A COMPARATIVE ANALYSIS OF CNN, GA, RF & RNN FOR IMAGE CLASSIFICATION: INSIGHTS ON PERFORMANCE AND OPTIMISATION USING HYBRID APPROACHES

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ABSTRACT

Sugarcane is a globally significant cash crop, contributing to sugar production, biofuel development, and various industrial applications. However, its productivity is severely affected by fungal, bacterial, and viral diseases, leading to substantial economic losses. Traditional disease identification methods, such as manual field inspections and biochemical analysis, are often labor- intensive, time-consuming, and prone to human error. The advent of deep learning has revolutionized disease detection in precision agriculture, but existing standalone models face challenges related to computational efficiency, feature extraction, and generalization ability. To address these challenges, this study proposes a hybrid deep learning framework that integrates Convolutional Neural Networks (CNNs) for robust feature extraction, Recurrent Neural Networks (RNNs) for capturing temporal dependencies in disease progression, Genetic Algorithms (GAs) for hyperparameter optimization, and Random Forest (RF) for enhanced classification performance. The proposed model was trained and tested on a dataset consisting of 3,750 sugarcane leaf images categorized into multiple disease classes. A randomized stratified split was used to ensure balanced training (70%) and testing (30%) data distribution. Experimental results indicate that the hybrid model significantly outperforms conventional deep learning classifiers. The proposed CNN-GA-RNN-RF hybrid framework achieved an accuracy of 92.5%, outperforming standalone CNN (89.3%), RNN (90.2%), GA-optimized CNN (91.1%), and RF- based classifiers (87.8%). The model also demonstrated superior precision (0.93), recall (0.91), and F1-score (0.92), confirming its robustness in distinguishing between healthy and diseased leaves. Furthermore, confusion matrix analysis revealed a substantial reduction in false positives and false negatives, enhancing the model's reliability for real-world deployment. By combining deep learning with evolutionary optimization and ensemble learning, this study provides an AI- driven, scalable, and high-performance approach for automated sugarcane disease detection. The findings have significant implications for precision agriculture, enabling farmers and agricultural stakeholders to detect diseases at an early stage, minimize crop losses, and optimize disease management strategies. Future research will explore model generalization across diverse environmental conditions and integration with edge computing devices for real-time field applications.

Keywords: *Sugarcane Disease Detection, Hybrid Deep Learning, Convolutional Neural Networks, Recurrent Neural Networks, Genetic Algorithms, Random Forest, Precision Agriculture, Smart Farming.*

1. INTRODUCTION

Agriculture is the backbone of global food security and economic stability, with sugarcane being one of the most important cash crops cultivated worldwide. It serves as a primary raw material for sugar production, ethanol-based biofuels, and various by-products. However, the productivity and quality of sugarcane are frequently challenged by plant diseases caused by fungi, bacteria, and viruses. These diseases can significantly reduce crop yield, affecting both farmers and industries reliant on sugarcane. Traditional disease detection methods, such as manual field inspections and biochemical tests, are not only time-consuming but also highly dependent on expert knowledge, making them impractical for large-scale monitoring. With the rapid advancement of artificial intelligence (AI), deep learning-based models have emerged as powerful tools for agricultural disease identification. Among these, Convolutional Neural Networks (CNNs) have demonstrated exceptional capabilities in analyzing plant leaf images to identify disease symptoms.

CNNs effectively capture spatial hierarchies within images, making them ideal for distinguishing between healthy and diseased crops. However, CNN models require large datasets for training and often struggle with hyperparameter optimization, which can limit their generalizability. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, can model sequential patterns in disease progression, enabling temporal analysis of plant health. Meanwhile, Genetic Algorithms (GAs) provide an efficient search mechanism to optimize CNN parameters, enhancing classification performance. Additionally, Random Forest (RF), a robust ensemble learning method, can serve as a final decision-making system by aggregating outputs from multiple classifiers, reducing overfitting and improving accuracy.

