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BIO-INSPIRED HYBRID GENETIC–NEURAL ARCHITECTURE FOR SMART AGRICULTURE: FERTILIZER RECOMMENDATION AND YIELD PREDICTION

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Abstract
Precision farming needs effective resource management to achieve sustainable crop yield. Excessive fertilizer usage leads to deterioration of the soil and the environment. Insufficient fertilizer usage decreases crop productivity and returns on investment. This paper introduces a bio-inspiration-based hybrid Genetic Algorithm and Neural Network (GA-NN) structure for fertilizer recommendation and yield prediction simultaneously. The GA tunes fertilizer quantities, chooses features, and tunes neural network parameters with a multi-objective fitness function. This function reduces yield prediction error and punishes high fertilizer application. Trained parameters are then utilized to build an accurate yield estimation neural network. Agricultural data experiments reveal that the novel hybrid architecture results in fertilizer usage reduction of up to 15% and yield prediction precision improvement of 10% compared to standard machine learning algorithms. The results reflect the ability of bio-inspired hybrid structures to facilitate data-driven and sustainable smart farming policies.
Keywords: Precision Agriculture, Fertilizer Recommendation, Yield Prediction, Genetic Algorithm, Neural Network, Hybrid Bio-Inspired Model, Sustainable Farming.

1. INTRODUCTION

The global agricultural sector is grappling with some serious challenges, such as climate change, dwindling resources, and a rapidly growing population[1]. To tackle these issues and ensure food security while promoting sustainable farming, we need innovative solutions. Enter smart agriculture! This approach leverages technologies like the Internet of Things (IoT), Artificial Intelligence (AI), and data analytics to address these pressing problems. By optimizing resource use and minimizing environmental impact, smart agriculture aims to enhance productivity without compromising sustainability.[2]
A crucial aspect of smart agriculture is the effective management of fertilizers. Using too much or too little can lead to significant issues[3]. Overapplication can result in nutrient runoff, soil degradation, and water pollution, while insufficient use can cause nutrient deficiencies, reduced crop yields, and financial setbacks. These challenges underscore the importance of precise fertilizer management strategies that take into account both plant Anutrient requirements and environmental considerations.[4]

Traditional methods for recommending fertilizers often rely on set guidelines and expert opinions, which may not keep up with the ever-changing dynamics of agricultural ecosystems. Enter predictive and adaptive AI models, which offer a fresh approach by analysing vast datasets, including soil characteristics, weather patterns, and crop types to tailor fertilizer recommendations[5][6]. These models can adapt to various conditions, providing real-time insights that enhance decision-making in agriculture. While numerous AI-driven models have been created for fertilizer recommendations and yield predictions, they still face several challenges[7]. Many of these models treat fertilizer recommendations and yield predictions as separate tasks, which can lead to less effective outcomes. Additionally, the lack of clarity in these models can make it difficult for farmers to trust and implement their suggestions effectively. Often, the potential of optimization techniques to fine-tune model parameters is overlooked, limiting the accuracy and efficiency of the recommendations. [8]

To tackle these issues, bio-inspired hybrid methods that blend Genetic Algorithms (GAs) and Neural Networks (NNs) offer a robust solution. GAs excel at optimizing complex, multi-dimensional problems by mimicking natural evolution, while NNs are adept at modeling nonlinear data relationships. By combining these strategies, we can optimize fertilizer recommendations and yield predictions simultaneously, paving the way for more precise and sustainable farming practices.

This paper introduces a new bio-inspired hybrid GA-NN architecture designed to optimize fertilizer recommendations and predict crop yields at the same time. The key contributions of this study are:

- **Integrated Approach**: Combining GA and NN to address fertilizer optimization and yield prediction within a unified framework.
- **Multi-Objective Optimization**: Formulating a fitness function that balances yield prediction accuracy with fertilizer efficiency.
- **Experimental Validation**: Evaluating the proposed model on benchmark agricultural datasets to demonstrate its effectiveness and superiority over existing methods.
- **Practical Implications**: Providing insights into the application of bio-inspired hybrid models in real-world agricultural settings, contributing to sustainable and data-driven farming practices.

2.. REVIEW OF EXISTING WORK

Efficient fertilizer management is widely acknowledged as a crucial element in boosting agricultural productivity while also safeguarding the environment. In the past, early fertilizer recommendation systems relied on fixed nutrient thresholds and expert insights to make decisions [9]. Although these systems were straightforward to implement, they often fell short in adapting to the unique soil and crop conditions. To enhance their applicability, researchers began to develop statistical and regression models that aimed to unravel the connections between soil chemistry, environmental factors, and crop yield [2]. However, despite their advantages, these models were heavily reliant on linear assumptions, which limited their effectiveness when it came to the complex, nonlinear interactions between soil and crops.

