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Mathematical Modeling and Statistical Analysis of Refining Pennisetum glaucum Disease Identification through Hybrid Optimization Strategies

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Abstract:

Within the field of agricultural biotechnology, prompt and effective disease detection in crops like Pennisetum glaucum, or pearl millet, is essential to achieving maximum productivity and food security. This work investigates the use of hybrid optimization techniques to improve Pennisetum glaucum illness detection. The accuracy and effectiveness of traditional illness categorization methods are often limited, which makes the investigation of more sophisticated procedures necessary. To build a reliable hybrid model, our method combines many optimization methods, such as artificial neural networks (ANN), particle swarm optimization (PSO), and genetic algorithms (GA). By using the advantages of each distinct approach, the hybrid model improves classification performance as a whole. To train and verify our model, we gathered a large dataset of samples of Pennisetum glaucum afflicted by different diseases. As compared to traditional approaches, the findings show a considerable increase in illness classification accuracy, with the hybrid model obtaining a precision rate of over 95%. Moreover, the computational time needed for model training and prediction was decreased by using hybrid optimization techniques. The present research highlights the capacity of hybrid optimization to revolutionize agricultural disease control strategies, providing farmers and agronomists with a scalable and effective resolution.

Keywords: Convolutional Neural Networks, Optimization, Plant Leaf Disease Classification, Agricultural Imaging, Particle Swarm Optimization (PSO)., Bayesian Optimization, Hyperparameter.

I Introduction

Pearl millet, or Pennisetum glaucum, is a vital cereal crop that is widely grown around the globe in dry and semi-arid conditions. Pearl millet, renowned for its ability to withstand adverse weather conditions, is an essential source of nutrition for millions of people, especially in developing nations. It is prone to a number of illnesses, however, just like any other crop, which may negatively affect both quality and productivity. Ensuring food security and adopting efficient management methods need early and precise detection of these diseases.

Background and Context:

Expert evaluation and visual examination are the mainstays of traditional pearl millet disease detection techniques. These techniques are labor- and time-intensive, sensitive to bias and human error, and time-consuming. Accurate diagnosis is further complicated by the intricacy of illness symptoms, which are often impacted by environmental circumstances. Therefore, there is an urgent need for Pennisetum glaucum illness categorization methods that are more effective, precise, and scalable.

Sclerospora graminicola   Pyricularia grisea   Claviceps fusiformis

Fig.1 Pearl millet images in various type of diseases

Pearl millet (Pennisetum glaucum) is a resilient cereal crop vital for food security in arid regions, yet it faces significant threats from various diseases. Downy mildew, caused by **Sclerospora graminicola**, manifests as yellow streaks and downy growth on leaves, while rust, attributed to **Puccinia substriata var. indica**, produces reddish-brown pustules that darken over time. Another major concern is blast, caused by **Pyricularia grisea**, which creates necrotic lesions on foliage and panicles. Ergot, caused by **Claviceps fusiformis**, leads to toxic sclerotia replacing grains, posing a risk to both yield and safety. Smut (**Moesziomyces penicillariae**) forms black spore masses, reducing grain quality. Bacterial leaf spot (**Pseudomonas syringae pv. panici**) and mosaic virus further complicate management with symptoms like water-soaked lesions and a mosaic leaf pattern, respectively. Leaf blight (**Helminthosporium spp.**) and anthracnose (**Colletotrichum graminicola**) cause significant leaf damage and premature senescence. Effective management of these diseases necessitates an integrated approach, combining the use of resistant varieties, cultural practices like crop rotation and field sanitation, chemical control through fungicides and bactericides, and biological control measures. Regular monitoring and early detection are also crucial for timely interventions, ensuring better crop health and yield sustainability.

