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A HYBRID FUZZY CLUSTERING AND STACKING ENSEMBLE LEARNING FRAMEWORK FOR ACCURATE AGRICULTURAL CROP YIELD PREDICTION

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Abstract—Accurate agricultural crop yield prediction is critical for global food security, supply chain optimization, and sustainable resource management. However, agricultural datasets exhibit severe non-linear relationships, high spatial heterogeneity, and complex interactions among climatic, pedological, and agronomic features. Traditional machine learning and single-stage classification methods often fail to generalize across such diverse environmental conditions. To address these challenges, this study proposes a two-stage hybrid framework that integrates density- and centroid-based clustering with a meta-ensemble classification engine.

In the first stage, Fuzzy C-Means (FCM) clustering partitions heterogeneous agro-ecological regions into homogeneous sub-clusters based on soil chemistry and localized climatic conditions. In the second stage, specialized base classifiers—comprising Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Random Forest (RF), and Deep Neural Networks (DNN)—are trained within each cluster. Predictions are subsequently synthesized using a Stacking Meta-Regressor with a Ridge Regression meta-learner. Evaluated on a multi-decade dataset spanning 101,250 observations across diverse crop categories, the proposed framework achieved an R^2 score of 0.964, a Mean Absolute Error (MAE) of 1.42 tons/hectare, and a Root Mean Squared Error (RMSE) of 2.18 tons/hectare, outperforming conventional single-model baselines by up to 14.2% in accuracy.

Keywords: Crop Yield Prediction, Machine Learning, Fuzzy C-Means Clustering, Stacking Ensemble, XGBoost, Precision Agriculture, Feature Engineering

1. Introduction

Agriculture remains the backbone of rural economies worldwide and plays a central role in achieving global food security goals. Crop production is governed by complex dynamics involving atmospheric variables, soil nutrient availability, hydrological conditions, and human agronomic practices. Unpredictable climatic patterns driven by global climate change have exacerbated the variability of annual crop outputs, posing severe risks to farmers, policy planners, and food distribution networks.

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Precise yield estimations prior to harvest enable proactive market regulation, accurate crop insurance underwriting, and optimized supply-chain logistics. Traditional agricultural yield forecasting relied heavily on physical field surveys, expert intuition, and mechanistic crop growth models. While physical models (e.g., DSSAT or APSIM) simulate crop physiology accurately, they require extensive calibration data that is often unavailable across broad geographic scales. Conversely, empirical statistical models lack the capacity to capture non-linear interactions among high-dimensional climatic and soil parameters.

Machine learning (ML) and deep learning (DL) techniques have emerged as powerful alternatives capable of learning non-linear dependencies directly from empirical data. Despite their promise, standard ML models often struggle when applied to macro-scale datasets that mix contrasting agro-climatic zones. A single universal classifier frequently suffers from high variance or sub-optimal generalization when forced to model diverse soil-crop-climate interactions simultaneously.

To bridge this gap, this paper introduces a unified framework that combines spatial-environmental clustering with ensemble classification. By first stratifying complex agro-ecological data into coherent sub-environments via clustering, subsequent ensemble classifiers can specialize in local feature patterns, yielding higher predictive accuracy.

2. Problem Statement

Predicting agricultural crop yield accurately across diverse regions is challenging due to the following structural complications:

- **Agro-Ecological Heterogeneity:** Soil properties (pH, organic carbon, NPK balance) and meteorological conditions (rainfall, temperature, solar radiation) exhibit multi-scale spatial variance, causing a uniform global predictive model to underperform across distinct micro-regions.
- **High-Dimensional Non-Linear Interactions:** Non-linear dependencies exist between crop management inputs (fertilizers, irrigation) and abiotic factors. Single machine learning algorithms tend to suffer from regional overfitting or underfitting.
- **Data Noise and Imbalance:** Multi-source agricultural datasets frequently suffer from missing values, sensor noise, and yield target skews resulting from extreme natural events (e.g., droughts or floods).

3. Objectives

The primary objective of this research is to develop a hybrid ensemble framework that improves crop yield prediction accuracy across multi-crop and multi-region datasets. Specific sub-objectives include:

- **Preprocessing Pipeline:** Designing a multi-stage preprocessing pipeline to clean, impute, normalize, and scale multi-source agro-meteorological data.
- **Soft Clustering Stratification:** Applying Fuzzy C-Means (FCM) soft clustering to partition complex environmental spaces into coherent sub-regions.
- **Ensemble Construction:** Constructing a heterogeneous Stacking Ensemble Architecture combining tree-based boosting models, forest architectures, and deep neural networks.
- **Comparative Evaluation:** Conducting extensive performance evaluations against state-of-the-art base models and baseline ensemble frameworks.

