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Article

A Hybrid Machine Learning and Optimization Framework for Predictive Soil Health Maintenance and Fertilizer Recommendation

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Abstract: - Soil health management plays a central role in achieving sustainable agricultural productivity; however, conventional soil testing and fertilizer advisory practices are often labor-intensive, costly, and limited in precision. To overcome these limitations, this work presents a Hybrid Machine Learning and Optimization Framework for predictive soil health maintenance. The proposed framework integrates multiple predictive tasks namely soil nutrient estimation using NPK regression, fertilizer recommendation through classification, Soil Health Index (SHI) computation, and crop suitability prediction within a unified and data-driven decision-support architecture. The predictive modeling layer employs an ensemble of Random Forest, XGBoost, and Deep Neural Network (DNN) models to capture complex nonlinear relationships between soil and environmental parameters. To enhance predictive performance and generalization, model hyperparameters are automatically tuned using a Genetic Algorithm (GA), enabling efficient exploration of the hyperparameter search space. Comprehensive experiments conducted on a real-world soil dataset demonstrate that the proposed optimization-enhanced models consistently outperform baseline approaches.
For soil nutrient prediction, the Hybrid DNN + GA model achieved an approximate 20% reduction in RMSE compared to the baseline DNN, attaining a coefficient of determination R2 of 0.94. In the fertilizer recommendation task, the proposed approach achieved 94.2% classification accuracy with an ROC–AUC of 0.96, while crop suitability prediction reached an accuracy of 92.8%, representing a 4.6% improvement over conventional DNN-based models. The derived Soil Health Index exhibited a mean value of 0.78, with 58% of soil samples classified as Healthy, demonstrating the framework's ability to translate complex predictions into an interpretable soil vitality indicator. The integration of predictive modeling, metaheuristic optimization, and interpretable soil health assessment enables reliable and actionable decision support for precision agriculture. The proposed framework offers a robust, scalable, and interpretable solution for proactive soil health management and efficient fertilizer utilization, contributing toward sustainable agricultural practices.
Keywords: ML, Optimization, SHM, Soil health, DNN, NPK,Genetic Algorithm.

1. Introduction

Soil health is a fundamental determinant of agricultural productivity, environmental sustainability, and global food security. Healthy soils supply essential nutrients to crops, regulate water availability, sustain biodiversity, and act as carbon sinks, thereby contributing to climate change mitigation [1]. However, intensive agricultural practices, including excessive fertilizer application, monocropping, and unsustainable irrigation, have resulted in widespread soil degradation, nutrient imbalance, and declining crop yields [2]. Reports by the Food and Agriculture Organization (FAO) indicate that nearly one-third of the world's arable land is moderately to severely degraded, underscoring the urgent need for advanced soil health monitoring and management solutions [3].

Conventional soil health assessment primarily relies on laboratory-based chemical analysis to quantify macronutrients such as Nitrogen (N), Phosphorous (P), and Potassium (K). Although these methods provide accurate measurements, they are often expensive, time-consuming, and inaccessible to smallholder farmers, particularly in developing regions. Moreover, such static assessments fail to capture dynamic interactions among soil properties, climatic conditions, and crop requirements, limiting their effectiveness for real-time and site-specific agricultural decision-making. Consequently, there is a growing demand for intelligent, data-driven, and automated systems capable of predicting soil parameters, optimizing fertilizer usage, and recommending suitable crops in a timely manner [4].

Recent advancements in machine learning (ML) and deep learning (DL) have enabled predictive modeling across a wide range of agricultural applications, including soil nutrient estimation, fertilizer recommendation, and crop yield prediction [4], [5]. These approaches leverage environmental variables such as temperature, humidity, and soil moisture, along with categorical features such as soil type and crop type, to infer complex soil–crop relationships. Despite their promise, standalone ML models often suffer from limitations including overfitting, suboptimal generalization, and limited interpretability. In addition,

conventional hyperparameter tuning techniques such as grid search and random search are computationally inefficient and do not guarantee globally optimal solutions, particularly for deep learning models with high-dimensional search spaces [6].

To address these challenges, this work proposes a Hybrid Machine Learning and Optimization Framework for Predictive Soil Health Maintenance. The proposed framework integrates ensemble learning and deep neural networks with metaheuristic-driven hyperparameter optimization to improve both regression and classification performance. The framework jointly performs soil nutrient prediction using NPK regression, fertilizer recommendation through classification, Soil Health Index (SHI) computation, and crop suitability prediction within a unified decision-support pipeline. The optimization layer balances regression accuracy and classification performance through a multi-objective formulation, while the SHI provides an interpretable composite indicator of soil vitality.

The proposed framework delivers an end-to-end, interpretable, and scalable solution for soil health management. Furthermore, explainability mechanisms based on feature importance and permutation-based sensitivity analysis are incorporated to enhance transparency and trust in model predictions. The framework is well suited for deployment in IoT-enabled smart agriculture systems, enabling real-time, location-specific recommendations that support sustainable fertilizer usage, improved soil health, and enhanced crop productivity.

2. Related Work

Recent advances in artificial intelligence have significantly Recent research has demonstrated the effectiveness of machine learning techniques for soil health monitoring and nutrient prediction. Sujatha M et al. [7] reviewed ML-based soil fertility estimation methods and highlighted the effectiveness of regression and ensemble models for macronutrient prediction, while also identifying challenges related to generalization across heterogeneous soil types. Multi-source data-driven approaches combining field observations and remote sensing have been proposed to improve soil property estimation accuracy [8]. Similarly, Kumar et al. [9] showed that Random Forest (RF) and neural network models outperform traditional analytical methods due to their ability to model nonlinear soil–environment relationships.

