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Drone-based reconnaissance for Paddy Leaf Disease Classification using a Superior Hybrid CNN Model: A Deep Learning Comparative Analysis

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Abstract: Unmanned Aerial Vehicles (UAVs), commonly known as drones, offer a revolutionary tool for precision agriculture. By leveraging their capabilities, we can efficiently gather high-resolution aerial imagery of agricultural landscapes, facilitating advanced techniques for disease detection and crop management. The paper presents a comprehensive framework for accurate and efficient paddy leaf disease sensing analysis with a hybrid convolutional neural network model. The combination of contrast-limited Adaptive Histogram Equalization (CLAHE) for image pre-processing and gray-level co-occurrence metrics (GLCM) for feature extraction seems well thought out, as these techniques can enhance the quality of input data for the classification model. Utilizing a hybrid CNN model to classify paddy leaves' diseases, demonstrates a sophisticated approach. The model can effectively learn complex patterns and features from the pre-processed images by incorporating convolutional neural networks (CNNs), which excel at image classification tasks. The reported superiority of the proposed model in paddy leaf classification compared to previous approaches is encouraging and highlights the potential of deep learning methods in agricultural applications. Farmers can take timely preventive measures to control the spread of infections and optimize crop yield by automating detection and classifying leaf diseases.

Keywords: *Paddy leaves, Leaf diseases, CLAHE, GLCM and hybrid convolutional neural network.*

1. Introduction

Paddy Leaf is undeniably a vital crop globally, ranking among the top agricultural products in cultivation area and production. Its significance as a livestock feed source and raw material for various manufacturing processes underscores the importance of ensuring its health and productivity [1-2]. The threat posed by Northeast foliage blight, primarily affecting maize grain, concerns farmers worldwide. Over recent decades, the gradual increase in grain production losses due to this disease emphasizes the urgency of accurately detecting and diagnosing crop leaf infections. Early detection is critical, as timely intervention can help mitigate the spread of the disease and minimize yield losses.

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Recognizing the initial symptoms, such as water-stained cigar-shaped patches on the leaves that gradually expand, is essential for farmers to take proactive measures. The sequent decline in corn output. Efforts to develop reliable detection and diagnosis methods for crop diseases, including Northeast foliage blight in maize, are crucial for sustainable agriculture and food security. By leveraging technological advancements, such as remote sensing, image processing, and machine learning algorithms, researchers and farmers can enhance their ability to monitor and manage crop health effectively. Early detection and targeted interventions help protect crop yields and contribute to agricultural systems' overall resilience and sustainability [3-4].

Refraining from relying solely on traditional methods and the expertise of farming professionals for maize disease identification can sometimes lead to misinterpretation of symptoms, resulting in ineffective chemical treatments. This contributes to environmental pollution and increases the concentration of insecticides in grains, posing potential health risks to consumers [4-6]. In India, rice is a staple food, with a significant portion of agricultural land dedicated to its cultivation. Odisha, a state in eastern India, ranks fourth in rice production among Indian states. Farmers typically follow a dual cropping system in this region, allowing for the cultivation of different rice crops during two agricultural phases annually. This approach optimizes land use and contributes to the region's agricultural productivity. Efforts to improve disease identification methods, such as incorporating modern technologies like remote sensing and machine learning, can complement traditional knowledge and enhance the accuracy of diagnosis [7]. Farmers can minimize reliance on chemical treatments and mitigate environmental and health risks by adopting integrated pest management practices and promoting sustainable agriculture while ensuring crop productivity and food security.

