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 [ijrset@gmail.com](mailto:ijrset@gmail.com)

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# Detection and Classification of Paddy Leaf Diseases using Image Processing and CNN+GRU Model

T S Prabhakar, Akash G, Udachappa Guddapa Talvar, Yashas Gowda D L, Rahul H U

Assistant Professor, Department of ISE, P E S College of Engineering, Mandya, Karnataka, India

UG Student, Department of ISE, P E S College of Engineering, Mandya, Karnataka, India

**ABSTRACT:** Global food security depends heavily on paddy agriculture, but the productivity and quality of crops are frequently compromised by a number of diseases. For efficient disease control and crop protection, early and precise detection of these diseases is essential. Using image processing and machine learning approaches, we present a unique strategy in this study for the automated detection of diseases in rice leaves. Using our approach, high-resolution photos of paddy leaves are first taken, and then preprocessing is done to improve the quality and retrieve pertinent information. In addition to a gated recurrent unit (GRU) for capturing temporal relationships in sequential data, we utilize a convolutional neural network (CNN) to extract spatial information from the images. The incorporation of both temporal and spatial data improves our model's ability to distinguish between damaged and healthy areas on paddy leaves. We use an extensive dataset with several kinds of paddy leaf diseases to validate our method. Experimental results validate the effectiveness of our suggested approach. Our method offers a simple and effective way to diagnose and treat paddy leaf diseases early on, and it has great potential for practical precision agriculture applications.

**KEYWORDS:** Paddy leaf diseases detection, Convolutional Neural Networks (CNN), Gated Recurrent Unit (GRU).

## I.INTRODUCTION

For a large section of the world's population, rice, or paddy, is a staple crop and is essential to maintaining food security. However, a number of diseases, such as bacterial, viral, and fungal infections, frequently damage the quantity and quality of rice crops. In order to minimize productivity losses and maintain sustainable agricultural practices, early detection and control of these diseases are critical. Agricultural scientists' hand inspection, which can be labour intensive, time-consuming, and prone to human error, is a major component of traditional techniques of disease identification in paddy crops. Recent developments in image processing and machine learning have opened up exciting new possibilities for automating plant disease identification and diagnosis, providing a more effective and precise solution for traditional methods.

In this study, we present an innovative approach based on image processing, convolutional neural networks (CNNs), and recurrent neural networks (RNNs) for the automated detection of paddy leaf diseases, with an emphasis on the Gated Recurrent Unit (GRU) architecture. In order to provide input data for our automated system, our methodology involves capturing high-resolution pictures of paddy leaves that show signs of disease. In order to extract spatial information from the input photos and identify patterns and structures suggestive of different diseases, our system's convolutional neural network (CNN) component is in charge. To further capitalize on the sequential structure of image data and provide more intelligent decisions, we further integrate a recurrent neural network (RNN) with GRU units to capture temporal dependencies in sequential data and make more informed predictions about the presence of diseases over time.

Our system learns to distinguish between healthy and diseased leaves, as well as to categorize the precise type of disease present, by training a hybrid CNN-GRU model on a dataset of annotated paddy leaf pictures. Additionally, we use methods like data augmentation and transfer learning to improve our model's robustness and generalization skills, which helps it perform better on unknown data. We do experiments utilizing an extensive dataset of images of paddy leaves gathered from multiple sources in order to assess the effectiveness of our suggested method. We evaluate our automated system against current techniques for paddy crop disease diagnosis, comparing its performance in terms of

accuracy. In order to improve agricultural practices and guarantee global food security, our project's ultimate goal is to create a scalable and affordable solution for the early diagnosis and management of paddy leaf diseases.