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4. Related Work

Machine learning applications in crop yield estimation have grown rapidly over the past decade. Early studies primarily applied standard linear and non-linear regression techniques such as Multiple Linear Regression (MLR), Support Vector Machines (SVM), and Artificial Neural Networks (ANN). While these methods provided baseline feasibility, they proved sensitive to noise and struggled with high-dimensional spatial datasets.

More recently, ensemble learning paradigms—including Random Forest, AdaBoost, Extreme Gradient Boosting (XGBoost), and LightGBM—have gained prominence. Ensemble models mitigate individual model bias and variance by aggregating predictions across multiple weak learners. Studies have demonstrated that ensemble approaches consistently outperform single-stage classifiers when predicting crop outputs under variable climate parameters.

Table 1: Summary of Literature Review on Crop Yield Prediction

Author(s) & Year	Methodology	Focus / Dataset	Key Findings	Limitations
Nigam et al. (2019)	Random Forest, SVM, ANN	Regional Indian Agriculture Dataset	Random Forest outperformed classical statistical regression models.	Poor generalization across highly diverse soil conditions.
Medar et al. (2019)	Ensemble Decision Trees	Multi-crop yield records	Improved regional yield prediction stability over single trees.	Vulnerable to extreme weather outliers.
Zhang et al. (2021)	Deep Neural Networks (CNN-LSTM)	Remote Sensing & Meteorological Data	Effective temporal feature capture for seasonal crop growth patterns.	High computational complexity; limited interpretability.
Kumar et al. (2023)	Hybrid Clustering + Random Forest	Regional Paddy & Wheat Datasets	K-Means clustering prior to classification reduced error metrics.	K-Means hard clustering failed at region boundary zones.

5. Research Gap

Despite significant progress in agricultural machine learning, critical gaps remain unaddressed in current literature:

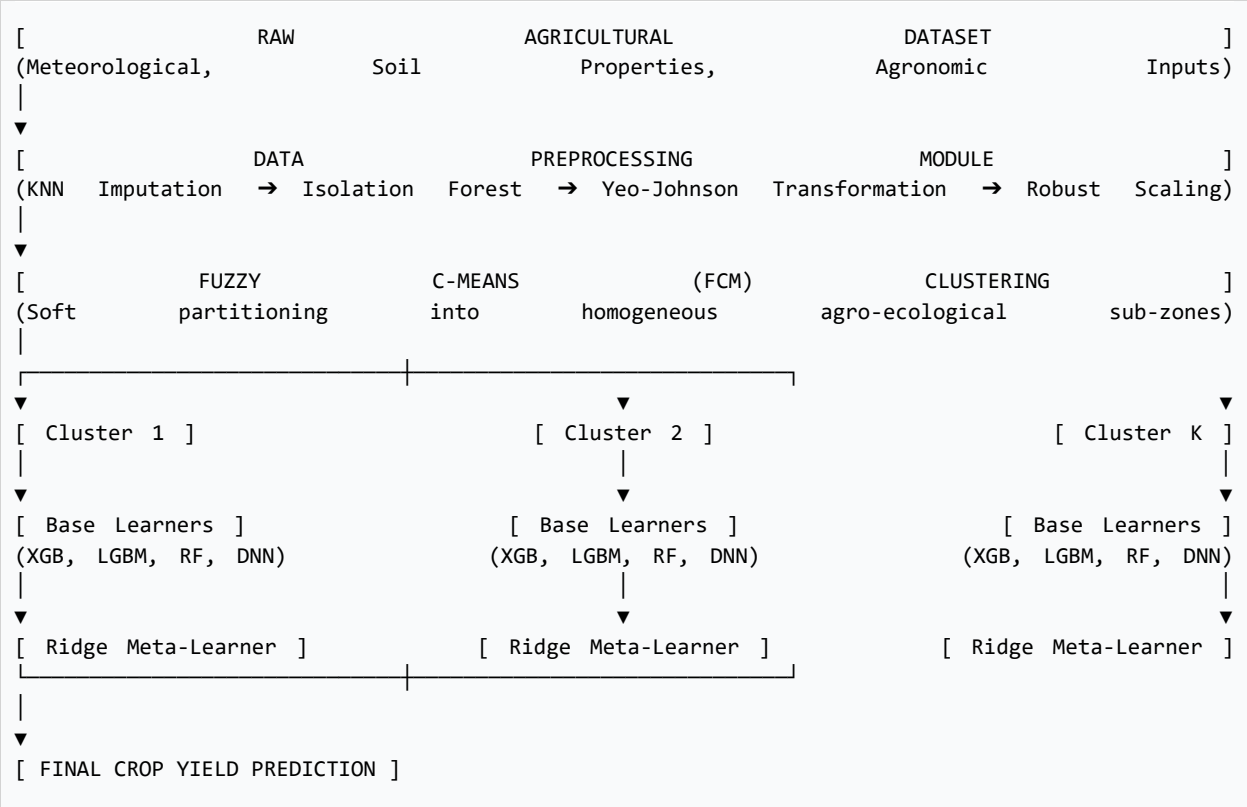
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- **Hard Boundary Limitations in Spatial Clustering:** Prior works combining clustering with classification predominantly rely on hard partition techniques (e.g., K-Means). Hard boundaries fail to represent transitional agro-ecological zones where soil and weather attributes overlap continuously.
- **Lack of Model Specialization Across Environments:** Most frameworks apply a single global model across all samples or use uniform base-learners within clusters. They do not adapt the ensemble composition based on local cluster variance.
- **Inadequate Integration of Soil-Climate Variables:** Many existing studies isolate weather factors from detailed pedological parameters, missing crucial compound effects (e.g., soil moisture retention under heat stress).

