Categorization of the Rice disease using deep learning technique

Raji.N
Department of Computer Science and Engineering
SRM Institute of Science and Technology
Chennai, India
rn5525@srmist.edu.in

Dr.S.Manohar
Department of Computer Science and Engineering
SRM Institute of Science and Technology
Chennai, India
manohars@srmist.edu.in

***Abstract*— Paddy crops must be protected through early disease identification. In the past, diagnosing diseases required observation or laboratory examination. Visual observation requires expertise, and it may differ for each person, leading to inaccuracy. Laboratory tests take longer and might not be capable to deliver results right away. To solve this problem, a machine learning approach based on visual processing is utilized to identify diseases and categorize them. Diseases affecting rice (Oryza sativa) were our main concern. The photographs include diseased leaves and stems that were gathered from paddy fields. The dataset includes four healthy leaves and three diseases from three different disease classes: (1) Bacterial Leaf Blight (2) Sheath Blight and (3) Rice blast. Farmers will be able to boost their produce with the help of early disease identification.**

Keywords*— *Deep learning, Rice diseases, Categorization, CNN, SVM

I. INTRODUCTION

Rice is one of the most important crops in the world, providing food for billions of people. However, rice crops are often susceptible to various diseases that can significantly reduce yields and quality. The early and accurate detection of these diseases is crucial for the proper management and control of rice crops. Deep learning techniques have shown great potential in the field of image recognition and classification. In recent years, deep learning-based models have been developed for the automatic detection and classification of various rice diseases using plant images. These models can analyse large amounts of image data to accurately identify and categorize different types of rice diseases.

The categorization of rice diseases using deep learning techniques involves training a model using a large dataset of labelled plant images, where each image is annotated with its corresponding disease label. The deep learning model learns to extract relevant features from the images and use them to classify new images into different disease categories. Various deep learning architectures, such as convolutional neural networks (CNNs), have been used for this purpose.The use of deep learning techniques for rice disease categorization offers several advantages, including high accuracy, fast processing times, and the ability to analyse large amounts of data. This can help farmers and agricultural researchers to detect and manage rice diseases early, leading to better crop yields and food security. For most a smaller scale rice mill vendors and cultivators, rice is their main source of income. When crops are afflicted with diseases, they suffer greatly.

Table 1. constitute the most prevalent illnesses that have a fatal impact on rice farming. We developed a model that can identify diseases and categorize the diseases of the plants that are impacted based on the photos scanned by the smartphone camera in order to provide a remedy for this crucial issue. 3,671 annotated photos from a dataset of four well-defined categories of rice illnesses is utilized as training images for the model we developed. The diseased plants should be categorized to make it easier for farmers to identify the problem. They can analyze the kinds of chemicals and fertilizers needed to increase productivity with its assistance. The outcome will determine the crop's overall healthiness percentage.

TABLE I. Rice Crop Diseases

Disease	**Affected Part of the Crop**
Bacterial Blight	Leaves, stems
Blast	Leaves, stems, grains
Sheath Blight	Sheaths, leaves
Brown Spot	Leaves, grains
Rice Tungro Virus	Grains, leaves
Rice Yellow Mottle Virus	Leaves, grains
Rice Leaf Folder	Leaves
Stem Borers	Stems, grains
Sheath Rot	Sheaths
Ufra	Grains

II. LITERATURE SURVEY

[1] These methods use K-mean clustering, SVM classifiers, standard image processing methods, genetic algorithms, etc. [2] Developed a smartphone app to help rice farmers identify nitrogen deficit based on the coloration of the plants. The device can be used as a substitute or along with the usual nitrogen use. It was suggested that farmers adopt an intuitive technology without any prior instruction. In order to produce results with a high degree of accuracy, this paper proposed automated image processing techniques. The z-score statistical method was used to calculate the desired outcomes.

[3] has used image analysis along with machine learning techniques to give an evaluation report on the contaminated rice samples. This study examined a number of image processing as well as machine learning techniques used for

the identification and classification of plant diseases. This study offered in-depth analyses of 19 research papers on rice crop diseases. Additionally, this study included a survey on important factors such as dataset dimensions, number of the classifier, accuracy, classifier shapes, and preliminary processing etc.

[4,5] proposed employing laser-induced fluorescence (LIF) to accurately and effectively dose nitrogen. The amount of vitamin B2 in rice was assessed by the LIF method utilizing UV rays (355 nm) as the excitation light source. This explained the variations in the fluorescence spectrum seen in rice leaves grown with and without nitrogen. From the emission spectra, the quantities of pertinent characteristics were then extracted and adjusted for the N fertilizer dose. For classification, the binary SVM algorithm has been utilized. Their system's accuracy was almost 95%.

[6] had looked into how to diagnose problems in rice plants using image processing techniques. On the basis of cutting-edge research, the authors presented feature extraction techniques, disease identification methods, and picture processing approaches. Along with discussing potential difficulties and prospects in the field of rice leaf diseases, this report also highlighted current advancements in automated rice diseases identification systems. [7] This method increases the network's speed and accuracy by using traditional neural network techniques to identify and categorize locations where several diseases have been present on plant leaves.

