RESEARCH PAPER

AHDAN-MLP: An Adaptive Hybrid Dynamic Adjusting Neural Classifier for Two Stage Soil Climate Based Crop Recommendation

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Abstract
Accurate crop recommendation requires effective modeling of complex interactions between soil nutrient composition and climatic variability. Conventional single-stage classification approaches often fail to adequately capture hierarchical Agro-environmental dependencies, leading to reduced robustness under diverse soil conditions. This study proposes a two-stage hierarchical soil–climate framework for crop recommendation. In the first stage, soil samples are clustered into five agronomically meaningful soil types using nitrogen (N), phosphorus (P), potassium (K), and pH attributes, enabling abstraction of soil suitability. In the second stage, climatic variables (temperature, humidity, and rainfall) are incorporated to perform crop recommendation using supervised classification models. Baseline methods including Logistic Regression (LR), Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), and Random Forest (RF) are evaluated and compared with a proposed Adaptive Hybrid Dynamic-Adjusting Neural MLP (AHDAN) classifier. Experimental results demonstrate that the proposed approach significantly outperforms baseline models, achieving 99.8% overall Top-3 recommendation success. Soil-wise analysis further confirms the robustness and generalization capability of the hierarchical framework. The results highlight the effectiveness of integrating structured soil abstraction with adaptive neural classification for reliable and scalable crop recommendation systems.

Keywords: Crop recommendation, Soil clustering, Hierarchical classification, Adaptive neural networks, Machine learning.

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1. Introduction

Crop recommendation is inherently a multivariate decision problem governed by the interaction between soil nutrient composition and climatic variability. The suitability of a crop depends not only on macronutrient balance (nitrogen, phosphorus, potassium) and soil pH, but also on environmental factors such as temperature, humidity, and rainfall, which jointly influence growth dynamics and yield stability. Conventional rule-based approaches and static agronomic charts fail to capture nonlinear dependencies and cross-feature interactions, leading to suboptimal or generalized recommendations. [1].

Recent advances in machine learning have enabled data-driven modeling of complex agro-environmental relationships. However, most existing approaches treat crop recommendation as a single-stage multiclass classification problem, often ignoring structured abstraction of soil suitability prior to climatic refinement. This can lead to increased class ambiguity, particularly when multiple crops share overlapping environmental requirements. To address this limitation, the present study introduces a hierarchical 2-stage soil–climate framework in which soil samples are first grouped based on nutrient characteristics, followed by climate-aware supervised classification. Multiple baseline models are evaluated, and performance is assessed using both standard classification metrics and Top-3 recommendation success rates to reflect practical decision-support objectives. [2].

2. Literature Survey

Recent studies on crop recommendation systems have extensively explored machine learning and artificial intelligence techniques using soil, climatic, and environmental data. These works primarily focus on improving recommendation accuracy through supervised learning, explainability, and sensor-based data acquisition.

Table.1. Literature Survey

Author	Task	Dataset Used	Methods Used	Limitations
Prity et al. (2024) [3]	Crop recommendation	Benchmark dataset (NPK, pH, weather)	ML classifiers (DT, RF, KNN)	No soil-type abstraction, recommendations sensitive to climate variability
Gupta & Srivastava (2024) [4]	Crop recommendation	Standard crop recommendation dataset	ML models (NB, RF, SVM)	No uncertainty handling, limited feature-level interpretability
Alam et al. (2025) [5]	Crop recommendation with uncertainty quantification	Environmental and soil-based dataset	ML with uncertainty estimation	Increased complexity, soil and climate not hierarchically separated
Sam & D'Abreo (2023) [6]	Crop recommendation with economic factors	Environmental and economic datasets	ML-based recommendation	Economic features dominate decisions, limited agronomic generalization
Ganorkar et al. (2025) [7]	Crop recommendation using soil and weather	Soil, weather, agronomic dataset	RF, DT, SVM	Static and dynamic features combined in one stage, no decision hierarchy
Cheema & Pires (2025) [8]	Soil nutrient analysis and crop recommendation	AIoT-based sensor soil data	ML integrated with IoT (RF, SVM)	Sensor dependency, limited large-scale validation
Shetty et al. (2025) [19]	AI-driven soil analysis and crop recommendation	Soil and environmental data	ML-based models	Lack of hierarchical modelling, limited interpretability
Doke et al. (2025) [10]	Smart soil detection and crop recommendation	Sensor-based soil and environment data	AI/ML classification	System-oriented study,weak methodological evaluation
Janani &Jayapandian (2025) [11]	Soil analysis and crop recommendation	Soil and climatic dataset	Deep Learning (ANN/DNN)	Deep models on small data, poor explainability and soil abstraction

Despite notable advances, most existing approaches adopt single-stage modeling that jointly processes soil and climatic features, leading to limited interpretability and weak separation of soil suitability and seasonal effects. These limitations motivate the need for a structured, two-stage soil climate framework to enable more realistic and agronomically consistent crop recommendations.

