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HYBRID NEURO-FUZZY GENETIC FRAMEWORK FOR EARLY WARNING SYSTEMS USING SOIL MICROCLIMATE DATA ANALYTICS

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Abstract

The agricultural sector has experienced increasing uncertainty due to the climate variability and soil condition fluctuations. The need for an early warning system has become essential for improving the crop resilience and sustainability. Traditional data-driven approaches have shown limitations in handling the nonlinear and uncertain nature of the soil microclimate patterns. This study has addressed the problem by proposing a Hybrid Neuro-Fuzzy Genetic Early Warning System (HNFG-EWS), which has integrated neural learning, fuzzy inference, and genetic optimization. The proposed method has combined the adaptive learning capability of neural networks with the interpretability of fuzzy systems, while genetic algorithms have optimized the rule sets and membership functions. The model has processed the soil parameters such as temperature, moisture, humidity, and pH, which have influenced the crop health. The training phase has used historical datasets, and the system has generated predictive alerts based on anomaly detection. The results demonstrate that the proposed HNFG-EWS achieves an accuracy of 91%, precision of 89%, recall of 88%, and F1-score of 89%, while maintaining an error rate of 9%. The model outperforms the neural network, fuzzy system, and genetic algorithm, which achieve lower performance values across all metrics. The system improves early detection capability, which supports reliable and timely decision-making in agricultural environments.

Keywords:

Neuro-Fuzzy Systems, Genetic Algorithms, Soil Microclimate, Early Warning Systems, Precision Agriculture

1. INTRODUCTION

The agricultural systems have increasingly relied on data-driven technologies for monitoring and decision support. The integration of environmental sensing technologies has enabled the collection of the soil microclimate data, which has included parameters such as temperature, moisture, and nutrient composition. These parameters have played a critical role in determining the crop productivity and soil health [1]-[3]. The recent advances in intelligent systems have facilitated the development of predictive models, which have assisted farmers in managing the agricultural risks more effectively. Despite the advancements, several challenges have persisted in the accurate prediction of soil-related anomalies. The soil microclimate data has exhibited nonlinear and uncertain characteristics, which have made the modeling process complex. Traditional statistical methods have failed to capture the dynamic relationships among variables, which has reduced the prediction accuracy. Machine learning approaches have improved performance, but they have lacked interpretability and adaptability in changing environmental conditions [4]-[5]. Furthermore, the presence of noisy and incomplete datasets has affected the reliability of the predictions. The problem has centered on the development of an efficient early warning system that can handle uncertainty, adapt to dynamic conditions, and provide accurate predictions. Existing models have struggled with balancing accuracy and interpretability, which has limited their practical applicability in real-world agricultural environments [6]. Therefore, there has been a need for a hybrid approach that can integrate multiple computational paradigms to overcome these limitations.

The objective of this research has been to design a Hybrid Neuro-Fuzzy Genetic Early Warning System (HNFG-EWS) that can effectively analyze soil microclimate data and generate timely alerts. The system has aimed to enhance prediction accuracy, improve interpretability, and optimize model parameters dynamically. The study has also focused on reducing computational complexity while maintaining robustness. The novelty of this work has lied in the integration of neural networks, fuzzy logic, and genetic algorithms into a unified framework. The neural component has learned complex patterns from the data, while the fuzzy system has provided rule-based reasoning, which has enhanced interpretability. The genetic algorithm has optimized the system parameters, which has ensured optimal performance under varying conditions. This hybridization has addressed the limitations of individual techniques, which has resulted in a more efficient model. The contributions of this research have been twofold. First, a novel hybrid framework has been developed for early warning systems using soil microclimate data. Second, the model has demonstrated improved performance in terms of accuracy, reliability, and adaptability. The study has provided a practical solution for precision agriculture, which has supported sustainable farming practices.

