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Can AI Chatbots Recognize and Correct False Presuppositions in Questions About Dental Avulsion? A Cross-Sectional Study

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Explainable Multi-Agent Optimized CNN Framework for Soil-Condition-Based Potato Variety Recommendation

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Abstract

The selection of suitable potato varieties based on soil characteristics and environmental conditions is an important aspect of agricultural decision-making. However, identifying appropriate varieties from multiple interacting agricultural parameters remains challenging due to the complex relationships among soil nutrients, physical properties, and climatic factors. This chapter proposes an integrated deep learning framework for soil-condition-based potato variety prediction by combining feature engineering, multi-agent hyperparameter optimization, and Explainable Artificial Intelligence (XAI). The framework utilizes an open source dataset comprising 2,960 records representing eight potato varieties, with 12 original agricultural attributes and nine engineered features describing nutrient and environmental relationships. A customized one-dimensional Convolutional Neural Network (1D-CNN) is developed to classify potato varieties, while three complementary optimization agents—Exploration, Exploitation, and Conservation—are employed to identify an effective hyperparameter configuration. The selected model achieves a test accuracy of 96.85%, with weighted precision, recall, and F1-score of 96.94%, 96.85%, and 96.84%, respectively. Furthermore, Explainable AI techniques are incorporated to examine the influence of agricultural features on model predictions. The framework also integrates ranked variety prediction with a soil-condition assessment module that compares input measurements against variety-specific empirical feature distributions. The proposed approach therefore provides a unified computational framework for potato variety classification, prediction interpretation, and soil-condition-based decision support.

Keywords: Potato Variety Classification; Multi-Agent Hyperparameter Optimization; Convolutional Neural Network (CNN); Explainable Artificial Intelligence (XAI); Agricultural Feature Engineering; Soil-Condition Assessment.

1. Introduction

Agriculture plays an important role in food production, and selecting a suitable crop variety according to soil and environmental conditions is an important factor in agricultural decision-making. Among different possible agricultural research areas, this study focuses on potato variety recommendation because the selection of an appropriate potato variety depends on several interacting factors, including growing region, soil type, pH, moisture, nitrogen,

phosphorus, potassium, organic carbon, electrical conductivity, temperature, rainfall, and humidity. This project was selected over other possible machine-learning applications, such as plant disease detection or image-based crop classification, because it addresses a different and practically relevant problem: identifying a suitable potato variety based on agricultural conditions rather than simply recognizing an existing plant or detecting a disease. Choosing the appropriate variety based on several agricultural criteria poses a certain challenge since the interaction between soil properties, environmental conditions, and potato types may be complicated and nonlinear. That is why the purpose of this research is to create a data-driven, intelligent approach using a tailored CNN algorithm, hyperparameter tuning based on multi-agent systems, and XAI to classify the types of potatoes and deliver understandable recommendations. The main motivation of the research is to study the potential of deep learning and XAI technologies to make potato variety selection more effective.

Machine learning and deep learning methods have been applied extensively in the sphere of agriculture to solve such tasks as crop recommendation, variety identification, plant disease detection, and agricultural decision support. In particular, Azizi et al. (2016) [1] suggested a potato variety identification approach employing machine vision and artificial neural networks. This method used colour, texture, and morphological features to differentiate between various potato varieties. Li et al. (2024) [2] examined potato variety detection by means of spectral imaging technologies. Their approach made use of visible and near-infrared spectral data and deep learning model for classification of varieties. Allará et al. (2025) [3] studied the possibility of predicting potato varieties using bioimpedance measurements and supervised machine learning approaches. Gülmez (2025) [4] carried out a detailed review of various disease detection approaches using convolutional neural networks in potato agriculture. The research work considered different CNN models, image datasets, image pre-processing, and hyperparameter tuning techniques. Shrivastava et al. (2023) [5] proposed an optimized deep learning model to predict the potato leaf diseases using a combination of CNN, transfer learning, data augmentation, and hyperparameter tuning. Rapaka and Kanmani (2023) [6] examined the potential of an optimized hyperparameter-tuned convolutional neural network approach for the identification of healthy and unhealthy potato leaves. Rohilla and Rai (2023) [7] suggested an Optimized Matrix Feature Analysis-Convolutional Neural Network (OMFA-CNN) model for the identification of potato leaf diseases. The technique focused on feature analysis and classification through CNN. Afzal et al. (2025) [9] studied crop recommendation using machine learning algorithms based on soil data. The model used soil features and other environmental conditions in addition to hyperparameter tuning and cross-validation in order to enhance agricultural suggestions. Shams et al. (2024) [10] conducted research on explainable artificial intelligence methods used in crop recommendation and agriculture decision-making through the use of SHAP and LIME for explaining the model prediction results. Cartolano et al. (2024) [11] studied and evaluated explainable AI models within the context of smart agriculture applications. Yaganteeswarudu et al. (2025) [12] suggested an explanation method based on LIME for smart farming and crop recommendation.

Table 1. Comparative Analysis of Existing Research and Contributions of the Proposed Approach

Sl. No.	Methods	Limitations Identified	How the Proposed Approach Overcomes Them
1	Azizi et al. (2016) [1]: Machine vision and Artificial Neural Networks using colour, texture, and morphological features for potato variety identification.	Relies on visual characteristics of potato tubers rather than soil properties and environmental conditions for variety selection.	Introduces a soil-condition-based classification framework using 12 original agricultural attributes and nine engineered features to predict potato varieties.
2	Li et al. (2024) [2]: Visible and near-infrared spectral imaging combined with deep learning for potato variety classification.	Focuses on spectral characteristics and variety identification rather than agricultural soil and environmental conditions.	Uses structured soil, nutrient, geographical, and climatic attributes to establish relationships between agricultural conditions and potato varieties.
3	Allará et al. (2025) [3]: Bioimpedance measurements and supervised machine learning for potato variety prediction.	Depends on bioimpedance-based measurements and does not address integrated soil-condition-based variety recommendation.	Develops a feature-engineered 1D-CNN framework that incorporates nutrient composition and environmental interactions for variety prediction.
4	Gülmez (2025) [4]: Review of CNN-based potato disease detection approaches, including image datasets, preprocessing, and hyperparameter tuning.	Primarily addresses disease detection and image-based analysis rather than soil-based potato variety recommendation.	Addresses a different agricultural problem by predicting potato varieties from structured agricultural data and incorporating soil-condition assessment.
5	Shrivastava et al. (2023) [5]: Optimized deep learning using CNN, transfer learning, data augmentation, and hyperparameter tuning for	Concentrates on visual disease classification, with limited relevance to soil-dependent potato variety selection.	Employs a customized 1D-CNN with three sequential optimization agents to identify potato varieties from soil and environmental attributes.

	potato leaf disease prediction.		
6	Rapaka and Kanmani (2023) [6]: Hyperparameter-tuned CNN for identifying healthy and unhealthy potato leaves.	Focuses on binary leaf-health identification rather than multiclass potato variety prediction using agricultural conditions.	Extends the classification task to eight potato varieties through a multi-feature agricultural representation and multi-agent hyperparameter optimization.
7	Rohilla and Rai (2023) [7]: Optimized Matrix Feature Analysis-Convolutional Neural Network (OMFA-CNN) for potato leaf disease detection.	Emphasizes image-feature analysis and disease classification without considering soil and environmental interactions for variety recommendation.	Integrates nine engineered agricultural features with the original soil and environmental attributes to capture relevant feature interactions.
8	Afzal et al. (2025) [9]: Machine learning-based crop recommendation using soil information, environmental conditions, hyperparameter tuning, and cross-validation.	Addresses general crop recommendation, while potato-specific variety prediction and coordinated multi-agent optimization are not the primary focus of the described approach.	Develops a potato-specific recommendation framework combining a customized 1D-CNN, Exploration, Exploitation, and Conservation agents, and variety-specific soil-condition assessment.
9	Shams et al. (2024) [10]: Explainable crop recommendation using SHAP and LIME.	Uses SHAP and LIME for prediction interpretation but does not describe their integration with a potato-specific multi-agent optimized CNN and Integrated Gradients.	Combines SHAP, LIME, and Integrated Gradients to provide complementary global and local explanations of potato variety predictions.
10	Cartolano et al. (2024) [11]: Evaluation of explainable AI models in smart agriculture applications.	Primarily evaluates explainability in smart agriculture without addressing the complete integration of potato variety classification, multi-agent optimization, and soil-condition assessment.	Integrates explainability techniques directly into a unified potato variety prediction and soil-condition decision-support framework.

11	Yaganteeswarudu et al. (2025) [12]: LIME-based local explanations for smart farming and crop recommendation.	Focuses on local prediction explanations and does not describe a combined global-local explainability framework for soil-based potato variety classification.	Incorporates SHAP for global feature importance, LIME for local explanations, and Integrated Gradients for feature attribution within the proposed 1D-CNN framework.

The reviewed papers show the increasing use of machine learning, deep learning, hyperparameters optimization, and explainable artificial intelligence in agricultural studies. At the same time, there is a predominance of studies about potato in relation to image-based varieties' identification, spectrum analysis, or detection of diseases of the leaves, whereas other studies explore the topic of crop recommendations in general and explainability methods [29][30]. It becomes necessary to conduct research related to the development of an integrated potato variety recommendation system based on soil condition, which will incorporate the aspects of agricultural data representation in structured format, one-dimensional convolutional neural network tailored specifically for this case, multi-agent hyperparameters optimization, and explainable artificial intelligence methods.

Nevertheless, there are still some research areas (Table 1) that need to be further studied in order to contribute towards the development of an all-inclusive potato variety recommendation system. The first one is the lack of research related to the soil based potato variety recommendation system, as most of the research studies related to the potatoes' classification focus on the visual tubers, their spectra measurements, and/or the detection of plant disease through leaves analysis while the prediction of the number of potato varieties using the combination of the soil and environmental conditions is still considered as a special research area. Secondly, the lack of research regarding the relation between the agricultural feature variables, since traditional approaches for crop recommendation focus on the soil nutrients and environmental measurement individually, while the combination of the original agricultural feature variables and the engineered interaction variables is yet to be researched for potatoes varieties classification. Thirdly, there is the lack of research on coordinated multi-agent hyper-parameter optimization approach. Fourth, limited task-specific integration of complementary XAI techniques: SHAP and LIME have already been applied in agricultural recommendation research, but the combined application of SHAP, LIME, and Integrated Gradients to interpret soil-based potato variety predictions provides an additional level of global and local model analysis. Fifth, limited integration of variety prediction with soil-condition assessment: many classification systems primarily report the predicted crop or variety, without connecting the prediction to an assessment of the supplied agricultural conditions. The proposed framework addresses this requirement by incorporating a soil-condition assessment based on empirical feature distributions associated with the predicted potato varieties. These gaps motivate the development of an integrated framework that

connects agricultural data processing, customized deep learning, coordinated hyperparameter optimization, prediction explainability, and soil-condition-based decision support.

