RESEARCH ARTICLE

Asian Research Association

INTERNATIONAL RESEARCH JOURNAL OF
MULTIDISCIPLINARY TECHNOVATION

DOI: 10.54392/irjmt26324

Enhanced Crop Prediction using Adaptive Mutation Swarm Optimized Multilayer Perceptron: A Data-Driven Approach to Maximizing Agricultural Productivity

P. Glaret Subin [a], **Sanjay Kumar** [a, *]

[a] Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, Vadapalani Campus, Chennai, 600026, India

* Corresponding Author Email: sanjayk2@srmist.edu.in

DOI: https://doi.org/10.54392/irjmt26324

Received: 26-09-2025; Revised: 04-04-2026; Accepted: 14-05-2026; Published: 30-05-2026

Abstract: Yield prediction and crop recommendations require precise methodology to increase efficiency of land, agriculture production, and usage of sustainable methods. Current statistical or machine learning methods are inadequate when attempting to model nonlinear associations among climatic environment, soil conditions and suitability of a crop for that particular area. An Adaptive Mutation Swarm Optimization Based Multilayer Perceptron (AMSO-MLP) was developed to produce intelligent crop recommendations according to varying soils and environments. This new algorithm combines particle swarm optimization (PSO) with an adaptive mutation approach through optimization of the multilayer perceptron's (MLPs') weights and biases through PSO. As a result of this approach, convergence and prediction are increased in both accuracy and speed, while preventing premature convergence due to local optima. The AMSO-MLP model uses key agricultural components such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, precipitation, and soil pH to identify the best crop that can be grown in these conditions. A benchmark data set containing agricultural features and was analyzed for accuracy through a 10-fold cross-validation analysis to demonstrate the effectiveness and strength of the results. Performance metrics included Precision, Recall, F1-Score, RMSE, MAE, and coefficient of determination (R2). The results demonstrate that the AMSO-MLP model is superior to existing neural network-based optimization approaches. The model achieved Precision of 0.989, Recall of 0.987, F1-score of 0.987, RMSE of 0.210, MAE of 0.125, and R^2 of 0.964, indicating high predictive accuracy and stability. These findings highlight the effectiveness of the proposed hybrid optimization framework for data-driven crop recommendation and precision agriculture, providing a reliable decision-support tool for sustainable agricultural management.

Keywords: Crop Prediction, Adaptive Mutation, MLP, PSO, AMSO-MLP

1. Introduction

Many factors influence crop yield including type of crop, soil quality, method of irrigation, the addition of fertilizer, sunlight, disease, and pests. Each of these factors play an essential part in the crop-growth process thus leading to complexity of yield prediction. However, yield estimates may be a crucial step towards the enhancement of crop traits and improvement of breeding strategies. Accurate estimates of both current crop yields and future crop yields is a necessity for reliable production [1]. Machine learning is an important tool that provides support for the decision making process in predicting crop yield. Machine learning assists decision making in regard to what crops to grow and what management practices to use when growing the crops. Many machine learning techniques have been utilized for agricultural yield prediction [2]. This study will investigate the possibility of an impact of the utilization of machine learning algorithms in modern farming practices. The intended use of these algorithms that recommend planting in agriculture is to increase crop yield and to decrease waste. To optimize crop farming, machine learning algorithms can rely on extensive agricultural datasets (climate, soil, crop growth stage, pests and diseases, etc.). Machine learning can provide farmers with accurate predictions of crop growth, yield, and quality based on historical data store [3]. To allow farmers to choose and grow the crop that provides the best opportunity of maximum profits, farmers must also have a level of understanding of the cultivation associated environmental factors and market factors. The model will also be able to analyze past market data, coupled with the environmental conditions, to predict future crop demand and better recommend dates and locations to plant [4]. Machine learning algorithms that evaluate the color, texture, and shape of fruits and vegetables are able to classify the ripeness and quality of these products. Using this information during the harvesting process can improve the harvesting technique and deliver only the best quality products to consumers [5].

While machine learning in agriculture is not without challenges, such as access to quality data, the generally high cost of sensors and other technologies, and the requirement of having specialists on each of the technologies to develop and utilize different solutions, the advantages of machine learning in agricultural production will become better defined. It is important to recognize, we are still early in the process of using machine learning in agriculture; our understanding of the educational and occupational opportunities that machine learning can provide will entail further investigation into the full extent of machine learning in agriculture. The initial results are encouraging, and it is likely that machine learning will take on a larger role in the upcoming future [6]. In the sectors of agro-environmental management and food security, being able to timely and accurately map crops and predict yield is extremely important. Remote Sensing (RS) data provides relative advantages over other sources of data to map crops and predict yield prior to harvest, due to its extensive coverage, rich spectral and spatial data, and potential for continuous collection and observation. While it can take time to gather a temporal record of the data, there are ways to advance the processing of data and deliver the information back to the practitioner. Machine-learning algorithms, particularly deep learning (DL) models, have demonstrated outstanding potential for understanding complex relationships between variables by automatically learning the complex features necessary for transplanting into intelligent crop mapping data and yield predictions. The application of DL algorithms in a range of RS models has resulted in extensive research; compared to other practices, the advantage of DL in crop surveillance and mapping is increasing [7].

In general, using machine learning algorithms to gather and analyze quality information is valuable. Collecting data is crucial for achieving precise outcomes and generating reliable forecasts, both in terms of quantity and quality. Big data typically consist of size, speed, and other attributes. Due to their vastness, the data can produce thorough results and helps to reduce unpredictability. Furthermore, data from large-scale analyses ought to be better organized. A higher success rate in analysis can be attained by leveraging multiple datasets from different origins. Adequate data sources encompass a diverse array of inputs, such as sensors, social media platforms, digital networks, physical devices, the stock market, and healthcare institutions. Direct access pathways, online gathering, and APIs are available ways to obtain this data. Static datasets and stream data are the two types of data that exist. The data processing activities combine data from several platforms. Utilizing these gathered data for analysis increases the importance of preprocessing and data cleaning when applying machine learning algorithms. Large volumes of data from IoT sensors and other sources can be analyzed by machine learning algorithms. It's a fast-expanding field that could revolutionize how we forecast and evaluate crop productivity. Machine learning algorithms allow computers to learn from experience without being explicitly programmed. The algorithms involve using math and statistics to analyze data, and make predictions about future events [8]. Deep Learning Multi-Layer Perceptron’s (DLMLP) are powerful tools for crop yield forecasting. For crop yield prediction, using remote sensing imagery, vegetation index produced from optical sensors provide early indication of crop yield. Additionally, developing strong, machine learning based crop yield forecasting models using soil health data measurement of soil quality will provide valuable results [9].

Despite the limited amount of research on machine learning and deep learning applications in agriculture and the increasing use of these methods, there are a number of constraints that have affected the current research. Most research using these methods has experienced premature convergence, failure to adequately optimize the weights of the neural networks and no or only limited ability of the optimization algorithms being used to adequately explore the possibility of multiple optimized solutions. Conventional techniques of training multi-layered perceptron (MLP) models can fail to find the optimum global minimum or can become trapped in local minima when working with complicated agricultural data sets containing nonlinear and heterogeneous characteristics. To improve upon this use of PSO, standard PSO inherently can still become stagnant and lack diversity in later phases of the search process. In response to this current limitation, this study has developed an Adaptive Mutation Swarm Optimization-based (AMSO) model employing the multi-layered perceptron (MLP) technique for predicting crops using soil and environmental factors. The unique method combines particle swarm optimization with a fitness-based adaptive mutation method in such a way that will allow for better versatility and will minimize the risk of premature closing of the optimum MLP weights through enhanced exploration as free of convergence. With respect to the model, the employment of the adaptive mutation strategy involves dynamically changing the intensity of the mutation based upon both the fitness of the individual particles and the diversity of the whole particle group enabling enhanced search capability throughout the entire solution space while improving crop prediction capabilities significantly. This Paper has the following Major Contributions:

1. A Hybrid Model of Adaptive Mutation Swarm Optimization (AMSO) and Multi-Layer Perception (MLP), which integrates MLP

learning together with Adaptive Mutation Swarm Optimization, to improve plant/crop prediction.

2. A Fitness-Based Adaptive Mutation Strategy which improves upon the Exploration process Capability of a Conventional PSO when training a neural network.
3. The Proposed AMSO-MLP Model was Developed, implemented and Tested using Historical Agricultural Data sets that contained Soil Nutrients and Environmental Conditions, in order to predict what the most suitable Outcome of a Crop will be.

The results presented in this paper serve to illustrate the Effectiveness of the Proposed Optimization Framework through Extensive Experimental Validation, by Comparing to the results of State-of-the Art Machine Learning Models, Applied to the same Data sets. The Paper is further organized as follows: Section 2 Contains a Review of the Literature in Crop Prediction Machine Learning Techniques in Agriculture. Section 3 contains a Description of the Proposed AMSO-MLP and Experimental Setup. Section 4 provides a Discussion of Results and Performance Evaluation, and Section 5 summarizes the Findings from this Study and Future directions for Research on this Topic.

2. Related Works

For many years crop yield forecasting has been the subject of a number of different studies, all of which employ various methodologies based upon historical and environmental variables. Yield forecasting models have typically evolved from statistical analysis looking at historical yield archetype data and examining the relationship of simple variables. Agricultural systems are very complex so many of the models developed so far do not adequately represent the levels of complexity associated with the relationships between multiple variables related to crop management practices, and also climate variables, and the physical condition of the soil.

In order to illustrate how previous studies relate, Table 1 presents an overview of selected studies involving the prediction of corn yield, including an overview of their methodology, data sets, contributions, and limitations. The overall comparison indicates that existing approaches are primarily based on conventional machine-aided learning (MAL) and therefore necessitates that we develop an optimized version of the MAL model.