Unfortunately, many young farmers lacking agricultural experience struggle to identify these diseases accurately [8-9]. The indiscriminate use of pesticides without a proper understanding of the specific types of diseases prevalent in rice paddies can be ineffective and wasteful. This underscores the importance of ongoing efforts to identify and categorize rice diseases in western India. Several rice diseases are commonly observed in this region, including bacterial blight, blast, brown spot, and tango. Traditional diagnostic methods such as physical examination or visual inspection are often employed to identify these diseases. However, such methods require trained individuals and can be time-consuming. Efforts to develop more efficient and accessible disease identification methods are crucial to assist farmers, particularly those lacking extensive experience. Modern technologies like image processing, machine learning, and remote sensing can offer faster and more accurate diagnosis of rice diseases, enabling timely and targeted interventions to mitigate crop losses [10]. By bridging the gap between traditional knowledge and modern technology, agricultural stakeholders can empower farmers with the tools and information necessary to protect their crops effectively and sustainably manage rice cultivation regions.

The advancement of web and mobile phone technologies has led to the development of numerous smartphone apps to assist producers in various agricultural tasks. Among these apps are Rice Doctor and Rice Expert, which offer functionalities tailored to aid farmers in diagnosing rice diseases and addressing crop-related issues. However, relying solely on these handheld apps for diagnosing rice illnesses may increase the likelihood of errors and reduce the effectiveness of the process, especially if the user needs more expertise or if the app's database needs to be more comprehensive and regularly updated [11]. In contrast, categorizing herbs based on color is a complex but intriguing topic for specialists. However, it poses challenges due to the vast diversity of colors and forms found within plant varieties. Despite these challenges, ongoing efforts to refine and improve categorization methods, possibly leveraging technological advancements such as image recognition and machine learning, can enhance our understanding and management of plant species.

This distinctiveness also extends to crop leaves, making foliage a valuable tool for plant classification. Consequently, leaf information is readily accessible from various biological sources, reflecting its importance in botanical studies and agriculture. Utilizing leaf characteristics for plant classification offers several advantages, particularly for marginal and small-scale producers [12-13]. It can lead to reduced water usage, cost savings, and increased harvest yields, making it an attractive option for resource-constrained farmers. However, it's important to note that initial training and skill development investments may be required, especially in regions with limited irrigation supply. In the context of paddy leaves, this study proposes a novel deep-learning model for prediction [14].

2. 2. Literature Survey

In this section, we will delve into an extensive literature survey of previous work conducted by numerous researchers in image recognition and classification. The earliest endeavors in image recognition and classification were made by several authors [15-16]. They utilized color and texture descriptors to extract features from the images. All these features were employed in training and classification using a KNN classifier. The proposed system achieved a remarkable 95percent accuracy rate. However, one notable limitation is that the dataset used for experimentation needs to be updated. Consequently, the system may not fully leverage recent developments in datasets related to fruits and vegetables.

The author [17] employed CNN to identify the causes of grain leaf damage. Their approach involves both one-stage and two-stage target determination techniques. In the one-stage technique, the primary objective is to conduct comprehensive image capture using a multi-scale process. The goal here is to efficiently detect and classify the causes of grain leaf damage in a single step, utilizing the capabilities of the CNN for both localization and classification tasks. The author has focused on data preparation techniques. Specifically, efforts were made to address the class imbalance problem, which arises when particular class objects are underrepresented in the dataset. By addressing this imbalance, the model becomes more robust and capable of accurately identifying even small objects, thus improving the system's overall performance. Overall, the implementation of CNN-based techniques by Sun et al. represents a significant advancement in agricultural image analysis. Their approach demonstrates the effectiveness of deep learning methods in addressing complex agricultural challenges, such as identifying grain leaf damage and paving the way for more accurate and efficient crop monitoring and management practices. The author [18] utilized the same dataset for their experiment, using K-means clustering to subtract the background of fruits and vegetables. The segmented images were then subjected to feature extraction.

In another paper by the author [19], focusing on the same experimental dataset, they analyzed the mean (μ) and standard deviation (σ) of all classes of fruits and vegetables. They found that the fused descriptor CCV + LTP produced the highest mean accuracy rate at 90.6percent, while the lowest was 3.8percent by CCV + CLBP. However, one drawback they identified was that CDH + SEH produced a lower mean accuracy rate, and CDH + SEH + CSLBP showed the highest standard deviation, indicating poorer performance than other methods. These findings highlight the importance of carefully selecting and combining descriptors to achieve optimal performance in fruit and vegetable classification systems.