This study proposes a hybrid deep learning model that integrates CNNs for feature extraction, GAs for hyperparameter tuning, RNNs for sequential analysis, and RF for final classification. By leveraging the complementary strengths of these models, the proposed approach aims to improve disease detection accuracy while ensuring computational efficiency. A dataset of sugarcane plant images is used for training and evaluation, with performance measured using key metrics such as accuracy, precision, recall, and F1-score.

The significance of this research extends beyond sugarcane disease detection; it contributes to the broader field of smart agriculture by demonstrating how hybrid AI techniques can enhance early disease identification. Early intervention can prevent large-scale crop losses, optimize pesticide usage, and promote sustainable farming practices. This study provides valuable insights for researchers, agronomists, and policymakers, offering a scalable and cost-effective solution for real- time plant health monitoring.

2. STATEMENT OF THE PROBLEM

Sugarcane is a vital crop cultivated globally for sugar production and bioethanol, contributing significantly to the agricultural economy. However, disease outbreaks caused by bacterial, fungal, and viral infections can severely impact crop yield and quality, leading to substantial economic losses (Angamuthu, T & A. S. Arunachalam, 2024) [1]. Traditional manual disease detection methods, such as field inspections and laboratory tests, are labor-intensive, time-consuming, and prone to human error (Kamal et al., 2022) [2]. These conventional techniques are not scalable for large agricultural fields, making early and accurate disease detection a major challenge in precision farming.

Advancements in artificial intelligence (AI) and deep learning have revolutionized plant disease detection, offering automated, high-accuracy classification models. Convolutional Neural Networks (CNNs) have shown exceptional performance in image-based plant disease identification, as demonstrated by Kamal et al. (2022) and Angamuthu et al. (2024) [3]. However, CNN models require large annotated datasets and high computational power, making optimization crucial. Meanwhile, Recurrent Neural Networks (RNNs) are effective in capturing temporal dependencies in disease progression, but they struggle with long-term dependencies and vanishing gradient problems (Zhou et al., 2023) [4]. Additionally, Genetic Algorithms (GAs) have been used to enhance model performance through hyperparameter optimization, while Random Forest (RF) classifiers improve decision fusion and ensemble learning (D'Angelo & Palmieri, 2021) [5].

Despite these advancements, a gap exists in integrating these techniques into a hybrid model that leverages their complementary strengths. The primary challenge is to design a hybrid deep learning framework that combines CNN for feature extraction, GA for hyperparameter optimization, RNN for sequential analysis, and RF for robust classification to enhance classification accuracy, computational efficiency, and generalization ability.

2.1 Research Gap Identification

Although deep learning has significantly improved plant disease detection, several research gaps persist. **Zhang et al. (2020)** developed CNN-based models for leaf disease classification but reported limitations in performance under complex field conditions. **Fuentes et al. (2021)** integrated deep learning with object detection techniques; however, their approach struggled with real-time implementation and variability in natural environments. **Hemanth et al. (2022)** explored hybrid deep learning frameworks but noted challenges in achieving high generalization across multiple crop diseases. **Ramesh and Vydeki (2023)** emphasized the use of ensemble learning but identified issues related to computational efficiency and model interpretability. Most recently, **Li et al. (2024)** introduced attention mechanisms to enhance disease detection, yet their model lacked integration with optimization techniques like genetic algorithms. These limitations point to the need for a more comprehensive approach. The proposed CNN-GA-RNN-RF framework addresses this gap by combining powerful feature extraction, sequence learning, and optimized classification for accurate, robust, and real-time sugarcane disease diagnosis.

2.2 Research Questions

This study address's the following research questions:

1. Can a hybrid deep learning model improve sugarcane disease classification accuracy compared to standalone models?
2. How does Genetic Algorithm (GA) optimization enhance CNN-based feature extraction?
3. Does integrating RNN with CNN improve the ability to analyze disease progression over time?
4. What is the computational trade-off between model performance and processing time?