III. CLASSIFICATION OF DISEASES

A. Methods

About 1.5 billion individuals in India eat rice as their main source of nutrition. Rice production contributes 2/3 of the total calories in a country and aids in 49% of its development. The complete protein need for each person can be obtained from one serving of rice. In recent years, rice production has reached a level of about 100 million tons, which is nearly constant over the intervening period. Therefore, rice takes on a crucial role for both the Asian countries and the people of India. However, rice plant diseases have the potential to reduce both the quantity and quality of rice production. If a true advance is not made in this way, it has real effects on the rice crops that affect each individual item's quantity, quality, and productivity. Different microorganisms, such as growth, viruses, tiny organisms, nematodes, and diseases, attack plant infections. These microorganisms frequently disrupt plant growth and the photosynthetic cycle. Recognizing and treating rice plant illness in its early stages is therefore a crucial task.

Farmers currently use their own intuition to spot diseases. Farmers overuse pesticides, which can't aid in the diagnosis of infection but can have an impact on plants, without being aware of plant diseases. Despite the fact that certain rice illnesses might cause similar flaws or sporting zones, different spots can also be caused by the same illnesses due to different rice kinds and local climatic or environmental variables. In this way, their inconsistent categorization has a terrible impact on the development of rice. They require advice from a competent practitioner familiar with rice sickness in this case.

Experts in rice disease aren't readily available to provide prompt treatments or advice to farmers in remote or provincial areas, and they probably need expensive equipment and a lot of time to physically identify and classify rice illnesses. On the other hand, manually preparing information necessitates a far greater number of individuals to double- and triple-check it for accuracy. However, a computerized system can recognize and classify images that have been affected by illnesses with greater accuracy than physical recognition methods. We suggested a mechanized architecture using AI techniques to overcome this problem. In order to characterize rice infections, a crossover network that combines Deep Convolutional Neural Network and Support Vector Machine has been proposed.

CNN is now frequently used to investigate contamination in more leaf diseases. Additionally, it has shown to be incredibly accurate in describing and recognizing such infections. Higher precision is also attained by using profound convolution neural organization. Additionally, SVM is a controlled AI computation that may be used to discover the best potential hyper plane and part margins for organizing tasks. Recently, large data processing and grouping tasks including pattern recognition and picture layout have been completed by combining CNN with SVM that produced incredibly accurate results.

B. Description of the dataset

Collection and pre-sorting of the affected paddy photos into several categories is the most crucial step in the dataset preparation process. A farm field was used to collect images of infected paddy, and certain web sources, such as IRRI, Plantix, BRRI, Tamil Nadu Agricultural University, BRKB, etc., were also used. At this point, we looked at major rice diseases that are most frequently found in India as well as other countries. These include False Smut. Brown Spot, Leaf Smut, Leaf Blight, Bacterial Tungro, Rice Blast, Red Stripe, and Sheath Blight. Generally speaking, leaf age, natural conditions, and varietal blockage influence the appearance, dimensions, and form of paddy impact disease. Paddy typically has an effect on the organs of the neck, nodes, leaves, and collar. In spite of classifying these two affected organs together, we organized them separately.

A significant number of photos are required to create the requisite model for some intricate training-based image organization and recognition tasks. Therefore, reduce the number of photographs in the picture-pre-handling process through manual clipping without lowering the quality of pictures that contain a variety of instances, and further improve the appearance of pictures by suppressing unwanted picture mutilations. Each of the images has been downsized to the model's desired size of 300 x 300 pixels. Additionally, the amount and variety of images increased as a result of various information expansion techniques, such as smooth interpretations, erratic flipping, and so on. (Fig. 1).

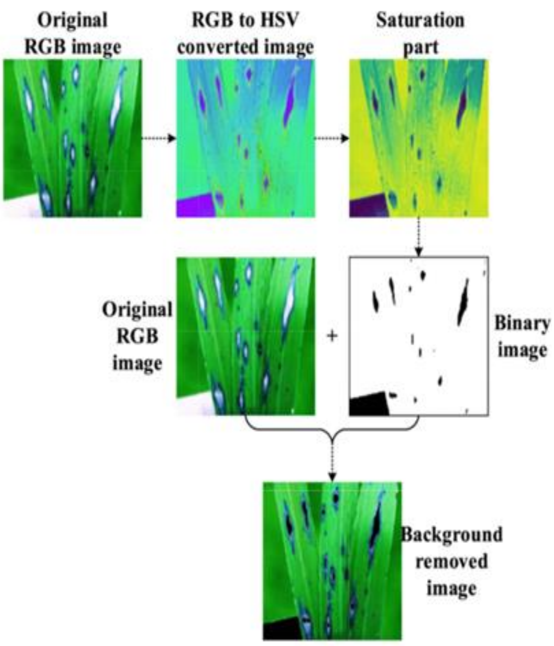

Fig 1. Example of a figure caption.

