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Research Article

An Intelligent Hybrid Machine Learning Model for Paddy Disease Detection

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Abstract: Most countries rely on paddy/rice as a preferred staple crop due to its desirable agronomic characteristics. However, during the growth cycle, undetected or delayed identification of diseases can significantly reduce crop yield. To address this, machine learning approaches are increasingly employed for early-stage disease detection. Traditional Recurrent Neural Networks (RNNs), while useful for sequential data, suffer from limitations such as inadequate memory retention, architectural complexity, and slower processing speeds. To overcome these challenges, this study proposes a hybrid deep learning model integrating RNN, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). In this framework, the RNN component captures temporal dynamics by accommodating variable intervals, such as daily, weekly, or custom-defined gaps, between image inputs for time-series analysis. The LSTM component ensures long-term sequential memory retention, while the GRU contributes a streamlined architecture that accelerates processing. The proposed model enables early disease identification and provides actionable recommendations, such as initiating pesticide application or determining the optimal time for harvest. It operates iteratively, reassessing disease status, whether eliminated or persistent, based on initial detection and subsequent input intervals. By integrating data preprocessing techniques and a well-defined predictive structure, the model achieves near-optimal accuracy and performance, thereby minimizing crop damage and enhancing overall yield.

Keywords: Hybrid Approach, Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), Paddy Disease Prediction, Accuracy, Performance

Introduction

Numerous crop varieties require systematic analysis; however, this study specifically focuses on paddy (rice), one of the most significant food commodities globally. As a staple crop, rice sustains billions of people and plays a critical role in global food security. Consequently, there is a pressing need to adopt technology-driven strategies and best practices that continuously enhance paddy yield while minimizing the impact of diseases.

Despite its importance, paddy cultivation remains vulnerable to a wide range of diseases that can substantially reduce productivity and threaten food availability. In response, researchers worldwide are actively developing and refining innovative approaches to manage and mitigate these pervasive threats. Early and accurate disease prediction is central to these efforts. While various machine learning algorithms have been individually employed for this purpose, with their performance and accuracy evaluated and compared, there remains scope for more robust, integrated solutions.

The proposed hybrid model, a modified Recurrent Neural Network (RNN) enhanced with Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, aims to address this gap. By

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enabling early disease detection, the model seeks to alert farmers promptly, facilitating timely interventions to minimize or eliminate disease outbreaks and safeguard crop yield.

The proposed methodology offers several key advantages, including a simplified architectural design that facilitates faster implementation and evaluation, while also effectively retaining long sequential dependencies. Table 1 presents a comprehensive overview of various machine learning methods relevant to this domain. In addition to the techniques listed, several conventional approaches, such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Feedforward Neural Networks (FFNN), and K-Nearest Neighbors (KNN) m have been comparatively analyzed, with their respective limitations identified as highlighted by Demilie (2024); Ngugi et al. (2024).

Complementary technologies have also been explored in the broader context of plant disease prediction. For instance, Shinde and Kulkarni (2017) demonstrated the integration of sensor-based data acquisition, IoT-enabled monitoring, and machine learning models for real-time anomaly detection and alert generation. In the domain of deep learning-based crop disease classification, Kabala et al. (2023) employed ResNet50 as a pre-trained model, alongside vision transformers and federated learning approaches, to enhance classification performance. Furthermore, transfer learning has been proposed as an effective strategy for paddy disease prediction, with comparative evaluations against traditional models such as CNN and SVM reported by Rautaray et al. (2020).

Synthesizing insights from these studies reveals persistent gaps across four critical dimensions: Memory retention, real-time accuracy, and processing speed, areas that the proposed hybrid model seeks to address. These improvements are particularly vital given that paddy crops, like many agricultural staples, remain vulnerable to a range of pathogens, including fungi, bacteria, viruses, and nematodes. Although some disease types occur less frequently, their collective impact on yield and grain quality is substantial, often resulting in significant economic losses for farmers. Figure 1 illustrates the projected yield losses associated with key disease categories, underscoring the urgency of deploying robust, early-stage prediction systems.