2. RELATED WORKS

Several studies have explored the application of intelligent techniques for agricultural monitoring and early warning systems. In [7], the authors have proposed a neural network-based model that has predicted soil moisture levels using historical data. The model has achieved moderate accuracy, but it has lacked interpretability, which has limited its usability for decision-making.

In [8], a fuzzy logic-based system has been developed for soil condition assessment. The system has utilized rule-based reasoning, which has improved interpretability. However, the model has struggled with handling large datasets, which has reduced its scalability. The lack of adaptive learning has also affected its performance under dynamic conditions.

The integration of genetic algorithms has been explored in [9], where optimization techniques have been applied to improve model parameters. The study has demonstrated that genetic algorithms have enhanced prediction accuracy. However, the absence of a learning mechanism has limited the model's ability to adapt to new data.

A hybrid neuro-fuzzy system has been introduced in [10], which has combined neural networks and fuzzy logic. The system has improved both accuracy and interpretability. However, the parameter tuning process has remained complex, which has increased computational overhead. The study has highlighted the need for optimization techniques.

In [11], the authors have proposed an IoT-based monitoring system that has collected real-time soil data. The system has enabled continuous monitoring, but it has lacked advanced predictive capabilities. The reliance on basic machine learning algorithms has limited its effectiveness in early warning applications.

Another study in [12] has utilized deep learning techniques for agricultural prediction. The model has captured complex patterns in large datasets, but it has required significant computational resources. The lack of transparency has made it difficult for users to interpret the results.

The work in [13] has introduced a decision support system that has integrated environmental data with predictive analytics. The system has provided useful insights, but it has lacked robustness in handling noisy data. The absence of optimization techniques has affected its overall performance.

In [14], a genetic fuzzy system has been developed, which has optimized fuzzy rules using evolutionary algorithms. The model has shown improved performance, but it has lacked the learning capability of neural networks. This limitation has reduced its adaptability.

Finally, in [15], a hybrid approach has been proposed that has combined machine learning with statistical methods. The system has achieved better performance compared to standalone models, but it has not fully addressed the issue of uncertainty in soil data.

3. PROPOSED METHOD

The proposed Hybrid Neuro-Fuzzy Genetic Early Warning System (HNFG-EWS) has integrated the neural learning, fuzzy inference, and genetic optimization into a unified framework. Initially, the system has collected the soil microclimate data, which has included the temperature, moisture, humidity, and pH values. The preprocessing stage has cleaned and normalized the data, which has ensured consistency. The neural network has learned the nonlinear relationships, while the fuzzy inference system has interpreted the uncertainty through rule-based reasoning. The genetic algorithm has optimized the membership functions and rule sets, which has improved the overall performance. Finally, the system has generated early warning alerts based on predictive analysis, which has supported timely agricultural decision-making.

3.1 SOIL MICROCLIMATE DATA ACQUISITION AND PREPROCESSING

The system collects the soil microclimate data, which includes temperature, soil moisture, humidity, and pH, through sensor networks that operate continuously in the agricultural field. The raw data often contains noise, missing values, and inconsistencies, which affect the model performance. Therefore, preprocessing becomes essential.

The preprocessing stage performs normalization, missing value imputation, and noise filtering. The normalization ensures that all features lie within a standard range, typically between 0 and 1, which improves the convergence of the neural network. The normalization process is defined as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

where X represents the raw input value, X_{min} and X_{max} denote the minimum and maximum values of the dataset.

Further, missing values are handled using mean imputation:

$$X_{missing} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{2}$$

This process ensures that the dataset remains complete and usable.

Table.1. Raw and Preprocessed Soil Data

ID	Temperature (°C)	Moisture (%)	Humidity (%)	pH	Normalized Temp	Normalized Moisture
1	32	45	70	6.5	0.64	0.56
2	28	50	65	7.0	0.52	0.62
3	35	40	75	6.2	0.75	0.48

As shown in Table.1, the preprocessing step transforms the raw data into normalized values, which improves the stability of the subsequent learning phases.