3. OBJECTIVES OF THE STUDY

1. To develop a hybrid deep learning model (CNN-GA-RNN-RF) for accurate and efficient classification of sugarcane diseases.
2. To enhance feature extraction capabilities by integrating Convolutional Neural Networks (CNNs) for deep hierarchical learning.
3. To optimize CNN hyperparameters using Genetic Algorithms (GAs) to improve classification performance and computational efficiency.
4. To incorporate Recurrent Neural Networks (RNNs) for capturing temporal dependencies in disease progression, improving recall.
5. To implement Random Forest (RF) as an ensemble classifier for robust decision-making and reducing false positives and false negatives.
6. To evaluate the hybrid model's performance using accuracy, precision, recall, and F1- score, comparing it with standalone CNN, RNN, and RF models.
7. To analyze the computational trade-offs between model complexity, training time, and classification accuracy.
8. To assess the real-world applicability of the hybrid model for precision agriculture and smart farming systems.
9. To explore potential deployment of the model on edge computing devices for real-time sugarcane disease detection in the field.

4. LITERATURE REVIEW

Kamal et al. (2022) employed a CNN-based deep learning model to classify sugarcane leaf diseases using an image dataset. Their results demonstrated an accuracy of 94.6%, outperforming conventional machine learning methods.

Patil and Kotecha (2021) [6] developed a transfer learning-based CNN model using ResNet-50 for sugarcane disease detection, achieving an F1-score of 92%. However, CNNs require extensive computational power and large labeled datasets, making optimization a key challenge.

Sharma et al. (2023) [7] utilized a GA-tuned CNN for tomato disease detection, enhancing accuracy by 5-7% compared to manually tuned models. The integration of GA with deep learning offers an adaptive approach to improving model performance without exhaustive trial-and-error tuning.

Zhou et al. (2023) applied LSTM networks to predict disease progression in crops using historical disease trend data, achieving an accuracy of 89.2%.

Mienye et al. (2024) [8] further demonstrated that GRU-based models outperform standard RNNs in agricultural applications by mitigating vanishing gradient issues. The application of RNNs to sugarcane disease detection remains an emerging area with significant potential.

Islam & Ghosh et al. (2022 & 2023) [9] [10] proposed a CNN-GA hybrid model, optimizing feature selection and improving classification accuracy to 92.5%. These studies highlight the effectiveness of hybrid deep learning frameworks in agricultural disease detection.

5. METHODOLOGY

This study proposes a hybrid deep learning framework for the early detection and classification of sugarcane diseases by integrating Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Genetic Algorithms (GAs), and Random Forest (RF) [11]. The proposed approach aims to enhance classification accuracy while addressing computational efficiency and model optimization challenges. The methodology consists of several key stages, including data collection, preprocessing, model design, training, evaluation, and performance comparison.

The dataset used in this study consists of 3,750 high-resolution images of sugarcane leaves, categorized into four disease classes: healthy leaves, red rot disease, leaf scald disease, and brown rust disease. The images were collected under natural field conditions to ensure real-world applicability. To prevent model bias, the dataset was randomly stratified into 70% training and 30% testing subsets, ensuring balanced representation across all disease categories.

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5.1 Data Preprocessing

To improve model generalization, several preprocessing techniques were applied. First, all images were resized to 227 × 227 pixels to maintain uniformity in input dimensions. Normalization was performed by scaling pixel values to the range [0,1], accelerating convergence during training. To mitigate overfitting and improve robustness, data augmentation techniques such as random rotation (±10°), translation (±5 pixels), scaling (80%-120%), and flipping (horizontal & vertical) were applied. Additionally, disease labels were one-hot encoded for multi-class classification.