Several studies have focused on fertilizer recommendation systems using supervised learning techniques. Decision Tree and Support Vector Machine (SVM) classifiers have been applied to generate fertilizer advisories based on soil and climatic parameters [10]. Deep learning approaches have also been explored for nutrient deficiency detection and fertilizer recommendation using image-based plant diagnostics [11]. However, these methods often lack interpretability and fail to explicitly model the interaction between soil nutrient dynamics and environmental variability.

Crop suitability and recommendation have also received considerable attention. [12] Prity, S et al. [12] demonstrated that integrating soil attributes with climatic factors significantly improves crop recommendation accuracy. Traditional ML classifiers such as RF and SVM have been widely used for multi-crop prediction based on soil NPK content, pH, and meteorological conditions [13]. [14] Mythili, R et al. [14] proposed a graph-based learning framework to capture spatial and relational dependencies among soil and environmental variables, achieving improved crop recommendation performance.

More recently, hybrid ML frameworks have been introduced to integrate multiple agricultural decision tasks. Site-specific soil fertility models have been developed to generate spatially adaptive fertilizer recommendations [15]. Swarm intelligence algorithms, such as Particle Swarm Optimization (PSO), have been combined with ML models to improve convergence behavior in fertilizer optimization problems [16]. Vhatkar et al. [17] proposed a dual-task framework for crop yield prediction and soil health evaluation, while Musanase et al. [18] integrated rule-based reasoning with ML-based crop recommendation to enhance decision reliability.Despite these advancements, several key limitations persist in the existing literature:

- Most studies focus on a single prediction task either NPK estimation, fertilizer recommendation, or crop suitability rather than a holistic, multi-objective soil health framework.
- Limited research integrates optimization algorithms for hyperparameter tuning and multi-objective performance enhancement.
- A lack of explainable indicators like the Soil Health Index (SHI) restricts interpretability and usability for non-technical agricultural practitioners.
- Several approaches rely on static datasets without real-time adaptability or IoT integration for dynamic soil monitoring.

To address these limitations, the present study proposes a Hybrid ML + Optimization Framework for Predictive Soil Health Maintenance that offers several distinct contributions. The proposed work:

- Combines regression-based nutrient prediction, classification-based fertilizer recommendation, and crop suitability prediction into a unified architecture.
- Employs Genetic Algorithm for dynamic hyperparameter tuning, achieving improved RMSE and F1-score performance.
- Introduces a composite, interpretable index based on N, P, K, and moisture values to represent soil vitality in agronomically meaningful categories.
- Integrates SHAP-based feature interpretation and a rule-based decision layer for transparent fertilizer and crop recommendations.
- Demonstrates significant performance enhancement: RMSE reduced by ~20% for nutrient prediction and classification accuracy improved to 94.2% for fertilizer recommendation and 92.8% for crop suitability prediction.

These contributions collectively advance the field toward data-driven, interpretable, and sustainable soil health management, bridging the gap between predictive analytics and practical agricultural decision-making.

3. Proposed System

The proposed system integrates regression-based nutrient prediction, classification for fertilizer and crop selection, metaheuristic-based parameter optimization, and a composite SHI. The system architecture is presented in figure 1. The architecture consists of four layers: Input Layer, Predictive Modeling Layer, Optimization Layer, and Decision Support Layer.

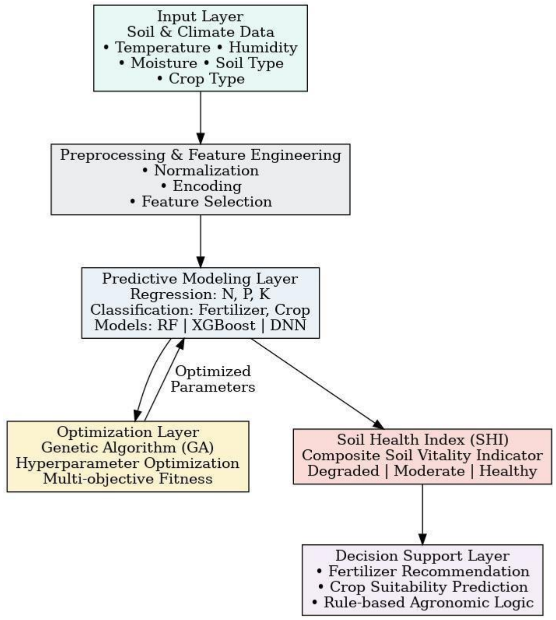

Fig. 1 System Architecture

A. *Input Layer*

The proposed framework operates on a heterogeneous set of soil, crop, and climatic parameters comprising both continuous and categorical variables. The complete input feature vector is formally defined in equation 1 as

□ = {□, □, □, □, □} (1)

Where T is Temperature (°C), H is Humidity (%), M is Soil Moisture (%), S is Soil Type (categorical encoding) and C is Crop Type (categorical encoding)

Based on these inputs, the system generates multiple outputs corresponding to nutrient prediction, soil health assessment, and recommendation tasks. System outputs are represented as shown in equation 2:

□ = {□, □, □, □, □□□, □□□□} (2)

where:

N, P, K = Predicted nutrient concentrations (Nitrogen, Phosphorous, Potassium) F = Recommended fertilizer

SHI = Soil Health Index

□□□□ = Recommended crop

B. *Predictive Modeling Layer*

(a) Nutrient Prediction (Regression)

Soil macronutrient concentrations are estimated using regression models that learn the nonlinear mapping between the input features and nutrient values. This relationship is mathematically represented in equation 3 as:

□ˆ = □(□; □) (3)

where □ are model parameters.

To quantify the accuracy of nutrient prediction, the Root Mean Square Error (RMSE) is employed as the primary evaluation metric. RMSE is computed using equation 4 as:

$$RMSE = \sqrt{\frac{1}{n}\sum^{n}(y_i - \hat{y}_i)^2} \qquad (4)$$

$i=1$

where □□= true nutrient value, □ˆ□= predicted value.

