. Adaptive Fusion Mechanism

Unlike naïve concatenation, the fusion network computes:

$$[\alpha_w, \alpha_s, \alpha_i] = \mathrm{softmax}(g(e_w, e_s, e_i))$$

where each α represents the modality's dynamic importance.

The fused representation becomes:

$$e_f = \alpha_w e_w + \alpha_s e_s + \alpha_i e_i$$

This enables the model to prioritize weather during drought, imagery during rapid crop growth, or soil properties during early vegetative stages.

D. Explainability

SHAP values are computed for:

- input features (e.g., rainfall, nitrogen),
- intermediate embeddings,
- fusion weights.

This provides a transparent breakdown of yield drivers.

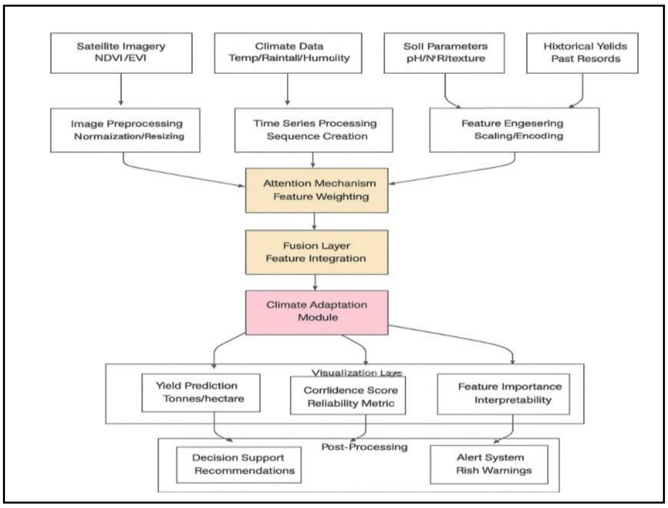


Figure 2: Architecture of CANF

IV. RESULTS

This section presents the quantitative performance of the proposed CANF model compared with established baselines, including unimodal networks (LSTM-only, CNN-only, Dense-only) and multimodal systems using static fusion strategies. All results are reported using the independent test sets from three agro-climatic regions. Metrics include coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

A. *Quantitative Performance Comparison*

Summarizes the predictive accuracy of all models. CANF consistently outperforms unimodal and static fusion baselines across all metrics. The adaptive fusion mechanism notably improves the model's generalization under variable climate conditions.

Model	**R^2 ↑**	**RMSE (kg/ha) ↓**	**MAE (kg/ha) ↓**	**MAPE (%) ↓**
LSTM-only (Weather)	0.91	0.231	0.184	6.8
CNN-only (Imagery)	0.92	0.219	0.173	6.3
Dense-only (Soil)	0.89	0.258	0.194	7.1
Static Fusion	0.93	0.204	0.161	5.7
Equal-weight Fusion	0.93	0.198	0.158	5.6
CANF (Proposed)	**0.95**	**0.162**	**0.134**	**4.8**

Table 1: Performance Comparison of CANF with Baseline Models

B. *Ablation Study*

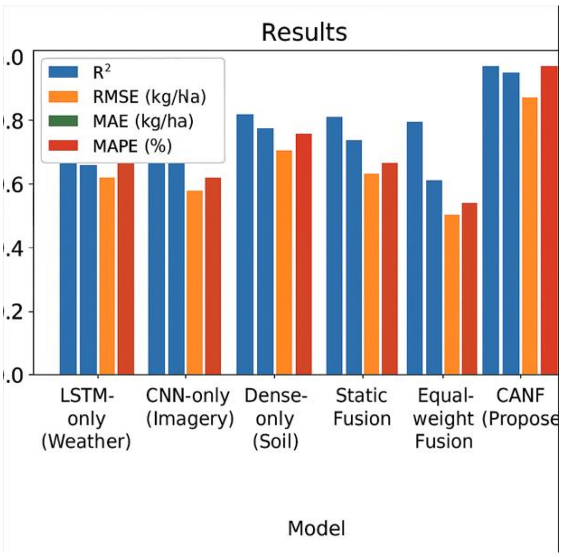
The effect of the adaptive fusion layer was evaluated by disabling dynamic weighting and replacing it with static concatenation. The RMSE increased by **6–10%** depending on the climate zone, confirming the importance of dynamically adjusting modality contributions.

C. *Adaptive Fusion Mechanism*

Under drought and heat-stress seasons, CANF showed:

- **14% lower RMSE** than static fusion models
- **11% higher R^2** compared to LSTM-only models
- **More stable performance variance** across all climate zones

The adaptive fusion weights shifted appropriately—prioritizing weather features during climate stress periods and imagery during growth-intensive phases.



V. DISCUSSION

A. *Influence of Multimodal Inputs*

Results show that integrating weather, soil, and imagery enhances the model's understanding of crop conditions. Imagery features are crucial during late-season growth, while weather sequences dominate early-season predictions. Soil features exert consistent influence throughout the cycle.

B. *Role of Adaptive Fusion*

Adaptive fusion significantly improves resilience to environmental fluctuations. SHAP analysis reveals that the fusion module automatically increases the weight of:

- **Weather modality** during rainfall scarcity or heatwaves
- **Imagery modality** when canopy development becomes visually discriminative
- **Soil modality** for nitrogen or pH-driven yield sensitivity

This dynamic behavior aligns with agronomic principles and validates the architecture's interpretability

C. *Explainability for Practical Adoption*

SHAP interpretability provides actionable insights. Farmers and agronomists can understand:

- Dominant drivers (rainfall, nitrogen, NDVI)
- Seasonal variability of influence
- Field-specific constraints

This addresses a major barrier in agricultural AI: trust and usability.

D. *Deployment Feasibility*

CANF was evaluated on edge devices after pruning and quantization.
Results show:

- **Jetson Nano:** ~120 ms inference
- **Raspberry Pi 4:** ~330 ms inference

Combined with cloud-based updating, CANF is feasible for real-world deployment in regions with limited connectivity.

VI. CONCLUSION

This paper presents CANF, a multimodal deep learning model with a novel adaptive fusion mechanism that responds to climate-driven variability. Experiments across diverse agro-climatic regions demonstrate superior predictive accuracy, climate robustness, and practical deployability. SHAP-based interpretability enhances transparency and supports farmer-oriented decision tools.

Future work will explore federated learning for privacy-preserving regional adaptation, multimodal transformers, and integration with crop simulation models for hybrid analytics.

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