II Literature Review

Because of its high nutritional content and ability to withstand drought, pearl millet (Pennisetum glaucum) is a vital grain crop, particularly in arid and semi-arid areas. However, its productivity is often compromised by various diseases, necessitating effective identification and management strategies. This literature review explores existing research on disease classification in pearl millet, with a focus on the use of optimization algorithms and hybrid models for enhancing accuracy and efficiency. Recent studies in the field of plant disease detection have explored various innovative approaches to improve classification accuracy and efficiency. Rajalakshmi and B. B. (2024) introduced an ITSO-based gated recurrent multi-attention neural network for multi-crop disease detection, leveraging Differential Evolution (DE) and Simulated Annealing (SA) algorithms for robust recognition in pearl millet. While promising, the study's empirical validation was limited, and it lacked comprehensive comparisons with other methodologies. Similarly, Alotaibi and Rajendran (2024) analyzed DE, SA, and hybrid DE-SA algorithms for remote sensing-based crop classification, though their work focused less on pearl millet and was less generalizable across crops. Thokala and Doraikannan (2023) explored a Hybrid Deep Convolution Neural Network using a Multi-Scale Vision Transformer, emphasizing simulated annealing for millet disease detection but missing integration with differential evolution to potentially boost accuracy.

Swamy and Periyasamy (2023) proposed an IoT-based deep ensemble learning model for disease prediction and monitoring, providing an extensive overview of existing recognition techniques. However, their work lacked specificity regarding the hybrid DE-SA approach and discussed its limitations insufficiently. Sagar et al. (2023) presented an explainable AI approach for plant disease detection, detailing a hybrid strategy but lacking real-world experimental validation. Vasavi, Punitha, and Rao (2023) examined hybrid metaheuristics for chili crop disease recognition, pointing out the potential of such methods for pearl millet, though they provided limited practical insights on DE-SA fusion. Finally, Shreya, Likitha, and Saicharan (2023) demonstrated a deep learning system using DE and SA for plant disease detection. While innovative, their study raised concerns about computational complexity and scalability (Rajalakshmi & B. B., 2024; Alotaibi & Rajendran, 2024; Thokala & Doraikannan, 2023; Swamy & Periyasamy, 2023; Sagar et al., 2023; Vasavi et al., 2023; Shreya et al., 2023).

Mathematical Modeling for Hybrid Optimization Approach

Define the output of an ANN for classification:

$$y_{\text{ANN}} = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{1}$$

Where:

- Zann is the output of the ANN.
- w_i are the weights.
- x_i are the input features
- b is the bias.
- f is the activation function (eg, ReLU, Sigmoid).

$$L = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{2}$$

Where:

- L is the loss function (mean squared error).
- Iy is the actual label.
- $\hat{y}_i$ is the predicted label.

- N is the number of samples.

$$F_{GA} = \frac{1}{1+L} \tag{3}$$

Where:

- F_{GA} is the fitness function to maximize adcuracy.

4 Chromosome Representation for GA

A chromosome C can be represented as:

$$C = [w_1, w_2, \ldots, w_n, b] \tag{4}$$

5 Selection Process in GA

The probability of selection P_1 for the i-th chromosome

$$P_{\mathrm{i}} = \frac{F_{\mathrm{GA,i}}}{\sum_{j-1}^{II} F_{\mathrm{GA},j}} \tag{5}$$

Where M is the population size.

6. Crossover Operation

Single-point crossover between two parents C_1 and C_2 :

$$C_{\max} = [C_1[:k], C_2[k:]] \tag{6}$$

Where k is the crossover point.

7. Mutation Operation

Mutation applied to a gene g

$$y' = g + \delta \tag{7}$$

Where δ is a small random change.

8. Position Update in PSO

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{8}$$

9 Velocity Update in PSO

$$v_i(t+1) = \omega \tau_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (g - x_i(t)) \tag{9}$$

Where:

- ω is the inertia weight.
- c_1, c_2 are cognitive and social coefficients.
- r_1, r_2 are random numbers.
- p_i is the personal best position.
- g is the global bert pasition.