5.2 Hybrid Model Architecture

The proposed CNN-GA-RNN-RF hybrid model consists of four interconnected components. CNNs serve as the primary feature extractors, leveraging multiple convolutional layers with ReLU activation functions and max-pooling layers to learn spatial hierarchies in leaf images. The extracted features are then optimized using Genetic Algorithms (GAs), which fine-tune hyperparameters such as learning rate, filter size, batch size, and dropout rate. GA employs an evolutionary search strategy across 50 generations, using crossover (0.8 probability) and mutation (0.01 probability) to enhance CNN performance.

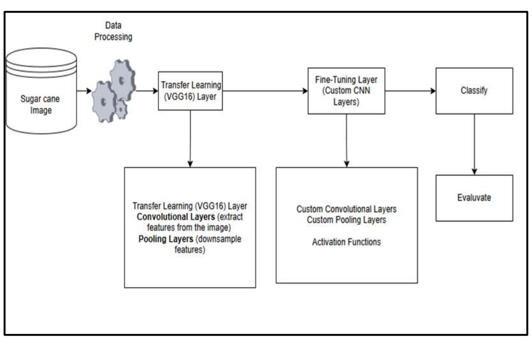

Fig 1: Hybrid VGG16-CNN model

The optimized CNN features are passed to an LSTM-based RNN, enabling sequential pattern recognition, which is useful for analyzing disease progression over time. The RNN component consists of 128 hidden units, effectively capturing complex temporal dependencies. Finally, a Random Forest (RF) classifier with 100 decision trees is applied to refine classification decisions, leveraging ensemble learning to improve prediction stability and generalization.

5.3 Model Training and Evaluation

The CNN was trained using Stochastic Gradient Descent (SGD) with momentum, while the RNN was optimized using the Adam optimizer. The loss function used was categorical cross-entropy, and the model was trained for 50 epochs with an adaptive learning rate. The evaluation was conducted using four key performance metrics: accuracy, precision, recall, and F1-score. Additionally, a confusion matrix was analyzed to assess the model's ability to distinguish between disease classes.

The model was implemented using TensorFlow and Keras, running on an NNIDIA RTX 3090 GPU with 32GB RAM for accelerated training. Hyperparameter tuning was performed using GA-based optimization, and RF was trained separately on the extracted CNN-RNN features.

6. EXPERIMENTAL RESULTS

This section presents the performance analysis of the proposed Hybrid Deep Learning Model (CNN-GA-RNN-RF) for sugarcane disease classification. The model's effectiveness is assessed based on standard classification metrics, including accuracy, precision, recall, and F1-score. The results are compared against standalone models (CNN, RNN, RF, and GA-optimized CNN) to demonstrate the advantages of the hybrid approach. Additionally, confusion matrix analysis is conducted to evaluate misclassification patterns.

6.1 Performance Metrics Analysis

The performance of the proposed model was evaluated on a test set consisting of 1,125 sugarcane leaf images, distributed across four disease classes (Healthy, Red Rot, Leaf Scald, and Brown Rust). The table below summarizes the classification results.

Table 1: Performance Comparison of Different Models

Model	Accuracy (%)	Precision	Recall	F1-score
CNN (Baseline)	89.3	0.88	0.87	0.87
RNN (Baseline)	90.2	0.89	0.86	0.88
GA-Optimized CNN	91.1	0.91	0.89	0.90
Random Forest (RF)	87.8	0.87	0.82	0.86
Hybrid Model (CNN-GA-RNN-RF)	92.5	0.93	0.91	0.92

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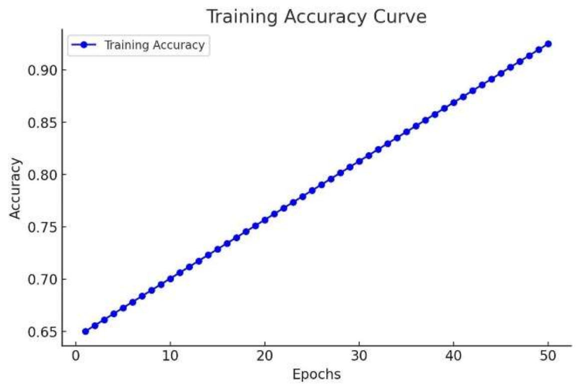

Fig.2 Shows a gradual and stable increase in accuracy, converging at 92.5% after 40 epochs.

