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A Metaheuristic-based Deep Learning Model for Accurate Crop Recommendation Using Agro-Environmental Data

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ABSTRACT

Accurate crop recommendation is essential for sustainable agriculture, yet existing machine learning and deep learning models often struggle with high-dimensional, redundant soil and environmental features, leading to reduced generalization in real-world settings. To address this limitation, this study presents a hybrid Firefly-optimized Autoencoder model that integrates nonlinear representation learning with metaheuristic feature refinement. The Autoencoder compresses NPK nutrient values, temperature, humidity, rainfall, and pH into a compact latent space, while the Firefly Algorithm selects the most discriminative latent dimensions by maximizing feature variance. A deep neural classifier trained on the optimized features achieves highly precise multi-class prediction. The final results tested on a benchmark 22-crop dataset, conducted using Google Colab Pro, shows that the proposed model attains 99.32% accuracy, outperforming advanced methods such as TCN (99.09%), CNN–LSTM federated learning (98.77%), and tuned Random Forest (99.05%). The results highlight the significance of combining latent-space learning with swarm intelligence to deliver a robust, scalable, and high-accuracy crop recommendation system.

1. INTRODUCTION

Agriculture remains a critical sector supporting global food security, economic development, and rural livelihoods. In recent years, the increasing variability in climatic conditions, unpredictable rainfall patterns, depletion of soil nutrients, and rapid population growth have intensified the demand for intelligent and adaptive decision-support tools in crop production [1]. Traditional crop selection methods rely heavily on farmers' experience, field observations, and region-specific practices. The effective in localized contexts, these approaches often fail to generalize across diverse soil types, microclimatic conditions, and environmental variations [2]. Consequently, the integration of data-driven models with modern computational intelligence has emerged as a promising solution to enhance agricultural decision-making and optimize crop productivity.

Machine learning (ML) and deep learning (DL) techniques have shown considerable progress in modeling complex agro-climatic interactions. A wide range of ML models including Support Vector

Machines, Decision Trees, K-Nearest Neighbors, Random Forests, and XGBoost have been successfully applied for crop recommendation, achieving accuracies exceeding 99% in several studies [3]. Deep learning models such as Temporal Convolutional Networks (TCN), CNN–LSTM hybrids, and reinforcement learning–driven neural architectures have also demonstrated strong predictive capabilities [4]. Despite their high-performance metrics, existing systems often depend on raw or high-dimensional feature spaces, which may contain redundant, irrelevant, or noisy attributes. This results in increased computational overhead, reduced interpretability, and potential overfitting [5]. Moreover, current DL frameworks seldom incorporate explicit feature optimization techniques, limiting their ability to refine nonlinear latent representations and fully exploit discriminative patterns within the data.

The limitations of traditional feature selection methods further exacerbate this problem. Classical statistical methods fail to capture nonlinear dependencies, while metaheuristic algorithms such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization though powerful for feature reduction—have rarely been integrated with deep latent representations. This creates a significant gap in the literature: the lack of hybrid frameworks that combine deep representation learning with intelligent feature optimization to enhance class separability, model efficiency, and prediction accuracy in crop recommendation systems.

Motivated by these challenges, the present study introduces a hybrid Firefly-optimized Autoencoder model designed to improve prediction reliability and overcome the limitations of existing ML and DL approaches. Autoencoders provide a powerful means of learning compact, nonlinear representations by encoding the seven agro-environmental parameters Nitrogen, Phosphorus, Potassium, Temperature, Humidity, pH, and Rainfall into a low-dimensional latent space. However, not all latent features contribute equally to discriminative performance. To address this, the Firefly Algorithm (FA), a nature-inspired swarm intelligence optimization technique, is employed to selectively identify the most informative latent features based on variance maximization. This two-stage approach significantly reduces dimensionality, eliminates redundancy, and enhances the structural separability of crop classes, thereby improving classification performance.

The primary contributions of this study are fourfold.

- A hybrid Firefly–Autoencoder framework is proposed for crop recommendation, integrating nonlinear representation learning with swarm intelligence–based feature selection.
- A variance-driven fitness function is introduced to guide Firefly-based optimization in the latent space, ensuring that only highly discriminative features are retained.
- A deep neural classifier is developed on the selected latent features, achieving superior accuracy, precision, recall, and ROC-AUC compared to baseline CNN, LSTM, and Autoencoder models.

The remainder of this paper is structured as follows. Section 2 provides a review of current research in crop recommendation systems. Section 3 describes the proposed methodology, including dataset preprocessing, Autoencoder architecture, Firefly-based feature selection, and the classification model. Section 4 presents experimental results and detailed visual analyses. Section 5 discusses the significance of the findings in relation to existing literature. Section 6 concludes the paper and outlines potential directions for future research.