Table 1. Comparison of Existing Crop Yield Prediction Studies

S.No	Author / Year	Method / Model Used	Data Source / Features	Key Contribution	Limitations
1	Shilpa *et al.,* 2024 [10]	IoT + Machine Learning	Soil moisture, temperature sensors	Real-time irrigation control and yield prediction	Requires expensive sensor infrastructure
2	Liu *et al.,* 2013 [11]	Parallel Genetic Algorithm	Land-use and agricultural planning data	Optimized large-scale land resource allocation	Focused on land optimization rather than yield prediction
3	Deepak, 2023 [12]	IoT + Machine Learning Models	Environmental sensor data	Improved winter crop yield prediction in local farming systems	Limited geographical scope
4	Kuradusenge *et al.,* 2023 [13]	Random Forest, Decision Tree	Meteorological and soil health data	Demonstrated superior performance over traditional statistical methods	Computational complexity for large datasets
5	Elbasi *et al.,* 2023 [14]	Multiple ML Algorithms	Historical crop and environmental data	Improved prediction accuracy using ML models	Model performance depends heavily on dataset quality
6	Agarwal & Tarar, 2021 [15]	Hybrid ML + Deep Learning	Agricultural production datasets	Increased prediction accuracy compared with traditional models	High computational cost

7	Maldonado *et al.*, 2020 [16]	ML + Biological agents	Soil microbial and agricultural data	Integration of biological agents with ML for productivity improvement	Limited scalability
8	Chaudhari, 2024 [17]	IoT + ML Framework	Multi-source agricultural data	Smart crop prediction system using real-time data	Data integration challenges
9	Hara *et al.,* 2021 [18]	Artificial Neural Network (ANN)	Remote sensing + environmental data	Modeled complex relationships between environmental factors and yield	Training complexity and parameter tuning required
10	Ndegwa *et al.,* 2023 [19]	Integration of Soil Fertility and Water Management	Soil fertility parameters and irrigation practices	Improved crop yield through integrated soil and water resource management	Requires continuous monitoring of soil and water parameters
10	Shah *et al.,* 2024 [20]	Review of Machine Learning Techniques	Environmental and agricultural datasets	Comprehensive review of ML algorithms for crop yield prediction and agricultural decision-making	Mainly theoretical review; no new predictive model proposed
11	Anbananthen *et al.*, 2021 [21]	Hybrid Decision Support System	Multiple agricultural datasets	Integrated several ML models to improve prediction accuracy across datasets	Increased model complexity and integration challenges
12	Provenzano & Sinobas, 2014 [22]	Technological and Management Approaches	Irrigated agricultural systems	Highlighted the role of innovative technologies and adaptive management practices for sustainable irrigation	Lacks implementation of predictive ML models
13	Saranya *et al.,* [23]	MapReduce Framework + Rocchio Classification	Large agricultural datasets in Farmer Managed Irrigation Systems (FMIS)	Distributed framework for processing large-scale agricultural data efficiently	Primarily focused on data management rather than prediction accuracy
14	Fegade & Pawar, 2020 [24]	Support Vector Machine (SVM) and Artificial Neural Network (ANN)	Agricultural yield datasets	Demonstrated improved prediction performance compared to traditional statistical models	High computational complexity
15	Jannat *et al.*, 2023 [25]	Lightweight Convolutional Neural Network (CNN)	Crop leaf disease image datasets	Efficient disease detection model that indirectly supports yield improvement	Focused on plant health monitoring rather than direct yield prediction

16	Suresh *et al.*, 2021 [26]	Random Forest Algorithm	Environmental and climatic variables	Effectively captured nonlinear relationships between environmental factors and crop yields	Scalability issues with very large datasets
17	Saha & Bauddh, 2020 [27]	Ecological Methods + Machine Learning	Soil health and environmental data	Integrated ecological approaches with ML to maintain soil health while predicting yield	Requires extensive environmental monitoring data
18	Ingole & Padole, 2024 [28]	IoT + Machine Learning	Smart irrigation and crop recommendation systems	Enabled precise irrigation management and improved agricultural efficiency	Dependence on IoT infrastructure
19	Ma *et al.*, 2024 [29]	Dynamic Bayesian Network	Crop water productivity and environmental data	Improved planting design and water productivity in arid regions	Requires large and high-quality datasets
20	Elsayed *et al.*, 2019 [30]	Machine Learning in Precision Agriculture	Drip irrigation and herbigation management	Demonstrated optimization of resource usage in precision agriculture	Application-specific limitations
21	Abdel-Salam *et al.* (2024) [31]	Hybrid Feature Selection + Optimized ML	Combines feature selection with ML optimization	Improves prediction accuracy through reduced dimensionality	Limited adaptability to dynamic environmental changes
22	Kalmani *et al.* (2025) [32]	CNN-LSTM with Attention & Skip Connection	Deep learning with temporal + spatial feature extraction	Captures complex patterns and dependencies effectively	High computational cost and requires large dataset
23	Patel *et al.* (2025) [33]	Optimized Deep Belief Network (DBN)	IoT-based data integration with optimization	Suitable for smart agriculture environments	May suffer from overfitting and complexity in training

3. Methodology

This section presents the proposed Adaptive Mutation Swarm Optimized Multilayer Perceptron (AMSO-MLP) model, the dataset utilized in this study, the architecture of the multilayer perceptron (MLP), and the amalgamation of Adaptive Mutation with Swarm.In order to ensure methodological reproducibility, all architectural and optimization parameters used in the AMSO-MLP framework are explicitly reported. Figure 1 illustrates the overall workflow of the proposed AMSO-MLP model. The aim of the model is to hybridize Adaptive Mutation methods within Particle Swarm Optimization (PSO) to optimize the weights and biases of a multilayer perceptron for crop recommendation under different soil conditions.

The first step of the process is to define and initialize a swarm of particles, where each particle represents a potential solution corresponding to a candidate set of weights and biases of the MLP. The swarm population size is set to 30 particles, and each particle encodes the full parameter vector of the MLP network. The MLP model consists of an input layer, three hidden layers, and an output layer. The hidden layers contain 64, 32, and 16 neurons respectively. Rectified Linear Unit (ReLU) activation functions are used in the hidden layers to improve learning efficiency, while the output layer uses a Softmax activation function to perform multi-class crop classification. During training, the soil features including nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, rainfall, and pH are provided as inputs to the network.

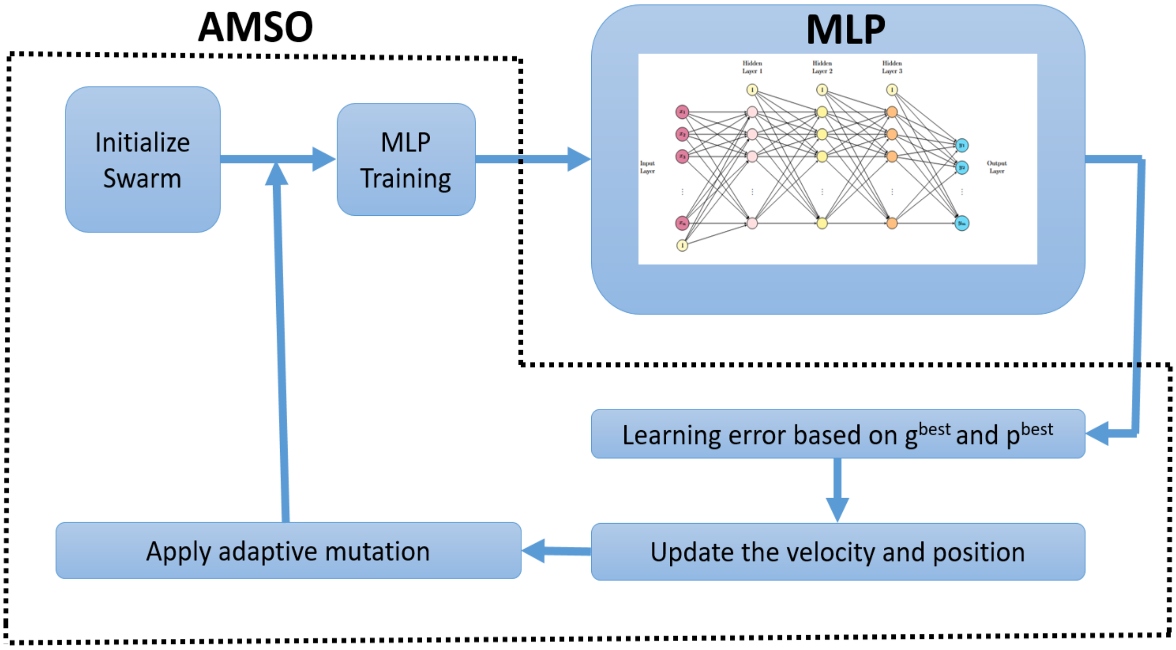

Figure 1. Workflow of the AMSO MLP model

The objective is to predict the most suitable crop label under the given environmental conditions. The model is trained using a batch size of 32 and a learning rate of 0.001. The training process runs for a maximum of 100 epochs, or until convergence is achieved when the validation loss improvement becomes less than 10^{-4} for five consecutive iterations.

For each particle, the MLP is evaluated using a fitness function based on the classification error rate, which reflects the prediction quality of the network. The mean prediction error is computed for every particle at each iteration while tracking the global best known position of the swarm (g^{Best}) and the best-known position of each individual particle (p^{Best}). The particles update their locations and speeds according to the customary PSO updating process. The definitions of the PSO parameters are the following - the inertia weight of the particles (ω) is 0.7, the cognitive coefficient (c_1) is 1.5, and the social coefficient (c_2) is 1.5. The maximum number of iterations of optimization is 100. These parameters help the swarm by balancing exploration and exploitation during the optimization process of the MLP parameters. To increase exploration capabilities and reduce the likelihood of the swarm reaching a local optimum prematurely, an adaptive mutation technique has been introduced into the PSO optimization process. Adaptive mutation provides controlled amounts of random perturbations to the positions of the particles in order for the swarm to be able to search unvisited areas of the search space. The bounds of the mutation are defined as $\mu_{min} = 0.01$ and $\mu_{max} = 0.1$ and the mutation will happen when the variance of the swarm fitness function is below a defined threshold of diversity $\sigma_f < 0.05$.