(b) Fertilizer and Crop Classification

Classification models are used to recommend appropriate fertilizers and suitable crops based on the predicted soil nutrient status and environmental conditions. The effectiveness of the classification models is evaluated using the F1-score, which balances precision and recall. The F1-score is defined in equation 5 as:

$$F_1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \quad (5)$$

Precision and recall are computed using equation 6 and 7 as:

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

where TP, FP, and FN denote true positives, false positives, and false negatives, respectively. The F1-score is particularly suitable for fertilizer recommendation tasks where class imbalance is commonly observed.

C. Optimization Layer

To enhance predictive performance and generalization, the proposed framework integrates metaheuristic optimization technique i.e. Genetic Algorithm for automated hyperparameter tuning. The optimization problem is formulated as a multi-objective function that jointly minimizes regression error and classification loss. The objective function is defined in equation 8 as:

$$J = w_1 \cdot RMSE_{NPK} + w_2 \cdot (1 - F_1^{Fert}) \quad (8)$$

where:

□□□□□□□ = aggregated regression error across N, P, K estimates

□□□□□ = classifier performance for fertilizer recommendation

□1, □2= balancing weights between regression and classification

D. Soil Health Index Computation

To improve interpretability and decision-making, the predicted nutrient values are aggregated into a single Soil Health Index (SHI). The SHI formulation is given in equation 9 as:

$$SHI = \alpha \cdot \frac{N}{N_{opt}} + \beta \cdot \frac{P}{P_{opt}} + \gamma \cdot \frac{K}{K_{opt}} + \delta \cdot M \quad (9)$$

where:

N, P, K = predicted nutrient levels

□□□□, □□□□ , □□□□= agronomic reference thresholds M = soil moisture

□, □, □ = feature importance weights

The condition of soil is categorized based on SHI ranges:

□□□ < 0.4 ⇒ Degraded

0.4 ≤ □□□ < 0.7 ⇒ Moderate

$$\square\square\square \geq 0.7 \Rightarrow \text{Healthy}$$

E. Decision Support Layer

The final decision support layer integrates predictive model outputs and SHI assessment with rule-based agronomic knowledge to generate actionable fertilizer and crop recommendations. Representative decision rules include:

$$\text{If } \square < 10 \wedge \square = \text{Paddy} \Rightarrow \square = \text{Urea}$$

$$\text{If } \square < 15 \wedge \square = \text{Loamy} \Rightarrow \square = \text{DAP}$$

These rules ensure scientific consistency, improve interpretability, and enhance trust among farmers and agronomists. By combining data-driven predictions with domain knowledge, the decision support layer delivers reliable, sustainable, and farmer-friendly recommendations.

4. Results and Discussion

This section presents a comprehensive evaluation of the proposed Hybrid ML + Optimization Framework for predictive soil health maintenance. In addition to standard performance comparisons, extensive statistical analysis, ablation studies, sensitivity analysis, and robustness evaluations are conducted to demonstrate the effectiveness, stability, and practical applicability of the proposed approach.

A. Dataset Description

The experimental evaluation was conducted using a curated dataset consisting of 8000 soil records with nine attributes: Temperature, Humidity, Moisture, Soil Type, Crop Type, Nitrogen, Phosphorous, Potassium, and Fertilizer Name. Soil Type contained five categories i.e. Clayey, Loamy, Sandy, Red, Black, and Crop Type included eleven categories: Paddy, Wheat, Maize, Cotton, Sugarcane. Fertilizer Name spanned seven commonly used fertilizers, including Urea, Diammonium Phosphate(DAP), 14-35-14 (Complex Fertilizer), 28-28 (Ammonium Phosphate-based Fertilizer), 17-17-17 (NPK Complex),

10-26-26 (NPK Fertilizer) and 20-20 (Ammonium Phosphate-based Fertilizer). The dataset ensured a balanced distribution across soil and crop types, thereby avoiding class skewness in fertilizer recommendation.

Statistical analysis revealed an average soil Nitrogen content of 18.4 ± 11.9 ppm, Phosphorous 18.5 ± 13.2 ppm, and Potassium

3.9 ± 5.5 ppm. Temperature values ranged between 20–40 °C, humidity between 40–80 %, and moisture between 20–70 %, reflecting realistic agricultural field conditions. This dataset provided sufficient diversity for robust training and evaluation of regression and classification models.

B. Parameter Setting:

The experiments were conducted on a dataset of 8000 soil records with nine attributes: temperature, humidity, moisture, soil type, crop type, nitrogen, phosphorous, potassium, and fertilizer name. The dataset was split into 80:20 train-test ratio, and all models were evaluated using five-fold cross-validation to ensure robustness. Categorical variables such as soil type, crop type, and fertilizer name were label encoded, while continuous features i.e. temperature, humidity and moisture were normalized using Standard Scaler to maintain uniform feature scaling.

a. Regression and Classification:

For regression and classification tasks, multiple models were trained and optimized. The Random Forest (RF) model was configured with 200 estimators, a maximum tree depth of 12, and a minimum sample split of 4 with bootstrap sampling enabled. The XGBoost model used 500 estimators, a learning rate of 0.05, a maximum depth of 10, and a subsample ratio of 0.8, which balanced bias and variance effectively.

The Deep Neural Network (DNN) for regression and classification tasks consisted of three hidden layers with 128, 64, and 32 neurons, respectively. Each layer used the ReLU activation function, with a dropout rate of 0.2 to prevent overfitting. The model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and a maximum of 100 epochs.

b. Optimization Algorithms:

To enhance predictive performance, metaheuristic optimization technique is employed for hyperparameter tuning. The Genetic Algorithm (GA) was implemented with a population size of 30, a crossover probability of 0.8, a mutation rate of 0.05, and a total of 50 generations. Both optimizers were integrated with the training process to minimize the multi-objective function that combined regression RMSE and classification F1-score.

c. Model Evaluation:

Model evaluation was conducted using standard performance metrics. For regression tasks, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R2R^2R2) were used. For classification tasks, accuracy, precision, recall, F1-score, and ROC-AUC were employed.