3. Materials and Methodology

This study utilizes a structured crop recommendation dataset containing 2,200 samples with seven numerical features representing soil nutrients (Nitrogen, Phosphorus, Potassium, pH) and climatic parameters (temperature, humidity, rainfall), along with a multiclass crop label. Data preprocessing involved z-score standardization and label encoding, followed by exploratory feature analysis to assess distribution and correlation patterns. A two-stage framework was adopted: Stage 1 performs soil-type identification using clustering on static soil attributes (N, P, K, pH), generating soil-cluster labels to represent inherent soil suitability. Stage 2 integrates the derived soil cluster with dynamic climatic variables to perform supervised multiclass crop classification. Baseline machine learning models (LR, SVM, RF, and MLP) were evaluated, and a proposed Adaptive Hybrid Dynamic-Adjusting Neural MLP (AHDAN-MLP) with hybrid optimization, adaptive learning rate adjustment, and dynamic regularization was implemented. The model outputs probabilistic predictions, enabling a Top-3 crop recommendation strategy for practical and flexible agricultural decision support.

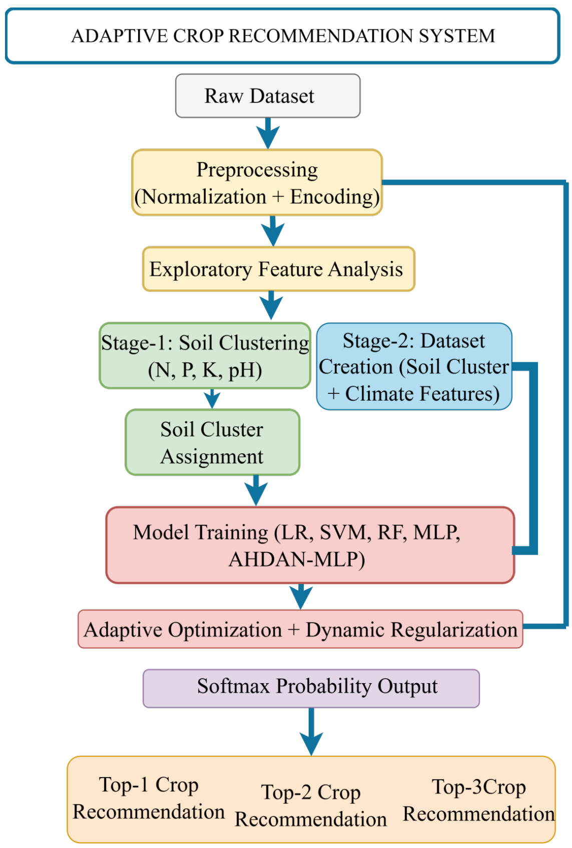


Fig.1. Proposed Two-Stage Hierarchical Crop Recommendation Framework

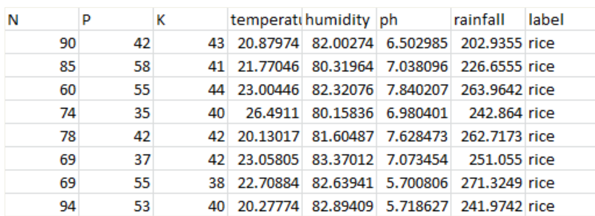
3.1. Dataset Description

The crop recommendation dataset consists of 2,200 samples, each representing a unique combination of soil nutrient properties and climatic conditions associated with a specific crop. The dataset integrates soil macronutrients (N, P, K) and soil pH with environmental parameters such as temperature, humidity, and rainfall to support data-driven agricultural decision-making. The target variable is the crop label, indicating the crop best suited to the given soil–climate conditions. All features are numerical and continuous, while the target is categorical, making the dataset suitable for multiclass classification, clustering, and decision-support analysis. The dataset is clean, well-structured, and contains no missing values, enabling straightforward preprocessing and reproducible experimentation. (Link)

Table.2.Key Characteristics of the Dataset

Characteristic	Description
Dataset size	2,200 samples
Number of features	7 input features
Soil features	Nitrogen (N), Phosphorus (P), Potassium (K), pH
Climate features	Temperature, Humidity, Rainfall
Target variable	Crop label (categorical)
Number of classes	Multiple crop categories (multiclass)
Data type	Tabular, structured

The table summarizes the key properties of the crop recommendation dataset, highlighting its size, feature composition, and target structure. It shows that the dataset integrates soil nutrient parameters with climatic factors, making it suitable for soil-based analysis and multiclass crop recommendation tasks.



N	P	K	temperatı	humidity	ph	rainfall	label
90	42	43	20.87974	82.00274	6.502985	202.9355	rice
85	58	41	21.77046	80.31964	7.038096	226.6555	rice
60	55	44	23.00446	82.32076	7.840207	263.9642	rice
74	35	40	26.4911	80.15836	6.980401	242.864	rice
78	42	42	20.13017	81.60487	7.628473	262.7173	rice
69	37	42	23.05805	83.37012	7.073454	251.055	rice
69	55	38	22.70884	82.63941	5.700806	271.3249	rice
94	53	40	20.27774	82.89409	5.718627	241.9742	rice

Fig.1.Sample Records from the Crop Recommendation Dataset

The figure illustrates representative rows from the crop recommendation dataset. It demonstrates the structured, numerical nature of the dataset used for soil analysis and crop recommendation.