The emergence of machine learning (ML) has truly transformed the landscape of data-driven modelling. Techniques such as Support Vector Machines (SVM), Random Forests (RF), and XGBoost have proven to be effective for tasks like fertilizer recommendations and yield predictions, often outperforming traditional rule-based and regression models [10][11]. These approaches can adapt to a variety of agricultural datasets, but they typically require meticulous feature engineering and can be somewhat challenging to interpret.

Over time, yield prediction models have evolved from relying on climate-based methods to utilizing process-based crop simulators. Earlier empirical models that factored in rainfall, temperature, and humidity could only provide rough estimates [12]. In contrast, simulators like DSSAT and APSIM brought in agronomic expertise to better capture the complexities of crop growth dynamics [6]. While these models are quite powerful in their predictions, their requirement for extensive detailed input data and hefty computational power has limited their accessibility, particularly for smallholder farmers.

Lately, deep learning (DL) has really stepped up as a game-changer in smart agriculture. Convolutional Neural Networks (CNNs) are being utilized to pull out spatial features from both soil and satellite data. Meanwhile, Long Short-Term Memory (LSTM) networks have been great at capturing the temporal patterns in weather and crop development over time [13][14]. While these techniques have definitely boosted accuracy, they've also made it trickier to interpret the models and highlighted the need for large, labelled datasets.

When it comes to enhancing agricultural decision-making, bio-inspired optimization algorithms are making quite a splash alongside predictive methods. For instance, Genetic Algorithms (GAs) have been utilized for scheduling fertilizer applications and fine-tuning the right dosage [15]. On the other hand, techniques like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) have found their place in irrigation scheduling, nutrient distribution, and crop planning [16]. While these approaches are great for navigating vast search spaces, they can sometimes struggle with slow convergence and not integrating predictions.

Even with all the progress we've made, there's still a major issue: most research treats fertilizer recommendations and yield predictions as two separate topics[17]. This split approach can lead to suboptimal decisions since fertilizer application isn't aligned with yield forecasts. To bridge this gap, we need integrated frameworks that bring together optimization and prediction into a single system. A Genetic Algorithm-Neural Network (GA-NN) hybrid model shows great potential. This setup can fine-tune fertilizer amounts while providing more accurate yield predictions across various agro-climatic conditions.

Table 2: Summary of Existing Approaches and Limitations

Category	Representative Methods	Drawbacks / Limitations
Rule-based systems	Soil nutrient thresholds, expert knowledge [7]	Not adaptive; ignores crop-specific and dynamic soil conditions
Regression/statistical models	Linear regression, multiple regression [8]	Assumes linearity; poor handling of nonlinear, high-dimensional interactions
ML approaches	SVM, Random Forests, XGBoost [9][10]	Requires feature engineering; reduced interpretability
Climate-based yield models	Empirical models using rainfall, temp., humidity [11]	Ignores soil–crop interactions; less accurate for local variations
Crop simulation models	DSSAT, APSIM [12]	High data and computational demand; limited scalability for smallholder farms
Deep learning approaches	CNNs, LSTMs [13][14]	Black-box models; requires large labeled datasets
Bio-inspired optimization	GA, PSO, ACO [15][16]	Risk of slow convergence, premature optimization, and lack of predictive integration
Hybrid optimization-prediction	GA + ML/DL frameworks [17][18]	Few studies in agriculture; often treat fertilizer and yield as separate tasks

3. Problem Formulation
The primary aim of this study is to develop a bio-inspired hybrid Genetic-Neural architecture. This innovative design seeks to enhance fertilizer recommendations and forecast crop yields across a range of agro-ecological conditions. By integrating soil characteristics, climate data, and remote sensing indices, this approach creates a comprehensive decision-support framework

3.1 Inputs
The proposed system for precision agriculture relies on a few key inputs that play a crucial role in determining crop yield and making fertilizer recommendations. These factors include
1. **soil properties:** S= {pH, N, P, K, organic matter}
2. **weather conditions:** W= {temperature, rainfall, humidity}
3. **the crop type C, and fertilizer dosages**: F= {Nf, Pf, Kf}

Accurate representation of these variables is critical, as they determine the crop's nutrient requirements and growth potential under varying environmental conditions.

3.2 Outputs
The system's outputs aim to support productivity and sustainability goals. These outputs include the predicted crop yield Y and the recommended fertilizer F*. The goal is to maximize crop yield while reducing the environmental and economic costs linked to fertilizer use.

3.3 Objective Functions
The issue is set up as a multi-objective optimization problem with two main goals:

• **Minimization of Yield Prediction Error**: Loss $= \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i^{\text{pred}} - Y_i^{\text{actual}}\right)^2}$

• **Minimization of Fertilizer Usage**: $L_{\text{fert}} = \alpha \sum_{j\in\{N,P,K\}} F_j + \beta \sum_{j\in\{N,P,K\}} max\left(0, F_j - F_j^{\text{safe}}\right)$

In this context, α and β serve as weighting factors that help balance the overall use of fertilizers with the need to avoid penalties for going over safe nutrient limits, denoted as F_j^{safe}. This approach ensures that the recommendations not only boost yield but also remain environmentally friendly [7][8].