The author [20] introduced a novel approach to recognizing fruits and vegetables. In their study, they fused multiple features with a classifier. The dataset they utilized consisted of 15 different classes of fruits and vegetables for their experiments. The feature descriptors they employed were primarily related to color and texture. Their results demonstrated that the proposed system reduced classification errors by up to 15percent. They also combined feature descriptors to handle more complex images with variability in number, illumination, and poses. However, one drawback they noted is that the system may need help to achieve a reasonable accuracy rate when combining weak features with a high-accuracy classifier. This emphasizes the importance of carefully selecting and balancing features when designing a classification system.

The author [21] introduced a framework for recognizing particular images belonging to a set of images per class. This approach, known as bag-of-features techniques, has shown promising results for recognition problems, as demonstrated by [22]. The author [23] also conducted experiments using different categories of fruits and vegetables, achieving a reasonable accuracy rate of 86percent. The author [24] embarked on a novel approach, utilizing a support vector machine (SVM) to identify paddy leaf rot based on the features extracted by the CNN. In their hierarchical architecture system, each network layer generates a response and extracts features, passing them to the next layer. This process continues until the final output layer, where the classification is made. It's noted that extracting unhealthy regions from agricultural photographs isn't always straightforward due to various factors such as lighting conditions, image quality, and the complexity of the leaf structures. The author [25] further pushed the boundaries of innovation by developing a system which is more performed to identify the plants of Malaysia which are in the use of medical practices. They employed a combination of various characteristics, including visual appearance, texture, size, and color, to classify plant leaves.

3. Proposed framework for Paddy Leaf Diseases*:*

Fig. 3 illustrates the proposed framework for classifying paddy leaves, which consists of several stages to identify different disease classes effectively. The experiment has been performed using Python programming Language. Here's an overview of each stage:

3.1 Input data Set:

UAVs provide an agile and efficient means of acquiring high-resolution images of paddy leaves, crucial for disease classification in agricultural settings. Equipped with advanced imaging systems such as multispectral or hyperspectral cameras, UAVs can capture detailed visual data encompassing various wavelengths of light. This enables the detection of subtle changes in leaf color, texture, and structure associated with different diseases. Moreover, UAVs offer the flexibility to adapt flight paths and altitudes, ensuring comprehensive coverage of large agricultural areas within a short timeframe. By employing UAVs for image acquisition, researchers and farmers alike can obtain accurate and timely information to effectively monitor and manage paddy diseases, ultimately optimizing crop health and productivity.

The image collection process using an Unmanned Aerial Vehicle (UAV) aka Drone with four propellers i.e., a quadcopter UAV in fields is illustrated in figures 1 and 2.

Fig 1: Image collection process of rice field based on quadcopter UAV[31].

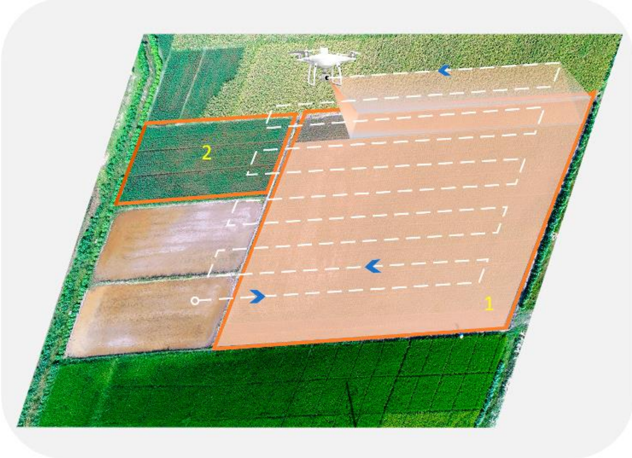

Fig 2: The image collection process in field 1 and field 2, respectively [31].

3.2 Augmentation of Original Paddy Leaves Images: In this stage, the original images of paddy leaves are augmented. Image augmentation techniques are commonly used to increase the diversity and quantity of training data, improving the classification model's robustness and generalization.

