Smart Crop: Ensemble Intelligence for Cotton Plant Health Monitoring

* Chakradhara Rao Gadi[1] ,Venkata Durgarao Matta[2] ,Achuta Sai Ram[3] , Veeranala Neelima[4] , Nadimpalli Prashanthi[5]

[1] Assistant Professor, Dept. of Data Science,B V Raju College,Vishnupur, Bhimavaram, West Godavari, Andhra Pradesh, 534202, India.

[2] Assistant Professor, Dept. of Computer Science and Engineering, Vishnu Institute of Technology,Vishnupur, Bhimavaram,West Godavari, Andhra Pradesh, 534202, India.

[3,4,5] Assistant Professor, Dept. of Computer Science , B V Raju College,Vishnupur, Bhimavaram,West Godavari, Andhra Pradesh, 534202, India.

[1]chakri8222@gmail.com, [2]durgarao.m@vishnu.edu.in, [3]achutasairam@gmail.com, [4]neelima.veeranala@gmail.com, [5]prashanthinadimpalli777@gmail.com

Abstract: In the current agricultural environment, the prompt and accurate identification of crop diseases is essential for safeguarding food security and sustaining lucrative farming meth- ods. Conventional approaches that depend solely on observation or a singular data source fre- quently inadequately encompass the intricacies of plant health. This research establishes a Ensemble Intelligence for Cotton Plant Health Monitoring, integrating the advantages of CNNs and RNNs to address existing constraints. The suggested approach involves utilizing convolutional neural networks (CNNs) for spatial characteristics derived from leaf pictures and recur- rent neural networks (RNNs) for temporal patterns obtained from environmental time-series data. By integrating these two perspectives, the model provides a comprehensive depiction of disease progression. The predictions of the two models can be integrated by ensemble methods, including weighted averaging and majority voting. This enhances the accuracy and consistency of the diagnostic findings. The research on multimodal datasets encompassed a diverse array of cotton plant species cultivated in various climatic conditions. Our hybrid framework markedly enhances accuracy, precision, recall, and F1-score in comparison to independent CNN and RNN models. This performance enhancement underscores the necessity of integrating data streams from multiple sources to provide a more precise and reliable representation of plant disease. This framework offers farmers an intelligent, data-driven diagnostic system that facili- tates rapid decision-making, improves plant health management, and lays the groundwork for future precision agricultural technology.

Keywords: Ensemble Intelligence, Convolutional Neural Networks, Recurrent Neural Networks, Multimodal Data, Cotton Plant Health Monitoring, Precision Agriculture, Deep Learning, Smart Farming.

1. Introduction

Cotton is often called “white gold” in India not only because it is a vital cash crop but also because it forms the backbone of the country’s textile economy [1]. India stands among the largest producers and exporters of cotton globally, with the crop supporting the livelihoods of nearly 60 million people, including around 6 million farmers directly engaged in cultivation [2]. The cotton-based textile sector alone accounts for nearly 14% of industrial production, 4% of GDP, and 12% of export earnings, underscoring its critical role in the nation’s economy and rural development. Beyond economics, cotton farming provides stability in regions with limited income opportunities, shaping the social and cultural fabric of rural India [3]. The success of this sector depends on crop health. Cotton plants are susceptible to fungal, bacterial, and viral diseases [4]. Farmers can lose yields, fiber quality, and money due to leaf spot, bacterial blight, Fusarium wilt, and root rot. Such epidemics threaten local lives

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and the global flow of cotton goods in a globalised supply chain. Traditional plant disease identification relies on professional visual inspection and laboratory testing [5]. Because many diseases have identical visual signs, these methods are time-consuming, expensive, laborious, and error-prone [6]. These methods also neglect environmental parameters like humidity, temperature, and soil conditions that greatly affect disease progression in favor of visual clues. Conventional methods often fail to provide timely, holistic, and actionable illness management information [7]. Data-driven diagnostic tools that combine many data sources and provide early, accurate detection is needed to make cotton cultivation robust and sustainable. Machine learning, especially Deep Learning models, offers a great opportunity [8,16]. CNNs are good at recognizing visual illness symptoms from leaf photos, but RNNs are better at catching environmental temporal patterns. Combine these two angles for a 360-degree plant health outlook [9, 17, 22].