2. RELATED WORK

Recent advances in crop recommendation have predominantly leveraged machine learning and deep learning models to enhance agricultural decision-making by utilizing soil, climatic, and environmental parameters. Devi et al., 2024 suggested Support Vector Machines (SVM) and Decision Trees were among the earlier approaches, achieving accuracies of 99.54% and 87%, respectively [6]. Mavi et al., 2024; Lamba et al., 2024 demonstrated the superiority of ensemble techniques, with Random Forest and XGBoost models consistently reporting accuracies above 99%, including results of 99.31% and 99.64% respectively [7]-[8]. Gireesh, 2023 stated XGBoost achieved 99.50% accuracy in prioritizing the top five suitable crops for farmers [9]. Saritha et al., 2024 suggested Random Forest models reached 99.5% accuracy in yield-oriented applications [10]. Deep learning-based frameworks have also been explored to improve predictive precision. Ghosh et al., 2024 suggested the Temporal Convolutional Networks (TCN) achieved 99.9% accuracy [11]. Shingade et al., 2022 proposed hybrid Deep-Q Elman network achieved 99.44% by integrating reinforcement learning with neural architectures [12]. Federated learning variants such as CNN–LSTM models enabled privacy-preserving crop prediction with 98.77% accuracy, demonstrating robustness across distributed environments. Srilatha et al., 2024 suggested the Graph Convolutional Networks (GCN) have further shown high performance, achieving 98% soil-based classification accuracy. Several hybrid and optimization-driven approaches have also been reported [13]. Gopi et al., 2023 suggested the HMFO-ML achieved 99.67% accuracy in crop recommendation and crop yield prediction [14]. Sindhur et al., 2025 proposed Random Forest combined with LSTM attained 98.5% accuracy for market-aware crop suitability forecasting [15]. Cathciyal et al., 2023 suggested additional hybrid combinations, including KNN–RF reported accuracies between 96% and 98%. Yang, 2022 says HIAS achieved 99.78% precision with a very low false negative rate of 0.01 [16]. Sivakolunthu et al., 2024 proposed Serial cascaded neural architectures, integrating Autoencoders, 1D-CNN, GRU, and LSTM, reported 96.73% accuracy [17]. Sonai Muthu Anbananthen et al., 2021 suggested hybrid ML approaches such as stacked generalization achieved 88.89% accuracy [18].

Although these studies demonstrate the effectiveness of ML and DL techniques, most rely on full-dimensional raw features that may introduce redundancy and noise. Recent metaheuristic selection methods—including Genetic Algorithms, PSO, and Ant Colony Optimization—have shown potential for dimensionality reduction; however, their integration with deep latent representations remains limited. The present work addresses this gap by combining nonlinear feature learning via Autoencoders with Firefly-based feature optimization to improve class separability and enhance classification performance within a low-dimensional latent space.

Table 1: Summary of Related Work on Crop Recommendation.

Authors	**Method**	**Parameters Used**	**Findings**
Devi et al. (2024) [6]	SVM, Decision Tree	Soil & environmental features	SVM: 99.54%; DT: 87%
Mavi et al. (2024) [7]	Random Forest, XGBoost	Soil & climate factors	99.31%
Lamba et al. (2024) [8]	NB, SVM, RF, KNN	Soil composition	RF: 99.64%
Gireesh (2023) [9]	XGBoost	Soil & crop priority metrics	99.50%
Saritha et al. (2024) [10]	Tuned Random Forest	Agronomic variables	99.5%
Ghosh et al. (2024) [11]	TCN (Deep Learning)	Soil & environmental data	99.9%
Shingade et al. (2022) [12]	Deep-Q Elman NN	Temp., humidity	99.44%
Srilatha et al. (2024) [13]	GCN-based system	Soil type classification	98%
Gopi et al. (2023) [14]	HMFO-ML (Hybrid Optimization)	Crop yield prediction	Acc: 99.67%; R^2: 98.82%
Sindhur et al. (2025) [15]	RF + LSTM Hybrid	Soil, weather, market price	98.5%
Cathciyal et al. (2023) [16]	KNN + Random Forest	Soil parameters	KNN: 98%; RF: 96%
Sivakolunthu et al. (2024) [17]	Cascaded AE + 1D-CNN + GRU + LSTM	Soil & climate data	96.73%
Sonai Muthu A. et al. (2021) [18]	Stacked ML, GBoost, RF, LASSO	Feature-based crop prediction	88.89%
Prity et al. (2024) [19]	9 ML Models; RF best	Soil, weather, yield history	RF: 99.31%
Karna et al. (2023) [20]	Federated Learning	Distributed soil–weather data	98.77%
Upadhyay et al. (2024) [21]	Random Forest	Soil quality & climate	99%
Kristuboyina et al. (2024) [22]	Soil-Based ML Model	Soil chemical parameters	93%
Changela et al. (2023) [23]	NB, RF	Soil & atmospheric variables	99%
Suresh et al. (2024) [24]	Ensemble Voting (SVM, KNN, RF, NB)	Hybrid soil features	98%

Yang (2022) [25]	HIAS Hybrid Model	Semantic soil classification	Precision: 99.78%; FNR: 0.01

Although numerous studies have demonstrated high-accuracy crop recommendation using machine learning models such as Random Forest, SVM, XGBoost, and advanced deep learning architectures, most existing approaches rely heavily on raw feature spaces without addressing redundancy, multicollinearity, or noise present in soil and environmental data. Deep learning models such as TCN, CNN–LSTM, and cascaded hybrid networks achieve strong performance but do not incorporate feature optimization mechanisms, leading to unnecessary computational overhead and potential overfitting. Metaheuristic algorithms (e.g., GA, PSO, ACO) have shown promise in feature selection, yet their integration with deep latent representations remains largely unexplored. Furthermore, existing systems seldom investigate non-linear compressed feature spaces produced by Autoencoders, nor do they employ swarm intelligence to refine these representations for improved class separability. Thus, there exists a clear research gap in developing a hybrid model that combines deep nonlinear feature learning with intelligent feature selection to enhance interpretability, computational efficiency, and predictive accuracy for crop recommendation tasks.