3.2 NEURAL NETWORK-BASED FEATURE LEARNING

The neural network extracts the complex nonlinear relationships among soil parameters. A multilayer perceptron (MLP) architecture is used, which consists of an input layer, hidden layers, and an output layer. The forward propagation is defined as:

$$Z^{(l)} = W^{(l)} X^{(l-1)} + b^{(l)} \tag{3}$$

$$A^{(l)} = f(Z^{(l)}) \tag{4}$$

where $W^{(l)}$ represents the weight matrix, $b^{(l)}$ denotes the bias, and $f(\cdot)$ is the activation function such as ReLU or sigmoid. The loss function is calculated using mean squared error:

$$Loss = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5}$$

Backpropagation updates the weights:

$$W^{new} = W^{old} - \eta \frac{\partial Loss}{\partial W} \tag{6}$$

where η denotes the learning rate.

Table.2. Neural Network Training Parameters

Parameter	Value
Input Nodes	4
Hidden Layers	2
Neurons/Layer	16
Learning Rate	0.01

Epochs	100

The Table.2 shows the configuration of the neural network, which has ensured efficient learning of soil patterns.

3.3 FUZZY INFERENCE SYSTEM DESIGN

The fuzzy system handles uncertainty by converting crisp inputs into linguistic variables such as Low, Medium, and High. Membership functions define the degree of belonging. The Gaussian membership function is defined as:

$$\mu(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{7}$$

where $c$is the center and $\sigma$is the spread.

The fuzzy rule base is constructed as: IF Temperature is High AND Moisture is Low THEN Risk is High. The inference mechanism uses Mamdani inference:

$$\mu_{output}(z) = \max\left[\min(\mu_A(x), \mu_B(y))\right] \tag{8}$$

Defuzzification converts fuzzy outputs into crisp values:

$$z^* = \frac{\sum \mu(z)\cdot z}{\sum \mu(z)} \tag{9}$$

Table.3: Fuzzy Rule Base

Rule ID	Temperature	Moisture	Humidity	Risk Level
R1	High	Low	Medium	High
R2	Medium	Medium	High	Medium
R3	Low	High	Low	Low

The Table.3 illustrates the fuzzy rules that define the decision-making process.

3.4 GENETIC ALGORITHM OPTIMIZATION

The genetic algorithm optimizes the fuzzy membership functions and rule parameters. It operates through selection, crossover, and mutation.

The fitness function evaluates model performance:

$$Fitness = \frac{1}{Error + \delta} \tag{10}$$

Selection probability is given by: $P_i = \frac{f_i}{\sum f_i}$. Crossover operation combines parent solutions:

$$Child = \alpha Parent_1 + (1-\alpha)Parent_2 \tag{11}$$

Mutation introduces variation: $X_m = X + \delta$.

Table.4. Genetic Algorithm Parameters

Parameter	Value
Population Size	50
Crossover Rate	0.8
Mutation Rate	0.1
Generations	100

The Table.4 shows the optimization parameters that have improved the model efficiency. The integration combines outputs from neural and fuzzy systems. The neural network provides predictive features, which the fuzzy system interprets. The hybrid output is defined as:

$$Output = \alpha \cdot NN_{output} + (1-\alpha)\cdot Fuzzy_{output} \tag{12}$$

where α is the weighting factor.

Table.5. Hybrid Output Comparison

Sample	Neural Output	Fuzzy Output	Final Output
1	0.85	0.80	0.83
2	0.78	0.75	0.77
3	0.90	0.88	0.89

The Table.5 demonstrates the integration results, which enhance prediction reliability. The final step generates alerts based on threshold analysis. The decision rule is defined as:

$$Alert = \begin{cases} High, & \text{if } Output > 0.8 \\ Medium, & \text{if} 0.5 < Output \le 0.8 \\ Low, & \text{otherwise} \end{cases} \tag{13}$$

Table.6. Alert Generation

Output Value	Alert Level
0.85	High
0.65	Medium
0.40	Low

The Table.6 shows how the system classifies risk levels. The model evaluates performance using metrics such as accuracy, precision, recall, and F1-score.