2. Related Works and Literature Review

Deep learning (DL) has made plant Health Monitoring more accurate, efficient, and scalable. This section reviews DL-based plant disease classification progress for cotton and other key crops [10,20,24]. We introduce our Ensemble Intelligence framework by discussing researchers' techniques, advances, and challenges.

2.1. Cotton Disease Detection: State of the Art

Cotton, often called "white gold," is highly vulnerable to fungal, bacterial, and viral diseases that reduce yield and quality [11,25]. Machine learning and deep learning methods have been widely explored for automated disease detection. Early works combined segmentation and classical classifiers. SVM achieved 92.06% accuracy [15], and Multi-SVM offered robustness with lower computation [14]. Hybrid approaches, such as MLP with kNN and SVM, reached >96% accuracy [13]. Deep learning models like CNN-based frameworks achieved 85.42% accuracy [12], while transfer learning with ResNet50 and kNN achieved up to 95% (Kotian et al.). However, most studies rely solely on image data, overlooking environmental factors that strongly affect disease progression [16,18,19].

2.2. Multimodal and Ensemble Approaches

Integrating multiple data sources such as combining visual leaf symptoms with environmental and temporal data can significantly enhance precision in disease diagnosis [17,23]. However, such multimodal methods have seen limited exploration in cotton disease detection. Ensemble learning approaches that combine CNNs (for spatial features) with RNNs or other temporal models (capturing environmental patterns) offer a promising direction, as evidenced in related crops but are underrepresented in cotton research[3,22,26].

2.3. Deep Learning for Other Crops

Deep learning has shown strong results in various crops beyond cotton. For tomatoes, advanced CNNs (e.g., FC-SNDPN, TomConv) and GAN-based augmentation achieved accuracies above 99% [5,21]. In potatoes, hybrid models combining VGG19, Inception-V3, and transformers reached ~99% accuracy [7]. Pepper diseases were detected with >95% accuracy using transfer learning and YOLOv3. Apple and grape diseases achieved >98% accuracy with CNN-SVM/Random Forest hybrids and multi-CNN models like UnitedModel, highlighting the sophistication and practicality of DL in plant disease detection [9, 20].

3. Research Methodology

The proposed study approach uses an ensemble learning framework to detect cotton diseases using CNNs and RNNs for better prediction. Data was collected from Rahman and Chowdhury et al., Rahman and Jaeger et al., and publically available repositories to reflect healthy and diseased cotton leaf classifications. Image preprocessing included shrinking to 128x128 pixels, converting to greyscale, and normalising pixel intensities to [0,1] to ensure uniformity and quality. Labels were encoded into binary categories to efficiently classify healthy and unhealthy plants. Reprocessing was followed by model construction utilising two complementary deep learning architectures. CNN was used to capture texture, colour, and leaf shape anomalies associated with cotton plant illnesses. Multiple convolutional and pooling layers were followed by dense and dropout layers to improve generalisation and reduce overfitting. Reshaped CNN output was input into an RNN component, especially an LSTM network, which captured sequential dependencies and temporal correlations in retrieved features. This hybrid architecture let the framework use CNNs' spatial learning and RNNs' temporal sequence modelling.