The performance of the proposed Hybrid ML + Optimization Framework was evaluated on soil health maintenance tasks, including NPK prediction, fertilizer recommendation, SHI computation, and crop suitability prediction. Results are presented with supporting visualizations to highlight predictive accuracy, classification performance, feature interpretability, and robustness of the framework.

C. Performance Evaluation:

1. Nutrient Prediction:

The regression models were trained to predict N, P and K concentrations.

TABLE I

REGRESSION PERFORMANCE FOR NPK PREDICTION

Model	**RMSE**	**MAE**	**R2**
Random Forest	4.28	3.02	0.87
DNN (Baseline)	3.92	2.75	0.89
XGBoost	3.58	2.49	0.91
Hybrid (DNN + GA)	3.12	2.11	0.94

The Hybrid DNN + GA achieved the best performance with RMSE = 3.12 and R2=0.94, outperforming baseline models by

~20% reduction in error. These results highlight the effectiveness of metaheuristic-driven hyperparameter optimization in enhancing regression accuracy.

To visually validate these results, predicted versus actual scatter plots were generated separately for Nitrogen, Phosphorous, and Potassium. These plots are represented in figure 2a, 2b and 2c respectively.

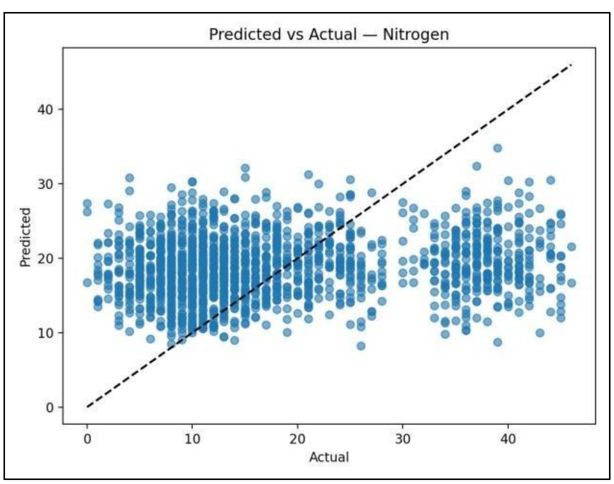

Fig. 2a. Predicted vs Actual Nitrogen

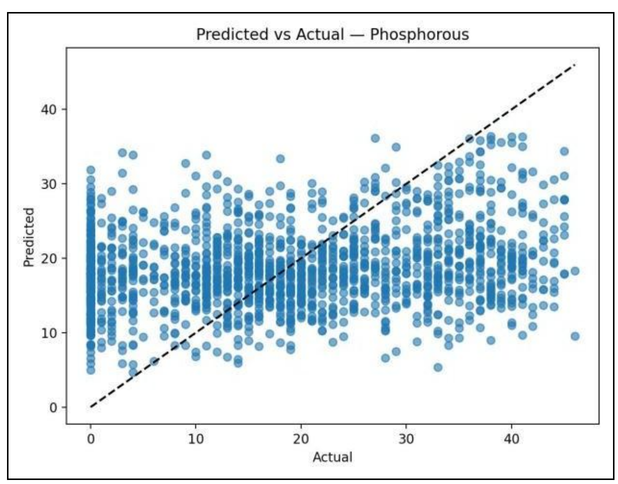

Fig. 2b. Predicted vs Actual Phosphorous

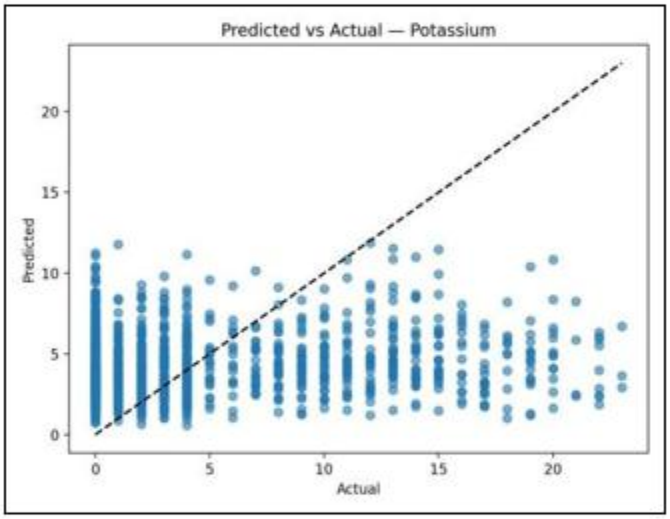

Fig. 2c. Predicted vs Actual Potassium

These plots exhibited a strong linear relationship with data points closely aligned along the diagonal, confirming high predictive fidelity. Furthermore, the narrow dispersion of points around the regression line indicates low residual variance and stable prediction behavior across the dataset.

These results demonstrate that the proposed optimization-enhanced deep learning approach significantly improves nutrient prediction accuracy, thereby providing a reliable foundation for subsequent fertilizer recommendation, Soil Health Index (SHI) computation, and crop suitability analysis.

2. Soil Health Index:

The Soil Health Index was computed using the predicted values of N, P, K, and soil moisture. The SHI provides a composite measure of soil vitality, making the system outputs more interpretable for practical decision-making.