In this research, the primary goal is to make predictions based on crops and this is treated as a multi-class classification problem as each target variable is represented by a crop class label. Therefore, classification performance is evaluated through the use of classification metrics (precision, recall and F1 score). Additionally, regression metrics (RMSE, MAE, and R^2) are included to evaluate the difference between predicted crop class probability distributions and one-hot encoded ground-truth labels. Regression metrics provide an alternative measure of prediction error and model calibration. As a result, both classification and regression metrics are utilized to evaluate predictive accuracy and prediction error respectively for the AMSO-MLP model.

The AMSO-MLP approach aims to provide reliable and accurate crop recommendations through a combination of optimized weight, bias, and the capability of locating optimal solutions via particle swarm optimization, along with adaptive mutation to increase diversity; in this way the AMSO-MLP will generate solid and trustworthy crop recommendations based on different soil types.

3.1 Dataset Description

This research paper examines a publicly available dataset from Kaggle called the Crop Recommendation Dataset, which has total 2200 samples of soils and environmental conditions collected through agricultural monitoring systems. Each sample includes seven independent variables: N, P, K, temperature, humidity, rainfall and ph. Each sample also has a crop recommendation label (the dependent variable). The crops represented in the dataset are rice, maize, chickpeas, kidney beans, pigeon peas, moth beans, mung beans, black grams, lentils, pomegranates, bananas, mangoes, grapes, watermelons, muskmelons, apples, oranges, papayas, coconuts, cotton, jute and coffee. To ensure that the data were accurate and reproducible, preprocessing was performed prior to model training. Initially, no records were found that had missing data. After that, the numerical features were normalized by converting them between 0 and 1 using Min-Max normalization, which makes it easier for neural networks to converge during training. The dataset's classes are balanced; each class contains about 100 samples. As a result, the dataset does not suffer from a significant class imbalance. However, to ensure fair evaluation, the dataset was randomly shuffled before splitting into training and testing subsets using an 80:20 ratio. The label is the target variable in this dataset, also known as the index, indicating which crop type is the most suitable for the given soil and environmental conditions. This dataset is widely used as a benchmark in agricultural predictive modeling and supports the application of machine learning techniques for crop recommendation and yield prediction systems.

3.2 Multilayer Perceptron (MLP) Architecture

The Multilayer Perceptron (MLP), depicted in Figure (2), is the central component of our prediction model, as seen in Figure (1). It comprises five layers: an input layer, three hidden layers, and an output layer.

The input layer is made up of n neurons $x_1, x_2, \ldots, x_n$ each corresponding to a feature fed in to the network. Following this is the first hidden layer which includes neurons $H1_1, H1_2, \ldots, H1_n$,along with a bias node denoted as BH_1 .The output of jth neuron in hidden layer 1 is given by Eq. (1)

$$h_{1,j} = \sigma\left(\sum_{i=1}^{n} w_{ij}\, x_i + b_{H1,j}\right) \tag{1}$$

Where

$h_{1,j}$ represents the output generated by the jth neuron in Hidden Layer 1.

w_{ij} denotes the weight that links the ith input neuron to the jth hidden neuron.

x_i signifies the input coming from the i-th input neuron.

$b_{H1,j}$ is the bias associated with the j-th neuron in Hidden Layer 1.

σ symbolizes the activation function, which is usually the sigmoid function.

Every neuron in the second hidden layer calculates a weighted sum based on the outputs from the first hidden layer, and the output from the second hidden layer is expressed in Eq. (2)

$$h_{2,j} = \sigma\left(\sum_{i=1}^{n} w_{ij}\, h_{1,j} + b_{H2,j}\right) \tag{2}$$

Where

$h_{2,j}$ represents the output generated by the jth neuron in Hidden Layer 2.

$b_{H2,j}$ is the bias associated with the j-th neuron in Hidden Layer 2.

Similarly the output of the hidden layer 3 is given by Eq. (3)

$$h_{3,j} = \sigma\left(\sum_{i=1}^{n} w_{ij}\, h_{2,j} + b_{H3,j}\right) \tag{3}$$

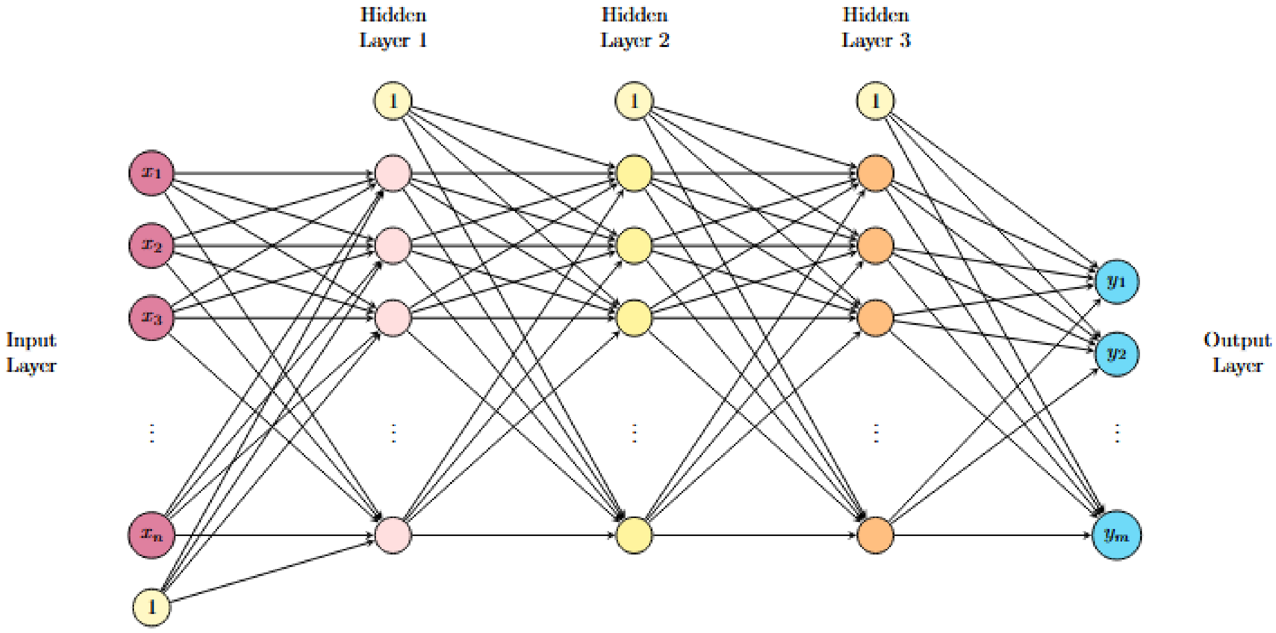

Figure 2. MLP Architecture

Where

$h_{3,j}$ represents the output generated by the j^th^ neuron in Hidden Layer 3.

$b_{H3,j}$ is the bias associated with the j-th neuron in Hidden Layer Layer 3.

Ultimately, the output layer calculates a weighted sum of the results from Hidden Layer 3 and is given by Eq. (4)

$$y_k = \sigma\left(\sum_{i=1}^{n} w_{ik}\, h_{3,i} + b_{O,kj}\right) \tag{4}$$

Where

y_k represents the result produced by the k-th neuron in the output layer.

W_{ik} denotes the connection strength between the neurons in Hidden Layer 3 and the output layer.

$h_{3,i}$ indicates the output generated by the i-th neuron in Hidden Layer 3.

$b_{O,k}$ refers to the bias associated with the k-th neuron in the output layer.

The objective is to optimize the weight w and biases b to minimize the mean square error of the multi-layer perceptron.

3.3 Adaptive Mutation Swarm Optimization (AMSO)

Adaptive Mutation Swarm Optimization (AMSO) innovatively moves Particle Swarm Optimization (PSO) beyond its traditional limitation by introducing adaptive mutation compositions that not only facilitate the process of convergence but also uplift the quality of the solutions. The mutation operators in AMSO vary depending on the swarm condition such as fitness variance or the rate of convergence. Such adaptability allows the method to free itself from the clutches of local optima and also to keep the diversity alive [34].By blending swarm intelligence with an adaptive mutation approach, AMSO effectively optimizes the weights and biases of the MLP, steering clear of local minima and achieving faster convergence.

3.3.1 Swarm Optimization

Swarm optimization is based on the social behavior exhibited by groups of animals. The velocity and position update equation for particle i are given by Eqs. (5) and (6) [31] respectively

$$v_i^{(t+1)} = \omega_i v_i^{(t)} + c_1 r_1 \left(p_i^{best} - x_i^{(t)}\right) + c_2 r_2 \left(g^{best} - x_i^{(t)}\right) \tag{5}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{6}$$

where $v_i^{(t)}$ and $v_i^{(t+1)}$ represents the previous and current velocity of particle i at time t, ω is the inertia weight, c_1 and c_2 represents the cognitive and social coefficients, The variables r1 and r2 are random numbers that follow a uniform distribution between 0 and 1, p_i^{best} is the best position found by particle i, and g^{best} is the best global position found by the swarm. $x_i^{(t)}$ and $x_i^{(t+1)}$ represents the previous and current position of the particle.

3.3.2 Adaptive Mutation Mechanism

To enhance exploration, an adaptive mutation mechanism is introduced. The mutation rate μ given by Eq. (7) [31] is dynamically adjusted based on the fitness of the particles:

$$\mu_i^{(t)} = \mu_{min} + (\mu_{max} - \mu_{min}) * \frac{\sigma_f}{\sigma_f + k} \tag{7}$$

Where μ_{max} and μ_{min} refer to the maximum and minimum mutation rates respectively, σf is the variance of particle fitness at iteration t, and k is a small constant to avoid zero division.