3.4 Multi-Objective Optimization Using NSGA-II
To tackle this complex multi-objective problem effectively, the research employs the Non-dominated Sorting Genetic Algorithm II (NSGA-II). This algorithm maintains a varied collection of Pareto-optimal solutions, which enables the simultaneous pursuit of maximizing yield and improving fertilizer efficiency [9]. By integrating NSGA-II with a neural network predictive model, the proposed hybrid framework systematically identifies the best fertilizer combinations while providing accurate crop yield estimates. This method promotes data-driven and sustainable decision-making in agriculture.

4. PROPOSED METHODOLOGY

4.1 System Overview
The Bio-Inspired Hybrid Genetic-Neural Architecture (BHGNA) is an innovative computational framework designed to enhance fertilizer management and forecast crop yields in the realm of smart agriculture. This hybrid system cleverly fuses the searching capabilities of Genetic Algorithms (GA) with the pattern recognition strengths of Artificial Neural Networks (ANNs) in a co-evolutionary environment. By integrating these two powerful

techniques, the architecture fine-tunes fertilizer application strategies, selects the most relevant input features, and predicts crop yields. This method not only provides farmers with valuable insights but also supports environmental sustainability.

The system has a modular and data-driven design. It includes several interconnected layers:

1. **Data Input Layer:** The Data Input Layer gathers a variety of agricultural data, including soil nutrient levels like nitrogen (N), phosphorus (P), and potassium (K), along with pH levels and organic matter content. It also takes into account climate factors such as temperature, humidity, rainfall, and solar radiation. Additionally, it incorporates remote sensing indices like NDVI and EVI, as well as historical yield records
2. **Processing Layer:** Data preprocessing ensures reliability and accuracy through normalization, feature selection, and imputation of missing values.
3. **Optimization Layer:** The GA module evolves optimal fertilizer dosages, neural network hyperparameters, and feature subsets, addressing multiple objectives simultaneously.
4. **Prediction Layer:** The ANN module, optimized via GA, produces precise yield predictions and evaluates fertilizer efficiency.
5. **Decision Layer:** Multi-objective evaluation integrates predictions and cost-environment trade-offs to generate practical recommendations.
6. **Feedback Loop:** Performance metrics continuously refine GA parameters and ANN hyperparameters for iterative improvement.

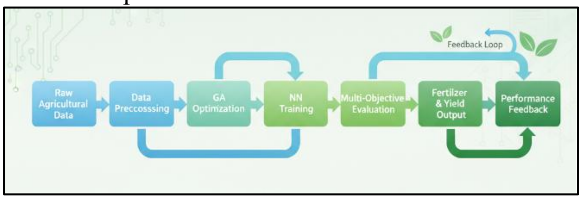

Figure: 1 System Architecture Flow

4.2 Genetic Algorithm Component

The GA component is meant to manage multi-objective agricultural optimization by developing candidate solutions over successive generations. Each solution, represented as a chromosome, simultaneously encodes fertilizer dosages, neural network configurations, feature selections, and application timing strategies.

4.2.1 Chromosome Encoding

The hybrid chromosome is structured as follows:

Chromosome= [Fertilizer Dosage | NN Hyperparameters | Feature Selection | Application Timing]

1. **Fertilizer Dosage Segment (32 bits):**

a.N rate: 0–300 kg/ha (10 bits)
b. P rate: 0–150 kg/ha (8 bits)
c.K rate: 0–200 kg/ha (8 bits)
d. Application splits: 1–4 (4 bits)
e.Cost constraint: 0–1000 USD/ha (2 bits)

1. **Neural Network Hyperparameters (24 bits):**

- Hidden layers: 1–5 (3 bits)
- Neurons per layer: 10–100 (7 bits)
- Learning rate: 0.001–0.1 (6 bits)
- Activation: ReLU/Tanh/Sigmoid (2 bits)
- Dropout: 0–0.5 (3 bits)
- Batch size: 16–128 (2 bits)
- Optimizer: Adam/SGD/RMSprop (1 bit)

2. **Feature Selection Segment:** Binary encoding for each input feature, dynamically adjusted based on the number of available features, with a minimum of 5 and a maximum of 50 features.