The visual manifestations of major paddy crop diseases are illustrated in Figure 1. Among these, rice blast is particularly destructive, characterized by diamond-shaped lesions that can lead to complete crop failure. Bacterial leaf blight presents as water-soaked patches that progressively turn straw-colored, while sheath blight forms large, diamond-shaped lesions that may render grains sterile. Brown spot begins as small, discrete brown lesions that gradually coalesce, and false smut transforms healthy flowers into black, spore-filled structures, resulting in grain infertility.

Effective detection of these diverse disease manifestations necessitates a robust analytical approach. To address this requirement, we propose a modified recurrent neural network architecture that integrates Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) modules for early disease prediction. This hybrid model is designed to provide timely alerts, enabling farmers to initiate appropriate preventive or remedial actions.

Literature Survey

Although many studies have explored various approaches for crop disease prediction, this study specifically demonstrates the design of a solution for paddy crop disease prediction. Demilie (2024) discusses several machine learning and deep learning methods, among which Convolutional Neural Networks (CNNs) are considered a good choice for image analysis and disease type classification, outperforming approaches such as Feedforward Neural Networks (FFNNs), k-Nearest Neighbors (KNN), Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Naive Bayes (NB), and others.

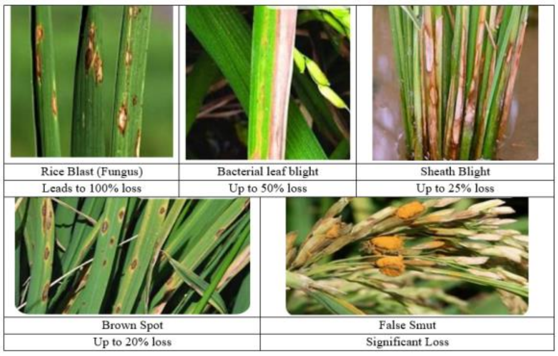

Fig. 1: Possible Hard diseases over paddy crop

Table 1: Possible ML methods

Method	Purpose	Metrics
MLR	A linear relationship between input variables	Cost-effectiveness
Random Forest	Multiple decision trees are formed	Accuracy and Interpretability
SVM	Separates data points into specific categories	Accuracy
Logistic Regression	Predicts the probability of a crop of a particular category	Accuracy
Naive Bayes	Classifies based on independent features	Accuracy

The challenging task addressed in this study is the prediction of diseases across multiple plant species. Shinde and Kulkarni (2017) demonstrated the use of IoT and sensors to measure external conditions such as weather, light, and other environmental factors, alongside machine learning techniques to predict plant diseases. In their proposed system, if signs of potential plant diseases or nutrient deficiencies are detected, a notification is sent to the farmer recommending appropriate actions.

Kabala et al. (2023) explored CNNs and their variants, finding that ResNet-50 performs well in federated learning settings. In contrast, vision transformer models (ViT-B16 and ViT-B32) require more computation time and higher communication costs, making them less suitable for federated learning. Ngugi et al. (2024) addressed multiple plant diseases using machine learning and deep learning methods, analysing SVM, KNN, CNN, and ANNs. They proposed a specific framework that combines both ML and DL for effective plant disease detection.

Nanda et al. (2023) discussed various classification methods for plant diseases and noted that automating the disease identification process helps farming communities take timely action. Most traditional methods were slow and time-consuming for disease discovery and mitigation. Shoaib et al. (2023) reviewed various ML and DL approaches along with their challenges and limitations in plant disease prediction, providing insights that may assist other researchers in disease identification and damage prevention. Many recent advancements, including multi-stage networks and segmentation, have been validated in these scenarios.

Domingues et al. (2022) demonstrated various approaches, RNN, CNN, deep learning, and computer vision, for disease prediction in tomato crops. For time-series images, RNNs are preferred. Their analysis concluded that deep learning is preferable for large datasets, and transfer learning is subsequently used to achieve controlled-condition performance.

Sharma et al. (2022) described various machine learning and deep learning techniques for rice plant disease identification, finding that InceptionResNet outperforms XceptionNet. Their study focused on three major diseases, and the results demonstrated that early identification can minimize crop damage and increase productivity. Ramanjot et al. (2023) discussed several techniques for disease prediction, including preprocessing, data augmentation, and feature extraction. They noted that such implementations require expert design and systematic engineering. However, their work was limited to detecting disease on a single leaf per frame, not on multiple leaves simultaneously.