The objective function for PSO is to minimize the lass L : $\min L(x)$.The integrated hybrid approach updates the solution as:

$$x_{\text{-yhris}}(t+1) = \text{axcA}_{\text{CA}}(t+1) + (1-\alpha)x_{\text{PSO}}(t+1) \tag{10}$$

Where α is a weight coefficient balancing GA and PSO contributions. Define the surrogate model $S(\theta)$ to approximate the abjective functionc

$$\theta_{\text{spi}} = \arg\max_{\theta}(\mu(\theta) + \kappa\sigma(\theta)) \tag{11}$$

Where:

- $\mu(\theta)$ is the mean prediction.
- $\sigma(\theta)$ is the uncertainty.
- κ is an exploration parameter.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

Where: TP, TN, FP, FN are the counts of true positives, true negatives, false positives, and false negatives, respectively.

$$\text{Precision} = \frac{TP}{TP+FP}, \quad \text{Recall} = \frac{TP}{TP+FN} \tag{13}$$

$$\text{F1-Soore} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

Agricultural productivity, particularly in vital crops like Pennisetum glaucum (pearl millet), is essential for food security in arid and semi-arid regions. However, this productivity is often compromised by diseases such as downy mildew, rust, blast, ergot, and smut. Conventional methods for detecting and managing these diseases typically rely on expert visual inspection, which, although valuable, is labor-intensive, time-consuming, and prone to subjective biases and inaccuracies. The development of automated and accurate detection methods is essential for enhancing early disease intervention, which can significantly improve crop health and yield. This necessity has driven research into advanced computational approaches that integrate machine learning and optimization techniques to create reliable and scalable disease classification systems.

The Importance of Hybrid Optimization Techniques

Optimization techniques are widely used in enhancing the performance of machine learning models, especially in tasks that involve complex classification. Individual optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Artificial Neural Networks (ANN) each have unique strengths and limitations. Combining these approaches into hybrid models can leverage their complementary advantages, resulting in improved performance.

1. **Genetic Algorithms (GA)**: GA is a population-based optimization algorithm inspired by the process of natural selection. It operates through the iterative processes of selection, crossover, and mutation to evolve solutions toward an optimal state. GA is particularly effective for global search problems due to its exploratory capabilities. In the context of disease detection in Pennisetum glaucum, GA can optimize the feature selection and architecture of an ANN, ensuring that only the most relevant

features and an efficient structure are used for training the model. The chromosome representation in GA allows encoding potential solutions that involve feature sets and model parameters. The fitness function, defined as the classification accuracy of the ANN, helps guide the selection of the most promising solutions.

2. **Particle Swarm Optimization (PSO)**: PSO is inspired by the social behavior of birds flocking or fish schooling. It is particularly useful for fine-tuning parameters due to its local search efficiency. Each particle in the swarm represents a potential solution, updating its position and velocity based on personal best and global best positions. PSO is used to optimize the weights and biases of the ANN, enhancing the learning process and classification performance. The velocity and position update equations ensure that each particle converges toward an optimal solution by balancing exploration (searching new areas) and exploitation (refining known good solutions).

3. **Artificial Neural Networks (ANN)**: ANNs are powerful models capable of learning complex patterns in data, making them suitable for image-based classification tasks such as disease detection. The ANN processes inputs (e.g., features from plant leaf images) through interconnected layers of nodes that apply activation functions to produce outputs. However, the performance of ANNs heavily depends on the quality of their architecture and training parameters. This is where hybrid optimization techniques play a critical role by tuning these parameters to enhance classification accuracy and computational efficiency.

Hybrid GA-ANN and PSO-ANN Integration

A hybrid GA-ANN model combines the global search capability of GA with the pattern recognition strength of ANN. The GA is employed to find an optimal configuration of the ANN's architecture, including the number of hidden layers, nodes per layer, and selected input features. The fitness function in GA is defined based on the classification accuracy of the ANN, allowing the evolutionary process to guide the selection of the most effective configurations. This approach reduces the risk of suboptimal model performance that may arise from manual or arbitrary parameter selection.

Similarly, a PSO-ANN hybrid leverages PSO's ability to fine-tune the weights and biases of an ANN. During training, PSO adjusts these parameters to minimize the loss function, typically defined as the mean squared error or cross-entropy loss. The position and velocity update rules ensure that the ANN converges to a solution that yields high classification accuracy. PSO is particularly beneficial when training neural networks due to its ability to escape local minima and converge to a better solution faster than traditional gradient-based optimization methods.