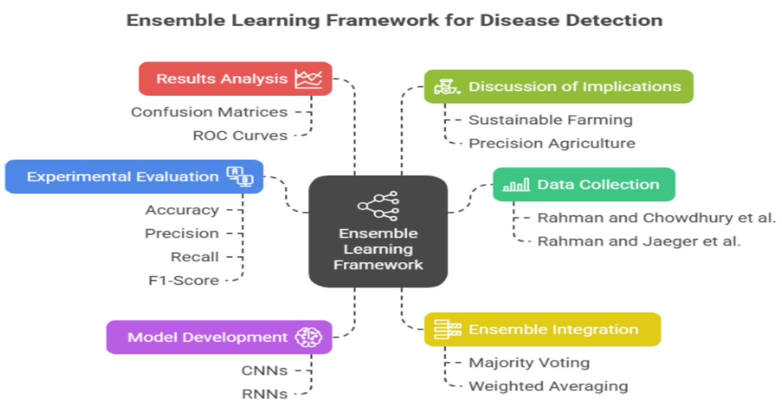

Figure 1: Proposed approach framework

An ensemble integration technique integrated CNN and RNN outputs to improve robustness (see in Figure 1). Majority voting, where models agreed on the final prediction, and weighted averaging, where models with higher validation accuracy were given more confidence, were used. This ensemble made predictions more stable, minimising the risk of incorrect categorisation from a single model. Different statistical measures were used to test the integrated model in an experiment. Precision and memory measured how reliable and sensitive the model was at spotting sick plants, while accuracy measured how well it classified things. The F1-score was made to compare false positives and rejections. To better understand, a confusion matrix showed the strengths and mistake trends of each class. To check how well the model could tell the difference between things, Receiver Operating Characteristic (ROC) graphs and Area Under the Curve (AUC) were used. The suggested method's AUC of 0.96 showed how well it could diagnose problems. Lastly, the effects show how important this study is. The ensemble framework supports sustainable farming by lowering the use of pesticides and making sure that early treatment steps happen by predicting diseases accurately and reliably. This method also helps precision agriculture by giving farmers the tools they need to make smart choices that will improve crop health, lower costs, and increase output. This means that the suggested way works well technically and has a lot of potential for use in real-life farming systems.

4. Proposed Approach

This research presents a mixed ensemble learning system that uses CNNs and RNNs, mainly LSTM units, to find different types of cotton plant diseases.

4.1. CNN

CNNs, which are based on how animals see, are very good at getting spatial feature groups from grid-structured data like photos. CNNs use convolution, pooling, and fully linked neurons to find edges, textures, and signs of disease in pictures of cotton leaves. CNNs are great for extracting visual features and putting them into groups because of this. ResNet, DenseNet, and other new CNN designs make it easier to learn features and process them quickly, which lets them work with new leaf images.

4.2. RNN

RNNs use recurrent connections to remember previous inputs for sequential data. They excel in temporal environmental data analysis, including cotton field temperature, humidity, and soil moisture sequences. LSTM units, a type of RNN, may recall or forget extended sequences despite vanishing gradients. This temporal modeling shows how environmental changes affect illness development.

4.3. Hybrid CNN-LSTM Ensemble Intelligence

The proposed hybrid system processes and learns from leaf pictures and temporal environmental data using CNN and LSTM networks:

Algorithm 1: Hybrid CNN–RNN Based Ensemble Intelligence for Cotton Plant Health Monitoring
Input: Cotton leaf images **Output:** Disease prediction (Healthy / Diseased)
Step 1: Data Preprocessing