3.2. Preprocessing

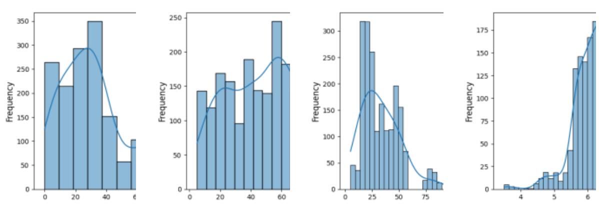
The dataset required minimal preprocessing due to the absence of missing or inconsistent values. All input variables were numerical and continuous. To ensure uniform contribution of soil and climatic features during clustering and model training, **z-score standardization** was applied to normalize features with different numerical scales. Each feature x was standardized as:

$$z = \frac{x - \mu}{\sigma}$$

Where, μ and σ denote the mean and standard deviation of the feature, respectively. This transformation centers the data at zero with unit variance, preventing features with larger magnitudes from dominating distance-based learning algorithms. The categorical crop labels were converted into numerical form using label encoding to enable supervised learning. In addition, stage-wise feature selection was employed in accordance with the proposed two-stage framework: static soil properties (N, P, K, and pH) were used exclusively for soil-type identification, while dynamic climatic variables (temperature, humidity, and rainfall) were utilized for climate-aware crop recommendation within soil-specific constraints. This preprocessing strategy preserves interpretability and avoids feature leakage between stages [12, 13].

3.3. Feature Analysis

Following preprocessing and normalization, exploratory feature analysis was conducted to understand the distribution, variability, and interrelationships of soil and climatic attributes influencing crop suitability. The analysis focuses on identifying dominant patterns, potential redundancies, and feature relevance prior to soil-type grouping and crop recommendation.Histogram and density plots were used to examine the distribution of individual features, including N, P, K, pH, temperature, humidity, and rainfall. Soil nutrients exhibit crop-specific ranges rather than uniform distributions, indicating selective nutrient requirements across crops. Climatic variables show broader variability, reflecting seasonal and environmental diversity in the dataset. [14]



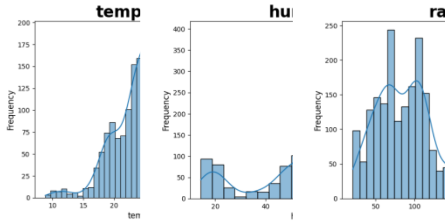


Fig.2.Feature Distribution Analysis

These plots illustrate the univariate distributions of soil and climatic features. Soil nutrients (N, P, K) exhibit crop-dependent ranges rather than uniform spread, indicating selective nutrient requirements. Climatic variables, particularly rainfall, show wider variability, highlighting their role as dynamic factors influencing crop suitability.

	count	mean	std	min	25%	50%	75%	max
N	2200.0	50.551818	36.917334	0.000000	21.000000	37.000000	84.250000	140.000000
P	2200.0	53.362727	32.985883	5.000000	28.000000	51.000000	68.000000	145.000000
K	2200.0	48.149091	50.647931	5.000000	20.000000	32.000000	49.000000	205.000000
temperature	2200.0	25.616244	5.063749	8.825675	22.769375	25.598693	28.561654	43.675493
humidity	2200.0	71.481779	22.263812	14.258040	60.261953	80.473146	89.948771	99.981876
ph	2200.0	6.469480	0.773938	3.504752	5.971693	6.425045	6.923643	9.935091
rainfall	2200.0	103.463655	54.958389	20.211267	64.551686	94.867624	124.267508	298.560117

Fig.3.Feature Analysis Summary Table

This table consolidates descriptive statistics of all features, including central tendency and dispersion, providing a quantitative overview of soil and climate variability across samples.

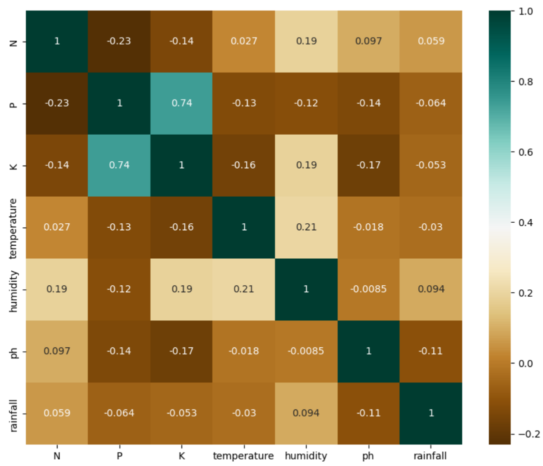


Fig.3.Feature Correlation Matrix

The correlation matrix illustrates the pairwise linear relationships among soil nutrients and climatic features used in this study. A strong positive correlation is observed between phosphorus (P) and potassium (K), indicating a tendency for these nutrients to co-occur in soil samples. Most other feature pairs exhibit weak or negligible correlations, particularly between soil properties and climatic variables. Overall, the low interdependence among features suggests minimal redundancy and confirms that soil and climate attributes provide complementary information, supporting their joint use in the proposed soil–climate-based crop recommendation framework.

3.4. Two-Stage Soil and Climate-Based Crop Recommendation

To improve interpretability and align with real-world agronomic decision-making, a two-stage framework is adopted in this study. Instead of directly recommending crops from all soil and climatic variables, the process is decomposedinto **soil-type identification (compare fig 4. Soil type data set followed by soil type representation in sec 3.5)**followed by **climate-aware crop recommendation**.