### II.SCOPE

Using image processing and machine learning approaches, the project seeks to establish an automated system for identifying and categorizing diseases of paddy leaves. For the purpose of temporal analysis, recurrent neural networks (RNNs), more especially Gated Recurrent Units (GRUs), are used together with preprocessing and image enhancement techniques. Convolutional neural networks (CNNs) are utilized for the extraction of spatial features. In addition, techniques for transfer learning and data augmentation will be investigated in order to improve model performance. The system is going to be assessed using measures like accuracy, once it has been trained on a large dataset of annotated pictures of paddy leaves. An evaluation will also be conducted on the model's robustness to changes in the view and surrounding conditions. The system's integration with precision agriculture frameworks for real-time monitoring and decision-support tools for agronomists and farmers will also be investigated. In order to confirm effectiveness, considerations including data availability, ethical consequences, and scalability will be addressed in conjunction with agricultural experts. In the end, the research hopes to develop sustainable crop management techniques and precision agriculture.

### III.SYSTEM ARCHITECTURE

The system architecture encompasses the processes of Dataset collection, Image Preprocessing, Feature extraction, Detect the diseases and provide the solution for that Diseases. To standardize format and improve quality, high-resolution images of paddy leaves exhibiting disease symptoms are gathered and put through preprocessing stage. After that, the preprocessed images are used to extract spatial features from Convolutional Neural Networks (CNNs), which identify complex patterns that may be symptomatic of different diseases. Recurrent Neural Networks (RNNs)—in particular, Gated Recurrent Units (GRUs)—when integrated with CNNs assess temporal connections in sequential data, making it possible to identify how a disease developed over time. Through the use of methods like data augmentation, which improve model performance and generalization, the combined CNN-GRU model is trained on annotated datasets. After training, the system is put through a rigorous evaluation process to determine accuracy and reliability using pre-established measures. The trained model is included into web services after a successful validation process, enabling real-time disease detection and deployment in precision agriculture frameworks. The method seeks to improve agricultural practices by assuring early diagnosis and efficient control of paddy leaf diseases through the documenting and distribution of findings.

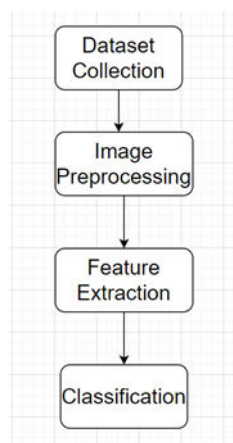


Fig. 1 Flow Chart

#### A. Dataset Collection

We collected the dataset from Kaggle where the dataset contains over 10000 images. It includes nine types of Paddy crop diseases i.e., Bacterial leaf blight, Bacterial leaf streak, Bacterial panicle blight, Blast, Brown spot, Dead heart,



Downy mildew, Hispa, Tungro and Normal. From Figure.2 we can see the various paddy crop diseases. Each image is around 100 KB size. Each image is named after its disease and the dataset is labelled.

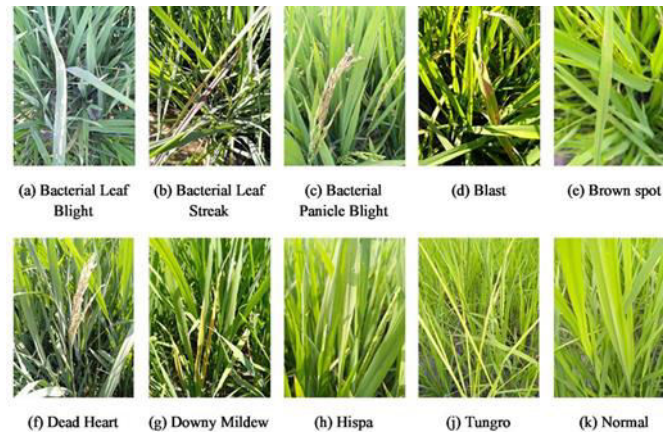


Fig. 2 Dataset

### B. Image Preprocessing

Methods for image processing that are essential to the preprocessing pipeline for deep learning models that are intended to identify diseases of paddy leaves. In order to stabilize and accelerate the training process, the images are first subjected to rescaling normalization, which guarantees that pixel values stay within the normalized range of [0, 1]. In addition, a variety of complex data augmentation techniques are used, such as rotation, shearing, zooming, changing width and height, and horizontal and vertical flipping. Through exposure to a wider range of potential scenarios, these augmentations help to mitigate overfitting, diversify the training dataset, and improve the model's generalization abilities. Moreover, grayscale conversion is carried out in order to simplify the color representation of the pictures, lowering computing complexity while maintaining crucial characteristics relevant to disease identification. Together, these image processing methods maximize the training data's quality, diversity, and interpretability, providing a strong basis on which to train the deep learning model that would later be used to classify diseases accurately and consistently.