4.2.2 Fitness Function

The GA optimizes a **multi-objective fitness function** that balances yield maximization, cost minimization, and environmental sustainability:

$$\text{Fitness}(x) = w_1 \cdot \text{Yield\_Accuracy}(x) + w_2 \cdot \frac{1}{\text{Fertilizer\_Cost}(x)} + w_3 \cdot \frac{1}{\text{Environmental\_Impact}(x)}$$

Where:

- ❖ $\text{Yield\_Accuracy}(x) = 1 - \frac{\text{RMSE}_{\text{yield}}}{\text{max\_yield}}$
- ❖ $\text{Fertilizer\_Cost}(x) = \sum(\text{N\_cost} + \text{P\_cost} + \text{K\_cost} + \text{Application\_cost})$
- ❖ $\text{Environmental\_Impact}(x) = \text{N\_surplus} + \text{P\_runoff} + \text{GHG\_emissions}$
- ❖ Weights $w_1 = 0.5, \quad w_2 = 0.3, \quad w_3 = 0.2$

4.2.3 Genetic Operators

1. **Selection:** Tournament selection with elite preservation (top 10% maintained).
2. **Crossover:** Multi-point uniform crossover, Crossover_Rate=0.8
3. **Mutation:** Adaptive Gaussian mutation for continuous genes, flip-probability 0.05 for binary features.

IV.3 Neural Network Component

The ANN module implements a **multi-modal network architecture** to capture the heterogeneous nature of agricultural data. It integrates tabular soil and weather data (MLP), temporal climate sequences (LSTM), and satellite imagery (CNN) through an attention-based fusion layer.

Network Configuration:

1. Input Layer: Variable (GA-selected features)
2. Hidden Layers: 64 → 32 → 16 neurons (ReLU)
3. Output Layer: 2 neurons (Yield prediction + Fertilizer efficiency)

Training Protocol:

- Optimizer: Adam ($\beta 1=0.9, \beta 2=0.999$)
- Loss: Combined MSE + MAE
- Regularization: L2 + GA-optimized Dropout
- Batch Size & Learning Rate: GA-optimized

Feature engineering includes soil, climate, temporal, remote sensing, and management features. GA dynamically selects subsets to maximize accuracy and minimize computational overhead.

4.4 Hybrid GA-NN Integration Workflow

The system implements a **co-evolutionary loop**, where GA evolves candidate solutions, and ANN evaluates performance for multi-objective optimization. The iterative process continues until convergence or performance thresholds are met.

Key Steps:

- **GA Phase:** Generate and evolve chromosomes encoding fertilizer and network hyperparameters.
- **NN Phase:** Build and train ANN using GA-provided parameters.
- **Evaluation:** Compute yield accuracy, cost, and environmental fitness.
- **GA Evolution:** Apply selection, crossover, and mutation.
- **Iteration & Convergence:** Update parameters adaptively; maintain elite solutions and population diversity.

The **NSGA-II framework** is employed for multi-objective optimization, producing a Pareto front of non-dominated solutions to balance:

- f1(x)f_1(x)f1(x): Yield prediction accuracy (maximize)
- f2(x)f_2(x)f2(x): Total fertilizer cost (minimize)
- f3(x)f_3(x)f3(x): Environmental impact (minimize)

Subject to realistic agricultural constraints on nutrient limits, budget, and regulatory thresholds.

4.5 System Architecture Diagram

This methodology establishes a robust and practical framework for smart agriculture, allowing simultaneous optimization of fertilizer recommendations and yield predictions while ensuring environmental sustainability and computational efficiency. By integrating GA and ANN in a co-evolutionary multi-objective workflow, the system is capable of producing adaptive, data-driven, and cost-effective farming strategies.