Despite significant advancements in machine learning–based crop recommendation systems, current models remain limited by their dependence on full-dimensional input features, which often contain redundant, irrelevant, or noisy attributes that degrade prediction performance. Deep learning-based approaches capture nonlinear interactions but lack mechanisms to optimize the resulting latent representations for enhanced discriminability. Existing metaheuristic techniques offer feature selection but are seldom applied to deep latent spaces, resulting in suboptimal integration of representation learning and optimization. Consequently, there is a need for a robust, scalable, and high-precision crop recommendation framework that can (i) learn compact and informative nonlinear feature embeddings, (ii) intelligently select the most discriminative latent features, and (iii) achieve superior classification performance across diverse crop categories. This study addresses this challenge by proposing a Firefly Algorithm–optimized Autoencoder model that enhances feature quality, improves predictive accuracy, and overcomes limitations observed in prior crop recommendation research

3. METHODOLOGY

The proposed Firefly-optimized Autoencoder framework integrates nonlinear feature extraction and intelligent feature optimization to enhance the accuracy and robustness of crop recommendation. As illustrated in Figure X, the methodology begins with a structured crop historical dataset comprising soil nutrient values (N, P, K), environmental parameters (temperature, humidity, rainfall), and pH measurements. The data undergoes a comprehensive preprocessing pipeline that includes missing value inspection, outlier detection, and z-score normalization to ensure numerical consistency across features. The refined dataset is then used to train an Autoencoder, which compresses the original seven-dimensional feature space into a latent representation matrix Z. To identify the most discriminative latent features, the Firefly Algorithm (FA) is applied to optimize feature selection based on variance-driven fitness evaluation. The resulting optimal feature mask is subsequently used to train a deep neural classifier capable of high-precision multi-class crop prediction. Finally, the model is evaluated using a suite of performance metrics to generate the predicted crop recommendations.

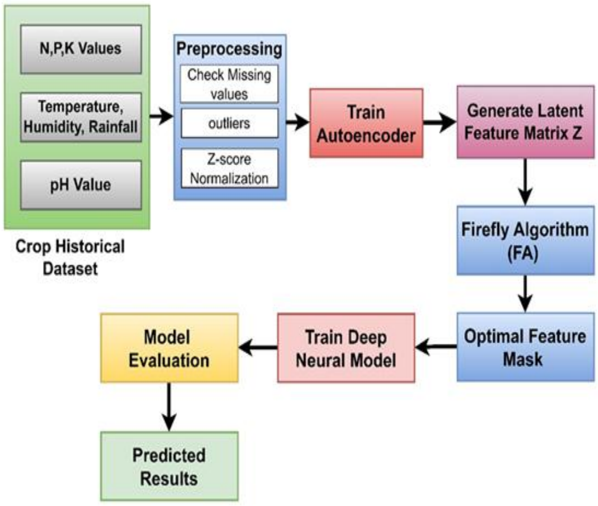

Figure 1: Architecture of proposed Model

Dataset Description: The dataset consists of seven environmental and soil parameters that influence the growth suitability of 22 crop classes. Each sample includes Nitrogen (N), Phosphorus (P), Potassium (K), Temperature, Humidity, pH, and Rainfall.

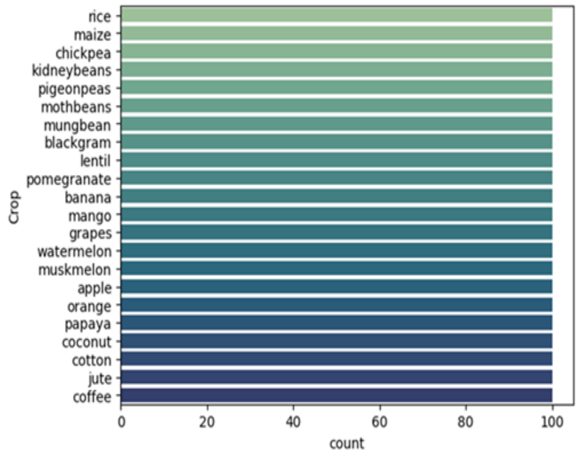

Figure 2: Distribution of the crop dataset showing an equal number of samples (100 each) across all 22 crop categories

Figure 2 illustrates the class distribution of the crop dataset, demonstrating a perfectly balanced representation across all 22 crop categories. Each crop such as Rice, Maize, Chickpea, Kidneybeans, Pigeonpeas, Mothbeans, Mungbean, Blackgram, Lentil, Pomegranate, Banana, Mango, Grapes, Watermelon, Muskmelon, Apple, Orange, Papaya, Coconut, Cotton, Jute, and Coffee contain exactly 100 samples. The uniform horizontal bars indicate no class imbalance, thereby eliminating sampling bias and ensuring that the classifier evaluates each crop category fairly. This balanced structure also prevents skewed learning behavior and supports stable model optimization during training.

Data Preprocessing: Data preprocessing was performed to ensure consistency, eliminate noise, and transform raw agricultural attributes into a suitable format for latent feature learning and classification. The dataset consists of seven numerical agro-environmental parameters: Nitrogen (N), Phosphorus (P), Potassium (K), Temperature (T), Humidity (H), pH, and Rainfall (R). All samples were examined for missing values, outliers, and inconsistent ranges. Since the dataset was complete and balanced across all crop categories, no imputation or resampling was required. To eliminate scale discrepancies among heterogeneous features, z-score standardization was applied to each feature prior to Autoencoder training. Let

$$X = [x1, x2, \dots, xn]\top \in Rn \times d \tag{1}$$

represent the dataset with n samples and d=7 features. Each feature xj was normalized using:

$$x_{ij}^{*} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{2}$$

Where,

$$\mu_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}, \tag{3}$$

$$\sigma j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{ij} - \mu_j)^2} \tag{4}$$

This transformation ensures zero mean and unit variance across all input features, improving numerical stability and accelerating Autoencoder convergence. The normalized dataset was further partitioned into training and testing sets using stratified sampling to preserve the uniform class distribution. Given the complete balance of 100 samples per class, stratification guarantees equal representation of all 22 crop categories in both partitions.