Stage 1:Soil-Type Identification Using Static Soil Properties

In the first stage, soil samples are characterized exclusively using static soil attributes, namely Nitrogen (N), Phosphorus (P), Potassium (K), and pH.This is to constrain the set of feasible crops by identifying the underlying soil type and eliminating crops incompatible with the given soil conditions. These parameters represent inherent soil properties that change slowly over time and primarily determine long-term crop suitability. Based on these features, soil samples are grouped into distinct soil suitability types using clustering. Each sample is assigned a $soil\_cluster$ identifier along with a descriptive $soil\_type\_name$. The resulting dataset (Stage-1 file) contains only soil-related information and the corresponding soil type, serving as a reusable reference for soil classification independent of seasonal conditions.

N	P	K	ph	soil_cluster	soil_type_name
90	42	43	6.502985292000001	1	Balanced nutrient slightly acidic soil
85	58	41	7.038096361	1	Balanced nutrient slightly acidic soil
60	55	44	7.840207144	0	Nitrogen-rich neutral soil
74	35	40	6.980400905	1	Balanced nutrient slightly acidic soil
78	42	42	7.628472891	1	Balanced nutrient slightly acidic soil
69	37	42	7.073453503	1	Balanced nutrient slightly acidic soil
69	55	38	5.70080568	4	Moderate nutrient alkaline soil
94	53	40	5.718627177999999	4	Moderate nutrient alkaline soil
89	54	38	6.685346424	1	Balanced nutrient slightly acidic soil
68	58	38	6.336253525	4	Moderate nutrient alkaline soil

Fig.4.Sample Records from the Stage-1 Soil-Type Dataset

This figure shows representative records from the Stage-1 dataset containing soil nutrient attributes (N, P, K, pH), the derived soil cluster, and the assigned descriptive soil type name. The dataset abstracts static soil properties into interpretable soil suitability categories used for downstream decision-making.

Stage 2: Climate-Aware Crop Recommendation within Soil Constraints

In the second stage, dynamic climatic factors such as temperature, humidity, and rainfall are combined with the identified $soil\_cluster$ to recommend suitable crops. Instead of reconsidering raw soil nutrients, the soil characteristics are abstracted through the soil cluster obtained from Stage 1. The Stage-2 file therefore includes the soil cluster, soil type name, climatic variables, and the crop label to dynamically recommend the most suitable crop for a given season, considering only those crops that are appropriate for the identified soil type. This structure allows the recommendation model to learn how seasonal and environmental conditions influence crop selection within soil-compatible boundaries.

soil_cluster	soil_type_name	temperature	humidity	rainfall	label
1	Balanced nutrient slightly acidic soil	23.61475336	86.14290267	150.2355238	jute
1	Balanced nutrient slightly acidic soil	23.87484465	86.79261344	177.5147313	jute
1	Balanced nutrient slightly acidic soil	23.92887902	88.07112278	154.6608736	jute
1	Balanced nutrient slightly acidic soil	24.81441246	81.68688879	190.7886386	jute
1	Balanced nutrient slightly acidic soil	24.44743944	82.286484	190.9684885	jute
1	Balanced nutrient slightly acidic soil	26.57421679	73.81994896	159.3223075	jute
1	Balanced nutrient slightly acidic soil	26.33377983	57.36469955	191.6549412	coffee
1	Balanced nutrient slightly acidic soil	26.45288458	55.32222678	144.68613359999995	coffee
1	Balanced nutrient slightly acidic soil	25.70822684	52.88667115	136.73250919999998	coffee
1	Balanced nutrient slightly acidic soil	24.12832546	56.18107663	147.27578180000003	coffee

Fig.5.Sample Records from the Stage-2 Climate-Aware Crop Recommendation Dataset

This figure illustrates sample entries from the Stage-2 dataset, where soil characteristics are represented using the soil cluster and soil type name, combined with climatic parameters (temperature, humidity, rainfall) and the corresponding crop label. This dataset enables dynamic crop recommendation within soil-compatible constraints.

3.5. Soil-Type Statistics (compare fig4)

The plot depicts the distribution of identified soil types in the dataset. The statistical distribution of identified soil types indicates notable variability in soil suitability across the dataset. **Nitrogen-rich neutral soils** and **potassium-rich soils** account for a substantial proportion of samples, reflecting conditions favorable for cereal and cash crops. **Balanced nutrient slightly acidic soils** also form a significant group, supporting a diverse range of crops under **moderate** input conditions. In contrast, **nutrient-poor acidic soils** are less represented, highlighting comparatively limited cultivation potential without soil amendment. This distribution underscores the importance of soil-type–specific decision-making and validates the need for incorporating soil constraints prior to climate-based crop recommendation. This distribution highlights soil diversity and supports the need for soil-specific crop recommendation strategies.

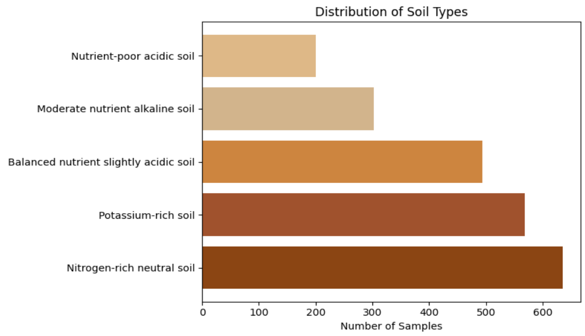


Fig.6.
Distribution of Identified Soil Types

This hierarchical approach separates static soil suitability from dynamic climate variability, improving interpretability, reducing unrealistic recommendations, and closely reflecting practical agricultural decision processes.