Tirkey et al. (2023) compared three approaches, InceptionV3, YOLOv5, and CNN, and found that YOLOv5 performed best in terms of processing speed. When applied to large sets of images, YOLOv5 processed and produced results rapidly. Sharma et al. (2023) explored numerous ML and DL techniques, including transfer learning models and DL with bitwise logical AND operations. Among these, DeepBatch performed well across all categories of nutrient deficiencies (nitrogen, phosphorus, and potassium), although the study again focused on only three significant diseases.

Yang et al. (2023) examined several methods, including a detection transformer, Hungarian algorithm, and ResNet2, finding that the detection transformer achieved the highest accuracy. Deng et al. (2021) proposed an ensemble approach combining three sub-models, SE-ResNet, ResNet, and DenseNet, applied to six rice plant diseases, achieving an accuracy above 91%.

Bari et al. (2021) demonstrated a Faster R-CNN model that accurately identifies diseased regions on a leaf. They observed improved training with real-time datasets, and their method addressed three significant diseases with accuracy approaching 99%. Rautaray et al. (2020) evaluated several ML methods and proposed transfer learning as an alternative to multi-layer CNNs, SVMs, and KNN. Transfer learning achieved better accuracy than the other models in detecting paddy crop diseases.

Hasan et al. (2023) addressed challenges in overcoming rice plant diseases and proposed a small, low-complexity CNN architecture suitable for image processing during both training and testing. The model achieved better-than-expected accuracy and was later ported to a mobile application for real-time prediction of rice crop diseases. Rahman et al. (2020) compared two two-stage CNN models against existing architectures such as VGG16, MobileNet, SqueezeNet, and NasNet. They found that a smaller CNN was more suitable for image classification, achieving higher accuracy and lower complexity than the other models.

Sethy et al. (2020) explored multiple strategies for rice crop disease identification, including feature selection, feature extraction, segmentation, processing techniques, and quantization methods. Their analysis highlighted strengths, limitations, and recommendations for future research. Sequeira et al. (2022) developed an automated approach using a custom CNN, carried out at the Lonavala Research Institute in India. This approach achieved 99.5% accuracy in identifying major rice crop diseases.

Udayananda et al. (2022) surveyed various deep learning approaches, outlining their drawbacks and strengths. Their analysis focused on the use of CNNs and other models, along with image processing techniques to identify infected regions, observing that all stages contributed to accurate identification. Venkatamohan et al. (2023) integrated AI and IoT to monitor the health of rice plants and support effective decision-making. Their machine learning approach helped detect diseases and alert farmers to prevent further spread. Liu et al. (2023) applied deep learning networks such as VGG and ResNet to rice-plant-specific diseases, reporting good accuracy as the primary evaluation metric.

Roy et al. (2023) demonstrated a CNN-based approach using networks such as MobileNet and transfer learning. They compared a standard CNN with a modified networked CNN combined with image processing and concluded that the latter method achieved better accuracy. Their study also elaborated on the drawbacks of other models, including SVM, KNN, ANN, and standard CNNs.

Methods

In this study, a modified Recurrent Neural Network (RNN) is defined using a combination of Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM). This hybrid approach eliminates the limitations of standard RNNs and ensures faster processing. Two key activities are demonstrated: First, the Entity-Relationship (ER) model of the hybrid approach, and second, the definition of a pseudo-procedure for implementing it.

Traditional RNNs suffer from issues such as an inability to retain long sequences and the vanishing gradient problem. These are addressed by using LSTM to capture long-term dependencies, while GRU handles simpler tasks and improves overall performance. The methodological approach follows a sequential architecture that incorporates RNN, LSTM, and GRU units, where LSTMs and GRUs jointly handle spatial-temporal features. Hyperparameter tuning is performed on parameters such as dropout rates, hidden units, sequence length, and optimizer selection.