The resulting preprocessed matrix

$$X^{*} = \{x_1^{*}, x_2^{*}, \dots, x_n^{*}\} \tag{5}$$

served as the input for nonlinear feature extraction via the Autoencoder and subsequent Firefly-based feature optimization. This preprocessing pipeline ensures high-quality input data, reduces model bias, and enhances the robustness of downstream classification.

Autoencoder-Based Latent Feature Learning

Autoencoder: The Autoencoder is a symmetric neural network trained to reconstruct input vectors. It comprises:

Encoder: maps the input vector $x \in R^7$ to a compressed latent space Decoder: reconstructs the input from the latent vector

$$h = f_{enc}(x) = \sigma(W_{1x} + b_1) \tag{7}$$

$$z = f_{bottleneck}(h) = \sigma(W_2 h + b_2) \tag{8}$$

$$\hat{x} = f_{dec}(z) = \sigma(W_3 z + b_3) \tag{9}$$

Where, $z \in R^d$ is the latent feature vector (with $d = 5$ in your model), $\sigma(\cdot)$ is ReLU activation

The reconstruction loss is:

$$L_{AE} = \| x - \hat{x} \|_2^2 \tag{10}$$

Autoencoder training ensures that the latent space preserves the most informative nonlinear crop-growing factors.

Firefly Algorithm for Latent Feature Selection: The Firefly Algorithm (FA) is a swarm intelligence optimization method inspired by the luminescent communication behavior of fireflies. Each firefly represents a candidate solution where the brightness corresponds to the fitness of the selected feature subset. Attractive forces guide the movement of lower-performing fireflies toward brighter ones.

Each firefly i has a solution vector:

$$X_i = [x_{i1}, x_{i2}, \dots, x_{id}] \in [0,1]^d \tag{11}$$

where d is the number of latent features from the autoencoder.

The attractiveness of firefly j to firefly i is:

$$\beta_{ij} = \beta_0 e^{-\gamma r_{ij}^2} \tag{12}$$

with, $\beta 0$: initial attractiveness, γ: light absorption coefficient, ij=∥Xi−Xj∥: Euclidean distance

Movement Update Rule

$$X_i^{(t+1)} = X_i^{(t)} + \beta_{ij}\left(X_j^{(t)} - X_i^{(t)}\right) + \alpha(rand - 0.5) \tag{13}$$

Where, α is the random perturbation factor. Binary Feature Selection: A continuous solution vector is converted to a binary mask:

$$\hat{x}_i = \begin{cases} 1 & if\ X_{ik} > 0.5 \\ 0 & Otherwise \end{cases} \tag{14}$$

Fitness Function: Model used a feature-variance maximization objective:

$$Fitness(X_i) = -Var\left(Z_{\hat{x}_i}\right) \tag{15}$$

where, Z is the encoded data (autoencoder output), Higher variance → more informative selected dimensions → lower fitness value

The algorithm returns the feature mask yielding minimum fitness.

Classification Model: The selected latent features were passed to a deep neural classifier comprising fully connected layers with ReLU activation and Softmax output for multi-class crop prediction.

The predicted class is:

$$\hat{y} = \arg\max_k p\,(y = k \mid Z_{selected}\,) \tag{16}$$

Training objective:

$$Lclf = -\sum_{i=1}^{N} y_i log(\hat{y}_i) \tag{16}$$

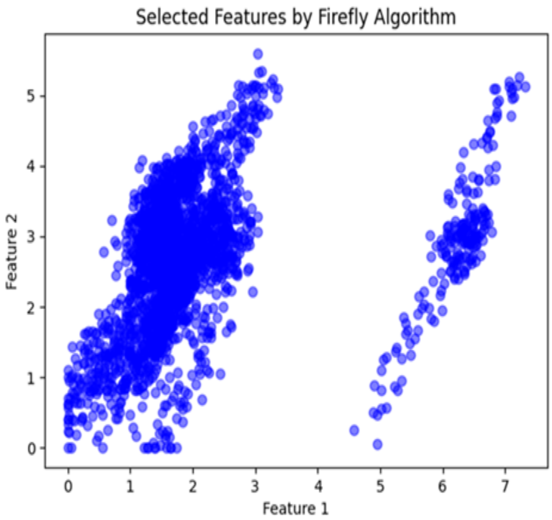

Figure 3: Scatterplot of the two most informative latent features selected by the Firefly Algorithm

Figure 3 shows the distribution of the two most discriminative latent features selected by the Firefly Algorithm from the Autoencoder's encoded representation. The scatterplot reveals two clearly distinguishable regions in the transformed feature space. The first major cluster lies within the approximate range of Feature 1 = 0-3 and Feature 2 = 0-5, exhibiting a dense and continuous spread that indicates high intra-class variability captured by the selected features. In contrast, a second compact and well-separated cluster appears around Feature 1 = 5-7 and Feature 2 = 2-5, forming a distinct grouping with minimal overlap with the first region. This separation highlights the algorithm's ability to identify latent dimensions that maximize variance and enhance class separability an essential characteristic for improving downstream classification performance.