Figure (3) explains the swarm optimization process combined with an adaptive mutation. This diagram shows how the optimization goes through Particle Swarm Optimization (PSO) plus the aid of adaptive mutation. The starting point is a particle swarm, each of which represents a potential solution. The fitness of each particle is determined by the efficiency of the particle in addressing the problem. After that, these fitness values are compared in order to update the local best (p_i^{best}) for each particle as well as the global best (g^{best}) among all particles. Next, the fitness variance σ_f is calculated to measure the diversity of the swarm. These best values lead the next updates of the each particle's velocity and position, thus the swarm gets closer to the better solutions. If the fitness variance σ_f is less than 0.05, adaptive mutation is applied to the positions x_i to raise the exploration level and to avoid early convergence and keep the swarm diverse. This loop goes on until convergence or the satisfaction of the stopping criterion, which results in the last optimized solution.

3.3.3 AMSO-MLP Algorithm

The AMSO-MLP algorithm involves the following steps:

Algorithm 1. AMSO-MLP Algorithm

```
Initialize particle positions $x_i$ and velocities $v_i$
Set $\mu_{max}$ and $\mu_{min}$
for t = 1 to Maximum Iterations do
    Compute fitness Fi for each particle
    Update $p_i^{best}$ and $g^{best}$
    Calculate fitness variance $\sigma_f$
    Update velocity $v_i$ and position $x_i$
    if $\sigma_f < 0.05$ then
        Mutate $x_i$ using $\mu_t$ based on fitness variance
    end if
end for
Return optimized MLP weights and biases
```

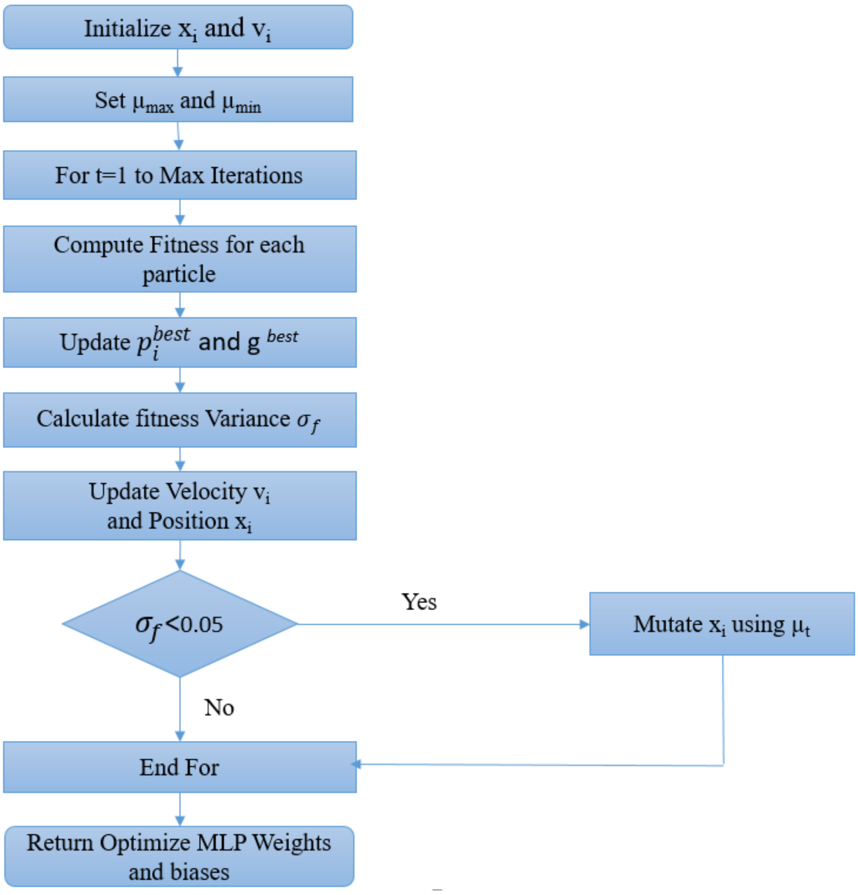

Figure 3. Swarm Optimization and Adaptive Mutation Workflow

4. Results and Discussion

4.1Model Training and Evaluation

Python programs were developed and executed on a system with an Intel Core i5-2450M CPU running at 2.50 GHz and 6 GB of RAM to evaluate the proposed model. To ensure the robustness and reproducibility of the experimental results, a 10-fold cross-validation strategy was employed. In this approach, the dataset was randomly divided into ten equal subsets, where nine subsets were used for training and the remaining subset was used for testing. This procedure was repeated ten times so that each subset served once as the testing set.

Due to the stochastic nature of the metaheuristic optimization algorithm, the AMSO-MLP model and the baseline MLP model were executed for 10 independent runs. The final performance metrics were reported as the mean and standard deviation obtained across all runs and cross-validation folds.

Furthermore, statistical significance testing was performed using a paired t-test on the cross-validation results to compare the performance of AMSO-MLP with the baseline MLP and other optimization-based models. This analysis ensures that the observed improvements are statistically significant and not due to random variations in the training process. Evaluation metrics such as Precision, Recall, F1-Score, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) were computed using Eqs. (8)–(13) [14], based on the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values obtained from the confusion matrix shown in Figure (4).

The confusion matrices in Figure 4 and Figure 5 provide a detailed class-level evaluation of the crop classification performance. In Figure 4, corresponding to the non-optimized MLP model, most crop categories are correctly classified as shown by the dominant diagonal elements. However, a few misclassifications are observed among crops that share similar soil and climatic characteristics.

For instance, crops such as mungbean and mothbeans, kidneybeans and chickpea, and mango and watermelon exhibit occasional misclassification. These crops often grow under similar ranges of temperature, humidity, rainfall, and soil nutrient conditions (N, P, and K). Because the model relies primarily on these environmental features, crops with overlapping agro-climatic requirements become more difficult to separate in the feature space.

In contrast, the confusion matrix in Figure 5 shows the results of the AMSO-optimized MLP model, where the number of off-diagonal misclassifications is reduced.