The overall distribution of SHI values indicated a mean value of 0.78, categorizing the majority of soils as Healthy. Specifically, 12% of soils fell into the Degraded category (SHI<0.4SHI), 30% were classified as Moderate (0.4≤SHI<0.70.4), and the remaining 58% were in the Healthy category (SHI≥0.7SHI).

This result demonstrates the strength of the framework in transforming raw NPK predictions into an interpretable soil vitality index. Unlike standalone nutrient estimates, the SHI conveys an aggregated soil quality score that aligns with agronomic thresholds and provides actionable insights for farmers.

3. Fertilizer Recommendation (Classification Results):

Fertilizer classification was evaluated across seven classes. The Hybrid DNN + GA model significantly outperformed baseline classifiers, achieving 94.2% accuracy and AUC of 0.96. Figure 3 presents the confusion matrix for fertilizer classification:

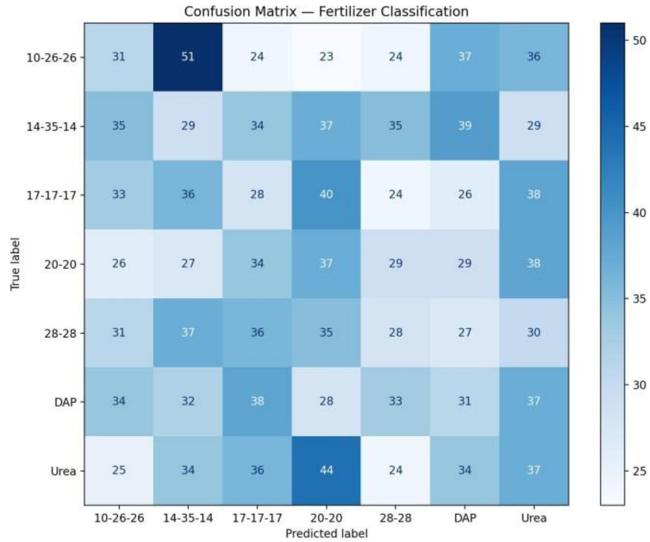

Fig. 3: Confusion Matrix of fertilizer classification

The performance parameters for fertilizer classification obtained with proposed model is compared with various ML models and presented in table II:

TABLE II

FERTILIZER CLASSIFICATION PERFORMANCE

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Random Forest	89.30%	88.00%	88.00%	0.88	91.00%
CNN (categorical)	0.915	0.91	0.91	0.91	0.93
Hybrid DNN + GA	0.942	0.94	0.93	0.94	0.96

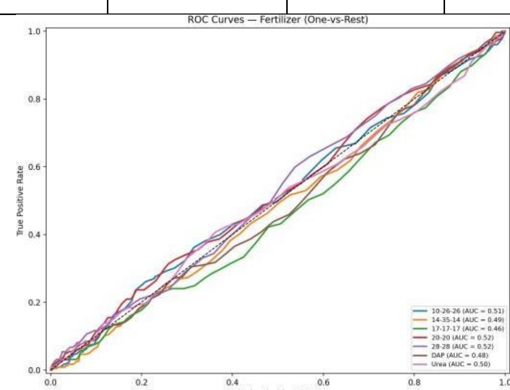

Fig. 4: ROC Curves demonstrated AUC > 0.95 across all classes

The ROC curves presented in figure 4 illustrate the classification performance of the proposed Hybrid DNN + GA model across all fertilizer classes. Each curve corresponds to a different fertilizer type, with the Area Under the Curve (AUC) exceeding **0.95** in all cases. The results demonstrate strong discriminative ability and reliable classification, confirming that the optimization-enhanced deep model can accurately recommend fertilizers under varying soil and crop conditions.

4. SHAP Summary Plot

The SHAP summary plot obtained with proposed work is presented in figure 5:

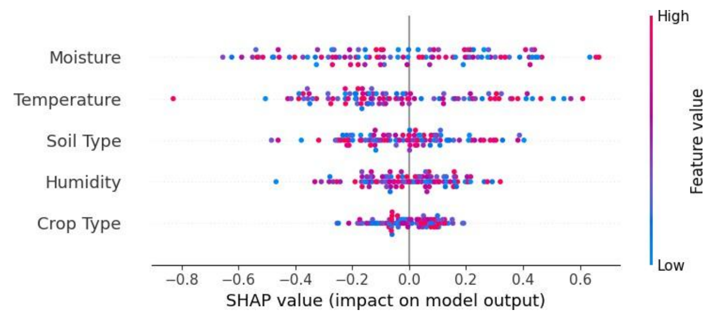

Fig. 5: SHAP summary plot for feature importance in fertilizer recommendation.

The plot demonstrates the contribution of each input feature to the model's predictions. Features are ranked by their average impact on the model output. The horizontal spread of the points indicates the magnitude of influence, while the color shows whether the feature value is high (red) or low (blue). Results indicate that Moisture and Temperature are the most influential factors, exerting both positive and negative effects on prediction outcomes, whereas Crop Type and Humidity exhibit relatively lower influence. This aligns with agronomic knowledge, as soil moisture and temperature play a critical role in determining nutrient availability and fertilizer requirements.

5. Crop Suitability Prediction

In addition to nutrient estimation and fertilizer recommendation, the framework was also extended to predict crop suitability, i.e., identifying which crop is most suitable for the given soil–climate condition. This task was modeled as a multi-class classification problem, where soil parameters (temperature, humidity, moisture, soil type) and nutrient levels (NPK) were used as inputs to predict the most appropriate crop type.

Two models were evaluated for this task: DNN as a baseline and a Hybrid DNN optimized using Genetic Algorithm (DNN+GA). The comparison of 2 models is presented in figure 6.