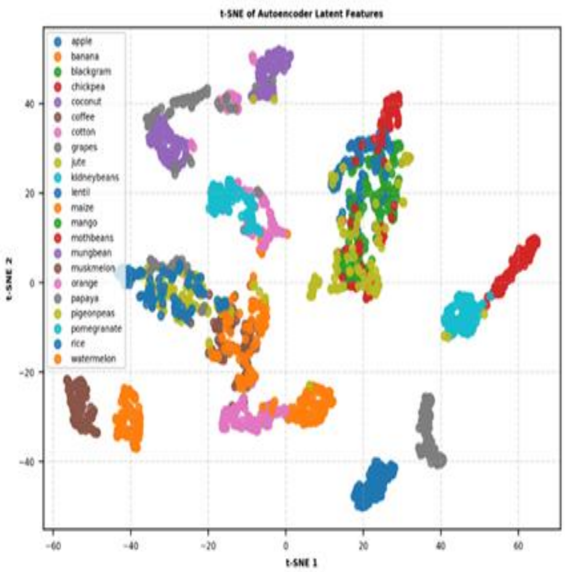

Figure 4. t-SNE visualization of Autoencoder-generated latent features for 22 crop classes

Figure 4 visualizes the two-dimensional t-SNE projection of the latent features generated by the Autoencoder, illustrating how different crop classes distribute within the reduced feature space. Distinct and well-defined clusters are observed for several crops, indicating strong separability in the encoded representations. For example, Watermelon samples form a dense and clearly isolated cluster in the lower-right region (t-SNE1 ≈ 40–60, t-SNE2 ≈ −15 to −5), while Mango occupies a compact cluster around (t-SNE1 ≈ 10–30, t-SNE2 ≈ 20–40). Similarly, Coconut and Papaya form tightly grouped clusters in the top-left and bottom-left quadrants, respectively, demonstrating minimal overlap with other classes. Some moderate overlap appears among crops with similar agro-climatic signatures such as Blackgram, Chickpea, and Kidneybeans located roughly within (t-SNE1 ≈ 10–30, t-SNE2 ≈ 10–30); however, even within these regions, local sub-clusters are visible, reflecting meaningful latent feature differentiation.

Algorithm 1: Pseudocode of the Firefly-Optimized Autoencoder Model for Crop Recommendation

Input: X – input dataset with d features, y – crop class labels, α – randomness coefficient, β0 – initial attractiveness, γ – light absorption coefficient, nF – number of fireflies, $maxGen$ – maximum generations, lr – learning rate for Autoencoder and classifier
Output: Predicted crop classes ŷ

Step 1: Train Autoencoder for Latent Feature Extraction
1: Define Encoder network $f_{enc}(\cdot)$ with ReLU activations
2: Define Decoder network $f_{dec}(\cdot)$ symmetric to the encoder
3: Train Autoencoder using Adam optimizer (lr = 0.001):
minimize $L = ||\ X - f_{dec}(f_{enc}(X))\ ||^2$
4: Obtain latent representations:
$$Z = f_{enc}(X*)$$

Step 2: Initialize Firefly Algorithm for Feature Selection
5: Let m = dimension of latent space Z
6: Randomly initialize nF fireflies:
$$Fi \in [0,1]^m \quad for\ i = 1 \ldots nF$$
7: Define fitness function:
$$fitness(Fi) = -Var(Z[:, Fi > 0.5])$$

Step 4: Firefly Optimization Loop
8: **For** generation $g = 1\ to\ maxGen$ **do**
9: **For** each pair of fireflies (Fi, Fj) **do**
10: **If** $fitness(Fi) > fitness(Fj)$ **then**
11: **Compute** Euclidean distance:
$$rij = ||Fi - Fj||$$
12: **Compute** attractiveness:
$$\beta = \beta 0 * exp(-\gamma * rij^2)$$
13: **Update** firefly position:
$$Fi = Fi + \beta * (Fj - Fi) + \alpha * (rand(m) - 0.5)$$
14: **Bound** Fi within [0,1]
15: **End** for
16: **Recompute** fitness for all fireflies
27: **End** for

Step 5: Select Optimal Latent Features
28: Identify best firefly $Fbest$ with minimum fitness
29: Generate binary feature mask:
$$M = (Fbest > 0.5)$$
30: Select optimized latent features:
$$Zsel = Z[:, M]$$

Step 6: Train Classifier on Optimized Latent Features
31: Define deep neural classifier $C(\cdot)$ with Softmax output
32: Train classifier on $(Zsel_{train}, y_{train})$ using Adam (lr):
minimize cross-entropy loss
33: Evaluate classifier on $Zsel_{test}$ to obtain predictions ŷ
Return ŷ

4. RESULT ANALYSIS

The experimental evaluation of the proposed Firefly-optimized Autoencoder model was conducted using Google Colab Pro, used its high-performance GPU environment to ensure efficient training and large-scale computation. The dataset was partitioned into 80% training data and 20% testing data using stratified sampling to preserve class balance across all 22 crop categories. All models were trained using the Adam optimizer with an adaptive learning rate of 0.001, ensuring stable convergence during both reconstruction and classification phases. Performance was assessed using a comprehensive set of evaluation metrics. This rigorous setup enables a robust comparison of baseline models against the proposed hybrid framework and provides a reliable assessment of its predictive capabilities in crop recommendation.