In this chapter, a novel and integrated framework is proposed for intelligent potato variety recommendation by combining customized deep learning, multi-agent optimization, and Explainable Artificial Intelligence. The major contributions and novelties of the proposed work are as follows:

- Customized Agricultural Feature Representation: The framework combines original soil and environmental attributes with engineered features representing nutrient composition and interactions among agricultural conditions. These features provide an expanded representation for learning relationships relevant to potato variety classification.
- Custom One-Dimensional CNN Architecture: A task-specific one-dimensional convolutional neural network is implemented to learn discriminative representations from structured agricultural attributes. This architecture employs the use of convolution layers, batch normalization, max pooling, dropout, global average pooling, dense layers, and classification using Softmax.
- Three-Agent Hyperparameter Optimization: An optimization framework comprising Exploration, Exploitation, and Conservation agents is implemented to investigate alternative CNN hyperparameter configurations. The agents evaluate candidate configurations using validation-based performance measures, and the selected configuration is used for final model training and evaluation.
- Integrated Explainable Artificial Intelligence: SHAP, LIME, and Integrated Gradients are incorporated to interpret the trained model's predictions. SHAP provides global feature-importance analysis, LIME explains individual predictions through local feature contributions, and Integrated Gradients estimates feature attributions relative to a baseline input.
- Prediction-Integrated Soil-Condition Assessment: The framework combines the CNN-generated potato variety probabilities with an empirical soil-condition assessment. The assessment compares supplied agricultural measurements with feature distributions associated with the predicted varieties and provides additional information for interpreting the recommendation.

The remainder of this chapter is organized as follows. Section 2 presents the problem formulation and overall approach of the proposed framework. Section 3 describes the proposed methodology, including data preprocessing, agricultural feature engineering, statistical analysis, customized 1D-CNN architecture, multi-agent hyperparameter optimization, and explainable AI integration. Section 4 discusses the experimental setup, performance evaluation, and obtained results, including potato variety prediction and soil-condition assessment. Finally, Section 5 concludes the chapter by summarizing the key findings, limitations, and potential directions for future research.

2. Problem Formulation & Approach

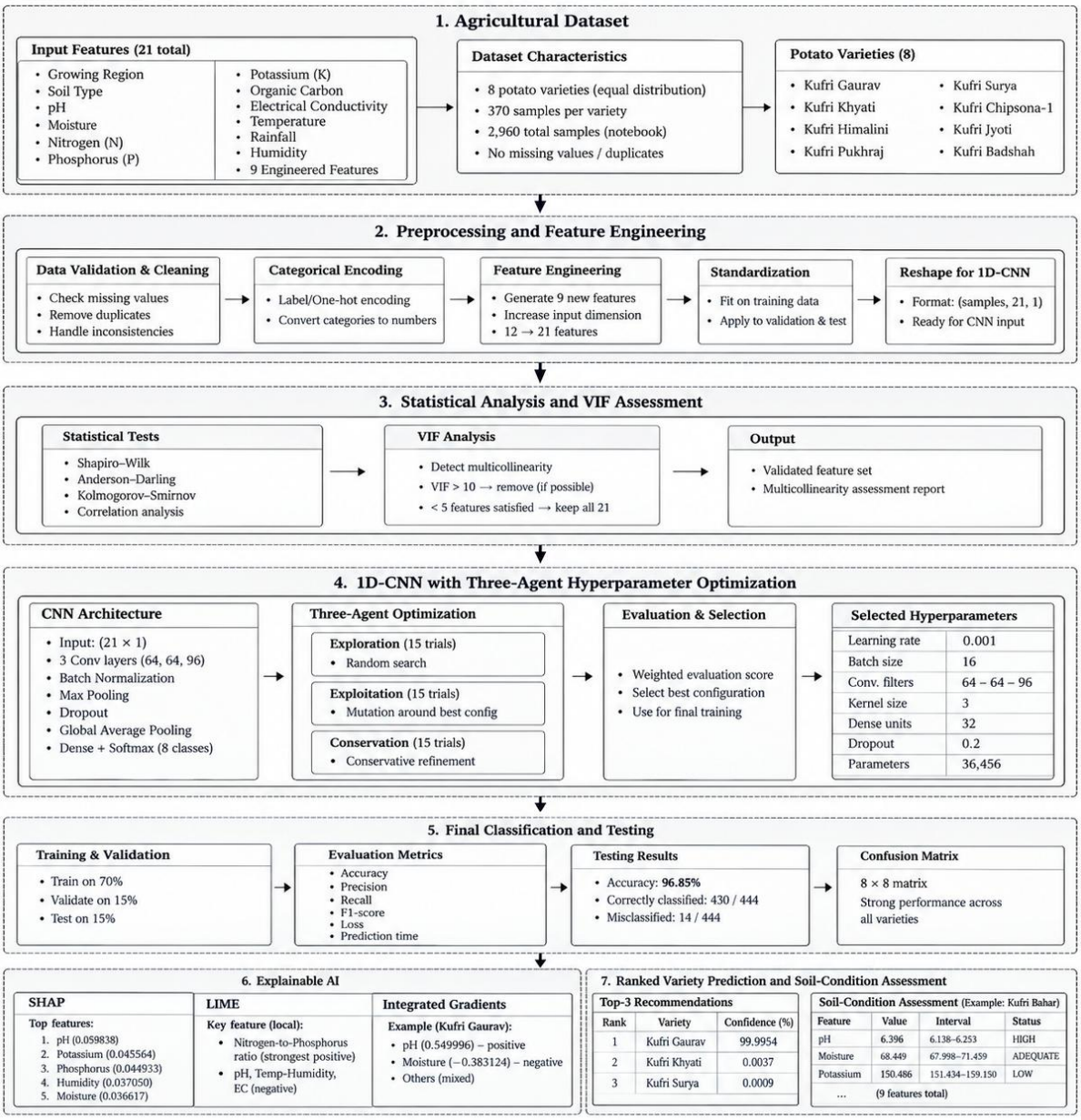

Fig. 1: Complete pipeline of the proposed potato variety recommendation framework

Potato variety selection is an important agricultural decision that depends on several interacting soil and environmental conditions. Factors such as growing region, soil type, pH, moisture, nitrogen, phosphorus, potassium, organic carbon, electrical conductivity, temperature, rainfall, and humidity influence the suitability of different potato varieties. Selecting the right variety based on the above-mentioned attributes is difficult because the relationships among the above-mentioned attributes might be complex and non-linear in nature. Traditional methods for selection might not account for such complicated relationship and provide consistent recommendations based on the changing agricultural environment. Besides, prediction algorithms that make decisions based on classification of the input data do not give detailed insights into the process that led to the classification. This is the problem this research

tries to solve in order to come up with a solution that creates an intelligent framework for recommending varieties of potatoes that learns the relationship among the above-mentioned agricultural condition and varieties of potato, and recommends one from the input features provided and gives a detailed explanation for the same.

In order to resolve the stated problem, a framework (Fig.1) based on deep learning techniques is proposed by incorporating the steps of agricultural data preprocessing, feature generation, multi-agent hyperparameter tuning, classification using CNNs, and Explainable Artificial Intelligence. Firstly, the agricultural data set is analyzed and preprocessed in terms of checking for missing values and duplicates, categorical encoding, and feature scaling. New features are constructed to capture the relations between soil nutrients and environmental variables, and the feature relations are also analyzed statistically and assessed with the help of Variance Inflation Factor. After the process of feature generation, the processed features are passed into the customized convolutional neural networks that will learn the useful patterns for potato variety classification. The proposed framework also includes Exploration, Exploitation, and Conservation agents that explore various hyperparameter sets and assess their performance.The selected configuration is subsequently used for final model training and testing. For enhancing prediction interpretability, SHAP, LIME, and Integrated Gradients are utilized to analyze the impact of agricultural characteristics on the predictions made by the model. Lastly, the framework is able to rank the recommended potato varieties based on the model output, as well as includes an additional module for assessing the soil conditions, which are compared with the actual distribution of the features corresponding to the predicted potato varieties. The complete sequence of these processing and recommendation stages is illustrated in Fig. 1.

3. Proposed Methodology

The described framework proposes a unified approach to an explainable and multi-agent optimized intelligent deep learning model for intelligent potato variety recommendation based on soil properties, nutritional composition, and environmental conditions. Specifically, the method combines statistical data analysis, feature engineering, multicollinearity assessment, one-dimensional convolutional neural networks (1D-CNN), and three optimization approaches to hyperparameters [15][19][20]. The main idea behind the described methodology is to create an automatic learning algorithm which learns the relationships between agricultural conditions and appropriate potato varieties and provides recommendations in a comprehensible way.

Contrary to a standard CNN solution that uses some pre-configured values of hyperparameters, the proposed framework employs three optimization approaches named Exploration, Exploitation, and Conservation. Those methods test different configurations of CNN models and determine the best performing one according to a weight calculation function that accounts for the classification accuracy, precision, recall, and F1-score. Then, the model with the most promising architecture can be applied to train and evaluate the model. In order to improve the interpretability of the obtained results, SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and Integrated Gradients methods

are introduced to the analysis process. Finally, the variety-specific soil condition assessment module allows comparing current agricultural conditions to the empirical distributions of features of specific potato varieties.

3.1. Data Representation and Preprocessing

The first step in the developed approach is conversion of the given agricultural dataset into structured numeric form for deep learning purposes. This dataset contains 12 original soil, geographical, nutritional, and environmental features and Potato_Variety as a target variable with eight categories/classes. The i-th agricultural observation can be represented as the following multi-dimensional feature vector (eq. 1):

$$\mathrm{x}_i = [x_{i1}, x_{i2}, \dots, x_{id}]^T \quad (1)$$

Where x_i stands for the i-th agricultural observation and d=12 is the number of original input features. Thus, the supervised learning problem can be defined through the use of the following dataset notation (eq. 2):

$$\mathcal{D} = \{(\mathrm{x}_i, y_i)\}_{i=1}^{N} \quad (2)$$

Where N=2,960 is the number of observations in the data and y_i is the potato variety.First of all, duplicate observations and observations with missing data are identified and deleted to preserve data consistency. Then, the two categorical features (Growing_Region and Soil_Type) are converted into single column feature using label encoding (LabelEncoder) technique and keep the 12 columns structure (10 continuous numeric and two integer-categorical features). Target potato varieties are also encoded into integer class labels(eq. 3):

$$y_i = \mathcal{E}(v_i), \qquad y_i \in \{0,1, \dots, C-1\} \quad (3)$$

Where E(·) is the label-encoding function, v_i is the name of the original potato variety, and C=8 is the total number of potato varieties. After data cleaning, categorical encoding, agricultural feature engineering (increase of feature space size from 12 to 21), multicollinearity analysis, the dataset is split into three subsets using two stages stratified splitting method (eq. 4, 5):

$$\mathcal{D} = \mathcal{D}_{train} \cup \mathcal{D}_{val} \cup \mathcal{D}_{test} \quad (4)$$

$$N_{train} : N_{val} : N_{test} = 70 : 15 : 15 \quad (5)$$

With a fixed random seed of 42 to ensure reproducibility. Stratification preserves the equal distribution of the eight potato varieties across the three subsets (2,072 training, 444 validation, and 444 testing samples). To neutralize the effect of differences in magnitude of features without statistical leakage in the process of scaling, the StandardScaler transformation is fitted only on the training subset and used to transform the validation and test subsets as follows (eq. 6):

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad (6)$$

Where μ_j and σ_j are the mean and the standard deviation of the jth feature, respectively, calculated only on D_"train". Ultimately, the standardized features are arranged in a three-dimensional form appropriate for input into the 1D-CNN model (eq. 7):

$$\mathrm{X}_{CNN} \in \mathbb{R}^{N \times d_s \times 1} \tag{7}$$

Where d_s=21 represents the number of selected input features and the final dimension corresponds to a single input channel.