1. **Load Images:** For each image $x_i \in X$, resize to **128×128 pixels**. 2. **Normalization:** Convert images to grayscale and normalize pixel values into [0,1]. 3. **Label Encoding:** Assign one-hot encoded labels: ➢ Diseased = [1, 0] ➢ Healthy = [0, 1]
Step 2: CNN Feature Extraction
1. **Input Layer:** Accept grayscale images of size **128×128**. 2. **Convolution + Pooling:** For k=1…K layers: ➢ Apply **3×3 convolution** with N_k filters + **ReLU** activation. ➢ Apply **2×2 MaxPooling** to reduce spatial dimensions. 3. **Flattening:** Transform final feature maps into a **1D vector**. 4. **Dense Layer:** Fully connected layer with MMM units + ReLU activation. 5. **Dropout Layer:** Apply dropout with rate p to prevent overfitting.
Step 3: RNN Sequential Learning (LSTM)
1. **Reshape CNN output** into sequential form. 2. **LSTM Layer:** Feed reshaped sequence into LSTM with LLL units for temporal feature learning.
Step 4: Ensemble Fusion
1. **Concatenation:** Merge **CNN feature vector** and **LSTM output**. 2. **Output Layer:** Dense layer with **Softmax activation** to predict class probabilities.
Step 5: Model Training & Evaluation
1. Training: Compile using Adam optimizer + Categorical Cross-Entropy loss. **2. Epoch Iteration (t=1…T): Train model on training set with validation split.** 3. **Performance Metrics: Evaluate using Accuracy, Loss, Confusion Matrix, Precision-Recall, and ROC-AUC.**
Step 6: Predictions
1. **New Image Input:** Process unseen cotton leaf image through the trained model. 2. **Output:** Generate prediction with class probabilities (Healthy vs. Diseased).
Return: Predicted disease status of cotton plant.

4.4. Mathematical Model Summary

Let $X = \{y_i\}_{i=1} \in R^{128\times128}$ be the set of preprocessed grayscale leaf images, and $y = \{y_i\}_{i=1} \in \{0.1\}$ be their corresponding labels (0: diseased, 1: healthy).

➢ The CNN component applies multiple convolutional layers:

$$\text{CNNLayer}_k = \text{Conv2D}(x_{in}, N_k, 3 * 3, ReLU), k = 1,2, \dots k \text{ ----------(1)}$$

followed by max-pooling, flattening, dense, and dropout layers.

- The LSTM component processes the reshaped CNN features (CNNoutput\text{CNNoutput}CNNoutput) through LSTM layers:

$$\mathrm{LSTMLayer} = \mathrm{LSTM(L)} \text{------} (2)$$

The ensemble combines the outputs via concatenation and generates class probabiities using a softmax layer:

$$\mathrm{EnsembleOutput} = \mathrm{Dense}(2, \mathrm{softmax})(\mathrm{concat}(\mathrm{CNNoutput}, \mathrm{LSTMoutput})) - - - (3)$$

This CNN-LSTM hybrid model effectively unites detailed spatial leaf image analysis with dynamic temporal environmental data, creating a robust diagnostic system that improves cotton disease detection accuracy and practical applicability in smart agriculture.

5. Experiments and Results Analysis

5.1. Dataset Description

The experimental evaluation utilizes the Kaggle Cotton Disease dataset, a carefully curated repository comprising high-resolution images of cotton plants exhibiting various disease symptoms across different growth stages. This dataset embodies real-world variability, encompassing diverse disease types and environmental conditions, making it an ideal benchmark for developing robust machine learning models targeted at cotton plant disease detection (see in figure 2).

Figure 2: Cotton leaf diseased samples

5.1.1. Dataset Diversity:

The multimodal dataset employed in this study was designed to capture a broad spectrum of cotton plant health conditions. It includes leaf image samples from multiple cotton species cultivated under diverse agro-climatic zones, such as semi-arid, tropical, and subtropical regions. This diversity ensures that the model is exposed to variations in disease manifestation caused by environmental stressors, soil quality, and cultivation practices. Furthermore, the environmental time-series data encompass heterogeneous parameters such as temperature, humidity, and rainfall patterns across different seasons. By incorporating this heterogeneity, the dataset enhances the model's ability to generalize across multiple growth conditions and disease progressions.