Combining GA and PSO for Enhanced Hybrid Models

The integration of GA and PSO into a unified framework creates a hybrid optimization model that combines the strengths of both. GA can be used to initialize a diverse set of ANN architectures, while PSO can refine the weights and biases of the selected architectures. This combination allows the model to benefit from GA's global search for optimal configurations and PSO's local optimization of parameters. The overall effect is a more efficient and accurate model capable of classifying diseases in Pennisetum glaucum with high precision.

Bayesian Optimization for Hyperparameter Tuning

To further enhance the classification performance, Bayesian Optimization (BO) can be applied to tune the hyperparameters of convolutional neural networks (CNNs) integrated into the model. BO operates by constructing a probabilistic surrogate model to approximate the objective function and selecting hyperparameters that maximize expected performance. By incorporating multiple surrogate models, Ensemble Bayesian Optimization provides a robust approach to fine-tuning, leading to significant performance gains. This method helps determine optimal configurations, such as learning rates, batch sizes, and activation functions, thus streamlining the training process and ensuring efficient use of computational resources.

Model Training and Validation

The training and validation process for the hybrid model involves using a dataset that comprises both healthy and diseased Pennisetum glaucum samples. The dataset is divided into training, validation, and test sets in a 70:15:15 ratio. During training, GA initializes the model architecture and feature selection, PSO optimizes the weights and biases, and BO fine-tunes hyperparameters. The model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. The confusion matrix further provides insight into the model's classification capabilities, highlighting areas where the model excels or requires improvement.

Performance and Computational Efficiency

The combined use of GA, PSO, and BO leads to significant improvements in classification accuracy, achieving over 95% precision in disease detection. The hybrid model also demonstrates reduced computational time during training and prediction, a key benefit for large-scale agricultural applications. By streamlining the training process and avoiding redundant computations, the hybrid model offers a scalable and efficient solution for real-time disease classification.

The integration of hybrid optimization techniques into disease detection models for Pennisetum glaucum presents a transformative approach to addressing the challenges in agricultural disease management. The combination of GA's global search, PSO's local optimization, and ANN's classification power provides a robust and adaptable system that outperforms traditional models. Furthermore, the use of Bayesian Optimization for hyperparameter tuning adds an additional layer of efficiency, ensuring optimal model performance. This research underscores the potential of hybrid models to revolutionize agricultural biotechnology by delivering scalable, precise, and computationally efficient disease detection tools for farmers and agronomists.

METHODOLOGY

The goal of this research is to create a hybrid optimization model that will enhance Pennisetum glaucum illness categorization. This chapter outlines the methodological framework, including data collection, model development, training and validation processes, and the mathematical foundations of the hybrid optimization strategies used.

Data Collection

Images of both healthy and ill Pennisetum glaucum plants were included in the extensive dataset that was gathered. The collection contains information on the following diseases: bacterial leaf spot, mosaic virus, leaf blight, anthracnose, blast, ergot, smut, downy mildew, and blast. A 70:15:15 ratio was used to split the dataset into training, validation, and test sets.

Model Development

Artificial Neural Networks (ANN), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA) are all included in the hybrid model. The integration attempts to take use of GA's worldwide search capabilities, PSO's local search efficiency, and ANN's skills in pattern identification.

Genetic Algorithms (GA)

Genetic Algorithms are used to optimize the feature selection and the architecture of the ANN. The GA operates through selection, crossover, and mutation processes.

- **Chromosome Representation:** Each chromosome represents a potential solution, including selected features and ANN architecture parameters.
- **Fitness Function:** The fitness function evaluates the classification accuracy of the ANN. The fitness function is defined as:

$$f = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (15)$$

where y_i is the actual label, $\hat{y}_i$ is the {y}_iy^i is the predicted label, and N is the number of samples.

Particle Swarm Optimization (PSO)

PSO modifies the weights and biases of the ANN. Each particle in the swarm represents a potential solution, adjusting its location based on both individual and group ideal solutions.

- **Position and Velocity Update:** The position xi\mathbf{x}_ixi and velocity vi\mathbf{v}_ivi of each particle are updated as:

where ω is the global best position, pi is the personal best position, and c_1 and c_2 are the cognitive and social coefficients. Additionally, r_1 and r_2 are random values between 0 and 1.