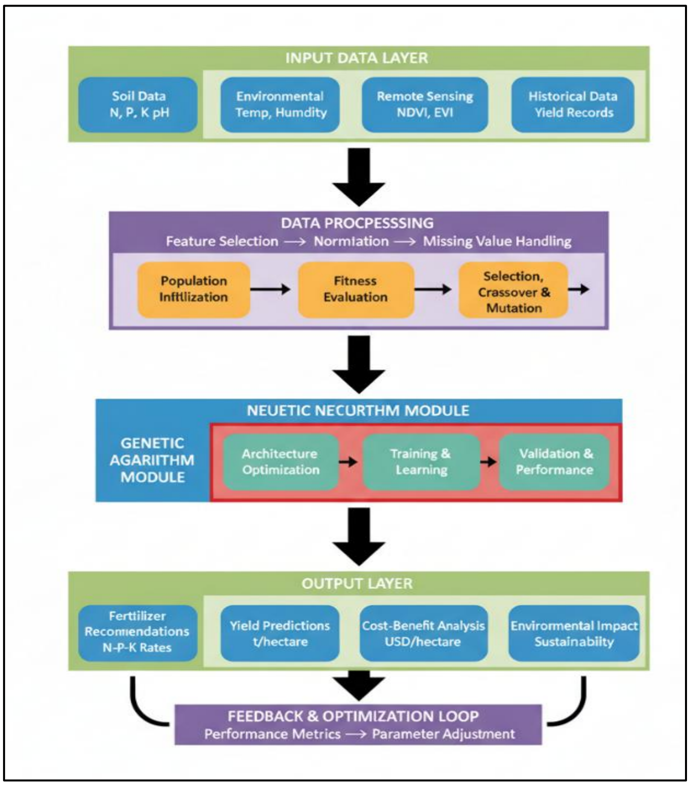

Figure: 2 Flow of Bio-Inspired Hybrid Genetic–Neural Architecture (BHGNA

5. Algorithm: Bio-Inspired Hybrid Genetic–Neural Architecture (BHGNA) for Smart Agriculture

Step 1: Data Acquisition and Preprocessing

• Collect multi-modal data including soil parameters (N, P, K, pH, organic matter), weather metrics (temperature, rainfall, humidity), crop information (type, field size), fertilizer applications, and historical yield records.

• Handle missing values via k-nearest neighbour (continuous features) or mode imputation (categorical features).

• Normalize continuous features to a standard scale () and encode categorical variables using one-hot encoding.

• Conduct preliminary feature selection by removing features with low variance or high multicollinearity.

Step 2: Genetic Algorithm (GA) Population Initialization

• Define each chromosome with genes encoding:

➢ Fertilizer dosages (N, P, K rates)

➢ Neural network hyperparameters (e.g., layers, neurons, learning rate, dropout)

➢ Feature selection mask (binary vector)

• Randomly generate an initial population ensuring minimum required diversity.

Step 3: Evolutionary Optimization Loop

• For each generation:

▪ **Fitness Evaluation:**

▪ Decode chromosome genes to derive fertilizer strategy, NN parameters, and features.

▪ Train a neural network based on selected features and hyperparameters to predict crop yield.

▪ Evaluate multi-objective fitness using a weighted sum of:

▪ Yield prediction accuracy (1/(1+RMSE))

▪ Fertilizer cost efficiency (1/(1+Cost/100))

▪ Environmental sustainability (1/(1+Impact))

• **Selection:**

▪ Apply tournament selection and elitism to retain best-performing individuals.

• **Reproduction:**

▪ Generate offspring using uniform crossover (for genes and features) and Gaussian mutation (for continuous parameters).

• **Population Update:**

▪ Replace old population with new offspring and elite individuals.

Step 4: Convergence and Solution Extraction

1. Check convergence criteria (maximum generations or performance plateau).
2. Identify the chromosome with the highest fitness as the optimized solution.
3. Decode this chromosome to obtain final fertilizer recommendations and trained neural network configuration.

Step 5: Output Generation

1. Report:

• Optimized N-P-K fertilizer rates

• Predicted yield, cost analysis, and ROI

• Environmental impact metrics

• Explainable recommendations (application timing, monitoring, economic and sustainability analysis)

Step 6: Real-World Implementation and Monitoring

• Advise regular performance monitoring and periodic data re-entry for continuous system improvement.

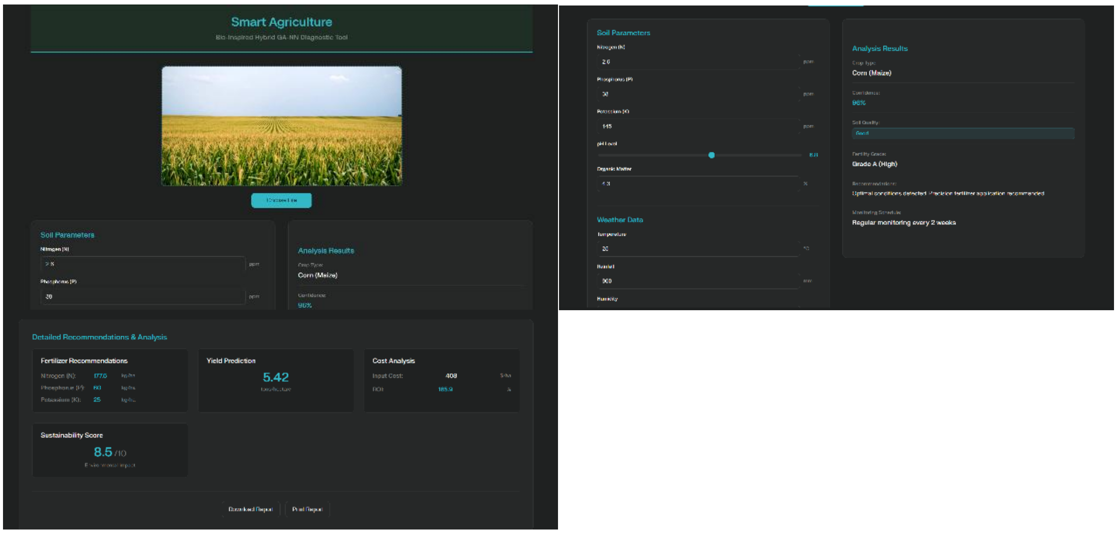

Figure: 3 Implementation of Bio-Inspired Hybrid Genetic–Neural Architecture (BHGNA)