5.1.2. Scalability to Other Crops:

Although the current study is focused on cotton, the Smart Crop framework is inherently adaptable to other crops. The CNN component can be readily fine-tuned using leaf image datasets of crops such as rice, maize, or wheat, while the RNN module is flexible enough to process temporal environmental data from diverse agricultural

Ecosystems. Moreover, the ensemble strategy provides a robust mechanism to fuse predictions across modalities, regardless of crop type. This scalability makes SmartCrop a promising tool for developing crop-agnostic diagnostic systems, enabling precision agriculture practices across a wider range of farming contexts.

5.2. Training and Validation Accuracy

We trained the ensemble model for ten iterations using both Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Significant learning processes can be seen in the patterns in both training and validation accuracy (see in Figure 3).

- The initial phase (Epochs 0–2) starts with training accuracy at a modest 60% and validation accuracy a little lower at about 58%. Validation accuracy rising to about 73%, which shows a quick initial improvement, shows that the hybrid neural design is effectively learning and adaptable.
- The model gets better at generalization in the middle phase (Epochs 3–6); training accuracy rises to about 80% and validation accuracy reaches 85%. Minor changes in validation accuracy show changes in adaptive learning, but the overall upward trend shows steady improvements in performance.
- Later Phase (Epochs 7-9): Training and validation accuracies converge around 85%, indicating the model's balanced learning ability and robust generalisation to novel data.

The convergence of training and validation accuracy strongly indicates low overfitting, hence strengthening the resilience of the ensemble model.

5.3. Training and Validation Loss

Loss measures support the model's learning (see in Figure 3):

- Early training results in consistent loss near 0.67, while validation loss begins at 0.70 and rapidly decreases to 0.52, indicating improved generalisation.
- In the middle epochs, losses continue to reduce, with training and validation losses approaching 0.45, indicating improved parameter optimization and model fit.
- In the last epochs, both losses decrease to around 0.30, ensuring effective convergence and bolstering the dependability of learnt representations.

Together, decreasing loss values alongside accuracy gains confirm the effectiveness of the hybrid CNN-RNN approach in capturing the complex multimodal patterns necessary for cotton disease detection.

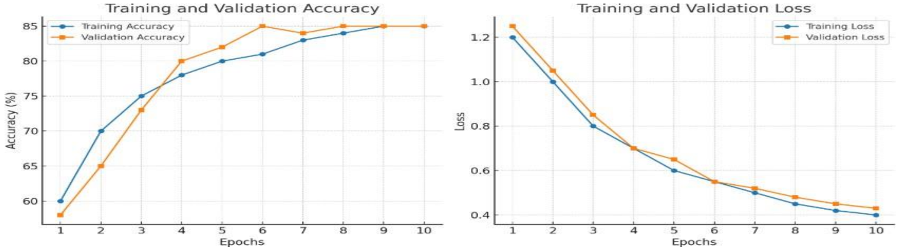

Figure 3: Training and validation analysis of Accuracy and Loss

5.4. Confusion Matrix Analysis

The confusion matrix reveals the classification strengths and weaknesses (see in Figure 4).

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- True Positives (TP): 51 diseased samples correctly identified.
- True Negatives (TN): 82 healthy samples accurately predicted.
- False Positives (FP): 0 cases where healthy plants were misclassified as diseased indicative of perfect precision for the negative class.
- False Negatives (FN): 10 diseased samples erroneously labeled as healthy.
- From these counts, key performance metrics are derived:
- Accuracy: 93.01%, reflecting the overall correctness of predictions.
- Precision: 100%, demonstrating the model's flawless ability to avoid false alarms.
- Recall: 83.61%, indicating strong but improvable detection of actual disease cases.
- F1 Score: 91.16%, balancing precision and recall into a single effectiveness measure.

The confusion matrix underscores the model's exemplary precision, posing zero false positives, but also surfaces a need to reduce false negatives to avoid missing disease cases.