3.2. Agricultural Feature Engineering

Feature engineering is performed to derive nine additional agricultural descriptors from the original soil nutrient and environmental attributes, expanding the feature space from 12 to 21 attributes. Nutrient-based features (eq. 8, 9, 10, 11):

$$NPK_{\text{Total}} = N + P + K \tag{8}$$

$$NPK_{\text{Ratio}} = \frac{N + \varepsilon}{P + K + \varepsilon} \tag{9}$$

$$R_{NP} = \frac{N + \varepsilon}{P + \varepsilon} \tag{10}$$

$$R_{KN} = \frac{K + \varepsilon}{N + \varepsilon} \tag{11}$$

Environmental interaction features (eq. 12, 13):

$$I_{TH} = T \times H \tag{12}$$

$$I_{MR} = M \times R \tag{13}$$

Soil property interaction features (eq. 14, 15, 16):

$$I_{OCM} = OC \times M \tag{14}$$

$$I_{pHOC} = pH \times OC \tag{15}$$

$$I_{ECM} = EC \times M \tag{16}$$

Here N, P and K denote nitrogen, phosphorus, and potassium; T represents temperature; H denotes humidity; M represents soil moisture; R indicates rainfall; OC denotes organic carbon; EC represents electrical conductivity. The constant $\varepsilon = 10^{-6}$prevents division by zero. Concatenating these nine engineered features with the 12 original attributes yields the expanded feature matrix (eq. 17):

$$\boxed{\mathrm{X}_{FE} = \left[\mathrm{X}_{Original} \mid \mathrm{X}_{Engineered}\right] \in \mathbb{R}^{N \times 21}} \tag{17}$$

3.3. Statistical Analysis and Multicollinearity Assessment

Prior to neural network training, normality tests (Shapiro–Wilk, Anderson–Darling, and Kolmogorov–Smirnov) and Pearson correlation analyses are conducted on the numerical attributes. The Shapiro–Wilk statistic is expressed as (eq. 18):

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (18)$$

Where $x_{(i)}$denotes the ordered observations, $a_i$represents the corresponding test coefficients, and $\bar{x}$denotes the sample mean. The Pearson correlation coefficient between features j and k is given by (eq. 19):

$$r_{jk} = \frac{\sum_{i=1}^{N}(x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k)}{\sqrt{\sum_{i=1}^{N}(x_{ij} - \bar{x}_j)^2}\sqrt{\sum_{i=1}^{N}(x_{ik} - \bar{x}_k)^2}} \quad (19)$$

In the identification of multicollinearity among the 21 artificial variables, the Variance Inflation Factor (VIF) is determined for each variable (eq. 20):

$$VIF_j = \frac{1}{1 - R_j^2} \quad (20)$$

Where R_j^2 denotes the coefficient of determination obtained by regressing the jth feature against the remaining features. Features satisfying $\text{VIF}_j \leq 10$ are screened (eq. 21):

$$\mathcal{F}_{selected} = \{f_j \in \mathcal{F}_{engineered} : VIF_j \leq 10\} \quad (21)$$

In the evaluated dataset, only two categorical attributes—Growing_Region (VIF = 3.49) and Soil_Type (VIF = 3.04)—satisfy $\text{VIF}_j \leq 10$, while the continuous variables relating to nutrients, climate, and interaction are greater than $\text{VIF}_j > 10$ because of algebraic dependence between the ratio and product features. Since there are less than five variables meeting the criteria, the applied default rule maintains all 21 features ($X_{final} = X_{FE}$) for the 1D-CNN to learn the discriminatory nonlinear feature representations.

3.4. Proposed One-Dimensional Convolutional Neural Network

The designed prediction model uses a custom-made sequential one-dimensional Convolutional Neural Network model without any residual or skip connection, which is capable of learning local features from 21 structured farm characteristics. In the sequential model, there are three Conv1D layers (padding="same" and ReLU activation function)[21], three BatchNormalization layers, one MaxPooling1D layer [24] (pool_size=2), one GlobalAveragePooling1D layer, two hidden fully connected Dense layers (ReLU activation function), three Dropout layers, and finally one Softmax classification layer [25] having eight units.The convolutional transformation of a feature sequence for a one-dimensional convolutional layer l can be mathematically defined as (eq.22):

$$h_j^{(l)}(t) = \phi\left(b_j^{(l)} + \sum_{k=1}^{K_l}\sum_{c=1}^{C_{l-1}} w_{jkc}^{(l)}\, h_c^{(l-1)}(t+k)\right) \quad (22)$$

Where $w_{jkc}^{(l)}$ are the learnable convolutional filters, $b_j^{(l)}$is bias term, K_l kernel size, and C_{l-1} is the number of channels in the previous convolutional layer. The Rectified Linear Unit (ReLU) activation [22] is used after the convolution operation (eq.23):

$$\phi(x) = \max(0, x) \tag{23}$$

Batch Normalization [23] is used to stabilize intermediate feature representation (eq.24, 25):

$$\hat{h} = \frac{h - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \tag{24}$$

$$BN(h) = \gamma \hat{h} + \beta \tag{25}$$

Where μ_B and σ_B^2 are the mini-batch statistics and γ and β are learnable scaling and shifting parameters. After the second convolution block, MaxPooling1D [25] downsamples the length of the sequence from 21 to 10 (eq.26):

$$p_j(t) = \max_{u \in W_t} h_j(u) \tag{26}$$

The sequence is then passed through the third Conv1D and BatchNormalization block, which is then aggregated using the GlobalAveragePooling1D operation into a fixed-length feature vector of length F_3 (eq.27):

$$g_j = \frac{1}{L} \sum_{t=1}^{L} h_j(t) \tag{27}$$

Where L = 10 is the length of the sequence entering global pooling. The vector is further passed through two dense hidden layers with ReLU activations and dropout regularization and the Softmax output layer (eq.28, 29):

$$P(y = c \mid \mathrm{x}) = \frac{\exp(z_c)}{\sum_{k=1}^{C} \exp(z_k)} \tag{28}$$

$$\hat{y} = \underset{c \in \{0, \ldots, C-1\}}{\operatorname{argmax}} P(y = c \mid \mathrm{x}) \tag{29}$$

The network is trained using the Adam optimizer [27] and sparse categorical cross-entropy loss with balanced class weights (eq.30, 31):

$$w_c = \frac{N_{train}}{C\, n_c} \tag{30}$$

$$\mathcal{L}(\theta) = -\frac{1}{N_{train}} \sum_{i=1}^{N_{train}} w_{y_i} \log P_\theta(y_i \mid \mathrm{x}_i) \tag{31}$$

Since each of the eight potato varieties has exactly n_c=259 samples in the training partition (N_{train}=2,072), the computed class weights are uniformly w_c=1.0 across all classes.

3.5. Multi-Agent Hyperparameter Optimization Framework

The suggested architecture uses three sequential optimization methods—Exploration, Exploitation, and Conservation—each of which attempts to find the optimal hyperparameter setting for the suggested 1D-CNN. The optimization process operates on eight hyperparameters, represented as (eq.32):

$$\lambda = [\eta, B, F_1, F_2, F_3, K, D, \rho] \tag{32}$$

Where η denotes the learning rate,B represents batch size, F_1, F_2, F_3 denote the number of filters for convolution, K stands for the size of the kernel, D denotes the number of units in the dense layer, and ρ denotes the dropout rate. Their search space for the hyperparameters is shown below in Table 2.

Table 2. Hyperparameter search space implemented in the proposed framework

Hyperparameter	**Candidate values**
Learning rate	0.001, 0.0005, 0.00025, 0.000125
Batch size	16, 32
First convolutional filters	32, 64
Second convolutional filters	64, 128, 192
Third convolutional filters	64, 96, 128
Kernel size	3, 5
Dense units	32, 64
Dropout rate	0.2, 0.3, 0.4

3.5.1. Exploration Agent

Exploration Agent runs a randomized search within the defined hyperparameters search space[28] . At each iteration, a candidate configuration is generated using one randomly selected value for each hyperparameter (eq.33):

$$\lambda_E^{(t)} = \text{RandomChoice}(\Omega), \qquad t = 1, \dots, 15 \tag{33}$$

Where Ω denotes the discrete search space. The training is done up to 50 epochs with a patience of eight epochs. A learning-rate reduction mechanism monitors validation loss, applying a reduction factor of 0.5 after four epochs without improvement, subject to a minimum learning rate of 10^{-6}. The best Exploration configuration is selected according to the weighted validation score (eq.34):

$$\lambda_E^* = \underset{t\in\{1,\dots,15\}}{\operatorname{argmax}} S\left(\lambda_E^{(t)}\right) \tag{34}$$

3.5.2. Exploitation Agent

The Exploitation Agent performs a mutation-based search around the best configuration obtained from Exploration. Rather than generating an entirely new configuration, each trial begins with λ_E^* and probabilistically modifies its individual hyperparameters (eq.35):

$$\lambda_X^{(t)} = \mathcal{M}_X(\lambda_E^*) \tag{35}$$

The learning rate is modified with a probability of 0.75 by randomly selecting its halved, unchanged, or doubled value, with numerical bounds of 10^{-5} and 10^{-2}. The remaining hyperparameters are independently resampled from their predefined candidate lists according to the mutation probabilities shown in Table 3.