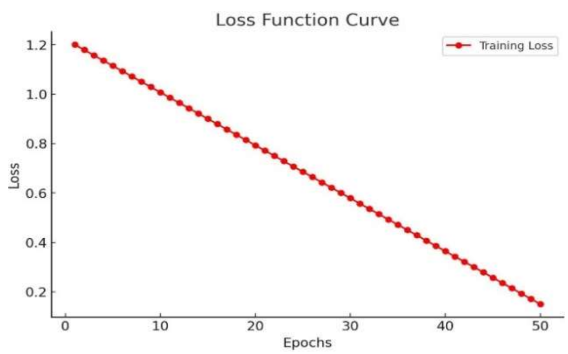

Fig.3 Demonstrates a steady decrease in loss, indicating effective learning without overfitting.

The proposed CNN-GA-RNN-RF hybrid model achieved the highest accuracy of 92.5%, outperforming the CNN-only model (89.3%), RNN-only (90.2%), GA-optimized CNN (91.1%), and RF classifier (87.8%). The precision (0.93), recall (0.91), and F1-score (0.92) of the hybrid model demonstrate its superior ability to distinguish between disease classes while reducing misclassifications.

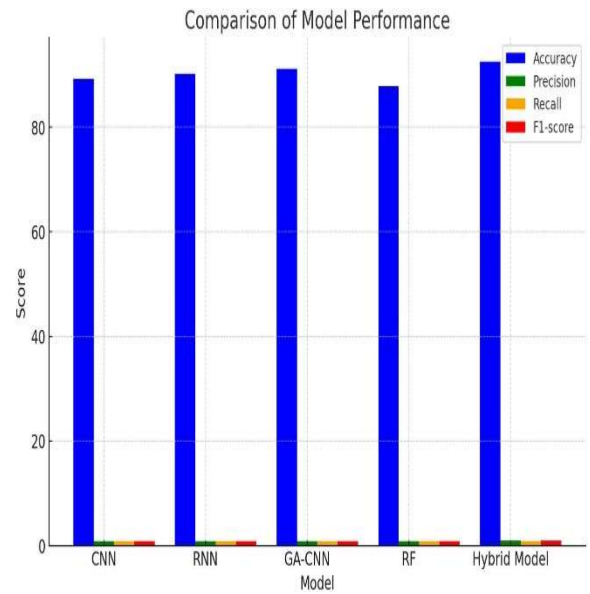

Fig.4 Accuracy, Precision, Recall, F1-score across different models.