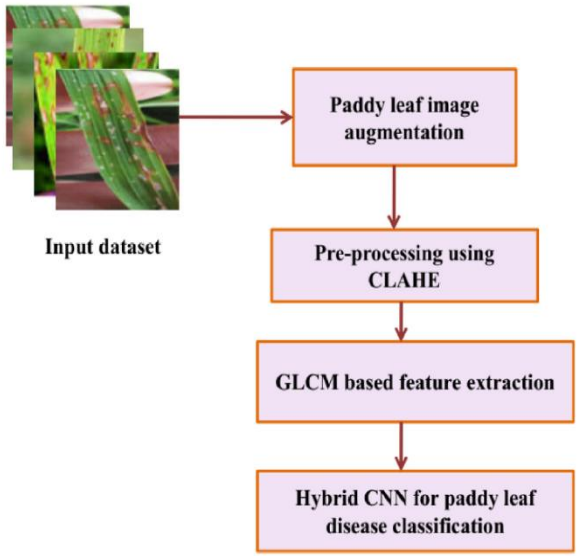

Fig 3: Proposed paddy leaves disease classification framework [32].

3.3 Pre-processing phase:

The CLAHE model is applied to pre-process the augmented paddy leaf images. CLAHE is a technique used to enhance the contrast of pictures while preventing over-amplification of noise. Pre-processing helps standardize the input data and improve the quality of features extracted in subsequent stages.

3.4 Feature Extraction using GLCM Model:

The features are being extracted using GLCM model from the pre-processed images. GLCM calculates the frequency of occurrence of pixel pairs with specific values and orientations within an image, providing texture information that can be useful for distinguishing between different disease classes.

3.5 Classification using Hybrid CNN Model:

Finally, the features extracted by the GLCM model are input into a Hybrid CNN model for classification. CNNs are well-suited for image classification tasks due to their ability to learn hierarchical features from raw pixel data automatically. The hybrid architecture may incorporate traditional CNN layers and additional components, such as recurrent or attention mechanisms, to enhance classification performance. The proposed framework uses image augmentation, pre-processing techniques, feature extraction methods, and deep learning models to classify paddy leaves into five disease classes accurately.

4. **Training and classification:**

4.1 Hybrid - convolutional neural network (CNN): Its architecture is deployed to classify the extracted features obtained from the previous section into various disease classes of the paddy leaves [27-28]. This HCNN architecture amalgamates three distinct CNN structures, identified as CNN 1, CNN 2, and CNN 3 [29-30] [32]. Each with unique characteristics and parameters. Here are the key components and characteristics of the proposed HCNN architecture.

4.2 Blend of CNN 1,2 and 3:

The HCNN architecture integrates three CNN structures, namely CNN1, CNN2, and CNN3. Each of these CNN structures contributes to the overall classification process, bringing different features and representations to the model.

4.3 **Number of Filters (Y):**

The convolutional layers in each CNN structure consist of a certain number of filters, denoted as Y. These filters are responsible for extracting features from the input data.

4.4 **Filter Sizes:**

The filter sizes for the convolutional layers in all three CNN structures are specified as 3 × 3 and 4 × 4. These filter sizes determine the receptive field of each convolutional layer and influence the types of features that can be extracted.

4.5 ReLU Activation and Batch Normalization:

Following each convolutional filter layer, ReLU activation and batch normalization operations are applied. ReLU activation introduces non-linearity to the network, while batch normalization helps stabilize and accelerate the training process.

4.6 **Dropout Rate and Max Pooling:**

Dropout layers with a dropout rate of 0.5 are utilized to prevent overfitting during training. Max pooling layers with a pooling factor of 2 and a size of 3 × 3 are included to down sample the feature maps and reduce spatial dimensions.

4.7 Residual Blocks:

The convolutional layers in the beginning are arranged in parallel and placed within the same residual block. This architecture helps in preserving important features and mitigating the vanishing gradient problem during training.