### C. Feature Extraction

The Convolutional neural networks (CNNs) are used in the feature extraction process for spatial feature extraction, whereas gated recurrent units (GRUs) are used for temporal feature extraction. The input paddy leaf images' spatial patterns and attributes are captured by the convolutional layers. In order to add non-linearity, the rectified linear unit (ReLU) activation function is applied after 64 filters with a kernel size of 3x3 are applied in the first convolutional layer (conv1). The feature maps are then down sampled via the max-pooling layers (pool1, pool2, and pool3) to reduce spatial dimensions while keeping the most noticeable features. In order to capture features that are more complex and abstract, the convolutional layers gradually increase the number of filters. The output feature maps from the last convolutional layer (pool3) are reshaped into a flattened vector representation using the Flatten layer, preparing them for further processing. Apart with extracting spatial features, It integrates a GRU layer to analyze temporal features. The final convolutional layer's (pool3) reshaped output is then further reshaped to fit the input dimensions that the GRU layer requires. Recurrently evaluating sequential feature maps to identify temporal dependencies in the picture data, the 128-unit GRU layer uses a rectified linear unit (ReLU) activation function. To stabilize training and enhance convergence, batch normalization is implemented on the GRU layer. Ultimately, a global max-pooling layer (maxpool\_gru) creates a fixed-length feature vector by aggregating temporal data throughout all time steps. Concatenate layer is used to combine spatial and temporal information from the outputs of flattened spatial features (flatten) and aggregated temporal features (maxpool\_gru). The next dense layers use this concatenated feature vector as their input for additional processing and classification. The diagnosis accuracy and resilience of the model are improved by its ability to recognize complex patterns and variations typical of many paddy leaf diseases, which is achieved by utilizing both spatial and temporal information retrieved from the input images.

#### D. Classification

Disease classification, in which the existence and kind of paddy leaf diseases are predicted using the retrieved geographical and temporal information. Dense neural network layers are used to achieve this classification task. These layers receive the concatenated feature vector, which is produced by fusing the temporal features from the GRU layer and the spatial features from the convolutional layers. The complex correlations and patterns seen in the feature space are learned by the dense layers, which then map them to different disease categories. Each disease category in this context, such as Bacterial leaf blight, Bacterial leaf streak, Bacterial panicle blight, Blast, Brown spot, Dead heart, Downy mildew, Hispa, Tungro and Normal is associated with a particular class labeling. The neural network model's output layer usually uses a softmax activation function to generate probability distributions over the disease classes, which allows the model to give each class a probability score. The most likely disease affecting the paddy leaf image is therefore estimated to be the class with the highest likelihood. The classification step facilitates timely decision-making and disease control efforts in agricultural operations by accurately and reliably identifying paddy leaf diseases by utilizing the extracted data and learned representations.

### IV. RESULT AND ANALYSIS

Unfortunately our project has achieved an accuracy of 70% in detecting the paddy leaf diseases using image processing and CNN+GRU model. The corresponding accuracy and loss function plots could be seen in Figure 3 and Figure 4.