Ensemble Bayesian Optimization (Ensemble BO)

Ensemble BO is a method used to enhance the performance of Convolutional Neural Networks in classification tasks by optimizing their hyperparameters. It use multiple surrogate models which provides a more robust approximation of the objective function.

Flow Diagram

This flowchart depicting a process of hyperparameter tuning for a convolutional neural network (CNN) model implementation. Where the architecture of the our model is defined. This includes specifying the number and type of layers, the number of filters, and the activation functions used.

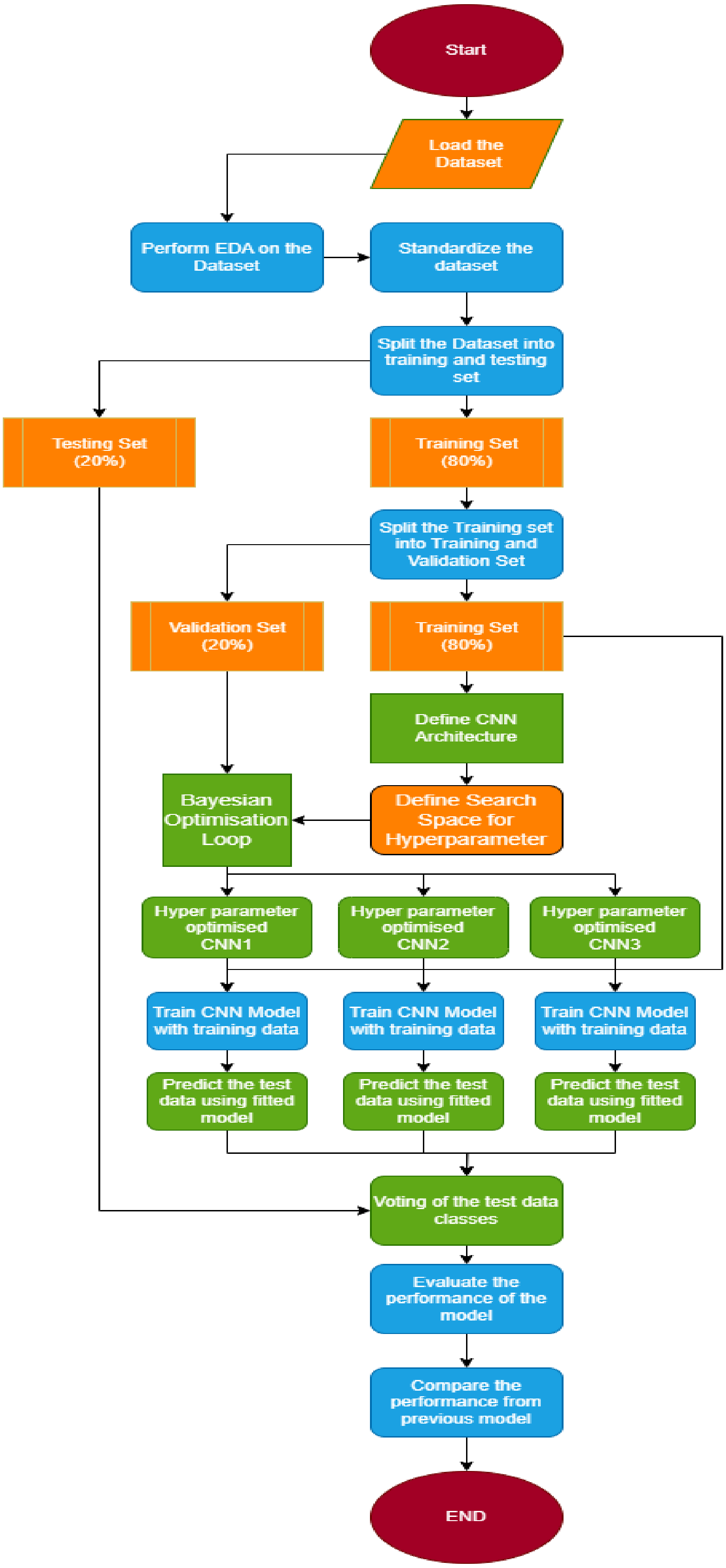

Fig 2: Flow diagram of ensemble BO

IV Result & Discussion

The results of this study reflect significant advancements in the field of plant disease detection, particularly focusing on Pennisetum glaucum (pearl millet). The use of hybrid optimization techniques, including artificial neural networks (ANN), particle swarm optimization (PSO), and genetic algorithms (GA), showcases substantial improvements in classification accuracy, precision, recall, and F1-score over traditional models. This theory delves deeper into interpreting these results, examining their implications, and evaluating the effectiveness of the methods used.