4.8 Design Considerations:

The convolutional layers are specifically designed to capture both vertical and horizontal features, with the filters that are assigned short, wide, and narrow characteristics based on their orientation.

5 Proposed fine-Tuned Model:

The framework of the Hybrid Convolutional Neural Network (HCNN), addresses the scalability limitations of traditional single neural networks by employing multiple CNNs (CNN1, CNN2, and CNN3) within the architecture**:**

5.1 Combination of Multiple CNNs:

The HCNN framework integrates three separate CNNs (CNN1, CNN2, and CNN3), each with its own architecture and parameters. By combining multiple CNNs, the framework can capture a broader range of features and representations from the input data, leading to more robust and accurate classification.

5.2 Fine-tuning Mechanism:

The combination of multiple CNNs allows them to fine-tune each other during the training process. If overfitting or underfitting issues occur, the CNNs can adjust their parameters collectively to improve performance. This fine-tuning mechanism helps prevent the model from getting stuck in suboptimal solutions and improves its ability to generalize to unseen data.

5.3 Mixing Layer:

This layer combines the outputs of the CNNs and serves as a mechanism for information exchange between them. By integrating information from multiple sources, the mixing layer enhances the diversity and richness of features used for classification.

5.4 Fully Connected Layer:

The corresponding output from the blended layer is then forwarded to a fully connected layer, which serves as the classification layer. This connectivity enables the high-level features extracted by the CNNs, facilitating the classification into various disease classes.

5.5 Feature Extraction:

Finally, the output of the fully connected layer is transformed into a 1-D feature vector through feature extraction. This feature vector contains the high-level representations of the input paddy leaf images, which are then used for classification.

6 Experiment and Results:

In this section, the performance evaluation of the proposed HCNN is juxtaposed with state-of-the-art techniques including DBN, DNN, RNN and LSTM. Multiple key metrics are scrutinized, with accuracy being a central emphasis throughout the assessment. The analysis aimed to compare the classification performance of these methods in identifying paddy leaf diseases. As depicted in Fig. 4, the accuracy of classification for paddy leaf diseases was evaluated. The proposed HCNN demonstrated the highest accuracy, achieving an impressive accuracy rate of nearly 95.43 percent. This significant achievement underscores the superior performance of the proposed HCNN model, potentially revolutionizing the field of machine learning and agriculture. The experiment has been performed using Python programming Language.