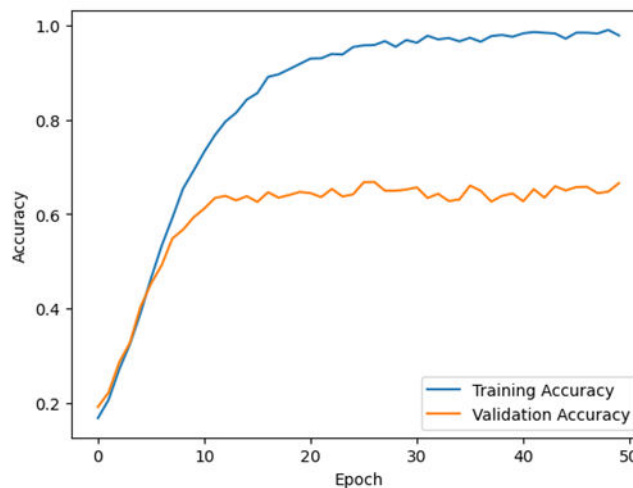


Fig. 3 Accuracy Plot

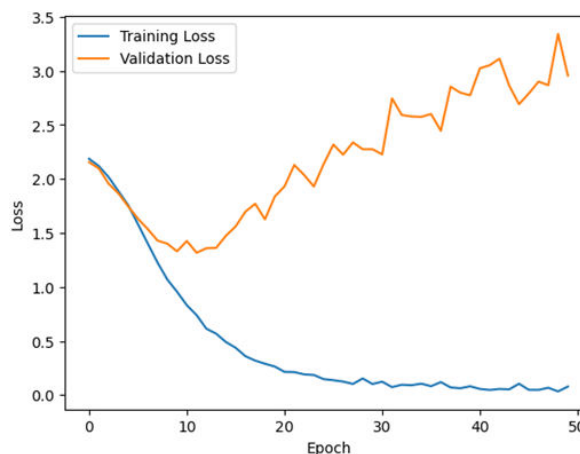


Fig. 4 Loss Plot

Here are some screenshots of the suggested system's output and user interface.



Fig. 5 User Interface

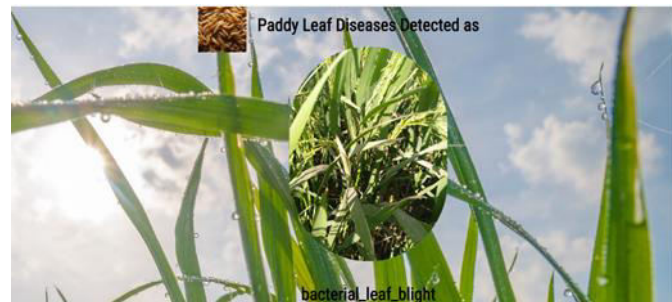


Fig. 6 Paddy leaf Diseases Detected as Bacterial leaf blight



Fig. 7 Paddy leaf Diseases Detected as Blast



Fig. 8 Paddy leaf Diseases Detected as Downy mildew

## V. LIMITATION

For optimal outcomes, constraints must be addressed. To begin with, there's a chance that the diversity and quantity of the dataset will be constrained, which will affect how well the model generalizes to new data. Furthermore, the augmentation methods that were employed to increase the dataset's size can unintentionally add biases or patterns, which could result in overfitting. Concerns around overfitting and the need for significant processing resources are brought up by the model's complexity, which includes both convolutional and recurrent layers—especially in the absence of significant hyperparameter adjustment. Furthermore, the model's "black box" design makes it difficult to understand the judgments it makes, making it difficult to get insight into the logic underlying forecasts. The dataset's class imbalance could further distort the model's results, giving majority classes preference over less common diseases. Refinement of the dataset, optimization of the model architecture, and implementation of interpretability approaches are necessary to overcome these restrictions, ensuring the system's reliability and effectiveness in real-world agricultural application.

## VI. CONCLUSION AND FUTURE ENHANCEMENT

The system has advanced the use of image processing and deep learning techniques to create an automated system for paddy leaf disease identification. The model can efficiently extract spatial and temporal characteristics from images of paddy leaves by utilizing convolutional and recurrent neural networks. This allows for the accurate categorization of diseases such as Bacterial leaf blight, Bacterial leaf streak, Bacterial panicle blight, Blast, Brown spot, Dead heart, Downy mildew, Hispa, Tungro and Normal. To further increase the system's functionality and suitability for use in practical situations, there are a number of areas that could be improved and refined in the future. First off, expanding the dataset to encompass a greater range of paddy leaf diseases and various environmental circumstances can improve the generalization and resilience of the model. Performance can also be enhanced and computational overhead can be decreased by adjusting hyperparameters and refining the model architecture using methods like neural architecture search. To further improve the predictability and transparency of the model and encourage farmers and agronomists to embrace it, interpretability techniques like attention mechanisms and layer-wise relevance propagation can be incorporated. Real-time disease monitoring and decision assistance in agricultural settings can be made possible by integration with precision agriculture frameworks and deployment on edge devices. Overall, the initiative can revolutionize paddy crop management and contribute to global food security through sustained research and development efforts in these areas.