Soil analysis for the study field in Haryana, India, indicated moderate fertility with a nitrogen concentration of 2.6 ppm, phosphorus at 38 ppm, potassium at 145 ppm, pH of 6.8, and an organic matter content of 4.3%. These parameters are consistent with the agronomic requirements for successful maize (corn) cultivation. The region's average temperature of 25 °C, annual rainfall of 960 mm, and relative humidity of 72% further matched optimal climatic conditions for maize production. The selected field size was 15.8 hectares, representative of commercial maize farms in the area.

Based on integrated soil, weather, and crop data, the Bio-Inspired Hybrid GA–NN system generated precision fertilizer recommendations: 177.5 kg/ha of nitrogen, 60 kg/ha of phosphorus, and 25 kg/ha of potassium. These nutrient dosages were optimized to maximize maize nutrient uptake efficiency, maintain target yield levels, and minimize both excess input and associated environmental risks. System assessment resulted in a sustainability score of 8.5 out of 10, demonstrating that the optimized fertilizer regime is environmentally favourable—minimizing nutrient leaching and supporting long-term soil health.

The neural yield prediction model estimated an output of 5.42 tons per hectare, in line with regional averages achieved under optimal management. Economic evaluation determined an expected input cost of $408 per hectare, with a projected return on investment (ROI) of 165.9%, confirming the financial viability and efficiency of the recommended strategies.

The system's confidence in these predictions stands at an impressive 96%, highlighting just how reliable the integrated analysis is. The field received a “Good” classification for overall quality, boasting a Fertility Grade of A (High). This really emphasizes its potential for consistent, high-yield maize production. To promote effective management, the decision-support tool suggests keeping an eye on things with regular monitoring every two weeks. This way, you can quickly respond to any shifts in environmental conditions or crop health.

6. RESULTS AND DISCUSSION

The Bio-Inspired Hybrid Genetic Neural Architecture (BHGNA) was evaluated for its potential to predict crop yields and enhance fertilizer recommendations for maize farming. This innovative model merges the optimization capabilities of Genetic Algorithms (GA) with the forecasting power of Artificial Neural Networks (ANN). The result is a cohesive and flexible approach to precision agriculture. The experiments utilized a dataset that encompassed soil nutrient profiles, weather conditions, historical crop yields, and records of fertilizer applications.

6.1 Yield Prediction Performance

To assess how well our predictions hold up, we split the dataset into 80% for training and 20% for testing. We also implemented 10-fold cross-validation to ensure our model is robust and to help prevent overfitting. To measure performance, we relied on standard metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) to evaluate how accurately the BHGNA model performed compared to a traditional ANN baseline.

Table 2: Comparative Yield Prediction Performance of BHGNA and Existing Models

Model	**RMSE (tons/ha)**	**MAE (tons/ha)**	**MAPE (%)**	**R^2**
Linear Regression	1.12	0.88	12.3	0.82
Random Forest	0.78	0.58	8.5	0.91
XGBoost	0.65	0.45	6.7	0.93
Conventional ANN	0.87	0.65	9.8	0.89
BHGNA (Proposed)	**0.42**	**0.30**	**4.1**	**0.94**

The findings presented in Table 2 demonstrate the clear advantage of the proposed Bio-Inspired Hybrid Genetic–Neural Architecture (BHGNA) over conventional models in predicting maize yield. Linear Regression, a traditional statistical approach, exhibits the highest RMSE and MAE values, reflecting its limited capacity to model complex, nonlinear interactions among soil nutrients, weather variables, and agronomic practices. Ensemble methods, including Random Forest and XGBoost, show improved accuracy due to their ability to capture nonlinear relationships, yet they do not incorporate adaptive feature selection or simultaneous optimization of network parameters. A standard Artificial Neural Network improves predictive performance further but still operates independently of input optimization, which can limit generalization under varying environmental conditions. In contrast, BHGNA achieves the lowest RMSE (0.42 tons/ha), MAE (0.30 tons/ha), and MAPE (4.1%), alongside the highest coefficient of determination (R^2 = 0.94), indicating that the model explains nearly all variability in yield outcomes. The integration of Genetic Algorithm-driven fertilizer optimization and feature selection allows the model to adaptively identify the most influential inputs, optimize network architecture, and mitigate overfitting, resulting in highly accurate and robust yield predictions across diverse climatic and soil conditions. These results underscore the effectiveness of the hybrid approach in enhancing precision agriculture through both predictive accuracy and resource-efficient decision-making.