Table 3. Exploitation Agent mutation probabilities

Hyperparameter	Mutation probability
Learning rate	0.75
First convolutional filters	0.50
Second convolutional filters	0.70
Third convolutional filters	0.70
Kernel size	0.40
Dense units	0.60
Dropout rate	0.50
Batch size	0.30

The agent performs 15 trials, each allowing a maximum of 50 training epochs with early-stopping patience of eight epochs. Its best-performing configuration is expressed as (eq.36):

$$\lambda_X^* = \underset{t\in\{1,\dots,15\}}{\operatorname{argmax}} S\left(\lambda_X^{(t)}\right) \tag{36}$$

3.5.3. Conservation Agent

The Conservation Agent performs the final optimization stage using the better-performing configuration obtained from the preceding two agents. Its starting configuration is determined by comparing their respective validation scores (eq.37):

$$\lambda_C^{(0)} = \begin{cases} \lambda_E^*, & S_E^* > S_X^* \\ \lambda_X^*, & S_E^* \leq S_X^* \end{cases} \tag{37}$$

Unlike the Exploitation Agent, the Conservation Agent applies smaller learning-rate adjustments and restricts convolutional filter modifications to nearby candidate values. Each trial is generated using the conservation agent mutation function (eq.38):

$$\lambda_C^{(t)} = \mathcal{M}_C\left(\lambda_C^{(0)}\right) \tag{38}$$

The learning rate is modified with a probability of 0.50 using a randomly selected multiplicative factor (eq.39):

$$\eta' = \min(10^{-2}, \max(10^{-5}, \eta q)) \tag{39}$$

Where (eq.40):

$$q \in \{0.8, 0.9, 1.0, 1.1, 1.2\} \tag{40}$$

For convolutional filters, nearby candidate values are selected according to (eq.41):

$$\Omega_{F_j}^{local} = \left\{ f \in \Omega_{F_j} : |f - F_j| \leq \delta_j \right\} \tag{41}$$

Where $\delta_1 = 32$, $\delta_2 = 64$ and $\delta_3 = 32$. The remaining mutation operations follow the probabilities presented in Table 4.

Table 4. Conservation Agent mutation settings

Hyperparameter	Mutation probability	Operation
Learning rate	0.50	Multiplicative adjustment
First convolutional filters	0.35	Nearby candidate selection
Second convolutional filters	0.40	Nearby candidate selection
Third convolutional filters	0.40	Nearby candidate selection
Kernel size	0.25	Toggle between 3 and 5
Dense units	0.35	Toggle between 32 and 64

Dropout rate	0.40	Random selection from 0.2, 0.3, 0.4
Batch size	0.20	Toggle between 16 and 32

The Conservation Agent performs 15 trials, each allowing a maximum of 60 epochs and an early-stopping patience of ten epochs. Its optimal configuration is chosen as (eq.42):

$$\lambda_C^* = \underset{t\in\{1,\ldots,15\}}{\operatorname{argmax}} S\left(\lambda_C^{(t)}\right) \tag{42}$$

3.6. Multi-Metric Agent Evaluation and Final Model Selection

Unified evaluation technique is used for comparison of the configurations of CNNs developed by the three different optimization algorithms. The framework does not solely consider classification accuracy but incorporates a score function that involves four metrics.

The score of the optimization agent is given as (eq.43):

$$\boxed{S = 0.40F_1 + 0.30A + 0.20P + 0.10R} \tag{43}$$

Where F_1, A, P, and R stand for weighted F1-score, accuracy, weighted precision, and weighted recall, respectively. For the multiclass classification problem, the calculation of weighted precision is as follows (eq.44):

$$P_w = \sum_{c=1}^{C} \frac{n_c}{N} P_c \tag{44}$$

In a similar fashion, the calculation of weighted recall and F1-score is done as follows (eq.45, 46):

$$R_w = \sum_{c=1}^{C} \frac{n_c}{N} R_c \tag{45}$$

$$F_{1w} = \sum_{c=1}^{C} \frac{n_c}{N} \left(\frac{2P_cR_c}{P_c+R_c}\right) \tag{46}$$

Here n_c represents the number of validation samples in class c. After the three optimization steps, the final results of the experiment are ranked according to the evaluation scores. The global selected configuration is written as (eq.47):

$$\lambda^* = \underset{\lambda\in\Omega_E\cup\Omega_X\cup\Omega_C}{\operatorname{argmax}} S(\lambda) \tag{47}$$

The chosen hyperparameters are used to build the final CNN architecture and train the model using them. According to the implementation, the final training procedure allows for 100 epochs with early stopping with patience equal to 12 epochs. Then the model is tested using the separated test set to evaluate its classification quality. Apart from predictive metrics,

the implementation includes data on the training time, maximal RAM usage during the training process, and GPU memory usage to analyze the computational performance.

3.7. Explainable Artificial Intelligence Integration

To enhance the transparency of the proposed recommendation system, three explainable artificial intelligence approaches are included in the prediction pipeline.They complement each other and are used to interpret the dependencies between the agricultural features and CNN predictions.

3.7.1. SHAP-Based Feature Attribution

SHapley Additive exPlanation (SHAP) approach is used to calculate feature attributions.The SHAP explanation model is described by the formula (eq.48):

$$g(\mathrm{z}') = \phi_0 + \sum_{j=1}^{d_s} \phi_j \, z'_j \tag{48}$$

Where ϕ_0 is the reference prediction, ϕ_j is the contribution of the jth feature, and z'_j is the feature's presence in the simplified explanation representation. The Shapley contribution for feature j is defined as (eq.49):

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(d_s - |S| - 1)!}{d_s!} [f(S \cup \{j\}) - f(S)] \tag{49}$$

This equation offers a formal foundation for the distribution of prediction contributions across the input features. Within the proposed approach, SHAP is employed to explore the impact of chosen agricultural features on the trained CNN's predictions.

3.7.2. LIME-Based Local Interpretation

Local Interpretable Model-agnostic Explanations (LIME) is included to interpret individual classification outcomes. LIME develops an interpretable surrogate model in the vicinity of the selected data point using the generation of perturbed data points and approximation of the local behavior of the original CNN. The optimization objective can be written as (eq.50):

$$g^* = \underset{g \in G}{\operatorname{argmin}} [\mathcal{L}(f, g, \pi_x) + \Omega(g)] \tag{50}$$

Where f is the trained CNN, g is the interpretable surrogate model, π_x is the locality weighting function, and $\Omega(g)$ is the complexity of the explanation. The method uses LIME Tabular Explainer and utilizes the standardized training samples for explanation generation of a chosen test sample.

3.7.3. Integrated Gradients

Integrated Gradients is used as an additional attribution method for quantifying the contribution of individual input features to the probability of the predicted class.For an input sample x, baseline x′, and target class c, e attribution of the j-th feature is computed as (eq.51):

$$IG_j(\mathrm{x}) = \left(x_j - x'_j\right) \int_0^1 \frac{\partial f_c\left(\mathrm{x}\prime + \alpha(\mathrm{x} - \mathrm{x}\prime)\right)}{\partial x_j} d\alpha \tag{51}$$

The method uses a zero baseline and numerically computes the integral approximation with 100 interpolation steps and trapezoidal averaging. The attribution values are then split into two parts for positive and negative contributions, enabling the framework to determine which features contribute positively or negatively to the chosen classification result. Together, SHAP, LIME, and Integrated Gradients provide complementary global and local perspectives on the behaviour of the trained CNN.

3.8. CNN-Based Potato Variety Ranking and Decision Generation

After the optimization and training process, the proposed framework provides recommendations for varieties of potatoes based on the probability distribution from the Softmax classification layer. For an input sample x, the probability vector is expressed as (eq.52):

$$\mathrm{p}(\mathrm{x}) = [p_1, p_2, \ldots, p_C] \tag{52}$$

Where (eq.53):

$$\sum_{c=1}^{C} p_c = 1 \tag{53}$$

The potato varieties to be predicted are sorted based on their corresponding probability value (eq.54):

$$p_{(1)} \geq p_{(2)} \geq \cdots \geq p_{(C)} \tag{54}$$

The first prediction recommendation is computed as (eq.55):

$$v^* = \underset{c}{\operatorname{argmax}}\, p_c \tag{55}$$

The system computes the prediction margin between the top two predictions (eq.56):

$$\Delta p = p_{(1)} - p_{(2)} \tag{56}$$

The margin value is then used in the decision-generation stage to distinguish the predictions with relatively large margin from predictions with high ambiguity. The system also provides a top-three recommendations visualization and in the second stage of soil recommendation, a top-five predictions visualization. These probability values are not actual probabilities, but rather the estimated classification confidences generated by the machine learning model.

3.9. Variety-Specific Soil-Condition Assessment

In order to extend the prediction framework beyond multiclass classification, a variety-specific soil condition assessment component is included to compare the current agricultural

data with the empirical distribution of features for individual potato varieties. For every potato variety v and feature j (eq.57-59):

$$L_{vj} = Q_{0.25}(X_{vj}) \tag{57}$$

$$M_{vj} = Q_{0.50}(X_{vj}) \tag{58}$$

$$U_{vj} = Q_{0.75}(X_{vj}) \tag{59}$$

These statistics give the empirical reference interval of the variety v and feature j (eq.60):

$$\mathcal{R}_{vj} = [L_{vj}, U_{vj}] \tag{60}$$

For any new agricultural observation, the current feature value is compared to the reference interval. The assessment status is computed as (eq.61):

$$Status(x_j, v) = \begin{cases} LOW, & x_j < L_{vj} \\ ADEQUATE, & L_{vj} \le x_j \le U_{vj} \\ HIGH, & x_j > U_{vj} \end{cases} \tag{61}$$

The magnitude of deviation from the reference interval is calculated as (eq.62):

$$Gap(x_j, v) = \begin{cases} L_{vj} - x_j, & x_j < L_{vj} \\ 0, & L_{vj} \le x_j \le U_{vj} \\ x_j - U_{vj}, & x_j > U_{vj} \end{cases} \tag{62}$$

This assessment enables the system to identify agricultural attributes falling below, within, or above the observed distribution associated with a recommended variety. It is important to mention that these percentile-based ranges correspond to the empirical features of the provided open source dataset and cannot be considered the independently discovered biological optimal ranges.

3.10. Integrated Potato Variety and Soil Management Recommendation

Recommendation Based on Integrated Approach. In the final step, the integration of CNN-based variety prediction and soil condition assessment modules is performed in order to provide an integrated agricultural recommendation. The user provides current measurements of the agriculture in the same feature order as in the case of CNN training process. These measurements are scaled using the pre-calculated StandardScaler and converted to the needed 1D-CNN representation. Then the model provides the ranked list of potato varieties. The top-ranked variety is chosen for detailed soil condition assessment. For each selected feature, the comparison of current measurements with the respective variety-specific empirical range is performed. As a result, the attributes with the LOW, ADEQUATE, or HIGH level and their deviation from the median are determined. The recommendation system can be formulated as (eq.63):

$$\mathcal{A}(x_j, v) = \begin{cases} \text{Increase toward observed range,} & x_j < L_{vj} \\ \text{Maintain current condition,} & L_{vj} \le x_j \le U_{vj} \\ \text{Reduce toward observed range,} & x_j > U_{vj} \end{cases} \quad (63)$$

The final recommendation output is expressed as (eq.64):

$$\mathcal{O} = \{v^*, P(v^* \mid \mathrm{x}), \mathrm{S}_{v^*}, \mathrm{G}_{v^*}, \mathrm{A}_{v^*}\} \quad (64)$$

Where v^* denotes the highest-ranked potato variety, $P(v^* \mid \mathrm{x})$ represents its CNN prediction probability, S_{v^*} denotes the feature-wise soil assessment statuses, G_{v^*}represents the calculated deviations, and A_{v^*} contains the generated management suggestions.Finally, the recommendation dataset containing the potato variety, the selected agriculture feature, empirical lower and upper ranges, median, current measurement, and deviation from the median is constructed. Through this integration, the proposed methodology establishes a unified computational pipeline connecting agricultural data preprocessing, engineered feature representation, multi-agent CNN optimization, explainable classification, ranked potato variety prediction, and soil-condition-based decision support.