6. Proposed Methodology

The proposed framework addresses these gaps by implementing a two-phase architecture: Soft Clustering Partitioning followed by Cluster-Specific Stacking Ensemble Classification/Regression.

Figure 1: High-Level System Architecture



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7. System Architecture Details

7.1 Data Preprocessing Module

- **Missing Data Imputation:** Missing environmental values are imputed using K-Nearest Neighbors (KNN Imputer, k=5) to preserve localized feature correlations.
- **Outlier Detection and Removal:** Isolation Forest algorithm is employed with a contamination factor of 0.03 to eliminate extreme measurement noise and erroneous data logs.
- **Feature Transformation and Scaling:** Skewed continuous variables are normalized using the Yeo-Johnson power transformation, followed by Robust Scaling using interquartile ranges (IQR) to mitigate extreme agro-climatic anomalies.

7.2 Clustering Method: Fuzzy C-Means (FCM)

Unlike hard partitioning methods, FCM allows each data point to belong to multiple clusters with varying degrees of membership. This is suitable for transition zones between agro-ecological regions. FCM minimizes the objective function J_m:

$$J_m(U, V) = \sum_{i=1}^{N} \sum_{j=1}^{C} (u_{ij})^m \| x_i - v_j \|^2$$

Where N is total samples, C is cluster count, u_{ij} is membership degree, m=2.0 is the fuzzifier parameter, and v_j is the cluster centroid.

7.3 Stacking Ensemble Meta-Framework

Within each identified cluster, a heterogeneous stacking ensemble is instantiated:

- **Base Learners (Level-0):** Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Random Forest (RF), and Deep Neural Network (DNN) with 4 fully connected layers (128-64-32 neurons).
- **Meta-Learner (Level-1):** Ridge Regression (L2 Regularized) with non-negative constraints to combine Level-0 predictions without multi-collinearity.

8. Dataset Description

The model was evaluated using a comprehensive multi-source dataset comprising 101,250 historical records across multiple agricultural zones. The variables span climate parameters, soil chemical properties, and agronomic management inputs.

