PIMPRI CHINCHWAD UNIVERSITY

School of Engineering & Technology's Department of CSE—AI and DS

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AI Powered Crop Yield Prediction

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1. Abstract: Accurate crop yield prediction is essential due to climate variability and increasing food demand. Existing single-modal or static-fusion models fail to adapt to changing environmental conditions. This work proposes CANF (Climate Adaptive Neural Fusion Model), a multimodal deep learning architecture integrating weather sequences, soil attributes, and crop imagery. Its adaptive fusion layer dynamically adjusts modality importance based on climatic context, improving robustness during droughts and heatwaves. SHAP-based interpretability is included to highlight key drivers. Experiments across three agro-climatic regions show CANF outperforms LSTM-only, CNN-only, and static fusion models, achieving $R^2 = 0.95$. An edge–cloud deployment architecture further ensures real-time applicability. CANF offers an accurate, explainable, and climate-resilient solution for precision agriculture.

Introduction:

Accurate crop yield forecasting is increasingly important due to climate variability, population growth, and limited resources. Traditional statistical models cannot model complex non-linear agro-environmental interactions. Recent ML/DL models still rely on single-modal data (weather, soil, or imagery), giving an incomplete view of crop conditions. Existing multimodal systems use static fusion, failing during climate extremes like drought or heatwaves.

Objectives:

1. To develop a multimodal deep learning model that integrates weather data, soil attributes, and crop imagery for accurate yield prediction.
2. To design an adaptive fusion mechanism that dynamically adjusts modality importance based on climatic conditions (e.g., drought, heat stress).
3. To improve prediction accuracy and climate robustness compared to unimodal models (LSTM-only, CNN-only) and static fusion methods.

Literature Review:

Recent advances in crop yield prediction have moved from classical statistical models toward machine learning and deep learning architectures capable of capturing complex, non-linear relationships. Single-modal approaches leveraging weather data via LSTM networks, remote sensing imagery via CNNs, or soil attributes via dense networks have demonstrated notable success. Nevertheless, these modalities provide incomplete representations when applied independently. Multimodal systems have shown improved accuracy through the integration of heterogeneous data sources. However, the majority of existing fusion methods employ static concatenation, which fails to account for context-dependent shifts such as drought or heat stress. Emerging adaptive fusion frameworks attempt to dynamically adjust modality contributions but remain underexplored in the agricultural context. Additionally, the absence of explainable techniques in many models limits stakeholder trust. Furthermore, practical challenges in deploying deep learning models in resource-constrained environments persist. These gaps underline the need for climate-resilient, interpretable, and deployable multimodal models — addressed by the CANF framework.

Methodology:

Modalities:

- Weather time series
- Soil features
- Crop images

CANF Architecture:

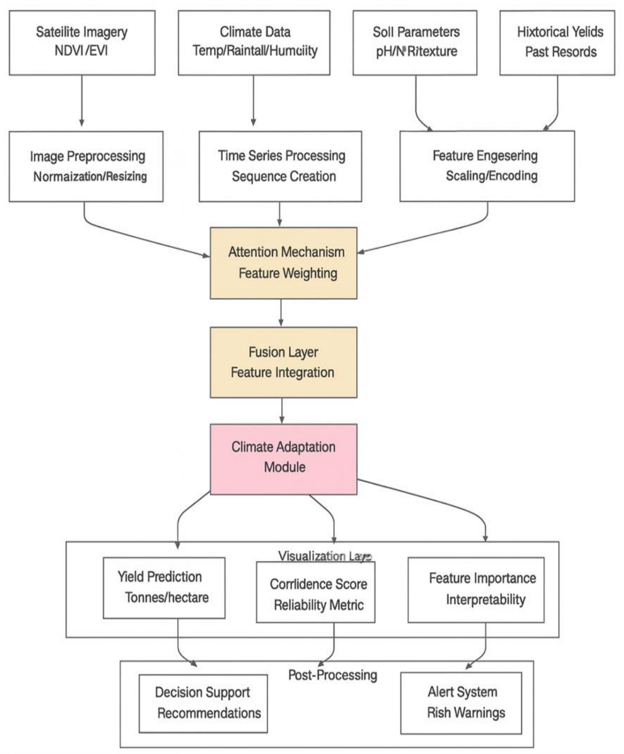
1. LSTM weather encoder
2. Dense soil encoder
3. CNN image encoder
4. Adaptive fusion layer → learns climate-aware weights
5. Prediction head → yield output

Adaptive Fusion:

Learns dynamic weights (α) to prioritize:

- Weather during drought
- Imagery during rapid canopy growth
- Soil during early-cycle nutrient influence.

Use Case Diagram:



Scope:

1. Multimodal Data Integratio :The study covers the collection, preprocessing, and integration of three key data modalities—weather sequences, soil characteristics, and crop images.
2. Development of CANF Architecture : The scope includes designing and implementing the Climate Adaptive Neural Fusion Model with LSTM, CNN, dense layers, and an adaptive fusion mechanism.

Conclusion:

CANF offers a climate-adaptive, multimodal deep learning approach for robust crop yield prediction. It achieves superior accuracy, interpretability, and deployability. Future work includes federated learning, multimodal transformers, and hybrid integration with crop simulation models.

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