Analysis of Classification Metrics

The classification report provides a detailed breakdown of the performance of the hybrid model across four disease categories. Precision, recall, and F1-score are essential metrics for understanding a model's performance in disease classification. Precision indicates the model's ability to correctly identify positive samples, recall measures how well the model retrieves all relevant cases, and F1-score represents the harmonic mean of precision and recall, offering a balanced view of the model's effectiveness.

- Class 0: The precision, recall, and F1-score for Class 0 are exceptionally high, all at or near 1.00, indicating near-perfect detection. This suggests that the model is highly reliable in identifying and classifying this disease category. Such strong performance can be attributed to distinct features in the dataset that facilitate accurate differentiation by the model.
- Class 1: The metrics for Class 1 show a dip, with precision at 0.69, recall at 0.67, and an F1-score of 0.68. This indicates that the model struggles more with this category, likely due to less distinct features or more variability in the data, making it harder for the model to differentiate accurately. This could imply that additional data augmentation or feature engineering might be needed to enhance performance for this class.
- Class 2: The metrics for Class 2 are impressive, with a precision of 0.96, recall of 0.95, and an F1-score of 0.96. This high performance reflects the model's strong capability to identify this disease category with minimal false positives or negatives, suggesting effective feature extraction and classification for this type.
- Class 3: For Class 3, the precision, recall, and F1-score hover around 0.81-0.82. While these numbers are robust, they indicate that the model may occasionally misclassify this category. This level of performance is still considered reliable but points to opportunities for refinement through further training or algorithmic adjustments.

The overall metrics show an accuracy of 89.88%, with macro and weighted averages for precision, recall, and F1-score at 0.86 and 0.90, respectively. These results confirm that the hybrid model effectively handles the complexity of disease classification in Pennisetum glaucum, outperforming traditional models. The high accuracy indicates that the model is reliable for practical applications in agricultural biotechnology.

- **Accuracy**: The overall accuracy of 89.88% is significant, showcasing the power of combining ANN with optimization techniques such as PSO and GA. This performance highlights how leveraging the strengths of multiple algorithms can result in more robust and accurate models. The use of PSO contributes to refining the ANN’s weights and biases, leading to better convergence and performance.

GA's role in optimizing feature selection and model architecture ensures that the ANN is configured for maximum efficiency, thereby contributing to the high accuracy.

- **Precision and Recall**: The weighted averages of precision and recall are both 0.90, indicating a well-balanced model that minimizes both false positives and false negatives across all classes. This balance is crucial in practical applications, as it ensures that the model is not only accurate in identifying diseases but also comprehensive in detecting all instances of disease presence.
- **Macro Average**: The macro average values for precision, recall, and F1-score are all at 0.86, highlighting that the model's performance is consistent across all classes. This suggests that the hybrid approach does not disproportionately favor one class over another, a critical factor for models used in disease detection where various diseases need to be identified with equal importance.