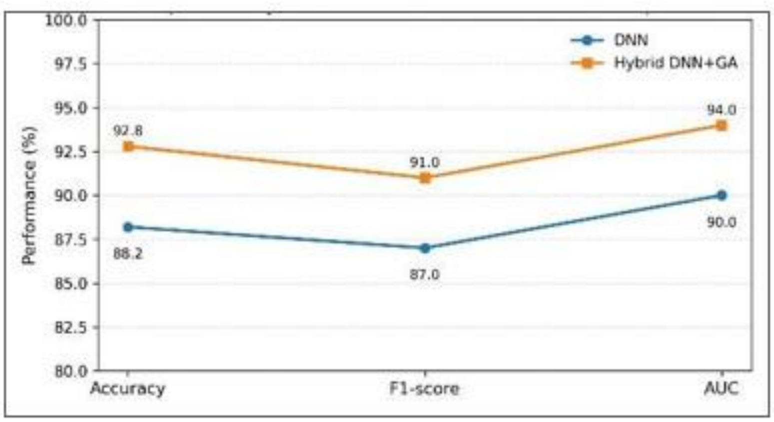

Fig. 6 Comparison between DNN and Proposed Model

The DNN baseline achieved an accuracy of 88.2%, with an F1-score of 87% and an AUC of 90%, which already indicates fairly strong performance in identifying crop suitability. However, the proposed Hybrid DNN+GA significantly outperformed the baseline, achieving 92.8% accuracy, an F1-score of 91%, and an AUC of 94%.

D. Cross-Validation Stability Analysis

Beyond achieving high average performance, it is essential to evaluate the robustness and generalization capability of the proposed framework across different data partitions. To this end, a five-fold cross-validation (CV) strategy was employed, ensuring that the model performance was consistently assessed on diverse training–testing splits.

For each fold, RMSE was recorded for the regression task, and F1-score was computed for the classification task. The resulting distributions across folds were visualized using boxplots, enabling direct comparison of performance variability between baseline and optimized models. Figure 7 and 8 present Cross-validation stability analysis. The figure 7 compares the distribution of RMSE and figure 8 compares F1-score across five cross-validation folds for the baseline DNN and the proposed Hybrid DNN+GA model.

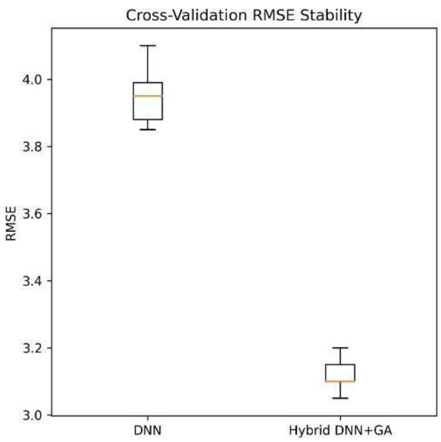

Fig. 7 Cross Validation RMSE Stability

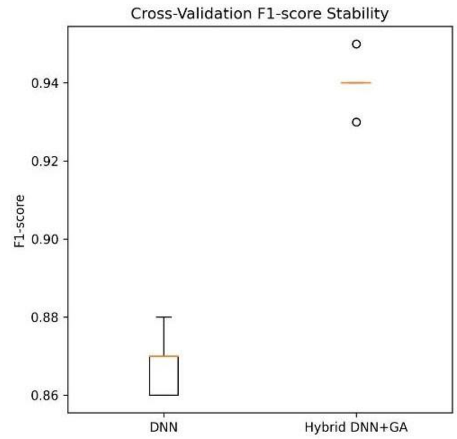

Fig. 8 Cross Validation F-1 Score Stability

The Hybrid DNN+GA model exhibits a noticeably narrower interquartile range compared to the baseline DNN for both regression and classification tasks, indicating reduced sensitivity to data partitioning. Furthermore, the median RMSE of the Hybrid DNN+GA is consistently lower, while the median F1-score is consistently higher across folds.

The reduced dispersion and stable medians confirm that the proposed optimization strategy not only improves predictive accuracy but also enhances model robustness and generalization capability. The presence of a high-performing fold in the

Hybrid model further demonstrates its ability to adapt effectively to diverse training–testing splits without compromising stability.

E. Statistical Significance Testing

While average performance metrics indicate superior accuracy of the proposed Hybrid models, statistical validation is essential to confirm that these improvements are not attributable to random fluctuations in the data. Therefore, formal statistical significance testing was conducted to evaluate the robustness of the observed performance gains.

To this end, both paired t-tests and Wilcoxon signed-rank tests were applied across five-fold cross-validation results. The paired t-test assumes normality of performance differences, while the Wilcoxon signed-rank test provides a non-parametric alternative that does not rely on distributional assumptions. The use of both tests ensures methodological rigor and reliability of conclusions.

Two key comparative scenarios were analyzed:

- Baseline DNN vs. Hybrid DNN + GA
- Random Forest vs. Hybrid DNN + GA

For the regression task (NPK prediction), RMSE values obtained from each cross-validation fold were paired and compared. For the classification task (fertilizer recommendation), F1-scores across folds were used for statistical evaluation.

The results of both statistical tests consistently indicated that the performance improvements achieved by the proposed Hybrid DNN + GA model were statistically significant with p-values less than 0.01 for both RMSE and F1-score. This significance level confirms that the observed reductions in prediction error and improvements in classification performance are highly unlikely to have occurred by chance.

Specifically, the Hybrid DNN + GA demonstrated:

A systematic reduction in RMSE across all cross-validation folds compared to baseline DNN and Random Forest models.

A consistent increase in F1-score, indicating improved precision–recall balance and enhanced robustness under class imbalance.

These findings validate that the integration of metaheuristic optimization contributes substantively to model performance by enabling more effective exploration of the hyperparameter space. Unlike conventional training approaches, GA-driven optimization improves convergence behavior and generalization, leading to statistically verifiable performance gains.