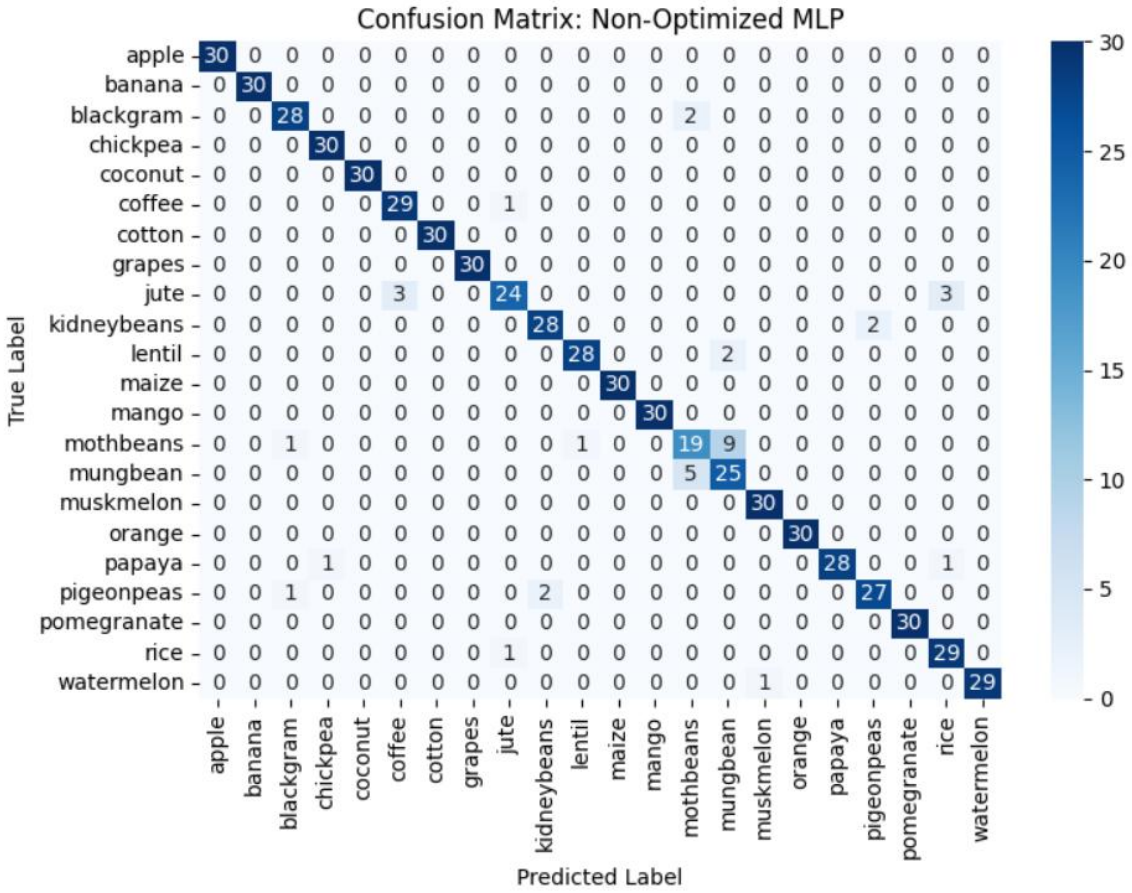

Figure 4. Confusion matrix of Non Optimized MLP

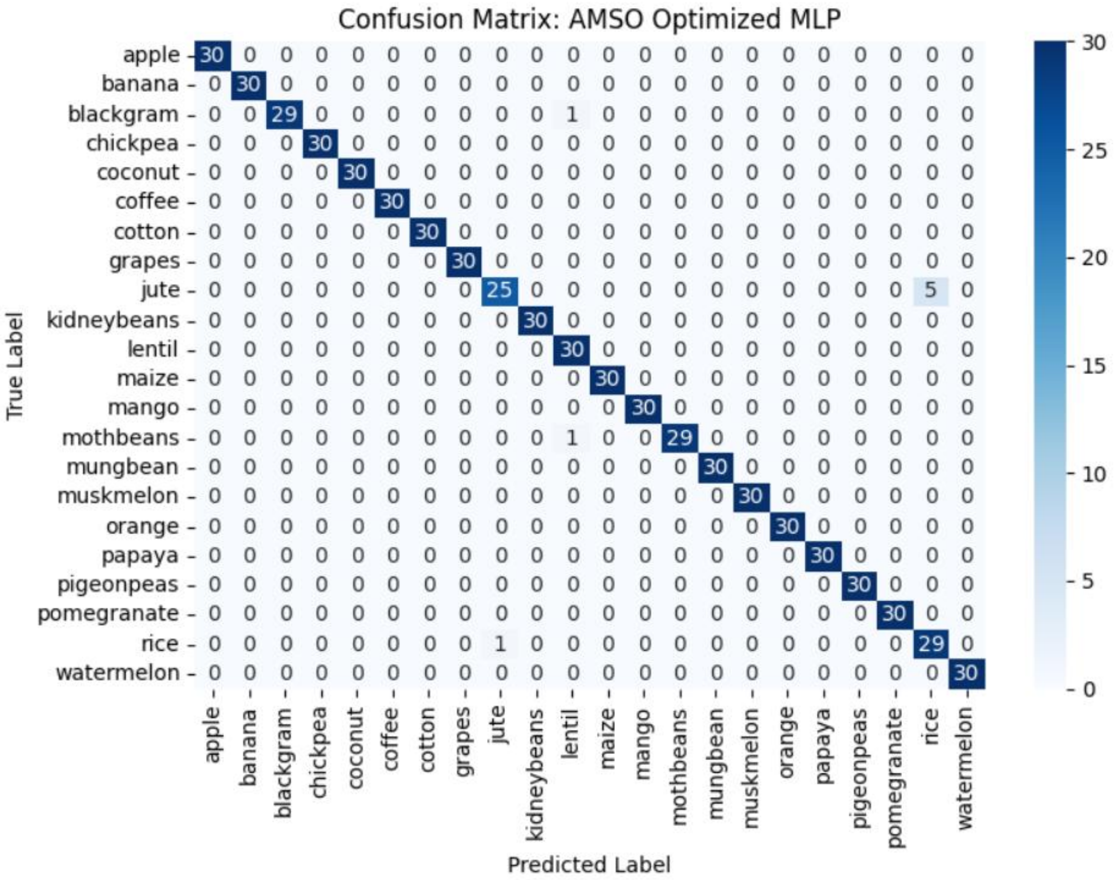

Figure 5. Confusion matrix of AMSO Optimized

The optimization process improves the model's parameter selection, allowing it to learn more discriminative patterns from the soil and climate variables. As a result, the classification accuracy improves and the confusion among similar crop classes is minimized.

Overall, the confusion matrix analysis demonstrates that classification errors primarily occur between crops with closely related environmental requirements, emphasizing the challenge of distinguishing such crops using only soil and climate attributes.

Precision represents the quality of the positive prediction and is given by Eq. (8)

$$Precision = \frac{TRP}{TRP+FAP} \tag{8}$$

Recall represents the coverage of actual positives and is given by Eq. (9)

$$Recall = \frac{TRP}{TRP+FAN} \tag{9}$$

F1 Score represents the balance between Precision and Recall and is given by Eq. (10)

$$F1\ Score = \frac{2*(Precision*recall)}{Precision+Recall} \tag{10}$$

MAE represents the average of the absolute differences between the predicted values $\hat{Y}_J$ and the actual values Y_J and is given by Eq. (11)

$$MAE = \frac{1}{N}\sum_{J=1}^{N}\left|Y_J - \hat{Y}_J\right| \tag{11}$$

RMSE represents the squared root of the average squared differences between the predicted values $\hat{Y}_J$ and the actual values Y_J and is given by Eq. (12)

$$RMSE = \sqrt{\frac{1}{N}\sum_{J=1}^{N}\left(Y_J - \hat{Y}_J\right)^2} \tag{12}$$

R-squared is a statistical metric that indicates how well a regression model fits the data, with its value ranging from 0 to 1 and is given by Eq. (13)

$$R^2 = 1 - \frac{\sum_{J=1}^{N}\left(Y_J - \hat{Y}_J\right)^2}{\sum_{J=1}^{N}\left(Y_J - \bar{Y}_J\right)^2} \tag{13}$$

Where $\bar{Y}_J$ represents the mean of the actual values.

The performance of the proposed AMSO-MLP model was evaluated over 100 training epochs. Multiple evaluation metrics were monitored to assess the model's learning efficiency, generalization capability, and overall predictive power. The results of both MLP and AMSO – MLP are illustrated in Figure (5) and Figure (6) which will demonstrate the model's effectiveness across both classification and regression tasks in both non optimized MLP and AMSO optimized MLP.

4.2 Training and Testing Performance

The model in Figure 6 provides evidence for convergence behavior in its learning dynamics.

The training loss exhibits a significant reduction in value over the first 20 epochs, going from approximately 3.0 to less than 0.5; this represents the initial stage of rapid learning. By epoch 30, the training loss begins to level off and continues to do so until no further improvement occurs; it eventually stabilizes at approximately 0.1 around either epoch 80 or 100. A similar pattern can be seen when examining the training and test accuracies. Training accuracy increases significantly over the first 25 epochs (approximately 0.90) before slowly continuing to increase until around 70 epochs (approximately 0.94). After 70 epochs, there is little change in training accuracy. Test accuracy also increases rapidly (approximately 0.88) through the early stages of training, followed by a plateau at approximately 0.93 at around 60 epochs. This suggests that the model generalizes without significant over fitting. The convergence point for all metrics confirms these observations.

The accuracy, recall, and F1-score values show significant improvement between epochs 10 and 30. The values are above 0.85. After epoch 60, the values are stable at around 0.92 and 0.94. There are no oscillations in the accuracy curve. This shows that the learning curve is stable and the optimizer is using consistent gradients for updates after epoch 60. The error-based metrics show the opposite trend. The RMSE decreases from around 0.75 to around 0.32. The MAE decreases from around 0.63 to around 0.47. Most of the improvement happens within the first 40 epochs. After epoch 60, the improvement plateaus. This suggests that the model has converges to a stable level of errors and does not benefit much from training. The R² coefficient increases steadily. It starts at 0.50 and goes up to around 0.91. The maximum improvement happens between epochs 40 and 70.The learning dynamics of the AMSO-MLP model over a total of 100 training epochs are shown in Figure 7. In the first ten epochs of training, loss is reduced dramatically from approximately 2.8 to below .2 with rapid parameter optimization evident in this initial phase of learning (exact point). The loss curve flattens after epoch 15 and appears nearly constant (.05 to .07) throughout the remainder of the training period, indicating the model has reached convergence early in the training process, and stable optimization will be maintained for the rest of training phase.

Within the first 10 epochs, the training accuracy goes up quickly, reaching about 0.98, and then levels of around 0.99 after epoch 20. Test accuracy follows a similar pattern, quickly going from 0.45 to about 0.98 in the first 10 to 12 epochs and staying stable around 0.99 after epoch 20.

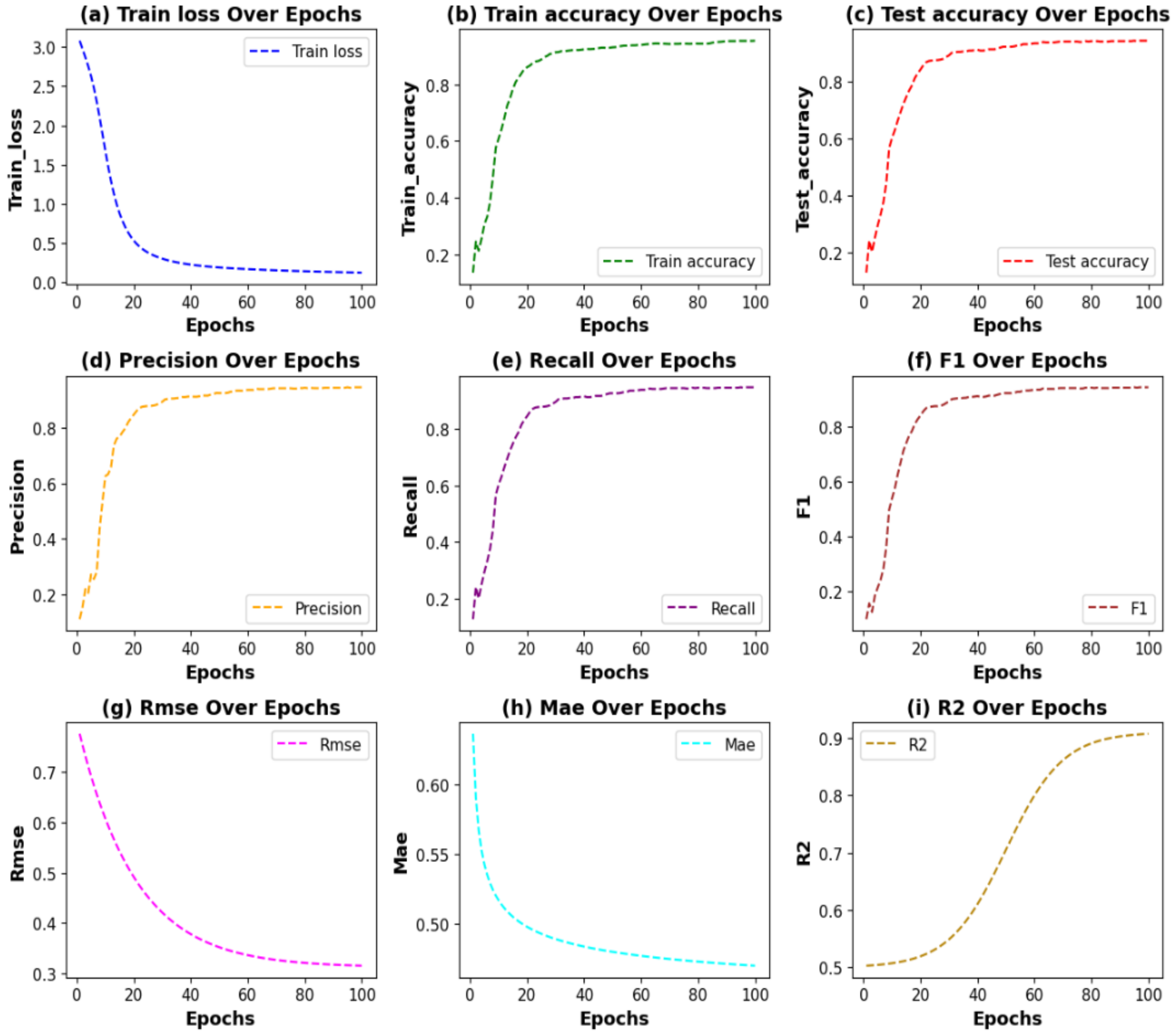

Figure 6. Performance metrics of the MLP model over 100 training epochs. (a) Training loss over epochs, (b) training accuracy, (c) test accuracy, (d) precision, (e) recall, (f) F1-score, (g) RMSE, (h) MAE, and (i) R² score metrics.