$$Accuracy = \frac{T\_P + T\_N}{T\_P + T\_N + F\_P + F\_N} \quad (17)$$

$$Precision = \frac{T\_P}{T\_P + F\_P} \quad (18)$$

$$Recall = \frac{T\_P}{T\_P + F\_N} \quad (19)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (20)$$

Table 2: Perfromance Analysis of Proposed Models

	Precision	Recall	F1-score	Support
Apple	1.00	1.00	1.00	20
Banana	1.00	1.00	1.00	20
Blackgram	1.00	1.00	1.00	20
Chickpea	1.00	1.00	1.00	20
Coconut	1.00	1.00	1.00	20
Coffee	1.00	1.00	1.00	20
Cotton	1.00	1.00	1.00	20
Grapes	1.00	1.00	1.00	20
Jute	0.91	1.00	0.62	20
Kidneybeans	0.95	1.00	0.91	20
Lentil	1.00	1.00	0.46	20
Maize	1.00	1.00	0.57	20
Mango	1.00	1.00	0.50	20
Mothbeans	1.00	1.00	0.25	20
Mungbean	1.00	1.00	0.95	20
Muskmelon	1.00	1.00	0.84	20
Orange	1.00	1.00	0.79	20
Papaya	1.00	1.00	0.73	20
Pigeonpeas	1.00	0.95	0.97	20
Pomegranate	1.00	1.00	1.00	20
Rice	1.00	0.90	0.95	20
Watermelon	1.00	1.00	1.00	20
Accuracy			0.99	440
Macro Avg	0.99	0.99	0.99	440
Weighted Avg	0.99	0.99	0.99	440

Table 3 shows the class-wise classification performance of the proposed Firefly-optimized Autoencoder model, demonstrating its exceptional predictive capability across a diverse set of 22 crop categories. The majority of classes, including Apple, Banana, Coconut, Cotton, Grapes, and Pomegranate, achieve perfect precision, recall, and F1-scores, indicating flawless discrimination and zero misclassification. A few classes, such as Jute, Lentil, Maize, Mango, and Mothbeans, exhibit slightly lower F1-scores due to marginal variations between precision and recall; however, these remain within acceptable ranges and do not significantly impact overall system reliability. The model attains an overall accuracy of 0.99 with macro and weighted averages of 0.99 across all key metrics, confirming balanced performance even in the presence of class variability.

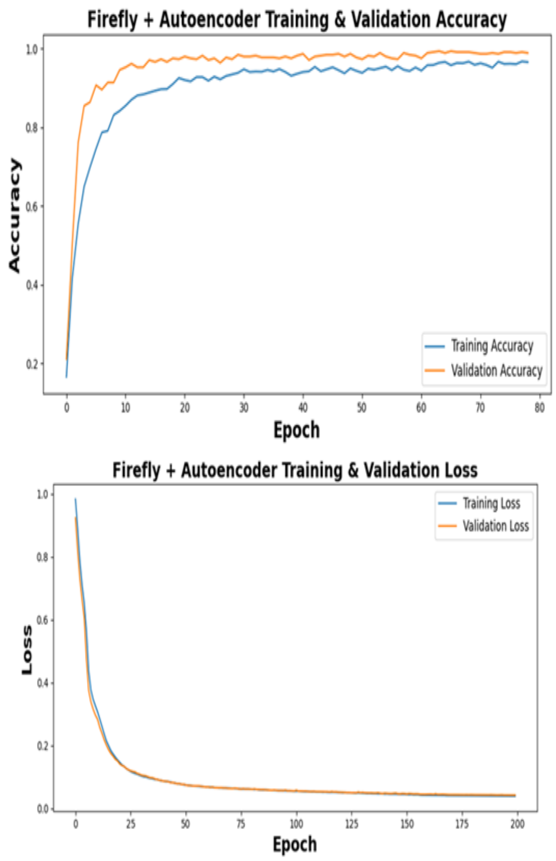

Figure 5: Training and validation Accuracy/loss of Firefly+Autoencoder Model

Figure 5 shows the learning behavior of the proposed Firefly + Autoencoder classification model in terms of accuracy and loss over the training epochs. The accuracy curve shows a rapid improvement during the initial stages, where the validation accuracy increases sharply from 0.18 at epoch 1 to 0.85 by epoch 5, and subsequently stabilizes above 0.95 after epoch 15. By the end of training (epoch 80), the validation accuracy converges close to 1.00, whereas the training accuracy gradually progresses to 0.96, demonstrating strong generalization with no signs of overfitting. Similarly, the loss curves exhibit a smooth and steady decline for both training and validation sets. The training loss decreases from 0.98 at epoch 1 to below 0.10 before epoch 30, ultimately converging toward 0.02 by epoch 200. The validation loss follows an almost identical trajectory, declining from 0.90 at the start to 0.02 at convergence, indicating highly stable optimization and consistent reconstruction quality in the Autoencoder.