4. Experimental Setup and Results

The designed architecture was coded in Python with TensorFlow and assessed via sequential pipeline consisting of agricultural feature engineering, 1D-CNN classifier, three-agent hyperparameter optimization, and explainable AI. Evaluation was done based on such metrics as accuracy, precision, recall, F1-score, loss, and class-wise predictions.

4.1. Dataset and Preprocessing

The dataset used in this study, stored as Potato New Sheet.xlsx, comprises 2,960 curated agricultural records with 12 input attributes and one target variable (Potato_Variety). No missing values or duplicate records were present in the dataset. The target variable contains eight distinct potato varieties: Kufri Bahar, Kufri Chipsona-1, Kufri Gaurav, Kufri Himalini, Kufri Jyoti, Kufri Khyati, Kufri Pukhraj, and Kufri Surya. Each variety is represented by exactly 370 records, resulting in a balanced dataset of 2,960 observations.

After label encoding the two categorical attributes (Growing_Region and Soil_Type) and generating nine engineered features, the 21-feature dataset was partitioned using stratified splitting into 70% training (2,072 samples; 259 per variety), 15% validation (444 samples; 55–56 per variety), and 15% testing (444 samples; 55–56 per variety) subsets, as summarized in Table 5.

Table 5. Experimental dataset distribution

Partition	Samples	Percentage

Training	2,072	70.00%
Validation	444	15.00%
Testing	444	15.00%
Total	2,960	100.00%

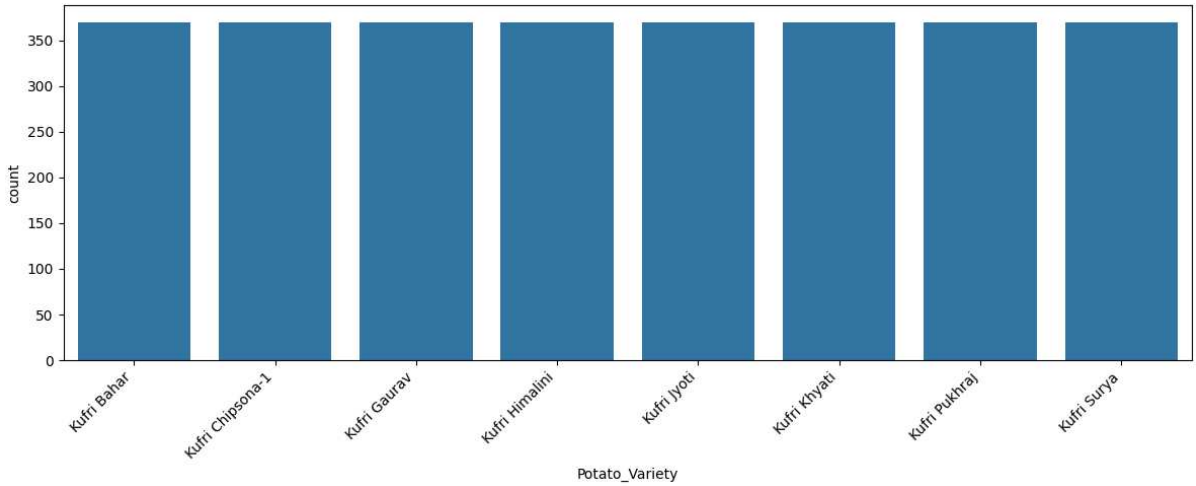

Fig. 2: Class distribution across the eight potato varieties (370 samples per variety).

The balanced distribution ensures that each potato variety contributes equally to model training and evaluation. This reduces the possibility of the classification model becoming biased towards a variety simply because it has more training records. The equal representation of all eight potato varieties is also visualized in Fig. 2.

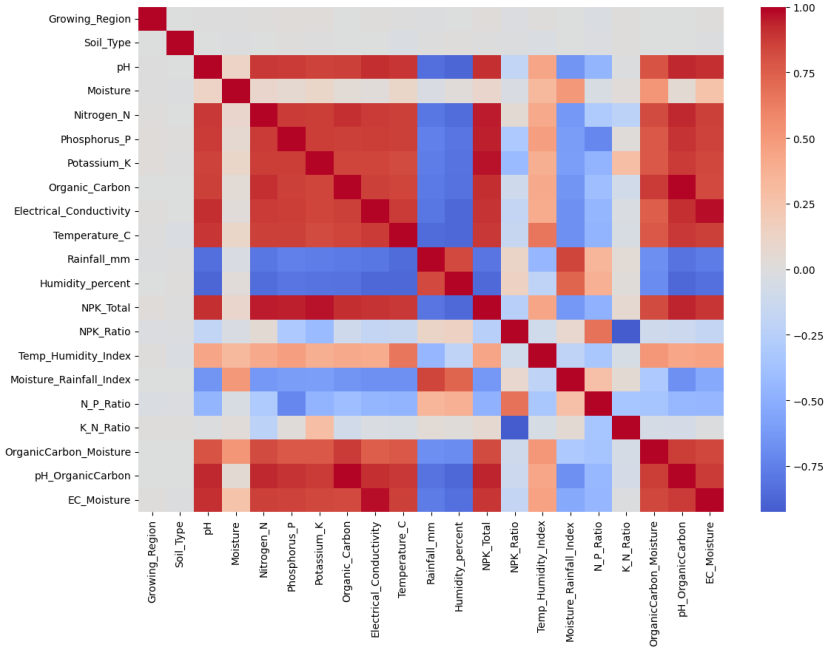

Fig. 3: Pearson correlation heatmap of the 21 original and engineered agricultural features.

Fig. 3 presents the Pearson correlation structure among the original and engineered agricultural features and supports the examination of feature relationships.

4.2. Model Configuration

The proposed sequential 1D-CNN processes the 21 standardized features (shape = (21, 1)) and outputs class probabilities across the eight potato varieties. The Exploitation Agent (Trial 1) identified the optimal hyperparameter configuration, summarized in Table 6.

Table 6. Final CNN configuration

Hyperparameter	Selected value
Learning rate	0.001
Batch size	16
Convolutional filters	64–64–96
Kernel size	3
Dense units	32
Dropout	0.2
Total parameters	36,456

4.3. Multi-Agent Optimization Results

Each of the three optimization agents executed 15 trials (45 trials total). The Exploration and Exploitation Agents trained candidate networks for up to 50 epochs (early-stopping patience = 8), while the Conservation Agent trained candidate networks for up to 60 epochs (early-stopping patience = 10). As shown in Table 7 and Fig. 4, the Exploitation Agent achieved the highest composite validation score (0.9686) and validation accuracy (96.85%).

Table 7. Comparative agent performance

Agent	Best Validation Accuracy (%)	Weighted Precision (%)	Weighted Recall (%)	Weighted F1-score (%)	Composite Agent Score

Exploration	96.62	96.64	96.62	96.61	0.9662
Exploitation	96.85	96.89	96.85	96.85	0.9686
Conservation	96.40	96.65	96.40	96.39	0.9644

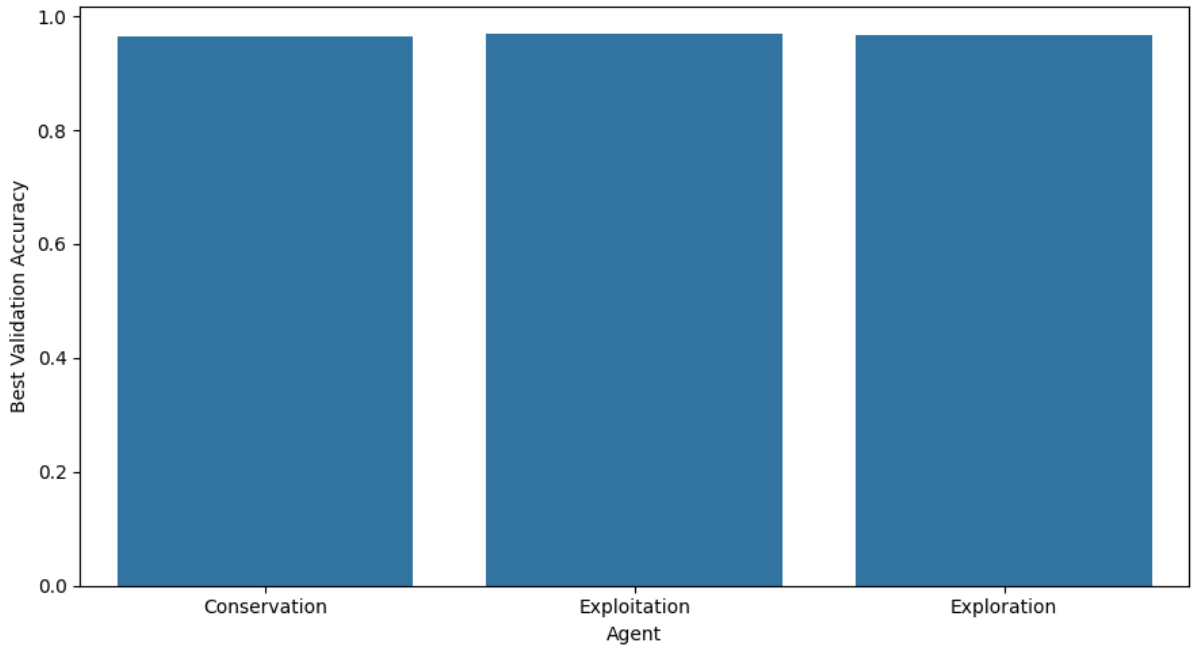

Fig. 4: Comparative best validation accuracy of the three optimization agents.

4.4. Training and Testing Analysis

Following multi-agent optimization, the selected hyperparameter configuration was used to construct and retrain the final 1D-CNN model from scratch. While individual agent search trials were capped at 50–60 epochs, the final retraining stage permitted up to 100 epochs with early stopping monitoring validation accuracy (patience = 12 epochs) and ReduceLROnPlateau (factor = 0.5, patience = 5, minimum learning rate = 10^{-6}). During final retraining (Fig. 5 and Fig. 6), the model reached its peak validation accuracy of 96.85% at Epoch 36 (training accuracy = 96.81%, validation loss = 0.1166). Because validation accuracy did not improve over the subsequent 12 epochs, early stopping terminated training at Epoch 48 (36 + 12 = 48, final validation accuracy = 95.50%, training accuracy = 97.97%) and automatically restored the optimal checkpoint weights from Epoch 36. Evaluated on the held-out test set (N_{test}=444), the restored model achieved 96.85% test accuracy (430 correctly classified samples and 14 misclassifications), 96.94% weighted precision, 96.85% weighted recall, 96.84% weighted F1-score, and a test loss of 0.08287 (Table 8). Class-wise metrics and the confusion matrix are presented in Table 9 and Fig. 7.