## REFERENCES

- [1] Muzaiyanah Binti Ahmad Supian, Hizmawati Madzin and Elmaliana Albahari "Plant Disease Detection and Classification Using Image Processing Techniques: a review", IEEE, 2019.
- [2] Swathika R, Srinidhi. S, Radha N and Sowmya.K "Disease Identification in paddy leaves using CNN based Deep Learning", 3rd IEEE International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV2021), DOI:10.1109/ICICV50876.2021.938855.
- [3] Pratiksha Kharatkar, Manali More, Uma Pillai, Apeksha Gawand and Payel Thakur "Identifying the Amount of Fertilization Required for Rice Crops using Image Processing System", Journal of Xi'an University of Architecture & Technology, Volume XII, Issue V, 2020.
- [4] Sethy, P. Kumar, Chinmaya Bhoi, Nalini Kanta Barpanda, Shwetapadma Panda, Santi K. Behera and Amiya K. Rath "Pest Detection and Recognition in Rice Crop Using SVM in Approach of Bag-Of-Words."
- [5] T. Gayathri Devi and P. Neelamegam, Image processing based rice plant leaves diseases in Thanjavur, Tamilnadu, Cluster Comput. vol. 22, no. s6 (2019) pp. 13415–13428.
- [6] P. G. Shinde, A. K. Shinde, A. A. Shinde, and S. P. Borate, Plant disease detection using raspberry pi by k-means clustering algorithm, Int. J. Electr. Electron. Comput. Syst. vol. 5, no. 1 (2017) pp. 92–95.
- [7] M. Sankar, D. N. Mudgal, T. V. Jagdish, N. W. G. Laxman, and M. M. Jalinder, "Green leaf disease detection using raspberry pi," in 1st International Conference on Innovations in Information and Communication Technology, (2019) pp. 1–6.
- [8] S. Ramesh and D. Vydeki, "Rice blast disease detection and classification using machine learning algorithm," in Proceedings - 2nd International Conference on Micro-Electronics and Telecommunication Engineering, (2018) pp. 255–259.



- [9]Nidhis AD, Pardhu CNV, Reddy KC, Deepa K. Cluster based paddy leaf disease detection, classification and diagnosis in crop health monitoring unit. *Comput Aided Intervent Diagnost Clinic Med Images* 2019;31:281–91.
- [10]Islam T, Sah M, Baral S, Choudhury RR. A faster technique on rice disease detection using image processing of affected area in agro-field. In: *In: Proc. Second International Conference on Inventive Communication and Computational Technologies*. p. 62–6.
- [11]S. Sarowa, H. Singh, S. Agrawal, and B. S. Sohi, “Design of a novel hybrid intercarrier interference mitigation technique through wavelet implication in an OFDM system,” *Digital Communications and Networks*, vol. 4, pp. 258–263, 2018.
- [12]R. Rajmohan, M. Pajany, R. Rajesh, D. R. Raman, and U. Prabu, “Smart paddy crop disease identification and management using deep convolution neural network and SVM classifier,” *International Journal of Pure and Applied Mathematics*, vol. 118, pp. 255–264, 2018.
- [13]K. Nagarajan, A. Rajagopalan, S. Angalaeswari, L. Natrayan, and W. Degife Mammo, “Combined economic emission dispatch of microgrid with the incorporation of renewable energy sources using improved mayfly optimization algorithm,” *Computational Intelligence and Neuroscience*, vol. 2022, Article ID 6461690, 22 pages, 2022.
- [14]C. R. Rahman, P. S. Arko, M. E. Ali et al., “Identification and recognition of rice diseases and pests using convolutional neural networks,” *Biosystems Engineering*, vol. 194, pp. 112–120, 2020.





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