For rice-dependent regions, particularly South India, an attention mechanism is integrated to highlight specific regions in the images. Experimental validation was conducted using Google Colab with a Python environment and a dedicated dataset. The dataset was sourced from Kaggle and includes fields such as image ID, disease label, paddy variety, and age. Real-time extracted images are stored in the cloud for both storage and security purposes. The images are saved in a customised cloud folder, and data preprocessing is applied to clean the images before they are processed by the hybrid model. Figure 2 shows an ER model of the RNN modules, outlining the entities, attributes, and significant activities involved.

The second module is the GRU, whose simpler architecture increases processing speed. Its update gate controls information flow from the previous state, the hidden gate represents current state information, and the reset gate determines how much of the previous state is discarded. The third module covers three major paddy diseases, rice blast, bacterial leaf blight, and sheath blight, which cause severe damage, requiring prompt action to prevent spread. The fourth module is the LSTM, which uses input, output, and hidden gates for long-term memory retention. The fifth module defines performance metrics such as accuracy, speed, cost-effectiveness, and minimum error rates, reflecting the overall efficiency of the hybrid system.

Figure 4 illustrates the key milestones achieved at different stages of the hybrid model. The effectiveness of the model is then evaluated based on accuracy and overall performance.

The pseudo-procedure of the hybrid approach is derived and illustrated in the following scenario:

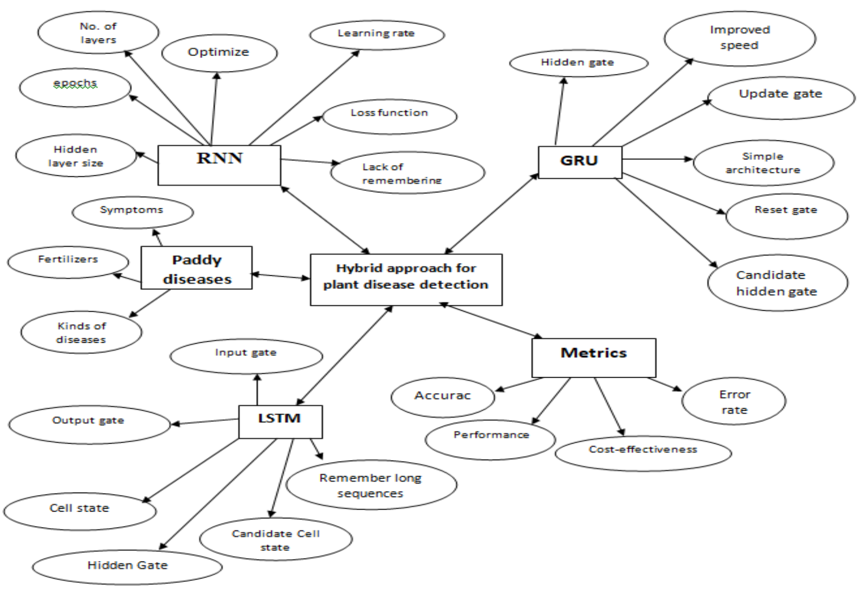

Fig. 2: ER model of hybrid approach for paddy crop disease identification

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PS1: Pseudo_Procedure Hyrbrid_ML_Technique (Images[][]):

Input: Captured images of the crop, Images

Output: Classification like Type1 or Type2 or Type3 or Mixed

Steps:

1. Load the database that consists of images, extracted from an online Kaggle source.
2. Apply data preprocessing to remove noise using filters and use histogram equalization to fix disease portions.
3. Define image data generator for training and use augmentation over attributes such as rotation, shearing, and horizontal flip
4. Define image data generator for Testing with the same batch size as training
5. Define model architecture in which device name is GPU
6. Apply Convolution layers two times with Max Pooling, then flattening, and then two LSTMs for temporal dependencies.
7. Run this for 10 Epochs for better accuracy.
   Accuracy = (Number of correctly classified images) / (Total number of images in testing set)
   Precision = (Number of true positives) / (Number of true positives + Number of false positives)
   Recall = (Number of true positives) / (Number of true positives + Number of false negatives)
   F1_score = 2 * (Precision * Recall) / (Precision + Recall)
8. Softmax activation is used in the output to determine the disease class Type1 or Type2 or Type3 or Mixed
9. Compute loss function in terms of categorical cross-entropy
   CCE = -Σ (y_true * log(y_pred)), where y_true denotes the probability distribution predicted by the model for a particular image, and y_pred denotes the probability distribution predicted by the model for a particular image.