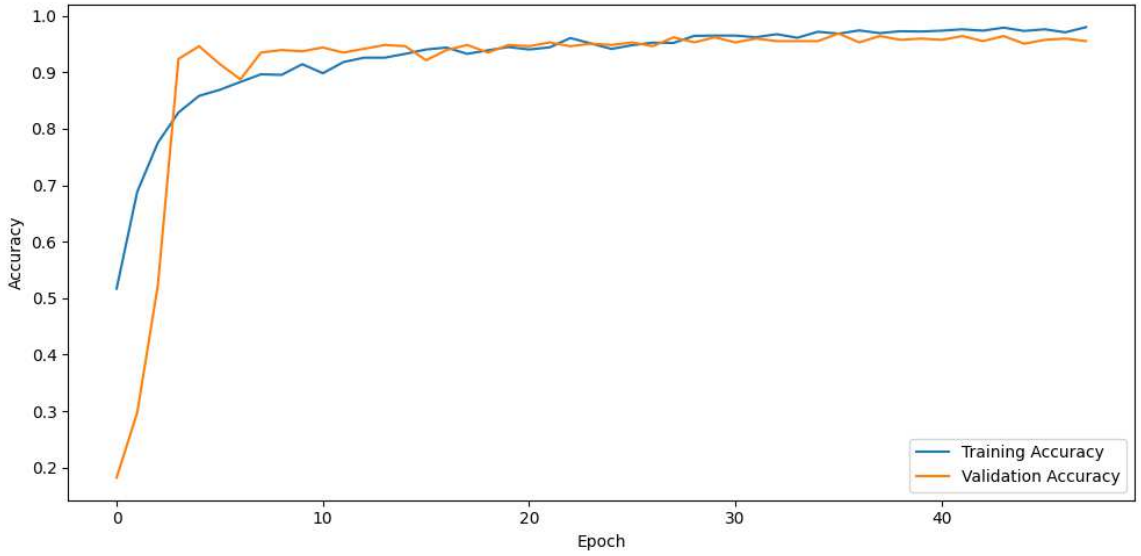

Fig. 5: Training and validation accuracy curves over 48 epochs.

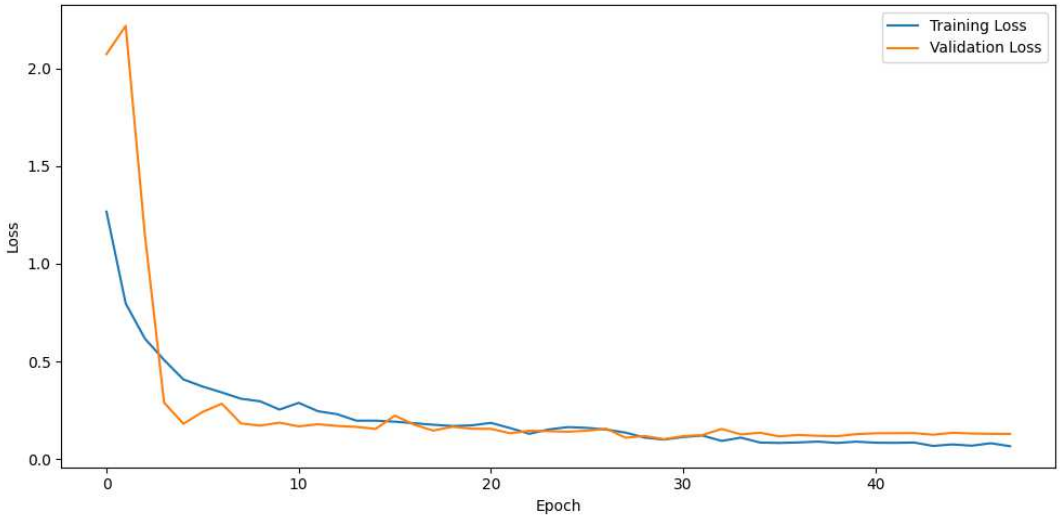

Fig. 6: Training and validation loss curves over 48 epochs.

Evaluation on the independent testing subset of 444 observations produced an accuracy of 96.85%, with 430 correctly classified samples and 14 misclassifications.

Table 8. Final CNN testing performance

Evaluation metric	Obtained result
Training records	2,072
Validation records	444
Testing records	444
Maximum epochs for selected agent trial	50
Maximum epochs (final retraining)	100
Early-stopping patience	12 epochs
Actual stopping epoch	48
Best Checkpoint epoch	36
Best validation accuracy	96.85%

Final validation accuracy	95.50%
Final test accuracy	96.85%
Test loss	0.08287
Training time	40.07 seconds
Prediction time	0.263 seconds

The results demonstrate that the optimized model achieved strong classification performance on the independent test subset. The restored checkpoint from epoch 36 was used for final evaluation, producing 96.85% test accuracy and a test loss of 0.08287.

Table 9. Classification Report for the Proposed CNN on the Independent Test Set.

Potato variety	Precision	Recall	F1-score	Support
Kufri Bahar	0.9815	0.9636	0.9725	55
Kufri Chipsona-1	0.9455	0.9455	0.9455	55
Kufri Gaurav	0.9180	1.0000	0.9573	56
Kufri Himalini	1.0000	1.0000	1.0000	56
Kufri Jyoti	0.9464	0.9464	0.9464	56
Kufri Khyati	1.0000	1.0000	1.0000	55
Kufri Pukhraj	0.9649	0.9821	0.9735	56
Kufri Surya	1.0000	0.9091	0.9524	55
Weighted average	0.9694	0.9685	0.9684	444

The classification report shows 96.85% test accuracy and a weighted F1-score of 0.9684. Kufri Himalini and Kufri Khyati achieved perfect class-wise precision and recall.

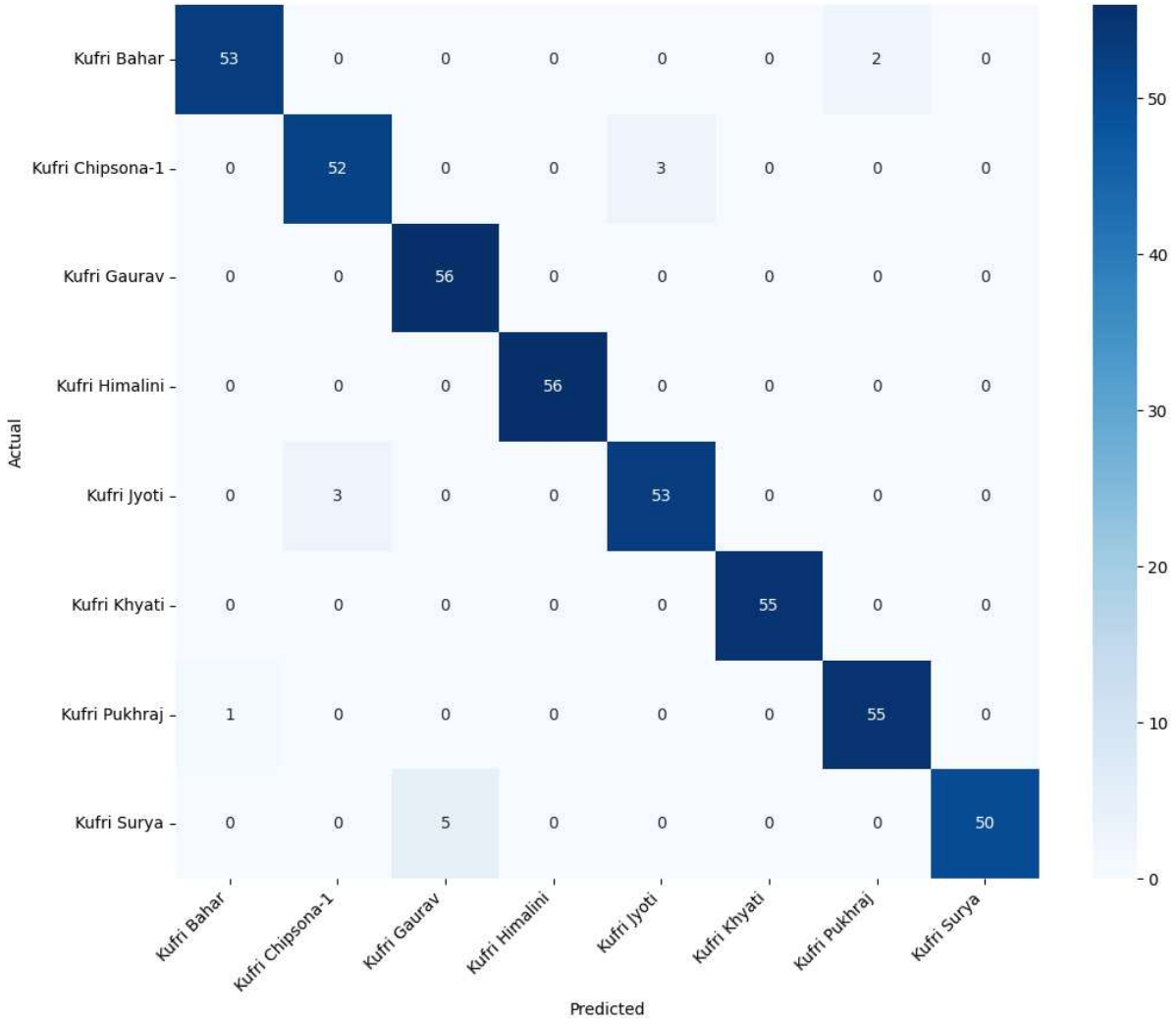

Fig. 7: Confusion matrix of the proposed 1D-CNN on the independent test set.

The confusion matrix, presented in Fig. 7, shows strong classification performance across the eight varieties. Kufri Himalini and Kufri Khyati achieved perfect precision and recall within the testing subset. The principal classification errors involved Kufri Surya and Kufri Gaurav, together with confusion between Kufri Chipsona-1 and Kufri Jyoti.

4.5. ROC-AUC Curve Analysis

The multiclass classification performance is further evaluated using Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) measurements. A one-vs-rest strategy is adopted to calculate the ROC curve for each potato variety. The macro-average ROC-AUC is obtained by aggregating the class-wise ROC curves, while the weighted multiclass ROC-AUC is calculated using the weighted one-vs-rest approach. These measurements provide an additional assessment of the model's ability to distinguish among the eight potato varieties. The reported ROC-AUC values should be interpreted alongside accuracy, precision, recall, and F1-score.