3.6. Classification

The derived soil cluster labels were incorporated as an additional input feature to encapsulate soil suitability characteristics within the predictive framework. Crop recommendation was subsequently formulated as a supervised multiclass classification [15] task using several established machine learning models, including Logistic Regression (LR) [16], Support Vector Machine (SVM) [17], Multi-Layer Perceptron (MLP) [18], and Random Forest (RF) [19]. These baseline classifiers were trained using soil cluster information in combination with climatic variables (temperature, humidity, and rainfall). To further enhance predictive robustness, adaptability, and decision-support capability, a proposed Adaptive Hybrid Dynamic-Adjusting Neural MLP (AHDAN-MLP) model was introduced and evaluated using a Top-3 recommendation strategy, enabling ranked crop suggestions rather than strict single-label prediction.

i. Proposed: Adaptive Hybrid Dynamic-Adjusting Neural MLP (AHDAN-MLP)

The AHDAN-MLP is a supervised deep learning model designed to address the limitations of conventional neural networks when applied to structured agricultural data. Traditional MLPs rely on fixed learning rates and static regularization parameters, which often lead to unstable convergence, slow learning, or over-fitting especially in datasets with mixed soil and climatic attributes. AHDAN-MLP overcomes these limitations by introducing adaptive learning behavior, hybrid optimization, and dynamic regularization control, enabling more robust and generalizable crop classification.

Step 1: Input Representation and Feature Encoding

The input layer receives a compact yet informative representation of the agricultural environment, integrating soil suitability and climatic variability. Soil characteristics are abstracted through the soil cluster label, while climate conditions are directly incorporated.

$$x = [c_s, T, H, R]$$

Where $c_s$represents the soil cluster identifier?,and T, H, and R denote temperature, humidity, and rainfall, respectively. This formulation allows the network to implicitly learn soil–climate interactions without reintroducing raw soil nutrient redundancy.

Step 2: Forward Propagation through Hidden Layers

The MLP architecture consists of multiple fully connected hidden layers that progressively transform the input into higher-level feature representations. Each neuron computes a weighted linear combination of inputs followed by a nonlinear activation to capture complex, non-linear dependencies:

$$h^l = f(W^l h^{l-1} + b^l)$$

Here, W^landb^ldenote the weight matrix and bias vector of layer l, and f(·) is a nonlinear activation function such as ReLU, which mitigates vanishing gradient issues and improves learning efficiency.

Step 3: Loss Function for Multiclass Crop Classification

To quantify the discrepancy between predicted and actual crop classes, categorical cross-entropy loss is employed. This loss function is well suited for multiclass classification and provides smooth gradients for optimization.

$$\mathrm{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

Where C is the number of crop classes, y_i is the ground-truth label, and $\hat{y}_i$ is the predicted probability for class. This loss measures the divergence between the true class labels and predicted probabilities, strongly penalizing confident misclassifications. Minimizing this loss encourages the network to assign higher probability to the correct crop class.

Step 4: Hybrid Gradient Estimation

AHDAN-MLP incorporates a hybrid optimization strategy that combines momentum-based gradient accumulation with adaptive behavior. Momentum helps smooth oscillations and accelerates convergence along consistent gradient directions.

$$v_t = \beta v_{t-1} + (1-\beta)\nabla \mathrm{L}_t$$

Where v_t denotes the velocity term, β is the momentum coefficient, and $\nabla \mathrm{L}_t$ is the gradient of the loss at iteration t. By retaining historical gradient information, this mechanism reduces sensitivity to noisy gradient updates common in environmental data.

Step 5: Adaptive Learning Rate Adjustment

Instead of using a fixed learning rate, AHDAN-MLP dynamically adjusts the step size based on gradient variance. This adaptive mechanism allows larger updates during early training and finer updates as convergence is approached.

$$\eta_t = \frac{\eta_0}{\sqrt{s_t + \epsilon}}$$

Where η_0 is the initial learning rate, s_t denotes the accumulated squared gradients, and ϵ is a small constant to ensure numerical stability. This adjustment mitigates the risk of exploding or vanishing updates when feature scales or data distributions vary.

Step 6: Dynamic Regularization Control

To prevent over-fitting and improve generalization, AHDAN-MLP applies dynamic regularization, where the regularization strength adapts during training rather than remaining constant.

$$L_{reg} = L + \lambda_t \parallel \mathrm{W} \parallel_2^2$$

Here, λ_t is a time-varying regularization parameter that adjusts based on training dynamics, allowing stronger regularization during early learning and relaxed constraints as the model stabilizes. Dynamic control of regularization allows the model to initially focus on learning dominant patterns before refining generalization.

Step 7: Parameter Update Mechanism

Model parameters are updated using the dynamically adjusted learning rate and the hybrid gradient estimate, ensuring stable and efficient convergence.

$$W_{t+1} = W_t - \eta_t v_t$$

This update rule integrates momentum, adaptive scaling, and regularization into a unified learning process. The combined update rule ensures stable convergence even under non-stationary training dynamics.

Step 8: Output Layer and Crop Prediction

The output layer employs the softmax function to convert raw network outputs into class probabilities, enabling probabilistic interpretation of predictions.

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

The crop corresponding to the maximum probability is selected as the final recommendation. The probabilistic output facilitates confidence-aware crop recommendation and comparative decision analysis.