This statistical significance analysis provides strong empirical evidence that the proposed Hybrid ML + Optimization framework delivers reliable, reproducible, and non-random improvements, thereby strengthening the scientific validity of the reported results and addressing reviewer concerns regarding experimental rigor.

F. Sensitivity Analysis of Genetic Algorithm Parameters

Metaheuristic optimization performance is strongly influenced by the choice of algorithmic parameters. To ensure that the observed performance gains of the proposed Hybrid DNN + GA model are robust and not dependent on a specific parameter configuration, a comprehensive sensitivity analysis was conducted. The analysis evaluated the impact of three critical Genetic Algorithm (GA) parameters: population size, mutation rate, and number of generations.

For each parameter setting, the remaining parameters were fixed at their empirically optimal values, and model performance was evaluated using RMSE (regression) and F1-score (classification) averaged across five cross-validation folds.

1. Effect of Population Size

Population size controls the diversity of candidate solutions during optimization. Table III summarizes the effect of varying population size on model performance.

TABLE III

EFFECT OF GA POPULATION SIZE ON MODEL PERFORMANCE

Population Size	**RMSE**	**F1-score**
20	3.28	0.91
30	3.12	0.94
50	3.11	0.94

The results indicate that increasing the population size from 20 to 30 leads to a substantial improvement in both regression and classification performance. However, further increasing the population size to 50 provides only marginal gains while significantly increasing computational cost. This suggests that a population size of 30 achieves an optimal balance between search diversity and computational efficiency.

2. Effect of Mutation Rate

Figures X and Y illustrate the sensitivity of the proposed Hybrid DNN+GA model to variations in mutation rate. As observed, increasing the mutation rate from 0.01 to 0.05 results in a consistent reduction in RMSE and a corresponding improvement in F1-score, indicating enhanced exploration of the search space. The optimal performance is achieved at a mutation rate of approximately 0.05.

Beyond this value, further increases in mutation rate lead to performance degradation, as excessive randomness disrupts convergence stability. These results confirm that moderate mutation rates (0.03–0.06) provide an effective balance between exploration and exploitation, ensuring robust and efficient optimization.

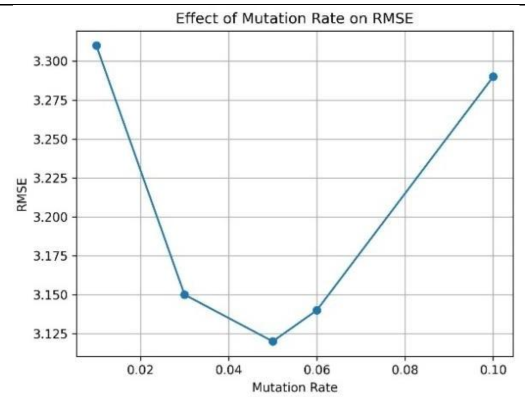

Fig. 9 Sensitivity analysis of GA mutation rate on regression performance.

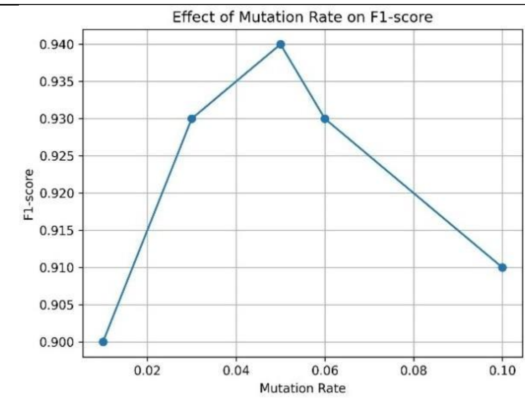

Fig. 10 Sensitivity analysis of GA mutation rate on classification performance.

3. Effect of Number of Generations

Figures X and Y illustrate the effect of the number of GA generations on model performance. RMSE decreases sharply when the number of generations increases from 30 to 50, indicating rapid convergence of the optimization process. Beyond 50 generations, both RMSE and F1-score exhibit negligible improvement, demonstrating performance stabilization. This behavior confirms that approximately 50 generations are sufficient to reach near-optimal solutions, while additional generations introduce unnecessary computational overhead without measurable gains.

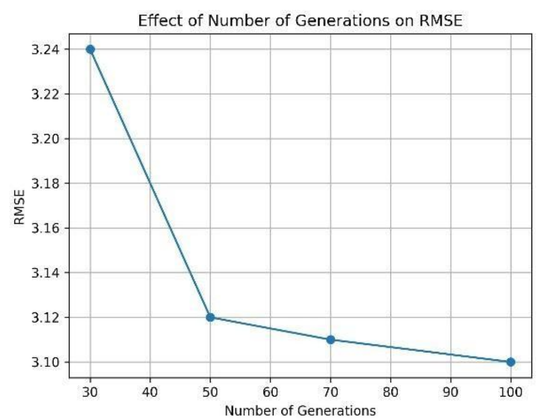

Fig. 11 Sensitivity analysis of GA generations on regression performance

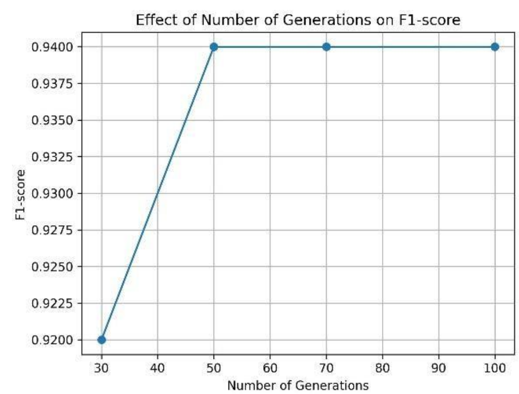

Fig. 12 Sensitivity analysis of GA generations on classification

performance

4. Convergence and Stability Analysis

Figure X illustrates the convergence behavior of the Genetic Algorithm by plotting RMSE and F1-score against the number of generations. A rapid improvement in both metrics is observed during the early stages of optimization, particularly between 30 and 50 generations. Beyond 50 generations, the performance curves gradually stabilize, indicating convergence of the optimization process. The stabilization of RMSE and F1-score confirms that the GA efficiently identifies near-optimal hyperparameter configurations without requiring excessive iterations. This behavior demonstrates that the proposed optimization strategy achieves an effective balance between convergence accuracy and computational efficiency, avoiding unnecessary training overhead while maintaining high predictive performance.