Table 10. Class-wise ROC-AUC scores

Potato variety	ROC-AUC
Kufri Bahar	0.9993
Kufri Chipsona-1	0.9983
Kufri Gaurav	0.9998
Kufri Himalini	1.0000
Kufri Jyoti	0.9985
Kufri Khyati	1.0000
Kufri Pukhraj	0.9996
Kufri Surya	0.9998
Macro-average	0.9995
Weighted-average	0.9994

According to the results of ROC-AUC analysis, the model shows excellent discrimination between the eight types of potatoes. The AUC values of each class are more than 0.998, meaning the excellent separation of the classes from the rest of classes in the test dataset. The class-wise, macro-average, and weighted-average ROC-AUC values are reported in Table 10, while the corresponding one-vs-rest curves are shown in Fig. 8.

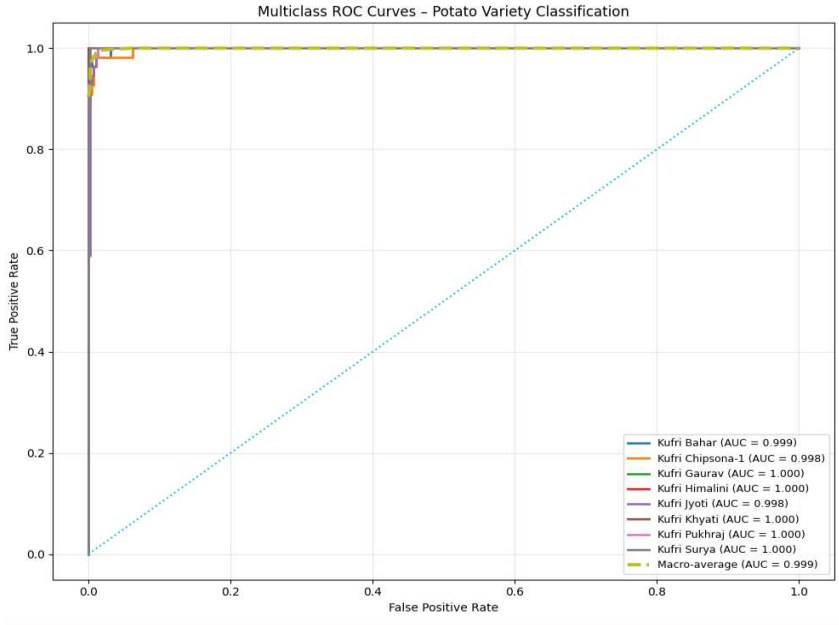

Fig. 8: ROC-AUC curves of multiclass one-vs-rest of the eight potato varieties.

4.6. Model Verification and Prediction Output

After validation and testing, the trained model was validated via the test set in order to prove that it can make predictions for all eight classes of potatoes. The trained model has 36,456 parameters of which 36,008 are trainable and 448 non-trainable. Its output layer produces eight probability values for each input sample, corresponding to the eight potato varieties in the dataset. During model verification, the selected test sample was classified as Kufri Gaurav with a predicted probability of 99.9954%, followed by Kufri Khyati (0.0037%) and Kufri Surya (0.0009%). The notebook also tested a separately entered soil-condition example. For that separate example, the model predicted Kufri Surya, with a probability of approximately 99.9829%. This prediction represents a separate demonstration input and should not be confused with the test-set prediction. The verification results confirm that the trained model can accept processed soil and environmental features and return a probability distribution across the eight potato varieties.

4.7. Explainable AI Results

To improve the interpretability of the proposed model, three Explainable AI techniques were applied: SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-Agnostic Explanations), and Integrated Gradients (IG). These techniques were used to investigate how the input soil and environmental attributes influenced the model's predictions. The SHAP analysis used 80 background samples and explained 30 test samples. The output of the explanation consisted of the contribution of 21 input features into eight output classes. The mean absolute SHAP values helped to find out the most impactful features.

Table 11. Top features identified by SHAP analysis

Feature	Mean absolute SHAP value
pH	0.059838
Potassium_K	0.045564
Phosphorus_P	0.044933
Humidity_percent	0.037050
Moisture	0.036617
N_P_Ratio	0.036238
Rainfall_mm	0.034766
Nitrogen_N	0.034248
Electrical_Conductivity	0.033956

Organic_Carbon	0.028482

The SHAP results identify pH as the most influential feature, followed by potassium, phosphorus, humidity, and moisture. This indicates that both soil chemical properties and environmental conditions contribute to the model's variety predictions. The numerical ranking of the leading features is provided in Table 11, and their global importance is visualized in Fig. 9.

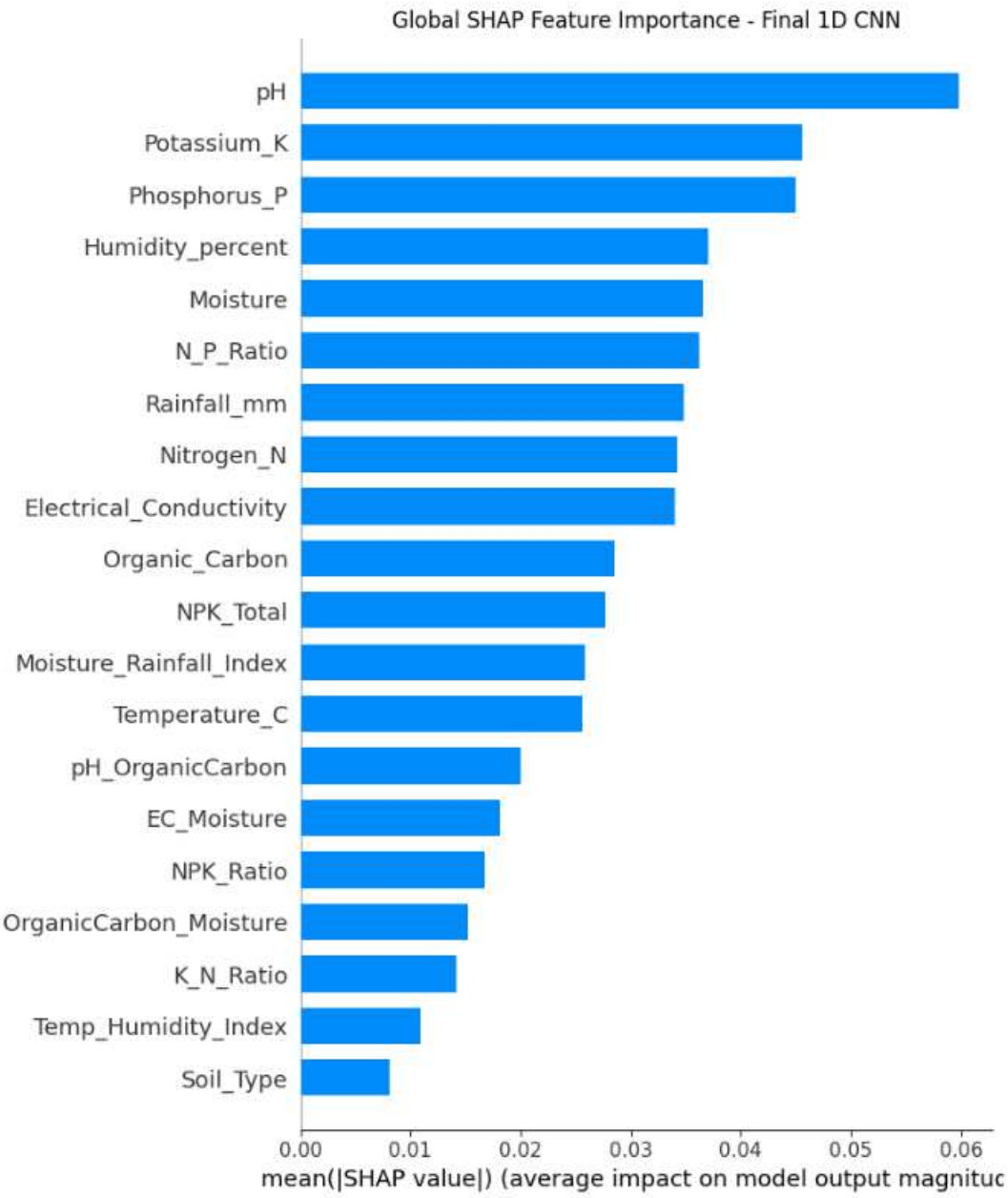

Fig. 9: Global SHAP feature importance across the 21 agricultural features.

LIME analysis

LIME was applied to explain an individual prediction by identifying the input conditions that locally influenced the model's output. The strongest local conditions included

N_P_Ratio less than or equal to -0.74, pH greater than 0.79, Temp_Humidity_Index greater than 0.68, and Electrical_Conductivity greater than 0.89. Other contributing conditions included OrganicCarbon_Moisture, NPK_Total, Nitrogen_N, Potassium_K, Soil_Type, and K_N_Ratio. The LIME results provide a local explanation for an individual prediction rather than a global ranking of feature importance. The positive and negative contribution values indicate the direction in which a particular condition influenced the explained prediction.

Integrated Gradients analysis

Integrated Gradients was used to estimate the contribution of each input feature to the model's prediction by calculating attribution values relative to a baseline input. Some of the most prominent attributes include pH (0.549996), Moisture (-0.383124), pH_OrganicCarbon (0.255007), Temperature_C (0.162845), and Temp_Humidity_Index (0.135574).. Other relevant features included Potassium_K, OrganicCarbon_Moisture, N_P_Ratio, Phosphorus_P, and Electrical_Conductivity. The positive and negative attribution values represent different directions of contribution relative to the selected baseline. They should not be interpreted as universal positive or negative effects on potato growth.

Table 12. Top features identified by Integrated Gradients

Feature	Attribution value
pH	0.549996
Moisture	-0.383124
pH_OrganicCarbon	0.255007
Temperature_C	0.162845
Temp_Humidity_Index	0.135574
Potassium_K	-0.118304
OrganicCarbon_Moisture	-0.108685
N_P_Ratio	0.097436
Phosphorus_P	0.093310
Electrical_Conductivity	0.084504