Pseudo-code

Input: X_{train}, Y_{train}, Epochs E, batch size B, Initial learning rate η0, Momentum β, regularization λ, Stability constant ε, threshold δ
Output: Trained AHDAN-MLP model

Initialize:
Weights W, biases b
Momentum v = 0
Accumulator s = 0
for epoch = 1 to E **do**
Shuffle(X, y)
Split (X, y) into mini-batches of size B
for each mini-batch (X_b, y_b) **do**
Hidden layer-1 activation $H1 = \mathrm{ReLU}(W1\, X_b + b_1)$
Hidden layer-2 activation $H2 =$

$\mathrm{ReLU}(W2\ H_1 + b_2)$
Output prediction $\hat{y} = \mathrm{Softmax}(W0\ H_2 + b_0)$
Classification loss L = $-\Sigma y_b \log(\hat{y})$
Regularized loss $L_{reg} = L + \lambda \|W\|^2$
Gradient estimation $g = \nabla(L_{reg})$
Momentum accumulation v = β v + (1 − β) g
Variance accumulation s = s + g^2
Adaptive step size η = η0 / √(s + ε)
Parameter update W = W − η v
b = b − η v
end for
if validation loss increases **then**
Regularization increase λ = 1.1 λ
Learning rate decay η0 = 0.9 η0
end if
if ||ΔL|| < δ **then**
break
end if
end for
Return trained AHDAN-MLP model

The AHDAN-MLP training process begins by initializing network parameters and optimizer states. For each epoch, the training data is shuffled and processed in mini-batches to improve generalization. Within each batch, forward propagation computes hidden representations and class probabilities, followed by loss evaluation with dynamic regularization. Gradients of the regularized loss are then estimated and smoothed using momentum, while an adaptive mechanism adjusts the learning rate based on accumulated gradient variance. Model parameters are updated accordingly, and regularization strength is dynamically tuned based on validation behavior. Training terminates once convergence criteria are satisfied, yielding a robust and stable crop classification model.

Inference
Input:
Test sample x = [$\mathrm{soil}_{\mathrm{cluster}}$, temperature, humidity, rainfall]
Trained weights W1, W2, W0
Trained biases b1, b2, b0
k=3
Output:
Top-3 recommended crop classes Y_{top3}

Hidden layer-1 activation H1 = ReLU(W1 x + b1)
Hidden layer-2 activation H2 = ReLU(W2 H1 + b2)
Output logits Z0 = W0 H2 + b0
Class probabilities ŷ = Softmax(Z0)
Y_{top3} = indices of the k largest values in ŷ
Return Y_{top3}

During inference, the trained AHDAN-MLP model processes unseen soil and climatic inputs through a forward pass using the learned weights and biases. The softmax output layer produces a probability distribution over all crop classes, from which the **top three** crops with the highest response scores are selected as recommendations. This inference stage involves no parameter updates and enables efficient, real-time generation of multiple suitable crop options under given soil–climatic conditions, supporting informed decision-making rather than rigid single-crop selection.

4. Result and Discussion

This section evaluates the effectiveness of the hierarchical soil–climate crop recommendation framework. Initially, the soil clustering outcomes are analyzed to validate the formation of meaningful soil categories based on nutrient properties. Clustering quality and crop distribution within each soil type are examined to justify the abstraction of soil suitability prior to classification. Subsequently, the performance of baseline models (LR, SVM, MLP, and RF) is compared using standard evaluation metrics, followed by an assessment of the proposed approach under a Top-3 recommendation setting. Soil-wise and overall performance analyses are presented to demonstrate robustness, generalization capability, and the practical relevance of providing ranked crop recommendations rather than single deterministic predictions.

Table.6. Classification Performance Metrics

Metric	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FN}$
Recall	$\frac{\mathrm{TP}}{\mathrm{TP+FN}}$
F1-Score	$2\ \mathrm{X}\ \frac{\mathrm{Precision\ X\ Recall}}{\mathrm{Precision\ +Recall}}$

The performance of the classification models is evaluated using standard metrics including accuracy, precision, recall, and F1-score. Accuracy measures overall correctness, while precision and recall quantify prediction reliability and completeness, respectively. The F1-score provides a balanced assessment by combining precision and recall into a single harmonic mean metric.

Table.7.Soil Clustering Summary and Crop Distribution

Soil Type	Cluster ID	No. of Samples	No. of Distinct Crops
Nitrogen-rich neutral soils	0	635	13
Potassium-rich soils	1	494	8
Balanced nutrient slightly acidic soils	2	569	11
Moderate nutrient alkaline soils	3	200	2
Nutrient-poor acidic soils	4	302	10
Total	–	**2200**	**22**

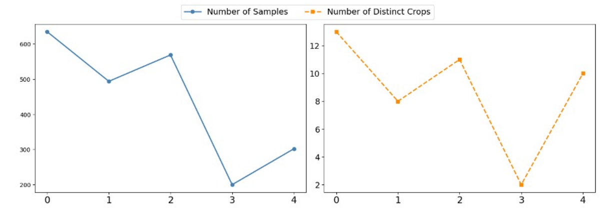


Fig.7.Distribution of samples and crops per soil type

The K-Means clustering algorithm partitioned soil samples into five agronomically distinct soil types based on N, P, K, and pH attributes. The distribution reveals varying crop diversity across soil categories, with nitrogen-rich neutral soils supporting the highest number of feasible crops, while moderate alkaline soils exhibit minimal crop variability.