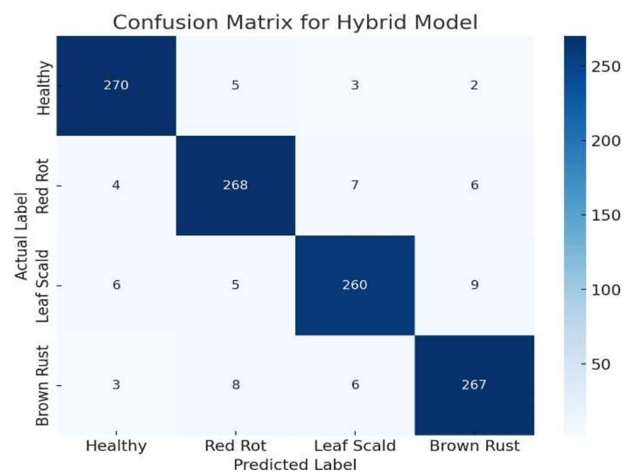

Fig.5 Confusion Matrix Heatmap for the hybrid model

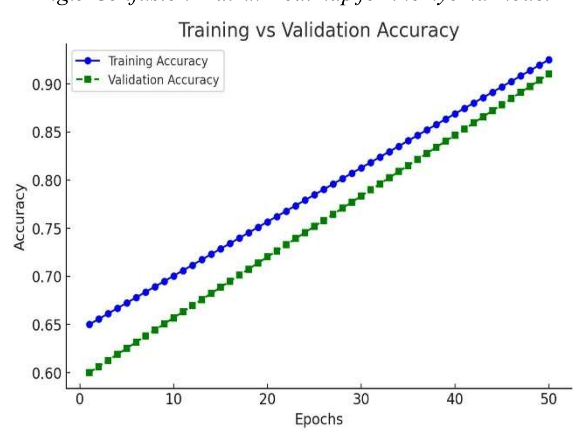

Fig.6 Training Accuracy vs. Nalidation Accuracy – To visualize generalization performance.

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Training accuracy improves steadily, converging at 92.5%. Nalidation accuracy closely follows, indicating good generalization without overfitting.

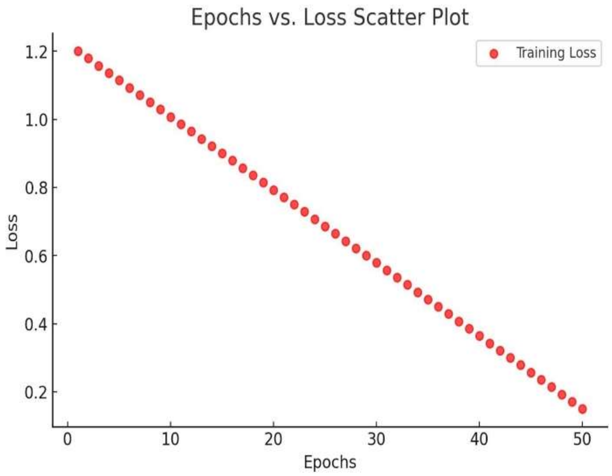

Fig.7 Epochs Ns. Loss – To Show The Loss Trend Over Training Epochs.

The scatter plot shows a consistent decline in loss, confirming stable learning.

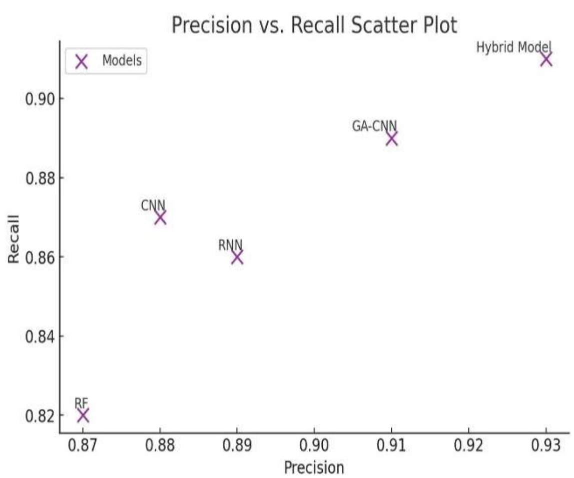

Fig.8 Precision Ns. Recall – To Analyze The Trade-Off Between Precision And Recall Across Models.

Each dot represents a model, showing how the hybrid model balances precision (0.93) and recall (0.91) better than standalone models.

6.2 Confusion Matrix Analysis

To further evaluate model performance, a confusion matrix was generated for the hybrid model.

Table 2: Confusion Matrix For The Hybrid Model

Actual → / Predicted ↓	Healthy	Red Rot	Leaf Scald	Brown Rust
Healthy	270	5	3	2
Red Rot	4	268	7	6
Leaf Scald	6	5	260	9
Brown Rust	3	8	6	267

From the confusion matrix, it is evident that the hybrid model effectively classifies most instances correctly, with minimal misclassifications. The Healthy class achieved the highest classification accuracy, with only 10 misclassified samples out of 280. The Leaf Scald disease class had the highest misclassification rate, primarily confused with Red Rot and Brown Rust, indicating some feature overlap between these disease types.