In pseudo-procedure PS1, the database is first loaded, followed by data preprocessing to obtain clean data. An image data generator is then applied to both the training and test datasets, ensuring that the batch size remains consistent across both. Next, the model architecture is defined using several convolutional layers, a flattening layer, and LSTM layers, with execution performed on a GPU device.

The model computes accuracy, precision, recall, F1 score, and loss. A lower loss value indicates superior model performance compared to other models.

The key metrics are defined as follows:

- Precision – the ratio of true positives (correctly predicted disease cases) to all positive predictions
- Recall – the ratio of true positives (correctly predicted disease cases) to all actual disease cases present in the test set
- F1 score – the harmonic mean of precision and recall, providing a balanced measure of both metrics

Results

The proposed hybrid approach is compared against individual GRU, LSTM, and RNN models. Table 3 reports accuracy, precision, recall, and F1 score for each method: Accuracy measures overall correct classifications; precision is the fraction of correct positive predictions; recall is the fraction of actual positives correctly identified; and F1 score is the harmonic mean of precision and recall. Figure 3 visualizes these metrics.

Table 2: Significant methodologies over plant diseases

Methodology	Purpose	Drawbacks
Machine Learning	Demonstrates many approaches, and signifies Random Forest model	Poor handling of high dimensional data, and overfitting issues results noise.
Deep Learning	Many were demonstrated, but signified with integration of other models for expected outcome	Experiences errors and computational power
Pretrained Networks	Explored VGG, ResNet, MobileNet, and many others	Architecture may support or may not ensure accuracy.
Transfer learning	Suitable in case of datasets unavailable	Data biasing in case of generality
AI and IoT	Monitoring equipment for measuring the plant healthiness	Complex

Table 3: Metrics comparison over methodologies

Method	Accuracy (%)	Precision (%)	Recall (%)	F1_Score (%)
MLR	75	70	72	73
Random Forest	85	83	82	84
SVM	82	80	81	81
Logistic Regression	78	76	77	77
Naive Bayes	72	70	71	71
RNN	85	85	85	85
GRU	90	90	90	90
LSTM	97	97	97	97
Hybrid approach (RNN, GRU, LSTM)	99	98	99	98

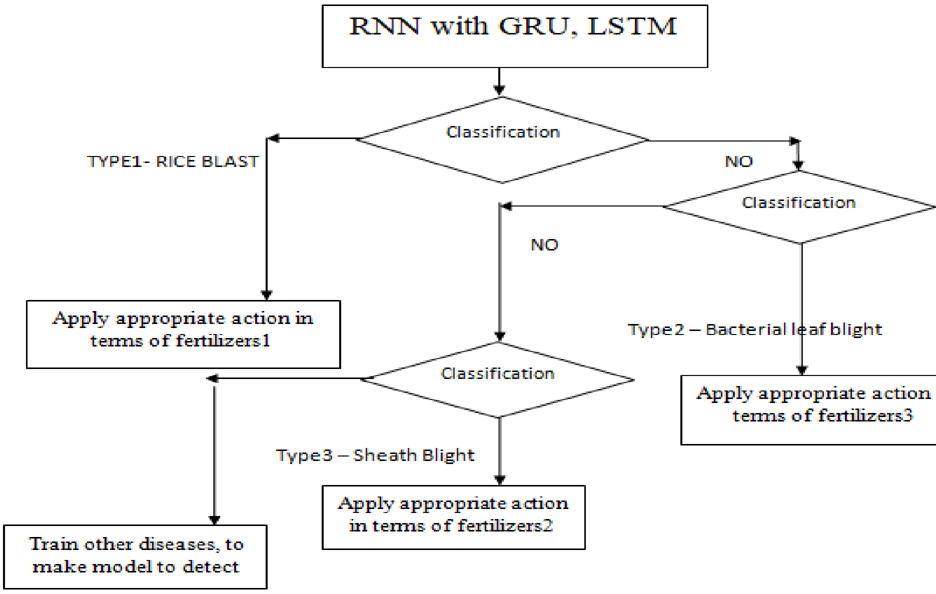

Fig. 3: Workflow of the Hybrid approach for paddy crop disease detection

Table 2 presents the evaluation metrics accuracy, performance, cost-effectiveness, and error rate for the individual RNN, GRU, and LSTM approaches. These observations are also illustrated in Figure 5. A lower error rate indicates higher performance and greater model reliability.