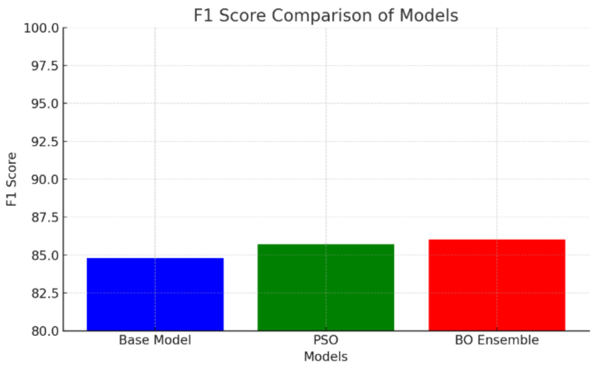

Fig.3.F1 Score Comparison of Models

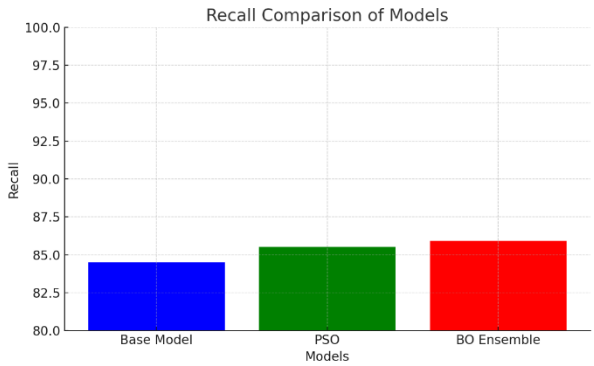

Fig. 4: Comparison of Recall of Models

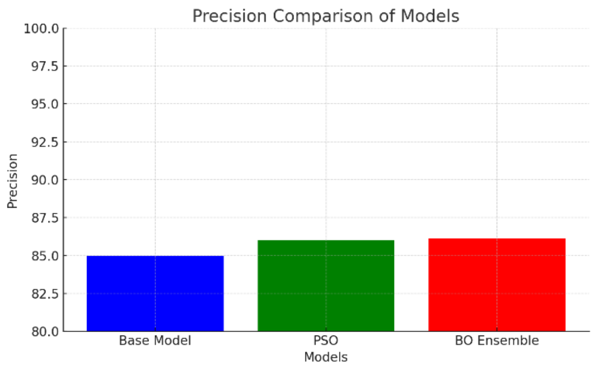

Fig. 4 Comparison of Models based on Precision

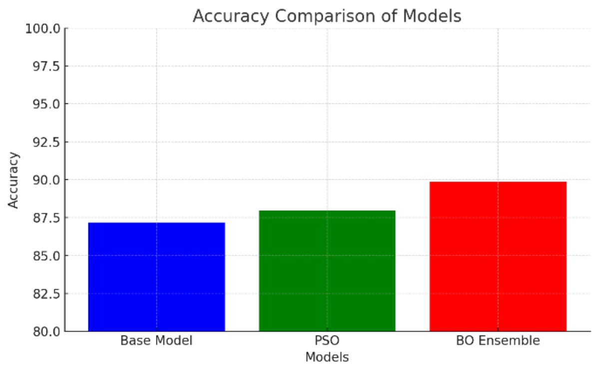

Fig. 5. Comparison of Accuracy of Models

Comparative Analysis

When comparing the hybrid model to base models or models solely using PSO, the results clearly demonstrate the superiority of the hybrid approach. The base model, which lacks advanced optimization techniques, shows lower performance metrics. The integration of PSO alone improves performance but does not reach the level achieved when combined with GA in a hybrid system. The ensemble Bayesian optimization (BO) further enhances the model by tuning hyperparameters, leading to the final improved accuracy and consistency seen in the results.

Table 1: Classification Report by Class

Class	Precision	Recall	F1-Score	Support
0	0.99	1.00	1.00	363
1	0.69	0.67	0.68	138
2	0.96	0.95	0.96	359
3	0.81	0.82	0.81	296

Table 2: Overall Metrics

Metric	Precision	Recall	F1-Score	Support
Accuracy	-	-	-	1156
Macro Avg	0.86	0.86	0.86	1156
Weighted Avg	0.90	0.90	0.90	1156