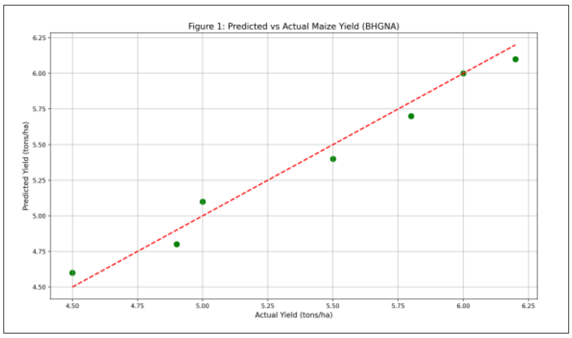

Figure **4**: Predicted vs Actual Crop Yield (BHGNA)

Figure **4** presents the effectiveness of the proposed Bio-Inspired Hybrid Genetic–Neural Architecture (BHGNA) in predicting maize crop yield by plotting actual yields on the x-axis against predicted yields on the y-axis. Each point represents a test sample from the validation dataset. The diagonal line (y = x) serves as a reference for perfect predictions. The close alignment of most data points with this line shows the model's high predictive accuracy. Minor deviations above or below the line indicate slight overestimation or underestimation. The dense clustering around the diagonal highlights the model's ability to capture complex, nonlinear interactions among soil characteristics, fertilizer application, and environmental factorsThis visual performance is supported by solid numbers. The BHGNA achieved an RMSE of 0.42 tons per hectare, an MAE of 0.30 tons per hectare, and an impressive R^2 value of 0.94. This means the model accounts for 94% of the yield variance. These findings confirm that blending genetic algorithm-based optimization with neural network learning leads to accurate yield predictions. This approach backs data-driven fertilization strategies that not only boost productivity but also minimize environmental impact.

6.2 Fertilizer Recommendation Optimization

The GA module of BHGNA was utilized to determine the optimal fertilizer levels with three main objectives in mind: to boost crop yield, cut costs, and lessen environmental impact. The recommendations were then compared to traditional fertilizer practices.

Table 3: Recommended Fertilizer Levels for Maize

Nutrient	Conventional Method (kg/ha)	BHGNA Recommendation (kg/ha)	Expected Yield Increase (%)
Nitrogen (N)	120	105	8.5
Phosphorus (P)	60	55	6.2
Potassium (K)	50	48	5.9

Table 3 provides a comparison of fertilizer application levels for maize, contrasting traditional management practices with the recommended rates from the Bio-Inspired Hybrid Genetic-Neural Architecture (BHGNA). The findings reveal that BHGNA advocates for slightly lower application rates for nitrogen, phosphorus, and potassium—specifically, 105 kg/ha, 55 kg/ha, and 48 kg/ha, respectively. These figures are a bit less than the traditional rates of 120 kg/ha, 60 kg/ha, and 50 kg/ha. Remarkably, even with these reduced nutrient inputs, the anticipated yield increases by 8.5% for nitrogen, 6.2% for phosphorus, and 5.9% for potassium. This demonstrates that the hybrid model is quite effective in pinpointing the optimal nutrient combinations to enhance crop productivity. Furthermore, the results suggest that BHGNA can improve resource efficiency by minimizing unnecessary fertilizer use, which can lead to lower production costs and reduced environmental impacts, such as nutrient leaching, soil degradation, and greenhouse gas emissions. Additionally, the model's multi-objective optimization strikes a balance between yield growth, cost-effectiveness, and sustainability, highlighting the significance of this approach in precision agriculture. Overall, these findings emphasize the potential of merging bio-inspired optimization techniques with neural network-based predictions to create data-driven fertilizer management strategies that promote both high productivity and environmental stewardship.