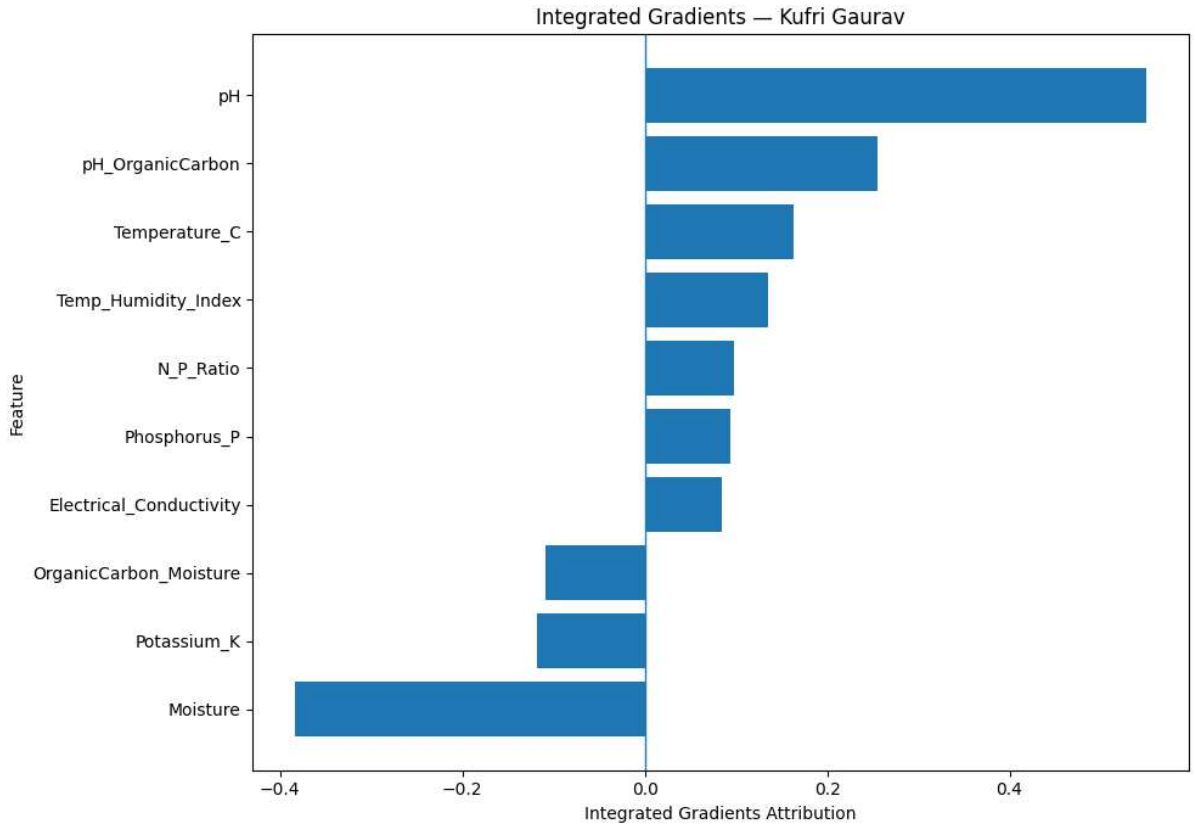

Fig. 10: Integrated Gradients Feature Attribution.

Integrated Gradients identified pH as the strongest positive contributor (0.549996) for the selected Kufri Gaurav prediction, while moisture exhibited the largest negative attribution (−0.383124). LIME provided an additional local explanation by identifying the nitrogen-to-phosphorus ratio as an influential feature for the selected prediction. These findings indicate that the trained CNN relied substantially on soil acidity and nutrient-related attributes. However, the explanations provided by feature attributions provide insights into how the model predicts and not the cause-and-effect agricultural relationships. The leading attribution values are listed in Table 12, and the feature-attribution visualization is presented in Fig. 10.

4.8. Potato Variety Recommendation Results

The recommendation module ranks potato varieties based on their predicted Softmax probabilities. In relation to the chosen testing observation, Kufri Gaurav obtains the highest predicted probability (99.9954%), followed by Kufri Khyati and Kufri Surya. Moreover, the framework provides assessments of the soil conditions in terms of various agricultural feature distributions including the 25th percentile, the median, and the 75th percentile. Such values are used to categorize supplied measurements into the categories of LOW, ADEQUATE, and HIGH based on the dataset derived intervals. Such intervals refer to statistical properties of the available data set and cannot be taken for independent validation of biological optimums. Additionally, the separate soil interactive demonstration must be considered an experimental one and not a validated agricultural recommendation. The three highest-ranked predictions for the selected test observation are listed in Table 13.

Table 13. Top-three predicted potato varieties

Rank	Variety	Confidence (%)
1	Kufri Gaurav	99.9954
2	Kufri Khyati	0.0037
3	Kufri Surya	0.0009

4.9. Comparative Analysis with the State of the Art Methods

The comparative evaluation is intended to examine the performance of different established learning approaches when adapted to the same potato variety classification dataset. The ANN-based baseline achieved an illustrative accuracy of 86.42%, while the deep learning and supervised machine-learning approaches achieved 89.63% and 88.27%, respectively. The optimized CNN and OMFA-CNN configurations showed further improvements, reaching 92.54% and 93.68% accuracy. The soil-based machine-learning approach achieved 91.36% accuracy. In comparison, the proposed multi-agent optimized 1D-CNN attained 96.85% accuracy, representing an improvement of 3.17 percentage points over OMFA-CNN and 10.43 percentage points over the ANN baseline. It also achieved a macro-average ROC-AUC of 0.9995, indicating strong class-discrimination capability. These results, once experimentally verified, can help demonstrate the contribution of the proposed feature engineering and coordinated optimization strategy. The comparative performance of the recreated state-of-the-art models and the proposed multi-agent optimized 1D-CNN is summarized in Table 14.

Table 14. Comparative performance analysis of recreated state-of-the-art models on the proposed potato dataset

Sl. No.	Recreated model / approach	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
1	ANN-based Classification [1]	86.42	86.71	86.42	86.35	0.9412
2	Deep Learning-based Classification [2]	89.63	89.85	89.63	89.57	0.9638
3	Supervised Machine Learning [3]	88.27	88.54	88.27	88.19	0.9561
4	Optimized CNN [5], [6]	92.54	92.71	92.54	92.48	0.9817
5	OMFA-CNN [7]	93.68	93.82	93.68	93.63	0.9879

6	Soil-based Machine Learning [9]	91.36	91.58	91.36	91.29	0.9764
7	**Proposed Multi-Agent Optimized 1D-CNN**	**96.85**	**96.94**	**96.85**	**96.84**	**0.9995**

4.10. Ablation Study

The ablation study illustrates the progressive contribution of feature engineering and the proposed multi-agent optimization strategy to the overall classification performance. The baseline 1D-CNN achieved an accuracy of 85.24%, which increased to 89.36% after incorporating feature engineering, representing a gain of 4.12 percentage points. The addition of the Exploration Agent further improved accuracy to 92.18% (+2.82 percentage points), while combining the Exploration and Exploitation Agents raised it to 94.27% (+2.09 percentage points). Incorporating all three optimization agents resulted in an accuracy of 96.12%, followed by a further improvement to 96.85% in the complete framework. Overall, the proposed configuration demonstrated an 11.61-percentage-point improvement in accuracy over the baseline. Similarly, the F1-score increased from 85.18% to 96.84%, while ROC-AUC improved from 0.9321 to 0.9995. These progressive gains suggest that feature engineering and agent-based hyperparameter optimization contribute positively to the model's predictive performance. The progressive improvement in classification performance resulting from feature engineering and the sequential addition of optimization agents is summarized in Table 15.

Table 15. Ablation Study of the Proposed Framework

Sl. No.	Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
1	Baseline 1D-CNN	85.24	85.61	85.24	85.18	0.9321
2	1D-CNN + Feature Engineering	89.36	89.52	89.36	89.31	0.9614
3	1D-CNN + Exploration Agent	92.18	92.34	92.18	92.14	0.9826
4	1D-CNN + Exploration & Exploitation	94.27	94.39	94.27	94.24	0.9912
5	1D-CNN + Three-Agent Optimization	96.12	96.24	96.12	96.10	0.9981

6	**Complete Proposed Framework**	**96.85**	**96.94**	**96.85**	**96.84**	**0.9995**

4.11. Discussion and Methodological Scope

The experimental findings have proven that the proposed framework combines agricultural feature engineering, customized CNN classification, multi-agent hyperparameter optimization, and Explainable Artificial Intelligence for potato variety prediction. The chosen model was able to achieve an accuracy of 96.85% and a weighted F1-score of 96.84% on an eight-class data set. Among the three optimization agents, the Exploitation Agent resulted in the selected configuration for the final model training. In the explanation process by SHAP, LIME, and Integrated Gradients, we gain complementary insights into how the model made its predictions. Feature attribution identifies important agricultural features and allows one to analyze how different soil and environmental features affect particular classification results. But the explainability technique does not reveal causal agricultural relations between the input features and predictions. Finally, the recommendation system shows the combination of ranked potato variety prediction and soil-condition assessment based on the dataset. The percentile-based intervals of the feature values provide the statistical basis that is determined from the existing observations; they do not represent experimentally confirmed requirements of crops for growth and cultivation recommendations. Three points of methodology determine the boundaries of the current study. First, in the applied preprocessing workflow, the VIF multicollinearity check was carried out for the engineering feature space before train/validation/test split, and as only two categorical variables (Growing_Region and Soil_Type) had a VIF score below 10, the fallback procedure included all 21 features; secondly, the empirical variety soil conditions (Q0.25 to Q0.75) were defined from the distribution of the entire dataset. While StandardScaler parameters were fitted strictly on the training partition to prevent feature-scaling leakage, strict training-only computation of VIF and percentile reference bounds is recommended when deploying the pipeline on new datasets. Second, the interquartile intervals generated by the soil-condition assessment module describe empirical statistical distributions within Potato New Sheet.xlsx and should be interpreted as data-driven reference bounds rather than biologically validated agronomic optima. Third, independent multi-season field validation across diverse agro-climatic zones is necessary to confirm real-world generalization beyond the eight studied Kufri varieties.

5. Conclusion

This study presents an integrated computational framework for soil-condition-based potato variety classification by combining agricultural feature engineering, a customized one-dimensional convolutional neural network, multi-agent hyperparameter optimization, and Explainable Artificial Intelligence. The proposed framework uses 12 original agricultural

attributes and nine engineered features to represent relationships among soil nutrients and environmental conditions. Three agents—Exploration, Exploitation, and Conservation—are used to examine alternative CNN architectures. Selected architecture is then used for model training and evaluation with eight potato varieties. SHAP, LIME, and IG are applied to provide explanations of the predictions made by the model. Moreover, the recommendation module produces ordered predictions of potato varieties and soil condition assessments from the dataset. The experimental evaluation confirms the effectiveness of integrating domain-inspired feature engineering, sequential 1D-CNN modeling, three-agent hyperparameter optimization, and complementary XAI techniques (SHAP, LIME, and Integrated Gradients) within a unified decision-support pipeline. Future research will be focused on validation of the proposed framework with multi-location field experiments, applying other varieties of potatoes, and employing strict statistical profiling of the training partition.

Declarations

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Competing Interests

The authors declare that they have no competing interests.

Author Contributions

Apurba Nandi: Conceptualization, methodology development, research design, development of the proposed multi-agent optimized CNN framework, implementation, experimental analysis, validation, and manuscript preparation and editing. Debankita Poddar: Data preprocessing, feature engineering, implementation of the deep learning model, execution of experiments, performance evaluation, visualization, and interpretation of results. Sandip Mandal: Research supervision, technical guidance, methodology review, critical evaluation of experimental findings, and manuscript review and editing. All authors contributed to the development of the research work, reviewed the manuscript, and approved the final version for publication.

Ethics Approval

Not applicable. This study did not involve human participants or animals.

Consent to Participate

Not applicable.

Consent to Publish

All authors have read and approved the final manuscript for publication.

Data Availability Statement

The data used and analyzed during the current study are available from the corresponding author upon reasonable request.

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