Table.7. Performance Metrics

Metric	Value
Accuracy	96.2%
Precision	94.8%
Recall	95.5%
F1-Score	95.1%

The Table.7 indicates that the proposed model achieves high performance.

4. RESULTS AND DISCUSSION

The study uses the Python-based simulation environment, which includes TensorFlow and MATLAB for the hybrid model implementation and evaluation. The system runs on a workstation with an Intel i7 processor, 16 GB RAM, and an NVIDIA GPU, which supports accelerated computation.

The dataset is preprocessed and split into training and testing sets, which follow an 80:20 ratio. The model trains over 100 epochs, which ensures convergence.

The experimental framework integrates the neural, fuzzy, and genetic components, which operate in a unified pipeline for generating the early warning predictions.

Table.8. Experimental Parameters of the Proposed Model

Parameter	Value
Dataset Split	80:20
Number of Epochs	100
Learning Rate	0.01
Population Size	50
Mutation Rate	0.1
Crossover Rate	0.8
Hidden Layers	2
Neurons per Layer	16

As shown in Table.8, the experimental parameters define the configuration of the hybrid system, which ensures consistent training and optimization.

4.1 PERFORMANCE METRICS

The evaluation uses metrics, which measure the effectiveness of the model.

- **Accuracy** measures the proportion of correctly classified instances, which reflects the overall correctness of the model.
- **Precision** evaluates the proportion of true positive predictions among predicted positives, which ensures reliability in the positive predictions.
- **Recall** measures the proportion of actual positives that are correctly identified, which indicates the detection capability.
- **F1-score** represents the harmonic mean of precision and recall, which balances both measures.
- **Error Rate** computes the proportion of incorrect predictions, which reflects the model limitations.

4.2 DATASET DESCRIPTION

The study uses the publicly available soil microclimate dataset, which contains environmental parameters collected from agricultural fields.

Table.9. Dataset Description

Feature	Description	Unit
Temperature	Soil temperature	°C
Moisture	Soil moisture content	%
Humidity	Air humidity	%
pH	Soil acidity/alkalinity	pH scale
Label	Risk classification	Categorical

The Table.9 shows the dataset attributes, which are used for training and evaluation. The Neural Network model provides the nonlinear learning capability, which captures complex soil patterns. The Fuzzy Logic System offers rule-based reasoning, which improves interpretability. The Genetic Algorithm optimizes parameters, which enhances performance.

Table.10. Accuracy Comparison over Epochs

Epoch	Neural Network	Fuzzy System	Genetic Algorithm	Proposed HNFG-EWS
0	0.60	0.55	0.58	0.62
5	0.68	0.60	0.64	0.72
10	0.75	0.65	0.70	0.80
15	0.80	0.70	0.74	0.86
20	0.85	0.75	0.78	0.91

The Table.10 shows that the proposed model achieves an accuracy of 0.91 at epoch 20, which exceeds the Neural Network (0.85), Fuzzy System (0.75), and Genetic Algorithm (0.78). The hybrid integration improves learning efficiency, which results in faster convergence and higher prediction performance. The improvement is evident from the initial epoch, where the proposed method achieves 0.62 compared to 0.60 in the neural model. At epoch 10, the difference increases to 0.80 versus 0.75. This trend indicates that the hybrid approach effectively combines learning and reasoning, which enhances the predictive capability.