Table 3 and Figure 5 further demonstrate the evaluation metrics for various methods in paddy crop disease detection.

Among traditional machine learning models, Multiple Linear Regression (MLR), logistic regression, and naive Bayes offer simplicity, interpretability, and low computational cost. However, they struggle with non-linear patterns and often rely on manual feature engineering. Random forest provides robustness for tabular data but is not well-suited for advanced sequence analysis. Support Vector Machines (SVMs) perform reliably with high-dimensional inputs but are computationally expensive.

In deep learning, RNNs effectively capture temporal dynamics but face training challenges related to vanishing gradients. GRUs offer a faster and more efficient alternative with balanced performance. LSTMs are the most reliable for sequential learning due to their ability to preserve long-term dependencies. Finally, the proposed hybrid model, combining RNN, GRU, and LSTM, outperforms all other methods by leveraging their complementary strengths, achieving superior accuracy, recall, and stability.

Table 4 shows that the hybrid model offers significant advantages over individual methods for disease detection. The most effective strategy for managing paddy diseases often involves an integrated approach that combines balanced fertilization, resistant crop varieties, local cultural practices, and the judicious use of fungicides when necessary.

As shown in Table 4 and Figure 6, the hybrid approach achieves better performance and accuracy than individual methods when applied to rice plant disease identification. Compared to existing models, the hybrid model delivers faster processing due to its GRU component and higher accuracy in correctly classifying instances.

Figure 7 demonstrates that the hybrid approach has a lower error rate in the classification process, meaning the difference between expected and actual disease identification is very small. The hybrid model's error rate is significantly lower than that of other models, confirming its robustness.

Table 4: Metrics comparison over methodologies

Method	Accuracy (%)	Performance (%)	Cost-effectiveness	Error rate (%)
RNN	85	85	Moderate	40
GRU	90	90	Moderate	30
LSTM	98	97	Above Moderate	20
Hybrid approach (RNN, GRU, LSTM)	99	99	High based on complexity	5

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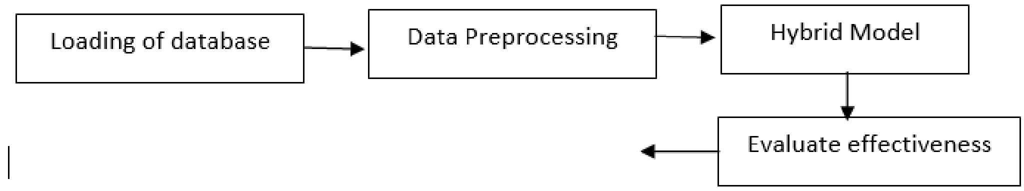