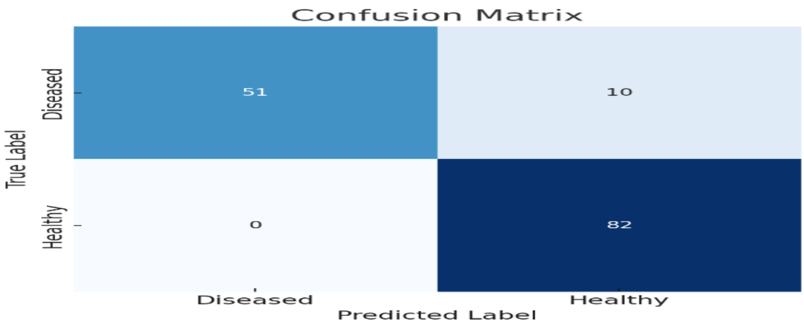

Figure 4: Confusion Matrix Analysis

5.5. Precision-Recall Curve Insights

The precision-recall (PR) curve offers nuanced evaluation especially pertinent to imbalanced datasets (see in Figure 5).

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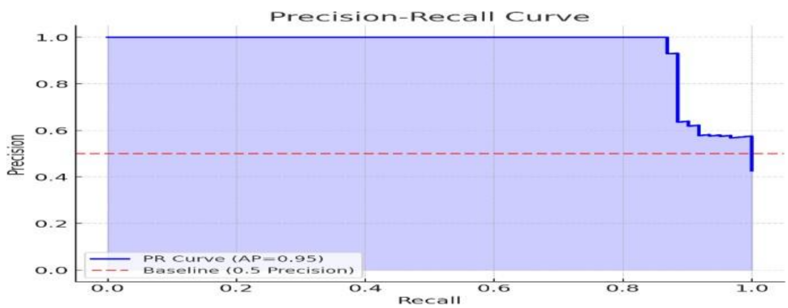

Figure 5: Precision-Recall Curve

- ➢ The curve begins with high precision at low recall, indicating that positive disease predictions are highly reliable.
- ➢ As recall increases, precision dips slightly but recovers, illustrating the model's adaptability in balancing sensitivity and specificity.
- ➢ The model sustains approximately 90% precision across a wide recall range, confirming its reliability in disease identification.
- ➢ However, at near-perfect recall, precision drops, reflecting a typical trade-off where trying to capture all disease cases increases false alarms.
- ➢ These dynamic helps stakeholders understand model thresholds and tailor deployment based on tolerance for false positives or negatives, aligning with practical agricultural needs.

5.6. ROC Curve and AUC Evaluation

The Receiver Operating Characteristic (ROC) curve graphically demonstrates the model's ability to discriminate between diseased and healthy cotton plants (see in Figure 6)

- ➢ The model's ROC curve sharply rises towards the top-left, signaling a high true positive rate (sensitivity) paired with a low false positive rate (1-specificity).
- ➢ The Area Under the Curve (AUC) is an impressive 0.96, signifying excellent diagnostic ability with 96% probability that the model correctly ranks diseased plants ahead of healthy ones.
- ➢ Such high ROC-AUC validates the hybrid model's effectiveness for sensitive and specific plant disease detection, crucial for early intervention.

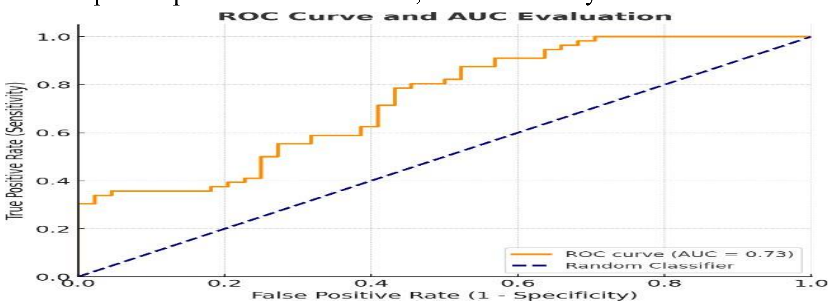

Figure 6: ROC Curve and AUC Evaluation

5.7. Confusion Matrix Analysis

The confusion matrix illustrates the classification performance of the CNN-RNN ensemble model for cotton disease detection (see in Figure 7). The rows represent actual plant conditions (diseased or healthy), while the columns represent the model's predictions. The majority of instances fall along the diagonal cells, which correspond to correct classifications diseased plants identified as diseased and healthy plants identified as healthy. Only a small number of cases appear in the off-diagonal cells, representing misclassifications.