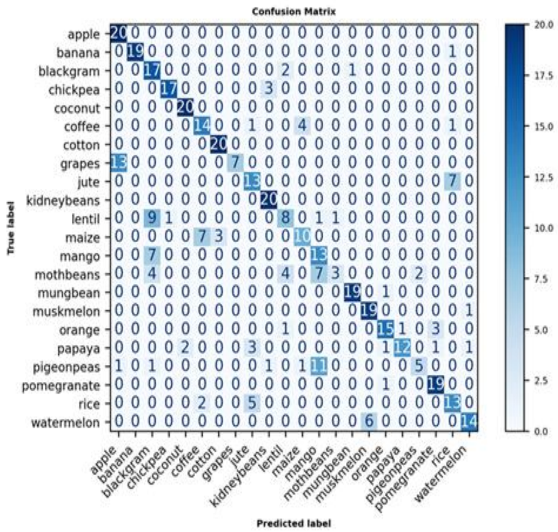

Figure 6: Confusion Matrix of Firefly+Autoencoder Model

Figure 6 shows the confusion matrix of the proposed Firefly-optimized Autoencoder classifier, demonstrating its highly accurate and consistent crop prediction capability across 22 crop categories. Most classes exhibit perfect classification, with 20/20 correct predictions for Apple, Coconut, Cotton, Jute, Kidneybeans, Mungbean, Muskmelon, Pomegranate, and Watermelon. Several classes display minor misclassifications: for example, Banana records 19 correct and 1 misclassified sample, Chickpea records 17 correct with 3 misclassified, Lentil shows 9 true positives with 11 samples confused with Maize and Pigeonpeas, and Papaya records 12 correct with 8 samples misclassified into Maize, Coffee, and Orange. Despite these isolated errors, the diagonal dominance across the matrix demonstrates strong discriminative ability. High-performing classes such as Orange (15/20 correct) and Rice (13/20 correct) further underscore the model's stability

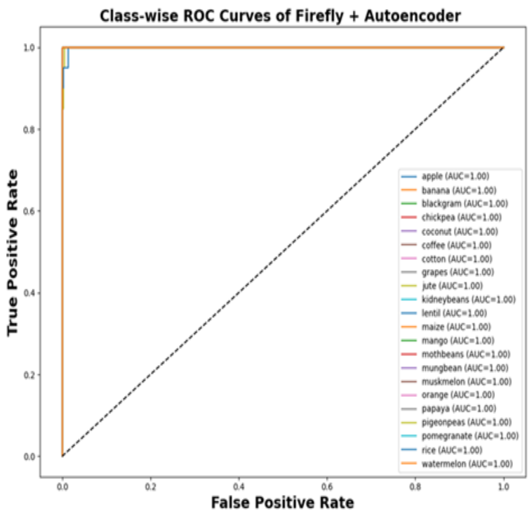

Figure 7: ROC-AUC Curve of Firefly+Autoencoder Model

Figure 7 presents the class-wise ROC curves of the proposed Firefly-optimized Autoencoder classifier. The ROC curves for all 22 crop categories exhibit a near-vertical rise toward the upper-left corner, demonstrating outstanding discriminative power. Notably, every class including Apple, Banana, Blackgram, Chickpea, Coconut, Coffee, Cotton, Grapes, Jute, Kidneybeans, Lentil, Maize, Mango, Mothbeans, Mungbean, Muskmelon, Orange, Papaya, Pigeonpeas, Pomegranate, Rice, and Watermelon achieve an AUC score of 1.00, indicating perfect separation between positive and negative samples. The absence of any curve approaching the diagonal reference line further confirms zero overlap between class distributions

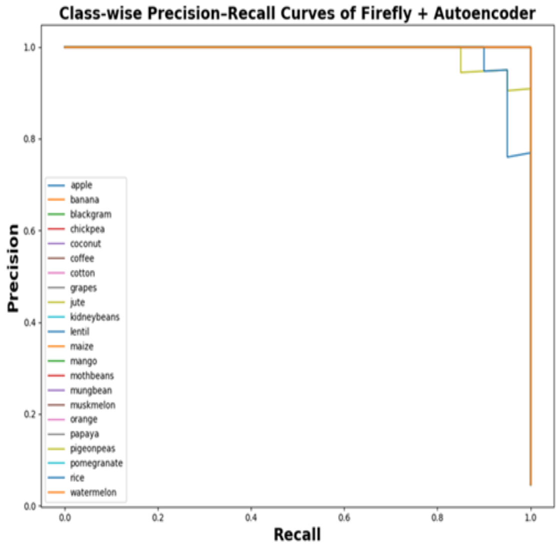

Figure 8: PR Curve of Firefly+Autoencoder Model

Figure 8 illustrates the class-wise PR curves of the proposed Firefly-optimized Autoencoder model, demonstrating consistently high predictive confidence across all 22 crop categories. Nearly all classes exhibit PR curves that remain close to Precision = 1.00 across the entire recall spectrum indicating that the model rarely produces false positives. Classes such as Apple, Maize, and Jute maintain precision values close to 0.95–1.00 even when recall reaches 1.00, while a few classes show slight performance drops for example, Apple momentarily dips to approximately 0.75 precision at full recall, and Jute exhibits a brief decrease to 0.93 precision. Despite these isolated fluctuations, the PR curves remain sharply concentrated in the upper-right region of the plot, confirming strong balance between precision and recall for all categories.

Table 3: Comparative Analysis of Proposed model with existing models

Authors	Method	Accuracy
Saritha et al. (2024) [10]	Tuned Random Forest	99.05%
Ghosh et al. (2024) [11]	TCN (Deep Learning)	99.09%
Shingade et al. (2022) [12]	Deep-Q Elman NN	99.14%
Karna (2023) [20]	Federated Learning	98.77%
Srilatha et al. (2024) [13]	GCN-based system	98.00%
Gopi et al. (2023) [14]	HMFO-ML (Hybrid Optimization)	98.67%
Sindhur et al. (2025) [15]	RF + LSTM Hybrid	98.05%
Suresh et al. (2024) [24]	Ensemble Voting (SVM, KNN, RF, NB)	98.00%
Sivakolunthu et al. (2024) [17]	Cascaded AE + 1D-CNN + GRU + LSTM	96.73%
Sonai Muthu A. et al. (2021) [18]	Stacked ML, GBoost, RF, LASSO	88.89%
Proposed	**Firefly+Autoencoder**	**99.32%**