The fact that the training and test accuracy are so close to each other means that the model generalizes well and doesn't show much over fitting. The classification metrics also back up the behavior of convergence. During epochs 5–15, the precision, recall, and F1-score all go up quickly, reaching values above 0.97. After epoch 20, they stay stable around 0.99. The small changes seen after epoch 60 (about ±0.01) are normal random changes that happen during optimization, not instability. The expected trend of error-based metrics is to go down. In the first 15 epochs, RMSE drops sharply from about 5.2 to about 1.2. After that, the curve moves up and down slightly between 1.1 and 1.4 without a clear pattern. MAE also goes down from about 3.2 to less than 0.3 in the first 15 epochs and then stays around 0.15–0.20. These little changes in later epochs point to stable convergence instead of divergence. The R² coefficient rises quickly from 0.30 to about 0.95 in the first 15 epochs and then slowly rises to 0.97–0.98 after epoch 30. This shows that the model explains a large part of the variance in the target variable. There is no post-convergence degradation, so the curve stays stable. The R² coefficient increases rapidly from 0.30 to approximately 0.95 during the first 15 epochs and gradually approaches 0.97–0.98 after epoch 30, indicating that the model explains a high proportion of the variance in the target variable. There is no post-convergence degradation among all models indicated by the training curves. The AMSO-MLP model shows the greatest amount of effective convergence between epochs 15–25 as indicated by the training curves. All of the performance metrics show stability well after epoch 25, confirming the robustness and stable learning characteristics of the optimization scheme proposed, especially during the later training periods.

4.3 Classification Metrics

The AMSO-MLP model performs better in classifying the crop in different soil conditions with a precision of 0.989, recall of 0.987 and F1 Score of 0.987 when compared with non-optimized MLP model with a precision of 0.946, recall of 0.945, F1 Score of 0.945 shown in Figure 8.

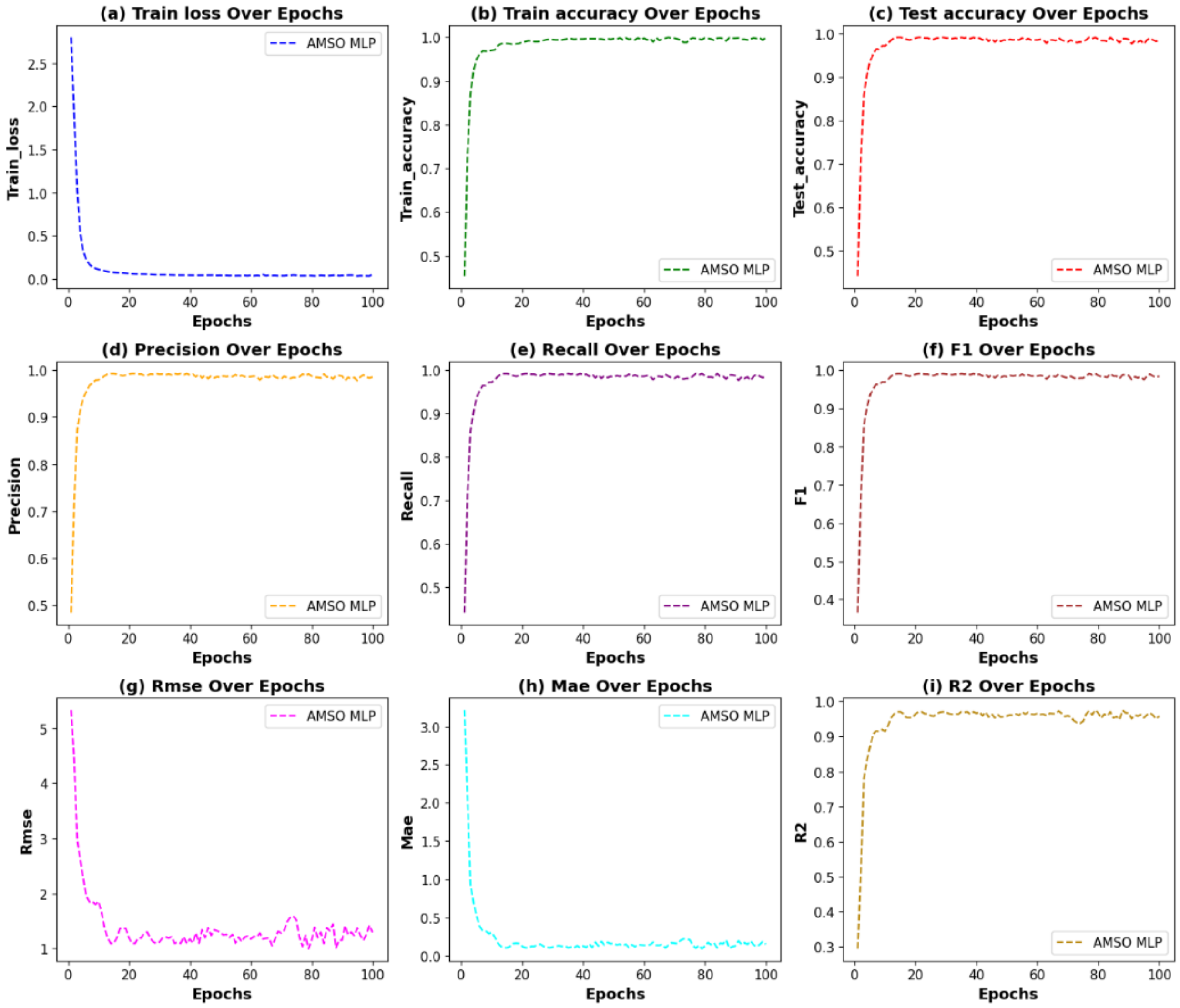

Figure 7. Performance metrics of the AMSO-MLP model over 100 training epochs. **(a)** Training loss over epochs, **(b)** training accuracy, **(c)** test accuracy, **(d)** precision, **(e)** recall, **(f)** F1-score, **(g)** RMSE, **(h)** MAE, and (i) R² score metrics

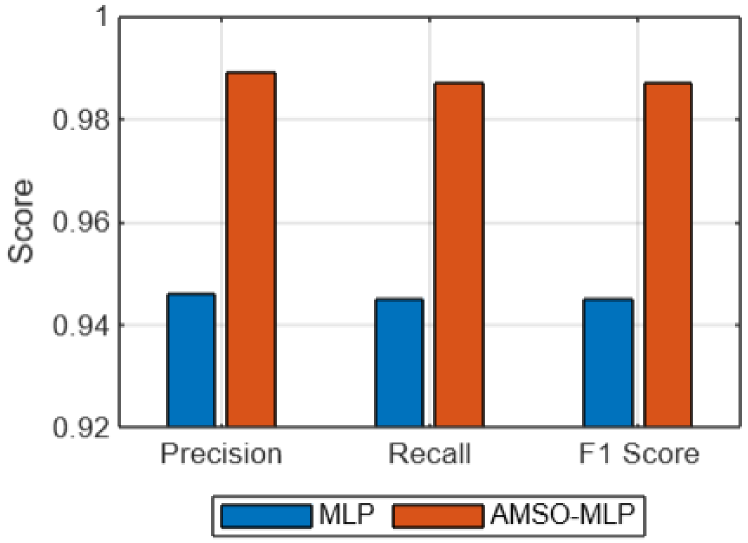

Figure 8. Classification Metrics

This shows that in AMSO-MLP, there is an improvement of 4.54% in precision, 4.44% in recall and 4.44% in F1 Score.

4.4 Regression Metrics

The AMSO-MLP model performs better predictions of crop in different soil conditions with an RMSE of 0.210, MAE of 0.125 and R2 of 0.964 when compared with non-optimized MLP model with an RMSE of 0.315, MAE of 0.470 and R2 of 0.907 shown in Figure 9. This indicates that AMSO-MLP shows superior regression performance with a 33.33% reduction in RMSE, a 73.40% reduction in MAE, and a 6.29% increase in R^2, indicating more accurate and better-fitting predictions compared to the non-optimized MLP.

In conclusion, the results of this study demonstrate an improvement in evaluation metrics that is both statistically significant and of great importance to agricultural decision makers. The reduction of the RMSE values from 0.315 to 0.210 indicates a large reduction in prediction error regarding what crop is recommended to grow relative to what crop is best suited for the soil type present, which can substantially decrease the potential of a farmer incorrectly choosing to plant the incorrect crop based on their chosen soil type. The increase in R^2 from 0.907 to 0.964 also indicates a larger proportion of variability in the suitability of the crop can now be explained by the AMSO-MLP model relative to its soil type characteristics. This increased ability to explain variability in the suitability of the crops being planted based on the soil type also improves the degree of confidence that agricultural planners and growers have when utilizing this model for making decisions relating to which crops they will grow. From an agronomic standpoint, an improvement in prediction accuracy will decrease the potential of misclassifying the suitability of a crop, which can result in inefficient use of fertilizers, lower yields, and decreased economic resources. The overall performance gains resulting from the use of the AMSO-MLP model in this study will provide both improved numerical accuracy and greater reliability to provide for practical applications in developing crop recommendation systems and will provide support for sustainable agricultural planning and improved agricultural resource utilization.