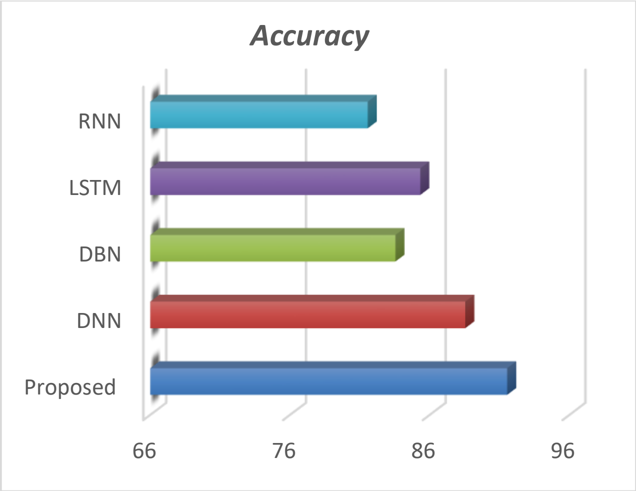

Fig 4: Comparative visualization of accuracy

In our comprehensive analysis of error prediction for describing paddy leaf diseases, we evaluated various cutting-edge methods. Our primary goal was to scrutinize the performance of these methods in predicting errors between the expected and actual outputs. The Hybrid CNN model, as depicted in Fig. 5, demonstrated the most promising results. It achieved the lowest error rate, with less than 3.89 percent errors. This underscores the Hybrid CNN model's exceptional accuracy in predicting paddy leaf diseases, with negligible discrepancies between the expected and actual outputs. On the other hand, LSTM and RNN, despite their potential, exhibited significantly higher error rates, approaching 23.14 percent and 34.77 percent, respectively. This suggests that while these methods could have been effective in predicting paddy leaf diseases, they resulted in more prediction errors. DNN and DBN showed lower error rates than LSTM and RNN, with 38.32 percent and 46.76 percent errors, respectively. While these methods still had some errors, they outperformed LSTM and RNN in predicting paddy leaf diseases. Including three CNNs in the Hybrid CNN model reduced the classification error, improving accuracy in predicting paddy leaf diseases. This significant reduction in error is visually represented in Fig. 5, underscoring the superior performance of the Hybrid CNN model compared to other methods.

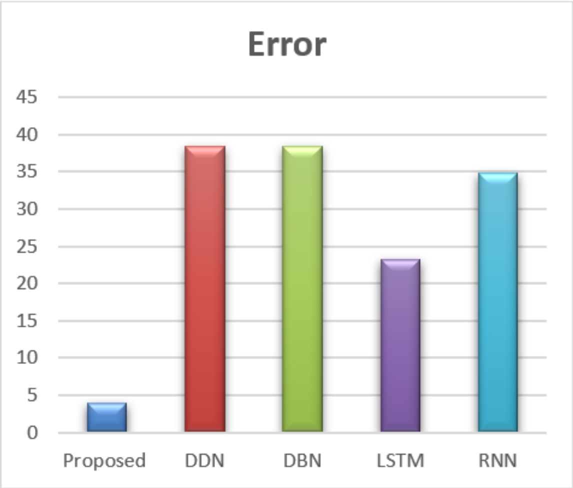

Fig 5: Comparative visualization of error.

In Fig. 6, the F-measure analysis of both the proposed Hybrid CNN and state-of-the-art techniques, is depicted. Notably, the proposed model attained the highest F-measure value, reaching an impressive 89.45 percent. This underscores the effectiveness and superiority of the Hybrid CNN model in accurately classifying diseases in paddy leaves compared to other advanced techniques. This indicates that the Hybrid CNN model effectively balances precision and recall, accurately classifying paddy leaf diseases. Compared to the other methods, the values of all methods are 75.43 percent, 71.23 percent, 68.54 percent, and 63.90 percent, respectively. These techniques exhibited lower precision and recall levels than the Hybrid CNN, leading to lower overall F-measure scores. The Hybrid CNN model outperformed the other methods in terms of F-measure, demonstrating its effectiveness in accurately classifying paddy leaf diseases.

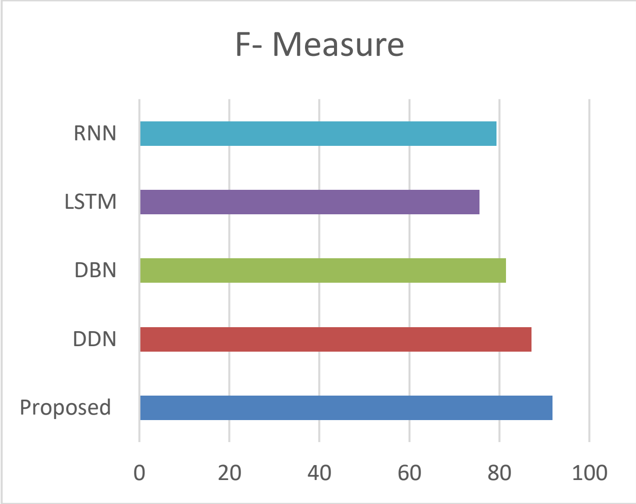

Fig 6: Comparative visualization of F- Measure.

Fig. 7 demonstrates the precision values for various approaches, showcasing the superiority of the proposed Hybrid CNN. With a precision of 91.78 percent, the Hybrid CNN model outperforms others, indicating its effectiveness in correctly predicting positive outcomes. Harnessing the capabilities of the Hybrid CNN model enhances the accuracy of predicting positive outcomes, thereby culminating in superior precision within the proposed approach. The lower precision values observed in other methods imply a lesser proportion of accurately predicted positive outcomes, as depicted in Fig. 8. Integrating the Hybrid CNN into the proposed approach elevates its precision beyond that of alternative techniques. Leveraging the capabilities of the Hybrid CNN model enhances the accuracy of positive outcome predictions, ultimately leading to superior precision in the proposed approach.