Fig. 4: Stage-wise representation of hybrid model RNN-LSTM-GRU with ensemble

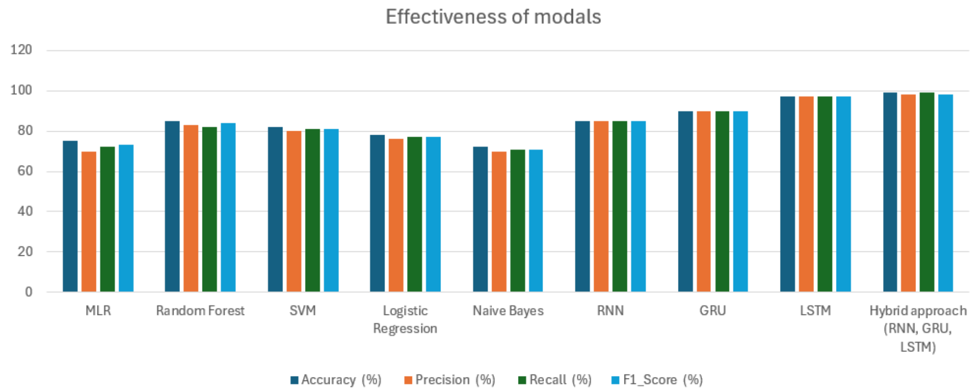

Fig. 5: Accuracy, Precision, Recall, and F1_score against the considered methods

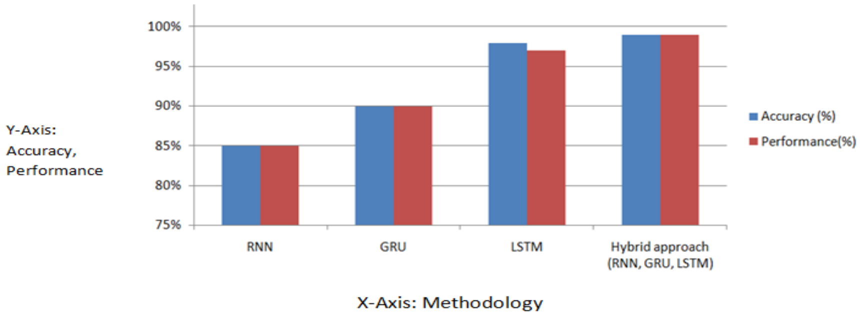

Fig. 6: Accuracies and Performances of Methodologies against the Hybrid Approach

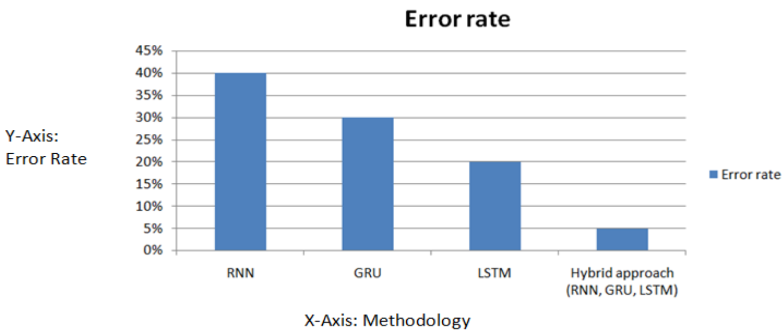

Fig. 7: Error rate of methodologies against the hybrid approach

Conclusion

This study focuses on several advantages, including improved performance, high accuracy, and low maintenance costs. However, a key limitation is the need to process large labeled datasets. A critical factor in determining model optimality is the error rate: A lower error rate indicates a better model for plant disease prediction. Therefore, RNN, GRU, and LSTM are combined into a hybrid approach, which achieves outstanding results compared to other models, as shown in Table 3 and Figure 4.

When captured images are loaded as input, they are preprocessed, then trained and processed by the hybrid model, producing an output vector. The study focuses on three major diseases. The output values for these diseases are close to 1 or above 0.5. If more than two entries exceed 0.5 or are close to 1, the crop is considered to have mixed diseases. A key strength of the hybrid approach is its ability to detect the presence of two or more diseases simultaneously in a paddy crop. In future work, the size of the output vector can be increased depending on the number of diseases to be identified.

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Authors Contributions

S. Hrushikesava Raju: Dataset preparation.

S. Adinarayna: Algorithm design.

U. Sesadri: Empirical evaluation.

K. Yogeswara Rao: Analytical modeling.

Vijaya Chandra Jadala: Software and tool development.

Y. Sreeraman: Result interpretation and scientific writing/edited.

All authors reviewed and approved the final version of the manuscript.

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Ethics

This study used only publicly available datasets. No experiments were conducted on human participants or animals. All data were used strictly for research purposes and handled in compliance with established ethical standards and data-use policies. Since no personal or sensitive information was involved, formal ethical approval was not required.

Data Availability Statement

The primary dataset used in this study is the Paddy Doctor: Paddy Disease Classification dataset, available on Kaggle. This dataset contains labeled images of paddy leaves affected by various diseases, along with metadata such as disease type, paddy variety, and plant age. The dataset can be accessed at https://www.kaggle.com/competitions/paddy-disease-classification.

All other data supporting the findings of this study are available from the corresponding author upon reasonable request.

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