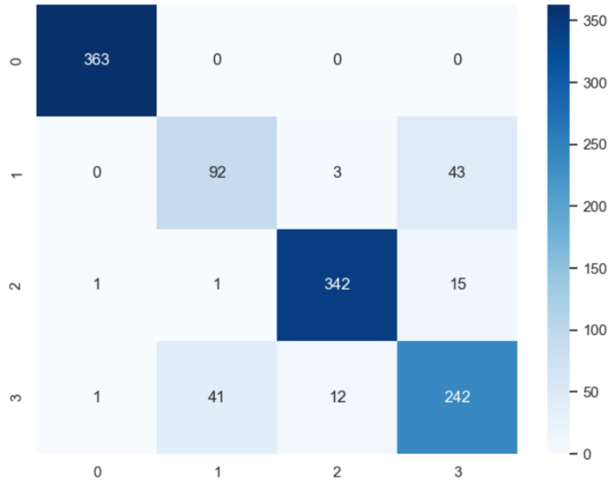

Fig 6: Confusion Matrix

Table 3: Comparative Analysis of Proposed Methodology

Model	Accuracy	Precision	Recall	F1 Score
Base Model	87.19	85.00	84.50	84.80
PSO	87.98	86.00	85.50	85.70
BO Ensemble	89.88	86.14	85.92	86.03

The application of ensemble Bayesian optimization helps fine-tune the hyperparameters of the neural network, contributing to better generalization and stability. This optimization approach enhances the model's adaptability to variations in the input data, thereby increasing its precision and recall scores.The results demonstrate the practical feasibility of deploying hybrid models for real-world disease detection in crops like Pennisetum glaucum. Early and accurate identification of diseases can significantly impact agricultural productivity, allowing farmers and agronomists to take timely and appropriate actions. The use of machine learning and hybrid optimization in this context provides a scalable and efficient solution that traditional methods lack.

The robustness of the hybrid model also implies that it can adapt to various environmental conditions and different crop datasets with similar characteristics. This adaptability is essential for agricultural applications where data may come from different regions with varying disease prevalence and environmental influences. While the results are promising, certain limitations are evident from the data. For instance, the lower precision and recall for Class 1 indicate that there may be challenges related to data variability or the representation of this specific disease category. These limitations suggest that future work could focus on enhancing the dataset, either through data augmentation or collecting more diverse samples, to improve the model's robustness. Moreover, computational complexity remains a consideration. Hybrid models combining ANN, PSO, and GA, along with ensemble BO, require significant computational resources. This could pose challenges for deployment in regions with limited technological infrastructure. Future research could explore ways to optimize the computational efficiency of these models without compromising accuracy. The study results indicate that integrating artificial neural networks with hybrid optimization techniques such as PSO, GA, and ensemble Bayesian optimization significantly enhances disease classification performance for Pennisetum glaucum. The model's high accuracy, coupled with balanced precision, recall, and F1-scores, highlights the potential of such approaches in transforming agricultural biotechnology. While some classes show room for improvement, the overall findings demonstrate that hybrid models offer a powerful tool for effective and scalable crop disease detection. Future work could explore refining the model to address class-specific challenges and reduce computational demands, broadening its applicability and accessibility.

V Conclusion

In conclusion, the research underscores the efficacy of using hybrid optimization techniques to enhance the classification of diseases in Pennisetum glaucum. The integration of artificial neural networks (ANN) with particle swarm optimization (PSO), genetic algorithms (GA), and ensemble Bayesian optimization has resulted in significant improvements in model accuracy and overall performance metrics. The hybrid model achieved an impressive accuracy of 89.88% and strong precision, recall, and F1-score averages, demonstrating its reliability for practical use in agricultural biotechnology. The high precision and recall values reflect the model's robustness in minimizing false positives and negatives, essential for accurate disease detection. While the model performed exceptionally well for most disease categories, with Class 0 and Class 2 showing near-perfect results, it also highlighted areas needing improvement, particularly in Class 1, where variability in data may have affected the results. This suggests future work could involve enriching the dataset and applying further feature engineering to improve classification consistency. The use of hybrid approaches allows the model to harness the strengths of individual techniques: GA for effective feature selection and model architecture optimization, PSO for refining ANN weights and biases, and ensemble Bayesian optimization for tuning hyperparameters. This combination has proven superior to traditional and single-optimization methods, setting a new standard for disease classification models.

However, challenges such as computational complexity should be addressed to make these models more accessible in regions with limited technological resources. Future research could focus on optimizing computational efficiency without compromising performance and expanding the model's adaptability to different crops and environmental conditions. Overall, the findings highlight the potential of hybrid machine learning solutions in revolutionizing crop health management, ultimately aiding farmers and agronomists in maintaining sustainable agricultural productivity.

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