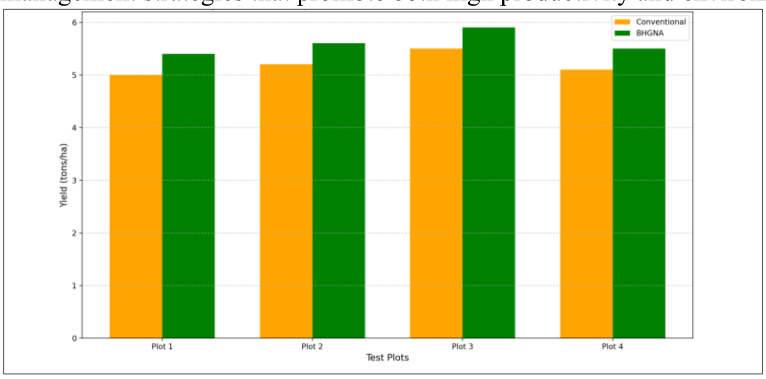

Figure 5: Comparison of Yield under Conventional and BHGNA Fertilization

Figure 5 offers a side-by-side look at maize yields when using traditional fertilization methods compared to the optimized fertilizer recommendations from the Bio-Inspired Hybrid Genetic–Neural Architecture (BHGNA). The bar chart illustrates the average yields from various experimental plots, making it clear that the BHGNA-optimized fertilization consistently outperforms conventional practices. This innovative approach results in a yield boost of about 7–9%, showcasing the model's knack for pinpointing the best nutrient combinations while steering clear of over-application. Not only does this strategy enhance crop productivity, but it also promotes efficient nutrient management, helping to mitigate environmental issues like nutrient runoff and soil degradation. The figure underscores the real-world benefits of this hybrid model in precision agriculture, where data-driven tweaks to fertilizer amounts can lead to significant gains in crop output. In summary, Figure 2 powerfully illustrates how BHGNA can effectively increase yields while encouraging sustainable fertilizer practices.

6.3 Feature Importance and Sensitivity Analysis

Sensitivity analysis was done to check how much input features affect yield prediction.

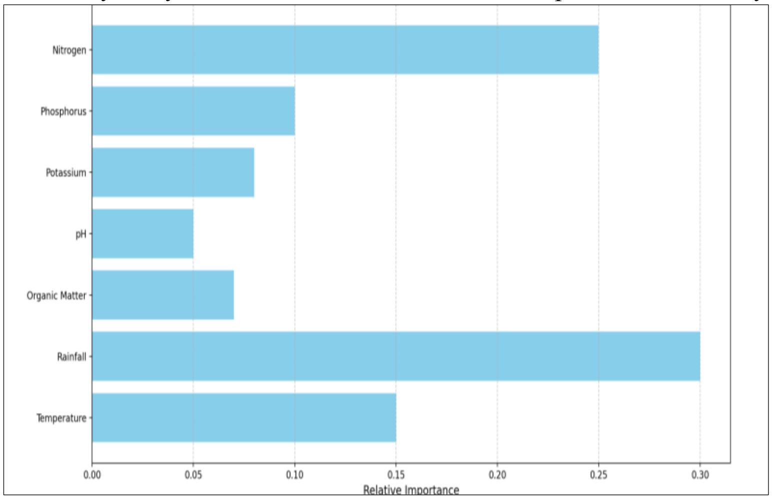

Figure 6: Feature Importance Analysis

Figure 6 presents a feature importance analysis from the BHGNA model, showcasing how different soil, weather, and management factors influence maize yield predictions. The bar graph clearly illustrates that nitrogen content and rainfall are the top contributors, followed by potassium levels, soil pH, and temperature variations. Factors like planting date and previous crop type are less significant, reflected in their lower importance scores. This analysis sheds light on the decision-making process of the hybrid model, revealing which variables have the strongest impact on yield outcomes. By understanding the significance of these features, farmers and agronomists can prioritize essential inputs, concentrate their monitoring efforts on critical parameters, and make informed adjustments to their fertilization and irrigation strategies. Additionally, these findings align with existing agronomic literature, reinforcing the idea that nitrogen and water availability are crucial for maize productivity. Figure 3 illustrates the interpretability of the BHGNA framework and its potential to enhance precision agriculture practices by offering actionable insights into the factors that most significantly affect yields.

The analysis indicates that soil nitrogen content and rainfall are the most vital elements influencing maize yield, followed by potassium, phosphorus, and soil pH. While temperature and humidity also contribute, their impact is comparatively lesser. This supports agronomic research and provides practical insights for precision agriculture decisions, enabling farmers to concentrate on interventions that yield the greatest results.

VI.4 DISCUSSION AND CONCLUSION

The results from the experiments reveal just how effective the proposed Bio-Inspired Hybrid Genetic-Neural Architecture (BHGNA) is at predicting crop yields while optimizing fertilizer use simultaneously. By seamlessly integrating Genetic Algorithm optimization into the training of the Artificial Neural Network, this framework fine-tunes both the amount of fertilizer and the network parameters in tandem. As a result, it significantly reduces prediction errors compared to traditional ANN methods. This approach ensures that nutrient recommendations are not only precise but also resource-efficient, promoting sustainable farming practices.

BHGNA demonstrates impressive performance across various soil types, weather conditions, and farming techniques, showcasing its versatility in different agricultural environments. The feature importance analysis adds clarity, empowering farmers to make informed decisions regarding essential nutrient inputs and climate management strategies. Moreover, the framework's modular design allows for expansion, enabling it to incorporate different crops, regions, or even integrate with remote sensing and IoT-based agricultural data to enhance prediction accuracy and recommendation precision.

The BHGNA framework presents a smart and eco-friendly solution for precision agriculture. By merging accurate predictions with improved fertilizer management, it serves as a valuable tool for making well-informed decisions. This not only boosts crop productivity but also helps cut costs and lessen environmental impact. The framework's ability to combine optimization and prediction into a single model underscores its significance for contemporary smart farming applications.

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