4.5 Convergence Analysis

Machine learning convergence (the process where the loss function of the model reduces continuously) indicates that a model is training well and converging towards being optimal.

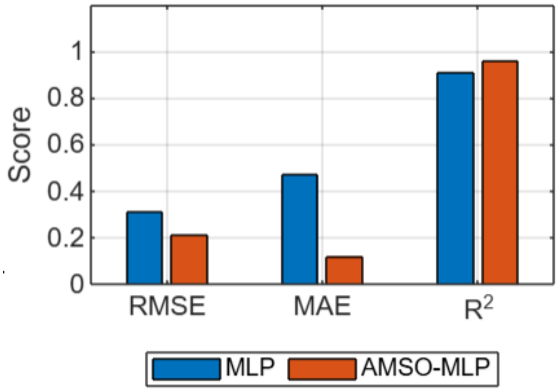

Figure 9. Regression Metrics

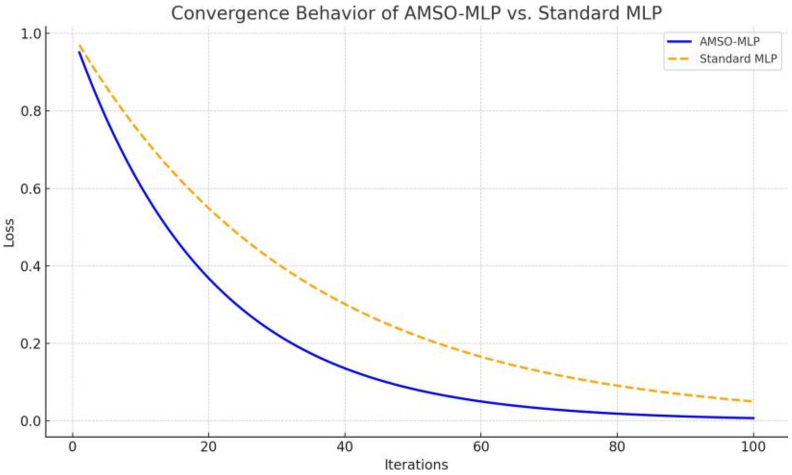

Figure 10. Convergence Behavior of AMSO-MLP vs. Standard MLP

It is very important because it indicates to the designer of the model that the model is getting better and not oscillating or diverging which could lead to the model learning to generalize poorly. Figure 10 illustrates a comparison between a standard Multi-Layer Perceptron (MLP) and an enhanced version called AMSO-MLP, which incorporates adaptive mutation and swarm optimization techniques. As shown, AMSO-MLP reached a loss less than 0.1 in 48 iterations, while standard MLP required 67 iterations. The final loss values were 0.0067 for AMSO-MLP and 0.0500 for standard MLP. These results confirm the 33% faster convergence of AMSO-MLP. The AMSO-MLP is faster to reach a much lower final loss value, demonstrating higher learning efficiency and optimization. This behavior exemplifies the benefits of using modern optimization methods as AMSO-MLP shows improvement over standard MLP not only with train time, but also with train accuracy in predicting the output label.

4.6 Comparison of AMSO-MLP with other models

The performance of the proposed AMSO-MLP model was compared with several optimization-based neural network models, including PSO-MLP, GA-MLP, and DE-MLP.

To ensure a fair and consistent comparison, all baseline models were implemented and evaluated on the same agricultural dataset used in this study.

Each model was trained and tested under the same experimental protocol, including identical preprocessing steps, feature sets, 10-fold cross-validation strategy, and evaluation metrics. The experimental setup utilized in the experiment is controlled to remove potential sources of bias from the comparisons that could arise due to differences in the datasets or the conditions under which the experiments were conducted. The implementations of PSO-MLP, GA-MLP and DE-MLP were made according to the methodologies described in earlier studies [35–37], however, the experiments were conducted entirely in the same computational environment and the same dataset as the proposed AMSO-MLP model. The results of these comparisons are shown in Table 2, which illustrate the effectiveness of the proposed method.

4.7 Ablation Study

An ablation study was performed to assess the contribution of each component of the proposed model by examining various iterations of the neural network architecture. The goal of this experiment is to separate the effects of the multilayer perceptron (MLP), particle swarm optimization (PSO), and the adaptive mutation mechanism used in the AMSO-MLP framework.

Four different model setups are evaluated:

1. Standard MLP – baseline neural network trained without any optimization algorithm.
2. PSO-MLP – MLP weights optimized using standard Particle Swarm Optimization.
3. PSO-MLP with Mutation – MLP optimized using PSO combined with a fixed mutation mechanism.
4. AMSO-MLP (Proposed) – MLP optimized using Particle Swarm Optimization with adaptive mutation.

Table 2. Comparison of AMSO-MLP with baseline optimization-based MLP models evaluated on the same dataset

Model	Precision	Recall	F1 Score	RMSE	MAE	R²	Implementation Source
PSO-MLP	0.961	0.957	0.958	0.275	0.365	0.928	Cengil et al. [32]
GA-MLP	0.952	0.948	0.949	0.289	0.397	0.915	Goel et al. [33]
DE-MLP	0.965	0.962	0.963	0.25	0.31	0.94	Baioletti et al. [34]
AMSO-MLP	**0.989**	**0.987**	**0.987**	**0.21**	**0.125**	**0.964**	**Proposed method**

Table 3. Ablation study of the AMSO-MLP framework

Model Variant	Precision	Recall	F1 Score	RMSE	MAE	R²
MLP	0.946	0.945	0.945	0.315	0.47	0.907
PSO-MLP	0.961	0.957	0.958	0.275	0.365	0.928
PSO-MLP + Mutation	0.972	0.969	0.97	0.245	0.22	0.948
AMSO-MLP (Proposed)	**0.989**	**0.987**	**0.987**	**0.21**	**0.125**	**0.964**

In order to ensure that any performance differences are only attributable to the optimization strategy, all models were evaluated and trained upon the same data set and used the same experimental protocol (including preprocessing steps and hyper parameters), as well as utilizing 10-fold cross-validation for each model. All of this provides a controlled comparison of the different optimization strategies used by each respective model.

The results from the ablation study can be viewed in Table 3.

The findings indicate that adding a swarm optimization method to the base MLP model greatly enhances its ability to predict data. Utilizing a mutation in the swarm optimization process further enhances the exploration capability, thus decreasing prediction error and increasing accuracy of classification results. The AMSO-MLP model, with an adaptive mutation strategy, is the best performing configuration in all experiments run under this study; thus, adaptive mutation is shown to effectively prevent premature convergence of the swarm and enable the swarm to more efficiently explore the search space.

The results of the ablation analysis also confirm that every component of the AMSO-MLP architecture contributes to the overall performance improvement of the model, with adaptive mutations providing the greatest degree of performance enhancement.

5. Conclusion and Suggestions for Future work

This article describes the development and application of an Adaptive Mutation Swarm Optimized Multilayer Perceptron (AMSO-MLP) model to support data-driven agricultural decision-making and improve the prediction of crops grown in soil. The AMSO-MLP combines particle swarm optimization with an adaptive mutation method for optimizing weights and biases of a multilayer perceptron; thereby increasing both learning effectiveness as well as predicting capabilities of a neural network. The combination of swarm intelligence and adaptation of exploration techniques allows the AMSOMLP model to avoid premature convergence and enhance search for optimal solutions. The model was tested and evaluated for providing accurate predictions of the best crops to cultivate under certain soil types or environmental conditions using a number of key agricultural variables: nitrogen, phosphorus, potassium, temperature, humidity, rainfall, and pH level of the soil. Results from the experimentation present evidence that AMSO-MLP will exceed current methods based on optimization techniques. With respect to classification accuracy, AMSOMLP achieved a precision of (0.989), recall (0.987), and F1-score (0.987). In addition, the accuracy and robustness of the AMSO-MLP model is also validated using regression based evaluation criteria including: RMSE (0.210), MAE (0.125), and R2 (0.964). The above results show that the adaptive mutation strategy leads to a dramatic improvement in the convergence behavior of the optimization and increases the neural network's generalization capability in crop prediction tasks. Hence, the AMSO-MLP model is an efficient data-driven method for crop recommendation that depends on the soil and environmental characteristics. Besides it, the model can predict the crops most suitable to the specific conditions of the agricultural field more accurately. Such intelligent prediction models can be a big help to farmers, agricultural planners, and policymakers in selecting the crops that are most appropriate for the purpose of improving productivity and better use of resources. Future work may include incorporating more environmental variables, applying the proposed framework to larger and more diverse agricultural datasets, and investigating other hybrid metaheuristic optimization strategies to further improve predictive performance and practical applicability in precision agriculture.