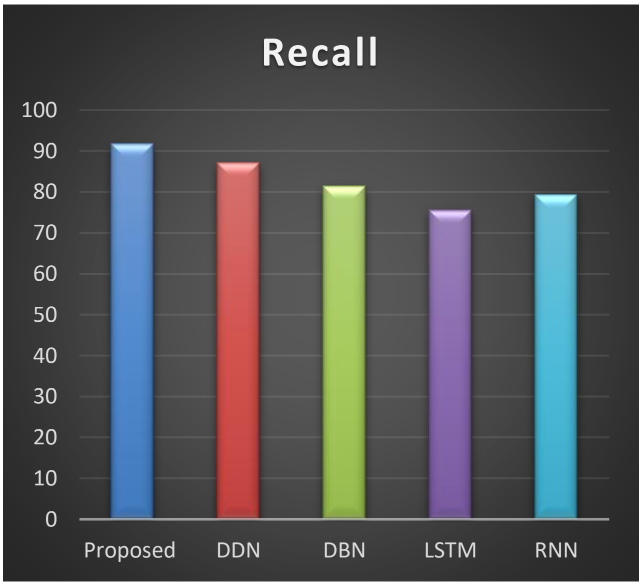

Fig 7: Comparative visualization of Recall.

This indicates that the Hybrid CNN model effectively identifies many positive cases, demonstrating its capability in sensitivity-based evaluation. These methods exhibited lower sensitivity than the proposed Hybrid CNN, indicating a lower proportion of correctly identified positive instances. The inclusion of the Hybrid CNN in the proposed approach contributed to its higher sensitivity value than other techniques. By leveraging the capabilities of the Hybrid CNN model, the proposed approach achieved more accurate identification of positive cases, leading to higher sensitivity.

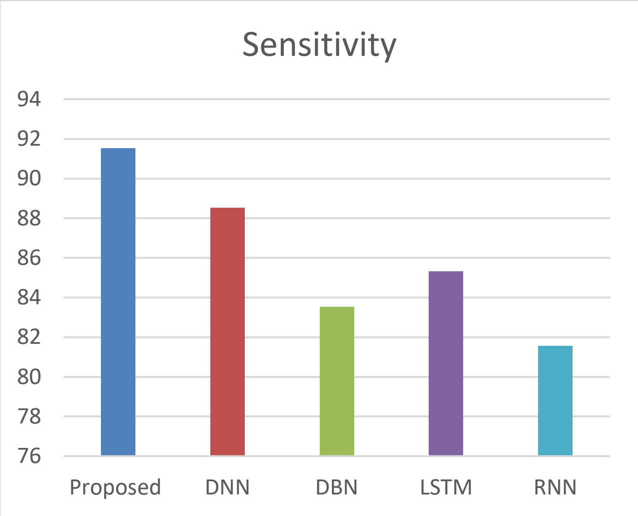

Fig 8: Comparative visualization of accuracy sensitivity.

7 Conclusion

The proposed hybrid CNN model showcased outstanding performance, boasting a percent accuracy, an error rate below 3.89 percent, and an F-measure of 75.43 percent. Additionally, the model demonstrated high recall at 91.78 percent and sensitivity at 91.4 percent; these results indicate the robustness and effectiveness of the hybrid CNN model in accurately classifying paddy leaf diseases. The paper concluded by highlighting the superiority of the proposed hybrid CNN model over other state-of-the-art techniques in paddy leaf disease classification. Future endeavors aim to enhance the model further by incorporating optimization approaches alongside deep learning techniques to broaden the classification scope to encompass a broader range of paddy leaf diseases, potentially expanding to include eight different leaf diseases.

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