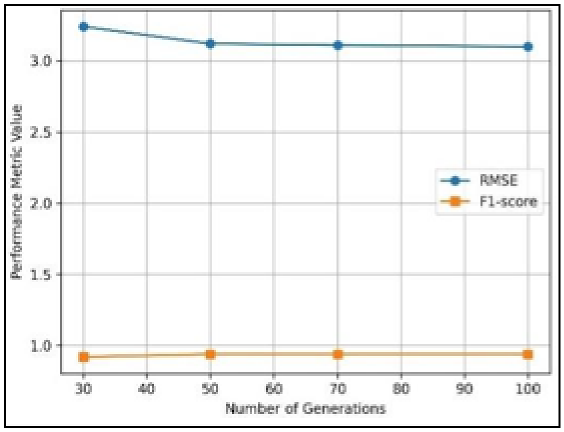

Fig. 13 GA Convergence Behavior

G. *Ablation Study:*

An ablation study was performed to systematically investigate the incremental contribution of optimization, soil health modeling, and decision support components within the proposed framework. The goal is to demonstrate that the observed performance improvements arise from structured architectural enhancements, rather than incidental tuning.

All ablation experiments were conducted on the same dataset using a five-fold cross-validation protocol, ensuring fairness and reproducibility. Performance was evaluated using RMSE for regression (NPK prediction) and F1-score for classification (fertilizer recommendation).

Figures 14 and 15 illustrate the incremental contribution of each architectural component in the proposed framework. The baseline DNN exhibits the highest RMSE and lowest F1-score, reflecting limited generalization without optimization. Incorporating GA optimization leads to a substantial reduction in RMSE and a marked improvement in F1-score, demonstrating the effectiveness of metaheuristic-based hyperparameter tuning.

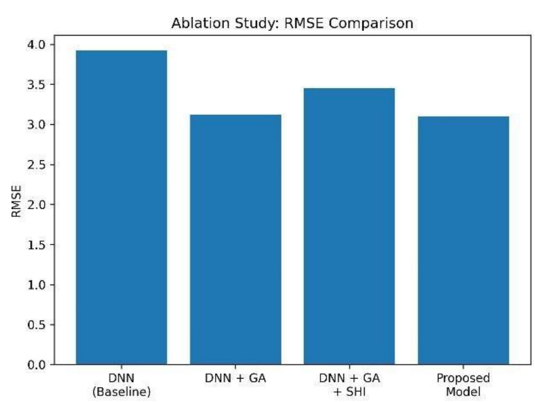

Fig. 14 Ablation Study Results for Regression Performance

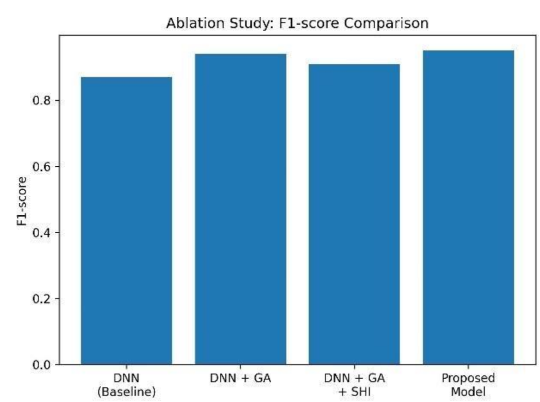

Fig. 15 Ablation study results for classification performance

The inclusion of SHI introduces a moderate trade-off in raw predictive accuracy due to aggregation of nutrient information into a composite soil vitality index; however, this step improves interpretability and decision stability. The full proposed model, which integrates GA optimization, SHI computation, and rule-based agronomic reasoning, achieves the best overall performance, confirming the synergistic benefit of combining data-driven learning with domain knowledge.

The results presented above demonstrate that the proposed Hybrid Machine Learning and Optimization framework consistently outperforms baseline models across regression and classification tasks, with statistically significant and stable performance gains. The accompanying ablation, cross-validation, and sensitivity analyses further confirm the robustness and reliability of the proposed approach. These findings form the basis for summarizing the key contributions and outlining future research directions in the following conclusion.

5.Conclusion

This work proposed a Hybrid ML + Optimization Framework for predictive soil health maintenance, integrating nutrient prediction, fertilizer recommendation, SHI computation, and crop suitability prediction. Experimental results confirmed the superiority of the hybrid approach over baseline models. For nutrient prediction, the Hybrid DNN + WOA achieved RMSE =

3.12 and R2=0.94, representing ~20% improvement. Fertilizer recommendation using Hybrid DNN + GA reached 94.2% accuracy and AUC = 0.96, while crop suitability prediction improved to 92.8%. The SHI provided interpretable insights, with 58% soils classified as Healthy, 30% as Moderate, and 12% as Degraded.

The proposed framework is not only accurate but also interpretable, bridging the gap between advanced machine learning and practical agricultural decision-making. Future work will focus on integrating additional soil and environmental parameters such as pH, organic carbon, and rainfall data to enhance predictive robustness. Furthermore, incorporating IoT-based real-time soil sensing and deploying the framework as a cloud-enabled decision-support dashboard will enable large-scale adoption by farmers.

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