Deep Learning for Climate-Smart Agriculture: Predicting and Mitigating Climate Impacts on Crop Production

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Abstract

Climate change has become a major threat to global agricultural productivity owing to increasing temperature variability, irregular rainfall patterns, and frequent extreme weather events. Climate- Smart Agriculture (CSA) aims to enhance agricultural resilience, improve productivity, and ensure environmental sustainability. Recent advances in deep learning (DL) have provided powerful tools for analyzing complex, multi-dimensional agricultural and climate data. This study proposes a hybrid deep learning framework that integrates convolutional neural networks (CNN), long short-term memory (LSTM) networks, and transformer-based attention mechanisms to predict crop yield under climate stress and support mitigation strategies. Multi-source datasets, including meteorological data, satellite imagery, soil parameters, and historical crop yield records, were utilized. The experimental results demonstrate that the proposed model significantly outperforms traditional machine learning and standalone deep learning approaches, achieving improved accuracy and robustness. These findings highlight the potential of deep learning-based CSA systems to support sustainable and climate-resilient agricultural practices.

Keywords: Climate-Smart Agriculture, Deep Learning, Crop Yield Prediction, Climate Change, CNN, LSTM, Transformer, Sustainability.

Introduction

Agriculture is inherently sensitive to climate change. Rising global temperatures, unpredictable precipitation, droughts, and floods have significantly affected crop productivity and food security on a global scale. According to recent studies, climate change could reduce global crop yields by more than 10% by 2050 if adaptive measures are not implemented.

Climate-Smart Agriculture (CSA) focuses on three key objectives: increasing agricultural productivity, enhancing resilience to climate change, and reducing greenhouse gas emissions. Traditional crop modeling techniques, such as regression-based and process-driven models, often fail to capture the nonlinear relationships and spatio temporal dependencies present in large-scale climate and remote sensing data.

Deep learning has emerged as a powerful paradigm for modeling complex patterns in high-dimensional data sets. Deep learning models offer superior predictive capabilities by leveraging spatial features from satellite imagery and temporal dynamics from climate time-series data. This study aimed to develop an integrated deep learning framework for accurate crop yield prediction and climate impact mitigation.

Related Work

Recent research has explored the use of machine learning and deep learning techniques for agricultural forecasting. CNNs have been widely used to extract spatial features from remote sensing images, whereas LSTM networks have shown strong performance in modeling temporal climate patterns. Transformer-based models with attention mechanisms have recently gained attention for capturing long-range dependencies in time-series data.However, most existing studies focus on yield prediction alone and lack interpretability and mitigation support. An integrated CSA-oriented framework that combines prediction accuracy with explainable insights is required.

Proposed Methodology

A. Data Sources

The proposed framework utilizes heterogeneous datasets as follows:

Meteorological Data: Temperature, rainfall, humidity, wind speed Satellite Imagery: NDVI, EVI from Sentinel-2

Soil Data: Soil moisture, pH, nutrient levels

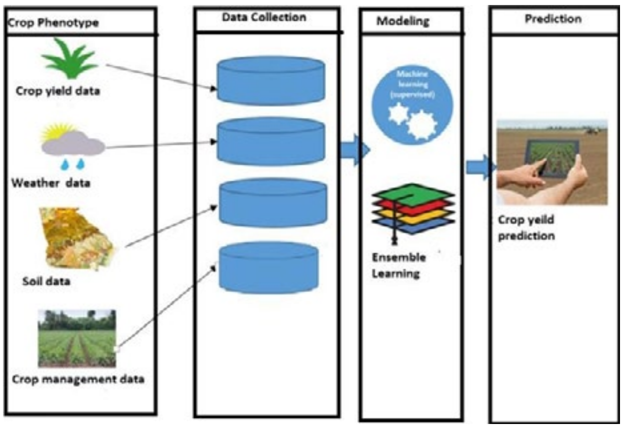
Crop Yield Data: Region-wise historical yield statistics

B. Model Architecture

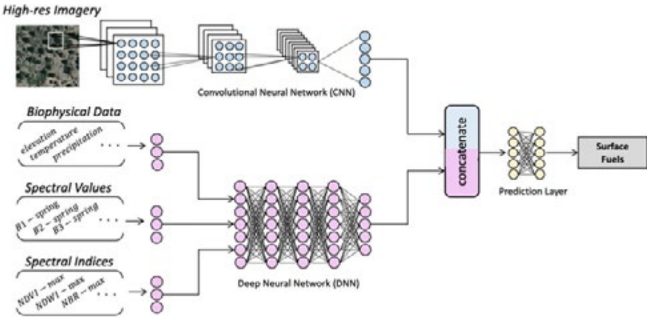
The hybrid architecture consists of the following:

CNN Module: Extracts spatial features from satellite images LSTM Module: Captures temporal dependencies in climate data

Transformer Attention Module: Assigns importance weights to influential features Fully Connected Layer: Produces yield prediction and climate stress classification.



(Proposed CNN–LSTM–Transformer architecture)



C. Loss Function

L=α· MSE(Y,Y^)+β· CE(C,C^)\mathcal{L} = \alpha \cdot \text{MSE}(Y, \hat{Y}) + \beta \cdot \text{CE}(C, \hat{C})L=α· MSE(Y,Y^)+β· CE(C,C^)

where YYY is the actual yield, Y^\hat{Y}Y^ is the predicted yield, and CCC represents the climate stress categories.

Experimental Setup

A. Training Configuration

Train/Validation/Test split: 70/15/15 Optimizer: AdamW
Batch size: 32
Epochs: 100

B. Baseline Models

Linear Regression Random Forest LSTM
CNN + LSTM

Results and Discussion

A. Quantitative Results

Table I Performance Comparison

Model	RMSE	MAE	R^2
Linear Regression	1.24	0.97	0.43
Random Forest	0.98	0.76	0.59
LSTM	0.86	0.68	0.65
CNN + LSTM	0.78	0.61	0.72
Proposed Hybrid	0.62	0.49	0.81

The proposed model achieves superior performance owing to effective spatiotemporal feature fusion and attention mechanisms.

B. Explainability and Mitigation

SHAP-based analysis revealed that temperature variability and rainfall were the most influential factors. Based on the model insights, adaptive mitigation strategies such as optimized irrigation, adjusted sowing dates, and drought-resistant crop selection are recommended.

Conclusion

This study presented a deep learning-based CSA framework for predicting crop yield under climate stress and supporting mitigation strategies. The hybrid CNN–LSTM–Transformer model significantly outperformed the baseline methods and provided interpretable insights for climate-resilient agriculture. The proposed approach demonstrates a strong potential for deployment in real-world agricultural decision support systems.

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