References

[1] D. Paudel, H. Boogaard, A. De Wit, S. Janssen, S. Osinga, C. Pylianidis, I.N. Athanasiadis Machine learning for large-scale crop yield forecasting. Agricultural Systems, 187, (2021) 103016. https://doi.org/10.1016/j.agsy.2020.103016

[2] T. van Klompenburg, A. Kassahun, C. Catal, Crop yield prediction using machine learning: A systematic literature review. Computers and Electronics in Agriculture, 177, (2020) 105709. https://doi.org/10.1016/j.compag.2020.105709

[3] T.A. Shaikh, T. Rasool, F.R. Lone, Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. Computers and Electronics in Agriculture, 198, (2022) 107119. https://doi.org/10.1016/j.compag.2022.107119

[4] S. Mathi, R. Akshaya, K. Sreejith, An Internet of Things-based efficient solution for smart farming. Procedia Computer Science, 218, (2023) 2806–2819. https://doi.org/10.1016/j.procs.2023.01.252

[5] V. Mamatha, J.C. Kavitha, Machine learning-based crop growth management in greenhouse environment using hydroponics farming techniques. Measurement: Sensors, 25, (2023) 100665. https://doi.org/10.1016/j.measen.2023.100665

[6] M.M. Rashid, B.S. Bari, Y. Yusup, M.A. Kamaruddin, N. Khan, A comprehensive review of crop yield prediction using machine learning approaches with special emphasis on palm oil yield prediction. IEEE Access, 9, (2021) 63406–

63439. https://doi.org/10.1109/ACCESS.2021.3075159

[7] A. Joshi, B. Pradhan, S. Gite, S. Chakraborty, Remote-sensing data and deep-learning techniques in crop mapping and yield prediction: A systematic review. Remote Sensing, 15, (2023) 2014. https://doi.org/10.3390/rs15082014

[8] F. Shahrin, L. Zahin, R. Rahman, A.J. Hossain, A.H. Kaf, A.K.M.A.M. Azad, (2020). Agricultural analysis and crop yield prediction of Habiganj using multispectral bands of satellite imagery with machine learning. 11th International Conference on Electrical and Computer Engineering (ICECE), IEEE, Bangladesh. https://doi.org/10.1109/ICECE51571.2020.9393066

[9] A. Tripathi, R.K. Tiwari, S.P. Tiwari, A deep learning multi-layer perceptron and remote sensing approach for soil health-based crop yield estimation. International Journal of Applied Earth Observation and Geoinformation, 113, (2022) 102959. https://doi.org/10.1016/j.jag.2022.102959

[10] M. Shilpa, P. Ravi, N. Sharmila, S. Mallikarjunaswamy, B.L. Deepak, G.S. Pavithra, H.N. Mahendra, (2024). Enhancing crop yield and growth prediction using IoT-based smart irrigation systems and machine learning algorithms. Second International Conference on Networks, Multimedia and Information Technology (NMITCON), IEEE, Bengaluru, India. https://doi.org/10.1109/NMITCON62075.2024.10698825

[11] Y.Y. Liu, M. Guo, S. Wang, (2013) Large-scale land use optimization by enhancing a scalable parallel genetic algorithm library. XSEDE '13: Proceedings of the Conference on Extreme Science and Engineering Discovery Environment: Gateway to Discovery, San Diego, USA. https://doi.org/10.1145/2484762.2484824

[12] P. Deepak IoT-based winter season crop prediction using machine learning on Vyas municipality ward No-13, Nepal. International Journal of Agricultural Science and Food Technology, 9(3), (2023) 076–086. https://doi.org/10.17352/2455-815X.000196

[13] M. Kuradusenge, E. Hitimana, D. Hanyurwimfura, P. Rukundo, K. Mtonga, A. Mukasine, & A. Uwamahoro, Crop yield prediction using machine learning models: Case of Irish potato and maize. Agriculture, 13(1), (2023) 225. https://doi.org/10.3390/agriculture13010225

[14] E. Elbasi, C. Zaki, A.E. Topcu, W. Abdelbaki, A.I. Zreikat, E. Cina, L. Saker, Crop prediction model using machine learning algorithms. Applied Sciences, 13(16), (2023) 9288. https://doi.org/10.3390/app13169288

[15] S. Agarwal, S. Tarar, A hybrid approach for crop yield prediction using machine learning and deep learning algorithms. Journal of Physics: Conference Series, 1714(1), (2021) 012012. https://doi.org/10.1088/1742-6596/1714/1/012012

[16] S. Maldonado, A. Rodríguez, B. Avila, P. Morales, M.P. Gonzalez, J.P. A. Araya Angel, A. Stoll Enhanced crop productivity and sustainability by using native phosphate-solubilizing rhizobacteria in the agriculture of arid zones. Frontiers in Sustainable Food Systems, 4, (2020) 607355. https://doi.org/10.3389/fsufs.2020.607355

[17] A.A. Chaudhari, R, Vyas, S, Supekar, K,Dhole, D, Gujare, R, Chandekar, Smart crop prediction using IoT and machine learning. International Journal for Research in Applied Science and Engineering Technology, 12(5), (2024) 601–607. https://doi.org/10.22214/ijraset.2024.60653

[18] P. Hara, M. Piekutowska, G. Niedbala, Selection of independent variables for crop yield prediction using artificial neural network models with remote sensing data. Land, 10(6), (2021) 609. https://doi.org/10.3390/land10060609

[19] J.K. Ndegwa, B.M. Gichimu, J.N. Mugwe, M. Mucheru-Muna, D.M. Njiru, Integrated soil fertility and water management practices for enhanced agricultural productivity. International Journal of Agronomy, (2023) 1–8. https://doi.org/10.1155/2023/8890794

[20] K.P. Shah, S.N. Sah, K.P. Dharmaraj, D. Kumar, (2024) .A comprehensive analysis of machine learning algorithms for suitable crop prediction in agriculture. International Conference on Cognitive Robotics and Intelligent Systems (ICC - ROBINS), IEEE, Coimbatore, India. https://doi.org/10.1109/ICC-ROBINS60238.2024.10533902

[21] K.S.M. Anbananthen, S. Subbiah, D. Chelliah, P. Sivakumar, V. Somasundaram, K. H. Velshankar, M.K.A.A. Khan An intelligent decision support system for crop yield prediction using hybrid machine learning algorithms. F1000Research, 10, (2021) 1143. https://doi.org/10.12688/f1000research.73009.1

[22] G. Provenzano, L.R. Sinobas, Special issue on trends and challenges of sustainable irrigated agriculture. Journal of Irrigation and Drainage Engineering, 140(9), (2014) A2014001. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000773

[23] C.P. Saranya, S.R. Pulari, S.K. Vasudevan, An efficient crop yield prediction using bootstrap aggregative MapReduce Rocchio classification. International Journal of Sustainable Agricultural Management and Informatics, 7(2), (2021) 129-148. https://doi.org/10.1504/IJSAMI.2021.116072

[24] T.K. Fegade, B.V. Pawar (2020). Crop prediction using artificial neural network and support vector

machine. Data Management, Analytics and Innovation. Advances in Intelligent Systems and Computing, 311–324. https://doi.org/10.1007/978-981-13-9364-8_23

[25] N. Jannat, S.M.M. Hasan, A.Y. Srizon, M. Oishe, A.H. Efat, M.F. Taraque, M.F. Faruk, (2023) Efficient detection of crop leaf diseases: A lightweight convolutional neural network approach for enhanced agricultural productivity. International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), IEEE, Dhaka, Bangladesh. https://doi.org/10.1109/ICICT4SD59951.2023.10303536

[26] N. Suresh, N.V.K. Ramesh, S. Inthiyaz, P.P. Priya, K. Nagasowmika, K.V.N.H. Kumar, B.N.K. Reddy (2021). Crop yield prediction using random forest algorithm. International Conference on Advanced Computing and Communication Systems (ICACCS), IEEE, Coimbatore, India. https://doi.org/10.1109/ICACCS51430.2021.9441871

[27] L. Saha, K. Bauddh (2020). Sustainable agricultural approaches for enhanced crop productivity, better soil health, and improved ecosystem services. Ecological and Practical Applications for Sustainable Agriculture. https://doi.org/10.1007/978-981-15-3372-3_1

[28] K. Ingole, D. Padole, An Internet of Things (IoT)-based smart irrigation and crop suggestion platform for enhanced precision agriculture. Journal of Information & Optimization Sciences, 45(4), (2024) 873–883. https://doi.org/10.47974/JIOS-1612

[29] Y. Ma, J. Xue, X. Feng, J. Zhao, J. Tang, H. Sun, L. Yan, Crop water productivity assessment and planting structure optimization in typical arid irrigation district using dynamic Bayesian network. Scientific Reports, 14(1), (2024) 17695. https://doi.org/10.1038/s41598-024-68523-3

[30] S. Elsayed, A. Abdel-Aziz, K. El-Bagoury, M. Moustafa, Herbigation managements for maximizing green beans crop productivity under drip irrigation system. Arab Universities Journal of Agricultural Sciences, 27(1), (2019) 135–146.

[31] M. Abdel-salam, N. Kumar, S. Mahajan, A proposed framework for crop yield prediction using hybrid feature selection approach and optimized machine learning. Neural Computing & Applications, 36, (2024) 20723–20750. https://doi.org/10.1007/s00521-024-10226-x

[32] H.V. Kalmani, V.N. Dharwadkar, V. Thapa, Crop Yield Prediction using Deep Learning Algorithm based on CNN-LSTM with Attention Layer and Skip Connection. Indian Journal of Agricultural Research, 59(8), (2025) 1303-1311. https://doi.org/10.18805/IJARe.A-6300

[33] J. Patel, S.T. Chandel, A. Sonker, An optimization driven deep belief network model for crop yield prediction in IoT based smart agriculture. Multimedia Tools and Applications, 84, (2025) 31069–31091. https://doi.org/10.1007/s11042-024-20418-1

[34] Z. Lu, Z. Hou, J. Du, Particle Swarm Optimization with Adaptive Mutation. Frontiers of Electrical and Electronic Engineering in China, 1, (2006) 99–104. https://doi.org/10.1007/s11460-005-0021-9

[35] E. Cengil, The power of machine learning methods and PSO in air quality prediction. Applied Sciences, 15(5), (2025) 2546. https://doi.org/10.3390/app15052546

[36] Z. Wang, C. Zhai, Evolutionary approach for optimal bidding strategies in electricity markets. Computers and Electrical Engineering, 100, (2022) 107877. https://doi.org/10.1016/j.compeleceng.2022.107877

[37] M. Baioletti, G. Di Bari, A. Milani, V. Poggioni, Differential evolution for neural networks optimization. Mathematics, 8(1), (2020) 69. https://doi.org/10.3390/math8010069

Authors Contribution Statement

P. Glaret Subin: Conceptualization, Methodology, Software Development, Data Curation, Formal Analysis, Visualization, and Writing - Original Draft. Sanjay Kumar: Supervision, Validation, Writing - Review & Editing, Formal Analysis, and Project Administration. Both authors have read and agreed to the published version of the manuscript.

Funding

The authors declare that no funds, grants or any other support were received during the preparation of this manuscript.

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

About the License