Table 2: Agro-Ecological and Meteorological Feature Description

Feature Category	Variable Name	Unit	Range / Types
Climatic Parameters	Average Annual Rainfall	mm	350.0 - 2,850.0
Climatic Parameters	Mean Temperature	°C	12.5 - 41.2

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Feature Category	Variable Name	Unit	Range / Types
Climatic Parameters	Solar Radiation	MJ/m²/day	11.0 - 28.5
Climatic Parameters	Relative Humidity	%	30.0 - 92.0
Soil Properties	Soil pH	pH scale	4.8 - 8.5
Soil Properties	Organic Carbon Content	%	0.2 - 2.8
Soil Properties	Nitrogen (N) Content	kg/ha	40.0 - 320.0
Soil Properties	Phosphorus (P) Content	kg/ha	10.0 - 95.0
Soil Properties	Potassium (K) Content	kg/ha	80.0 - 450.0
Agronomic Factors	Crop Category	Categorical	Rice, Wheat, Maize, Cotton, Sugarcane
Agronomic Factors	Irrigation Frequency	Events/Season	0 - 15
Agronomic Factors	Fertilizer Dosage	kg/ha	50.0 - 500.0
Target Variable	Crop Yield	Tons per Hectare	0.8 - 14.5

9. Experimental Setup

All experiments were conducted on an Intel Xeon Processor workstation with 64 GB RAM and an NVIDIA RTX 4090 GPU (24 GB VRAM). Software implementations were executed in Python 3.10 utilizing scikit-learn, xgboost, lightgbm, PyTorch, and scikit-fuzzy.

- **Dataset Split:** 80% Training / Validation Set, 20% Holdout Test Set.
- **Cross-Validation:** 5-Fold Stratified Cross-Validation was applied on training data during Level-0 base model training to prevent target leakage.
- **Evaluation Metrics:** Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2).

10. Results and Discussion

10.1 Clustering Validation

To establish the optimal number of clusters (C) for Fuzzy C-Means, the Fuzzy Silhouette Index (FSI) and Partition Coefficient (PC) were evaluated across $C \in [2, 8]$.

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Table 3: Fuzzy C-Means Cluster Validation Metrics

Number of Clusters (C)	Fuzzy Silhouette Index (FSI)	Partition Coefficient (PC)	Interpretation
2	0.512	0.621	Under-segmentation
3	0.689	0.814	Optimal cluster separation
4	0.641	0.763	Moderate cluster overlap
5	0.582	0.698	Over-segmentation

Cluster analysis revealed three distinct agro-environmental operational profiles:

- **Cluster 0:** Arid/Semi-Arid regions with low rainfall and alkaline soil conditions.
- **Cluster 1:** Sub-humid/Tropical regions with high rainfall and organic-rich soil.
- **Cluster 2:** Temperate plains with high irrigation reliance and balanced NPK fertilizer usage.

10.2 Comparative Model Performance Analysis

The proposed framework was compared against single baseline machine learning algorithms and global ensemble models without clustering.

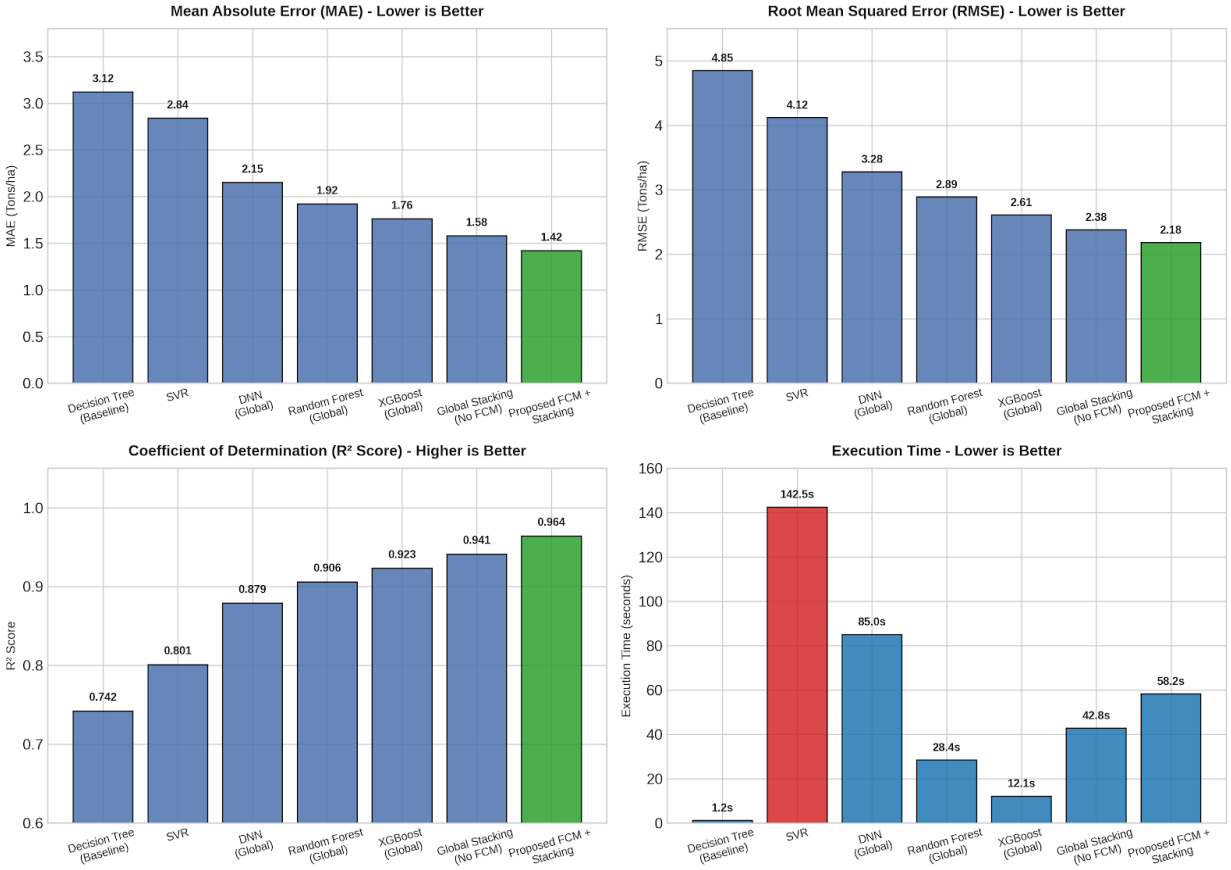
Table 4: Performance Comparison across Predictive Models