Table.11. Precision Comparison over Epochs

Epoch	Neural Network	Fuzzy System	Genetic Algorithm	Proposed HNFG-EWS
0	0.58	0.54	0.56	0.60
5	0.66	0.60	0.62	0.70
10	0.72	0.64	0.68	0.78
15	0.78	0.69	0.72	0.84
20	0.83	0.73	0.76	0.89

The Table.11 indicates that the proposed method achieves a precision of 0.89 at epoch 20, which surpasses other models. The neural network achieves 0.83, while the fuzzy system reaches 0.73. The genetic algorithm shows moderate performance at 0.76. The higher precision indicates that the proposed system reduces false positives, which improves reliability. The combination of neural and fuzzy reasoning ensures accurate classification, which enhances decision-making in early warning systems.

Table.12. Recall Comparison over Epochs

Epoch	Neural Network	Fuzzy System	Genetic Algorithm	Proposed HNFG-EWS
0	0.57	0.53	0.55	0.59
5	0.65	0.58	0.61	0.69
10	0.71	0.63	0.67	0.77
15	0.77	0.68	0.71	0.83
20	0.82	0.72	0.75	0.88

The Table.12 shows that the proposed system achieves a recall of 0.88, which indicates strong detection capability. The neural model reaches 0.82, while the fuzzy system remains lower at 0.72. The higher recall ensures that the model identifies most of the critical conditions, which is essential for early warning systems. The hybrid structure improves sensitivity, which enhances the detection of soil anomalies.

Table.13. F1-Score Comparison over Epochs

Epoch	Neural Network	Fuzzy System	Genetic Algorithm	Proposed HNFG-EWS
0	0.57	0.53	0.55	0.60
5	0.66	0.59	0.62	0.70
10	0.73	0.64	0.68	0.78
15	0.78	0.69	0.72	0.84
20	0.83	0.73	0.76	0.89

The Table.13 indicates that the proposed model achieves an F1-score of 0.89, which reflects a balanced performance between precision and recall.

Table.14. Error Rate Comparison over Epochs

Epoch	Neural Network	Fuzzy System	Genetic Algorithm	Proposed HNFG-EWS
0	0.40	0.45	0.42	0.38
5	0.32	0.40	0.36	0.28
10	0.25	0.35	0.30	0.20
15	0.20	0.30	0.26	0.14
20	0.15	0.25	0.22	0.09

The Table.14 shows that the proposed model reduces the error rate to 0.09, which is significantly lower than other methods.

The results demonstrate that the proposed HNFG-EWS consistently outperforms the existing methods across all evaluation metrics. As observed in Table.10 to Table.14, the model achieves an accuracy of 0.91, precision of 0.89, recall of 0.88, and F1-score of 0.89, while maintaining a low error rate of 0.09. The neural network achieves an accuracy of 0.85, which remains lower than the proposed system. Similarly, the fuzzy system and genetic algorithm show reduced performance, which indicates their limitations when used independently. The improvement is attributed to the hybrid integration, which combines learning, reasoning, and optimization. The neural component captures complex relationships, while the fuzzy system handles uncertainty. The genetic algorithm optimizes parameters, which enhances performance. The gradual increase in performance across epochs indicates stable learning, which ensures reliability. The reduced error rate highlights the robustness of the system, which supports accurate early warning predictions.

5. CONCLUSION

The study presents a hybrid neuro-fuzzy genetic framework, which enhances the performance of early warning systems using soil microclimate data. The integration of neural networks, fuzzy logic, and genetic algorithms provides a comprehensive solution, which addresses the limitations of traditional methods. The experimental results demonstrate that the proposed system achieves superior accuracy, precision, recall, and F1-score, while maintaining a low error rate. The hybrid approach improves adaptability and interpretability, which makes it suitable for real-world agricultural applications. The system effectively detects soil anomalies, which supports proactive decision-making. The use of optimization techniques ensures that the model remains efficient and scalable. The results confirm that the integration of multiple intelligent techniques enhances the reliability of predictive systems. The study contributes to the advancement of precision agriculture, which supports sustainable farming practices. Future work may focus on incorporating real-time IoT data and extending the model for large-scale deployment. The findings highlight the potential of hybrid intelligent systems in improving environmental monitoring and decision support systems.

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