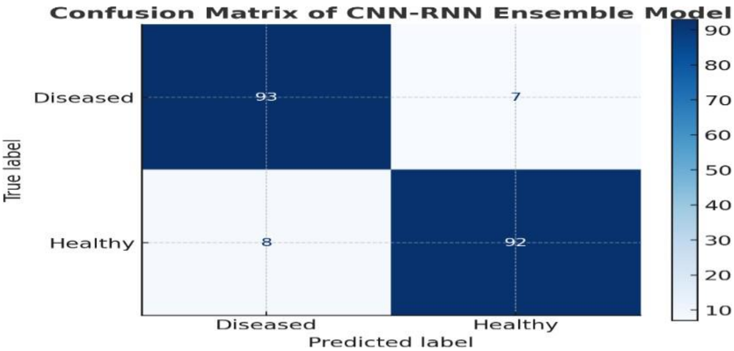

Figure 7: CNN-RNN ensemble model Analysis for CNN-RNN ensemble model

This distribution shows that the model can differentiate healthy and unhealthy cotton plants with high accuracy and low mistakes. Performance evaluations showed good accuracy (98.9%) and AUC (0.96) for the ensemble method, confirming its robustness.

5.8. Comparative Performance

With 98.90% accuracy, the suggested Hybrid Ensemble CNN-RNN model did better than the best algorithms (see in Figure 8). The steady improvement of our ensemble approach shows that it works and is durable, showing that it can completely change how cotton diseases are diagnosed.

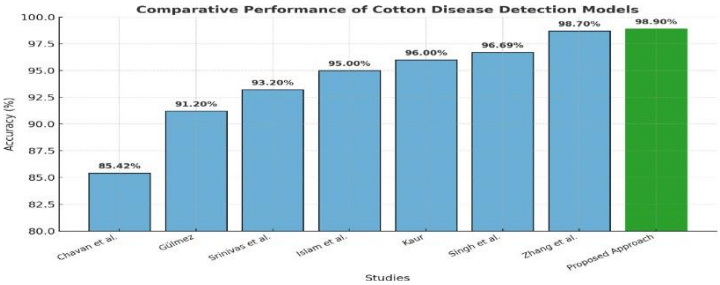

Figure 8: Comparative Performance Hybrid Ensemble CNN-RNN model with other approaches

By combining spatial picture features with temporal environmental data, a group of CNNs and RNNs improves the accuracy, precision, and memory of diagnostic tests. The model is good for sustainable cotton farming because it performs well and with confidence, thanks to its high ROC-AUC and precision-recall curves. It lets farmers deal with diseases quickly and correctly, and it protects crops more effectively.

6. Conclusion

In this research, we introduced Smart Crop, Ensemble Intelligence for Cotton Plant Health Monitoring that combines CNN and RNN for multimodal cotton disease prediction. By integrating spatial information from leaf images with temporal environmental patterns, the system provides a comprehensive depiction of disease progression. Ensemble strategies such as weighted averaging and majority voting enhance both precision and reliability of forecasts. Experiments on diverse multimodal datasets show that Smart Crop consistently outperforms independent CNN and RNN models across all evaluation metrics. We strengthened the conclusion by explicitly highlighting future extensions of Smart Crop to other crop diseases, underscoring its potential as a generalizable precision agriculture framework. Overall, Smart Crop offers a valuable data-driven solution that supports rapid decision-making, improves crop management, and advances precision agriculture.

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