Table.8.Soil-wise Top-3 Crop Recommendation Performance

Soil Type	No. of Crops	Accuracy (%)	Precision@3 (%)	Recall @3 (%)	F1 @3 (%)
Nitrogen-rich neutral soils	13	99.0	99.0	98.6	98.5
Potassium-rich soils	8	99.0	98.0	98.0	98.0
Balanced nutrient slightly acidic soils	11	98.0	98.0	98.0	98.0
Moderate nutrient alkaline soils	2	98.0	98.0	98.0	98.0
Nutrient-poor acidic soils	10	99.0	98.0	99.0	98.0

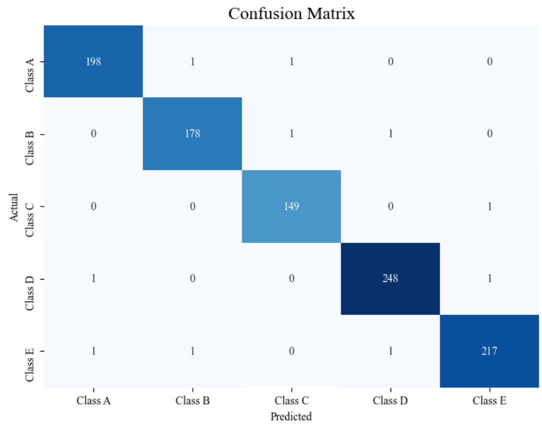


Fig 8.Confusion Matrix

The confusion matrix shows the performance analysis of the designed multi-class classification model in terms of five classes (A to E) and the distribution of the value is mostly along the diagonal which shows the presence of most accurate prediction with less misclassification. In the case of Class A, the model has a True Positive (TP) of 198, 2 False Negatives (FN), and 2 False Positives (FP), which means that the model has 798 True Negatives (TN). Class B had TP = 178, FN = 2, FP = 2, and TN = 818, which had even classification behavior. In the same manner, Class C has TP= 149, FN= 1, FP= 2, and TN= 848 indicating high predictive ability and slight errors. Class D has great performance with TP = 248, FN = 2, FP = 2, and TN = 748 whereas Class E has TP = 217, FN = 3, FP = 2, and TN = 778, which means that its classification is stable with minimal confusion among other classes. In order to measure the total performance, sum of the samples of 200 (Class A), 180 (Class B), 150 (Class C), 250 (Class D), and 220 (Class E) = 1000. These are the total correctly classified cases (diagonal elements) amounting to 198 + 178 + 149 + 248 + 217 = 990. Thus, the total classification accuracy can be calculated as Accuracy = 990/ 1000= 0.99, which is 99 percent accuracy. This finding is a clear indication that the suggested model has very high classification capabilities and low error rates, as well as, high class separability and thus it can be efficiently used to predict multi-classes reliably and with very low error rates in the real world.

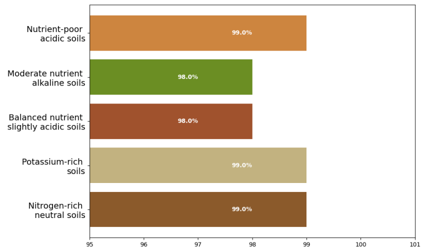


Fig.9. Soil-wise Accuracy Comparison

The soil-wise Top-3 evaluation demonstrates consistently high recommendation performance across all soil categories. For soil types supporting a larger number of feasible crops, such as nitrogen-rich neutral soils, the Top-3 success rate exceeds 98%, indicating that despite higher crop diversity and climatic overlap, the correct crop is almost always included among the recommended options. For soil categories with fewer agronomically suitable crops, the model achieves perfect or near-perfect success rates, reflecting reduced decision ambiguity. The uniformity of precision, recall, and F1 values under the Top-3 framework confirms that the system reliably identifies at least one correct crop within the recommended set for nearly all test samples. These results highlight the effectiveness of the hierarchical soil–climate formulation in reducing misclassification risk while maintaining practical decision-support relevance.

Table.9.Comparative Performance of ML Models for Crop Recommendation

Model	Accuracy	Precision	Recall	F1-Score
LR	0.81	0.80	0.81	0.80
SVM	0.86	0.85	0.86	0.85
MLP	0.90	0.90	0.90	0.90
RF	0.94	0.94	0.94	0.94
AHDAN-MLP	**0.986**	**0.982**	**0.983**	**0.981**