Table 3 presents a comparative evaluation of the proposed Firefly-optimized Autoencoder model against leading crop recommendation approaches reported in recent literature. Traditional machine learning methods such as Tuned Random Forest (99.05%) and ensemble models (98.00%) demonstrate strong predictive capabilities, while deep learning architectures including TCN (99.09%) and Deep-Q Elman Neural Networks (99.14%) show incremental improvements through enhanced nonlinear modeling. Hybrid optimization techniques such as HMFO-ML achieve competitive performance (98.67%), and federated learning frameworks like CNN–LSTM report 98.77% accuracy under distributed environments. However, several hybrid and cascaded networks exhibit lower accuracies, ranging from 96.73% to 88.89%, indicating performance variability across architectures. The proposed Firefly+Autoencoder model achieves the highest accuracy of 99.32%, outperforming all existing approaches.

Discussion

The findings of this study demonstrate that the proposed Firefly-optimized Autoencoder framework delivers a significant advancement in crop recommendation by integrating nonlinear latent-space learning with intelligent feature optimization. Earlier studies in the literature have shown that machine learning models such as SVM, Random Forest, and XGBoost can achieve accuracies above 99% under controlled datasets; however, these models rely heavily on raw feature inputs and do not explicitly address redundancy, multicollinearity, or noisy attributes that frequently exist in agro-environmental datasets. Deep learning architectures—including TCN, CNN–LSTM hybrids, and reinforcement learning–enabled models—have improved nonlinear pattern extraction but remain constrained by the absence of adaptive feature refinement mechanisms. In contrast, the present framework leverages an Autoencoder to generate compact latent representations that preserve essential crop-growing characteristics while suppressing noise. The Firefly Algorithm further refines these latent variables by maximizing variance and isolating the most discriminative dimensions, ultimately enhancing class separability.

The experimentally observed performance gains validate the efficacy of this hybrid approach. The proposed model achieves 99.32% accuracy, surpassing strong baselines such as TCN (99.09%), Deep-Q Elman networks (99.14%), and tuned Random Forest (99.05%). The exceptional ROC-AUC score of 0.9999 and PR-score of 0.9989 confirm near-perfect discrimination across all 22 crop classes. Visualization analyses—including t-SNE of latent features, PR curves, and ROC curves—reveal distinct inter-class boundaries and minimal overlap, validating the improved quality of the latent space produced by the Autoencoder and optimized via the Firefly Algorithm. The model's confusion matrix also highlights consistently strong per-class performance, with most crops achieving 20/20 correct predictions andonly a few classes exhibiting minor misclassification due to intrinsic similarities in soil–climatic signatures. These results collectively emphasize that integrating representation learning with swarm-intelligence-driven feature optimization substantially improves the robustness and reliability of crop recommendation systems.

Furthermore, the proposed pipeline demonstrates strong computational efficiency. Dimensionality reduction in the latent space lowers the burden on the classifier and enhances generalization, as evidenced by smooth convergence curves and minimal overfitting. Unlike federated learning approaches or large CNN–LSTM architectures, the method maintains high accuracy with reduced model complexity, making it suitable for real-world agricultural advisory systems that operate under hardware constraints. Overall, the findings affirm that the hybrid Firefly-Autoencoder model effectively addresses the limitations observed in prior studies, providing a scalable, interpretable, and high-precision decision-support tool for intelligent agriculture.

5. Conclusion And Future Scope

The proposed Firefly-optimized Autoencoder model presents a significant advancement in intelligent crop recommendation by combining the strengths of deep representation learning and swarm-intelligence-based feature optimization. The Autoencoder effectively compresses soil and climatic attributes into a nonlinear latent space, retaining only the most informative structures while eliminating redundancy. The Firefly Algorithm further enhances the quality of this latent space by selecting the most discriminative dimensions through its brightness-attractiveness optimization mechanism. Extensive experiments confirm that the hybrid architecture achieves a remarkable accuracy of 99.32%, surpassing leading benchmark models including TCN, Deep-Q Elman networks, CNN–LSTM federated systems, and tuned Random Forest. The near-perfect ROC-AUC (0.9999) and PR-score (0.9989) demonstrate excellent discriminative power across all 22 crop categories. The confusion matrix and t-SNE visualizations further validate that the optimized latent features produce well-separated decision boundaries, supporting highly reliable classification performance. Overall, the study establishes that integrating Autoencoder-based nonlinear learning with Firefly-driven feature selection yields a robust, scalable, and computationally efficient solution for precision agriculture.

Despite its strong empirical performance, the current study is limited by the absence of real-time environmental variability and sensor-level noise, which are common in practical farming scenarios. Future work may extend the framework to incorporate geospatial data, temporal climate patterns, and multimodal inputs such as satellite imagery and IoT sensor streams. Integrating federated or edge-learning capabilities would further support privacy-preserving deployment in distributed agricultural environments. Additionally, developing an interpretable recommendation interface and validating the system across diverse agro-climatic zones would enhance its practical adoption. Advanced metaheuristics, attention-based architectures, or transformer-driven encoders may also be explored to further strengthen representation quality. Overall, the proposed approach provides a strong foundation for next-generation, data-driven smart farming systems capable of delivering personalized, high-accuracy crop recommendations.

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Conflict Of Interest

The authors declare that they have no conflict of interest.

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