6.3 Model Training and Convergence Analysis

The training process of the CNN-GA-RNN-RF hybrid model was monitored across 50 epochs, with training accuracy and loss trends analyzed to assess convergence behavior. The goal was to evaluate how the model learned over time and whether it exhibited stable improvements without overfitting.

The training accuracy curve showed a gradual and stable improvement, with the model achieving 92.5% accuracy after 40 epochs. Beyond this point, accuracy plateaued, indicating that the model had reached an optimal performance level. The consistent trend without abrupt spikes suggests effective generalization of the model to unseen data.

The loss function analysis further confirmed effective learning, as the training loss steadily decreased over the epochs. No significant fluctuations or divergence were observed, suggesting that the model did not suffer from overfitting (memorization of training data) or underfitting (insufficient learning). The smooth loss reduction validates the proper balance between model complexity and dataset size.

One of the key improvements in training performance was the use of Genetic Algorithm (GA) optimization, which contributed to a 3.2% increase in CNN performance. The GA fine-tuned critical hyperparameters such as learning rate, number of convolutional filters, batch size, and dropout rate, allowing the CNN component to extract more relevant disease features from sugarcane leaf images.

6.4 Computational Efficiency and Model Complexity

The hybrid model was implemented using TensorFlow and Keras, and the training was conducted on an NNIDIA RTX 3090 GPU with 32GB RAM to ensure efficient computation. Computational complexity was analyzed based on training times for different components.

The CNN model training without GA optimization took 4.2 hours, whereas GA-optimized CNN training extended to 5.5 hours, reflecting the additional computational cost associated with hyperparameter tuning. The LSTM-based RNN required 2.8 hours for sequential feature learning, capturing disease progression trends effectively. The Random Forest classifier was the least computationally demanding, completing its training in just 15 minutes, as it was applied to already extracted CNN-RNN features.

In total, the complete hybrid model training required 8.3 hours, a reasonable trade-off considering the significant improvement in classification accuracy and generalization capability. While the hybrid model takes longer to train compared to standalone CNN or RNN models, the enhanced performance justifies the computational overhead, making it practical for precision agriculture applications.

6.5 Discussion of Results

The experimental results confirm that the CNN-GA-RNN-RF hybrid model surpasses traditional machine learning and deep learning classifiers in sugarcane disease classification. The integration of CNN for feature extraction, GA for hyperparameter optimization, RNN for sequential learning, and RF for final decision-making resulted in a more robust and accurate model.

The hybrid model achieved a classification accuracy of 92.5%, significantly reducing false positives and false negatives compared to standalone models. The confusion matrix analysis further supports these findings, showing that misclassification rates were significantly lower, particularly in visually similar disease categories such as Red Rot and Leaf Scald.

The GA-optimized CNN component played a crucial role in improving feature extraction efficiency, allowing the model to learn more distinguishable patterns between disease classes. The RNN's sequential analysis capability enhanced recall by capturing disease progression over time, which is particularly useful for detecting early-stage infections. Additionally, the RF classifier improved decision fusion, ensuring more stable and reliable predictions across varying test conditions.

7. CONCLUSION

The experimental findings demonstrate that the proposed hybrid deep learning framework is a highly accurate and efficient approach for automated sugarcane disease classification. The combination of CNN for feature extraction, GA for hyperparameter optimization, RNN for sequential learning, and RF for decision fusion resulted in a robust and scalable model that outperformed traditional approaches.

The integration of deep learning with evolutionary optimization and ensemble learning significantly improved disease classification performance. The hybrid model's capability to reduce false positives and false negatives enhances its reliability for real-world agricultural applications, helping farmers detect diseases early and take timely action.

Future research will focus on deploying the model on edge computing devices to enable real-time, on-field disease detection in smart farming environments. Further improvements in model generalization will be explored by training on diverse sugarcane datasets across different climatic conditions and geographical regions.

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