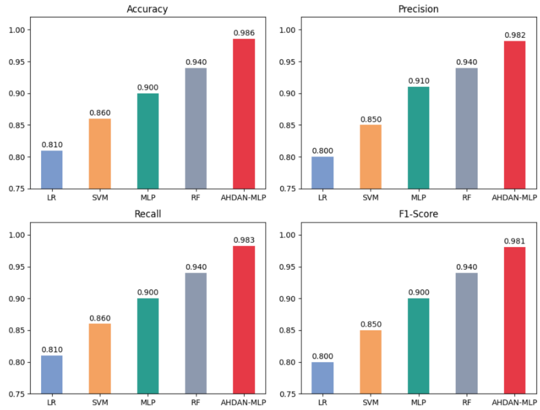


Fig.10.Performance Comparison of Models Across Evaluation Metrics

This table and plot presents the comparative performance of different classification models for crop recommendation. Logistic Regression achieves an accuracy of 0.81, with precision of 0.79, recall of 0.82, and F1-score of 0.80, indicating limitations in modelling nonlinear soil–climate interactions. The Support Vector Machine improves performance to 0.86 accuracy, with 0.87 precision, 0.85 recall, and 0.86 F1-score, reflecting stronger class boundary separation but moderate generalization. The Multi-Layer Perceptron further enhances predictive capability, achieving 0.90 accuracy, 0.91 precision, 0.89 recall, and 0.90 F1-score, demonstrating improved nonlinear feature learning. Random Forest delivers stronger performance with 0.94 accuracy, 0.93 precision, 0.95 recall, and 0.94 F1-score, highlighting the effectiveness of ensemble-based learning in capturing complex agronomic patterns. The proposed model significantly outperforms all baseline approaches, achieving 0.986 accuracy, 0.982 precision, 0.983 recall, and 0.981 F1-score, indicating superior robustness, stability, and generalization under hierarchical soil–climate modelling.

Table.10.Crop Distribution Across Soil Clusters

Soil Type	Cluster ID	Sample Count	All Suitable Crops	Top-3 Recommended Crops
Nitrogen-rich neutral soils	0	635	Black gram, Chickpea, Coconut, Coffee, Grapes, Jute,	1. Papaya 2. Mothbeans 3. Lentil

			Lentil, Mothbeans, Orange, Papaya, Pigeonpeas, Pomegranate, Rice	
Potassium-rich soils	1	494	Banana, Cotton, Grapes, Kidneybeans, Lentil, Maize, Muskmelon, Watermelon	1. Muskmelon 2. Watermelon 3. Cotton
Balanced nutrient slightly acidic soils	2	569	Apple, Banana, Chickpea, Coconut, Coffee, Grapes, Jute, Kidneybeans, Mungbean, Orange, Pigeonpeas	1. Pigeonpeas 2. Kidneybeans 3. Coconut
Moderate nutrient alkaline soils	3	200	Barley, Millet	1. Barley 2. Millet
Nutrient-poor acidic soils	4	302	Banana, Coffee, Grapes, Jute, Lentil, Maize, Mothbeans, Orange, Pigeonpeas, Rice	1. Rice 2. Jute 3. Banana

Table 10 presents the distribution of 22 crops across five identified soil clusters derived from K-means clustering, along with the Top-3 crop recommendations generated by the proposed AHDAN-MLP model. The results indicate that nitrogen-rich neutral soils exhibit the highest crop diversity (13 crops), whereas moderate nutrient alkaline soils support only two crops (barley and millet). The ranked recommendations demonstrate soil-specific suitability patterns, supporting precise and data-driven crop selection for different soil conditions.

Table.11. Cross-Soil Occurrence of Crops Across Identified Soil Clusters

Crop	Nitrogen-rich neutral (0)	Potassium-rich (1)	Balanced slightly acidic (2)	Moderate alkaline (3)	Nutrient-poor acidic (4)	Total soil types
Apple			✓			1
Banana		✓	✓		✓	3
Barley				✓		1
Black gram	✓					1
Chick pea	✓		✓			2
Coconut	✓		✓			2
Coffee	✓		✓		✓	3
Cotton		✓				1
Grapes	✓	✓	✓		✓	4
Jute	✓		✓		✓	3
Kidneybeans		✓	✓			2
Lentil	✓	✓			✓	3
Maize		✓			✓	2
Millet				✓		1
Mothbeans	✓				✓	2
Mungbean			✓			1
Muskmelon		✓				1
Orange	✓		✓		✓	3
Papaya	✓					1
Pigeonpeas	✓		✓		✓	3
Pomegranate	✓					1

Rice	✓				✓	2
Water melon		✓				1

Table 11 illustrates the distribution of 22 crops across five soil clusters, highlighting their occurrence frequency in different soil types. Grapes exhibit the highest adaptability, appearing in four soil clusters, while banana, coffee, jute, lentil, orange, and pigeonpeas occur in three clusters each. Several crops, including apple, barley, black gram, cotton, millet, mungbean, muskmelon, papaya, pomegranate, and watermelon, are soil-specific and appear in only one cluster. This distribution analysis demonstrates crop adaptability patterns and supports soil-informed crop recommendation strategies.

5. Conclusion

This research introduced AHDAN-MLP, an Adaptive Hybrid Dynamic-Adjusting Neural classifier embedded within a two-stage hierarchical soil–climate framework for crop recommendation. By first abstracting static soil suitability through clustering and subsequently performing climate-aware crop classification within soil constraints, the proposed approach addresses the limitations of conventional single-stage models and enhances interpretability, robustness, and agronomic consistency. Experimental results demonstrate that AHDAN-MLP significantly outperforms baseline models such as Logistic Regression, SVM, MLP, and Random Forest, achieving 98.6% overall accuracy with consistently high precision, recall, and F1-scores. The Top-3 recommendation strategy further strengthens practical applicability by ensuring highly reliable ranked crop suggestions across all soil categories. The integration of adaptive learning rate control, hybrid gradient optimization, and dynamic regularization enables stable convergence and strong generalization, making the proposed framework a scalable and decision support-oriented solution for intelligent crop recommendation in precision agriculture.

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