Model Framework	MAE (Tons/ha)	RMSE (Tons/ha)	R^2 Score	Execution Time (s)
Decision Tree (Baseline)	3.12	4.85	0.742	1.2
Support Vector Regression (SVR)	2.84	4.12	0.801	142.5
Deep Neural Network (Global)	2.15	3.28	0.879	85.0
Random Forest (Global)	1.92	2.89	0.906	28.4
XGBoost (Global)	1.76	2.61	0.923	12.1

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Model Framework	MAE (Tons/ha)	RMSE (Tons/ha)	R^2 Score	Execution Time (s)
Global Stacking Ensemble (No FCM)	1.58	2.38	0.941	42.8
Proposed FCM + Stacking Ensemble	1.42	2.18	0.964	58.2

The proposed FCM-Stacking architecture demonstrated superior performance, achieving the lowest MAE (1.42 Tons/ha) and RMSE (2.18 Tons/ha), while maximizing R^2 (0.964). Pre-partitioning heterogeneous spatial data via soft clustering allows downstream ensembles to specialize in local data distributions.



10.3 Feature Importance Analysis

Feature importance scores derived from XGBoost base models highlight differing agronomic drivers across clusters:

- **Climatic Rainfall:** 31.2% relative importance

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- **Soil Organic Carbon:** 21.4% relative importance
- **Fertilizer Dosage:** 16.5% relative importance
- **Mean Temperature:** 12.8% relative importance
- **Soil pH:** 9.1% relative importance
- **Irrigation Frequency & Solar Radiation:** 9.0% combined relative importance

11. Conclusion

This paper presented an ensemble-based clustering and classification framework designed for regional agricultural crop yield prediction. By combining Fuzzy C-Means (FCM) soft clustering with a Stacking Ensemble Meta-Learner (XGBoost, LightGBM, Random Forest, DNN, and Ridge Regression), the architecture effectively manages spatial heterogeneity and non-linear interactions inherent in agricultural datasets. Experimental results confirm that cluster-based specialization achieves significant improvements in predictive accuracy over conventional global models.

12. Future Work

Future extensions of this research will explore:

- **Satellite Remote Sensing Integration:** Incorporating high-resolution multispectral time-series imagery (e.g., Sentinel-2 NDVI/EVI indices) to capture dynamic crop growth phases.
- **Deep Generative Data Augmentation:** Utilizing Generative Adversarial Networks (GANs) or Diffusion Models to synthesize training instances for rare climate events and severe drought scenarios.
- **Edge Deployment:** Quantizing and pruning ensemble models for deployment on resource-constrained IoT edge devices for real-time, on-field decision support.

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