C. Setup for experiments

The perfect extraction of all important details from an image using DCNN is its best feature. However, because DCNN's hidden lair contains the most teachable bounds and is further tweaked there, as an image classifier, it basically isn't all that impressive. In any event, SVM gets rid of this barrier and gives us high order accuracy for a one-dimensional element vector with perfectly clean separation. Since then, we have thought of using a DCNN model with the incredibly simple yet reliable SVM classifier to frame a complex image organization for the most accurate depictions of the rice disease. The entire approach to recognizing and categorizing rice diseases is broken down into a couple of sub-areas: element extraction with CNN and deep SVM as a classifier.

D. Feature Extraction Process

A picture's highlight is an important and unique aspect. Utilizing a suitable calculation to extract these important details from a picture is known as extraction. The non-linear classifier can use Deep-CNN highlight to remove entirely similar data from the initial information then display it in dimensional space. In view of the fact that a classifier won't be able to fully understand images with weakly chosen highlights, it is therefore regarded as an important post handling project. CNN's top preference in this situation is the fact it can extract details from images devoid of the use of a well-constructed include choice computation. CNNs have the capacity to naturally choose out complex, balanced highlights from images by using a variety of channels while they're prepping.

The most complex and difficult DCNN architecture is Inception-V3. Each image is divided into groups by the Inception-V3 model utilizing about 24.5 million educable and 0.5 million non-educable borders. As a result, this engineering requires powerful computers with lots of memory. In order to prepare the organization, we research more learning techniques that allow us to significantly reduce preparing time and computation complexity while fully utilizing the workload of a prepared organization. 42 frozen prime layers are used to protect the 316 layers in the Inception V3 model from refreshing loads. With damaged images of rice plants, the remaining layers are constrained.

The formula for calculating the required number of iterations in the retraining measure is:

Number of cycles= (Number of Tests / Batch size) * Number of Ages.

The accuracy of the group intelligent planning was increased using a back-spread computation, which will reduce error rate significantly after a few iterations. A collection of photographs of rice that have been infected with nine of the majority of prevalent illnesses. Eighty percent of the pool of photos from our collection, that include approximately two thousand impacted images, were used in the training stage of preparation once the training model had been established. In order to validate the Deep-CNN, nearly 300 images were separated, which amounts to around 20% of the entire training dataset. Our main objective is to use a Deep-CNN model to achieve high precision while extracting traits that remain consistent during rice infections. Every image had a precision of approval exceeding 89%. Although the hour of planning was condensed by roughly a little distance from case 1 to 4, the approval precision was only reduced by 2%.

TABLE II. COMPARISON OF MACHINE LEARNING MODELS

Algorithm	Accuracy	Precision	Recall
Logistic Regression	0.85	0.86	0.84
Decision Trees	0.78	0.79	0.77
Random Forests	0.88	0.88	0.88
SVM	0.87	0.87	0.86
KNN	0.80	0.81	0.79
Neural Networks	0.90	0.90	0.90

TABLE III. COMPARISON OF MACHINE LEARNING MODELS

Algorithm	F1 Score	AUC-ROC
Logistic Regression	0.85	0.91
Decision Trees	0.78	0.83
Random Forests	0.88	0.94
SVM	0.87	0.92
KNN	0.80	0.87
Neural Networks	0.90	0.95

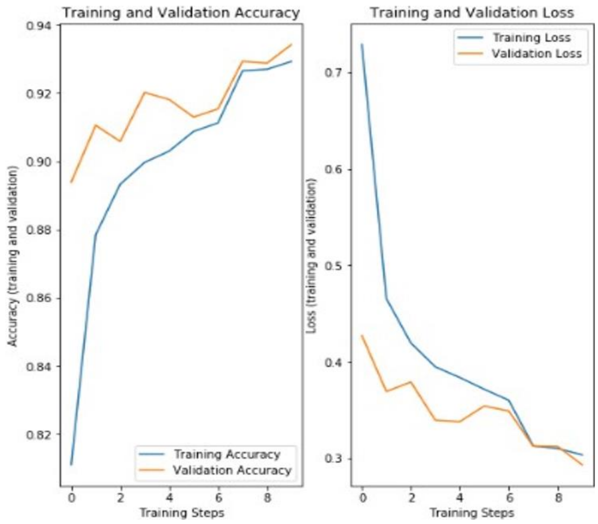

Fig2. Training and Validation performance

IV. Conclusion

Images of sick paddy leaves, such as those caused by bacterial leaf blight, brown spot, and sheath rot, are gathered from fields. RGB photos are converted to HSV images in order to remove the pre-training basis, and part coverage is achieved depending on the tint. For the categorization of afflicted and healthy leaves, a grouping technique is used. The Jaya Optimized Algorithm's optimal loads are used to order infections in the suggested Deep Neural Network. In our framework, a critique circle is formed to demand security. The test results are evaluated and compared to some of the existing models using the following metrics: exactness, precision, F1-score, accuracy etc. DNN method achieved a high level of exactness with respect to alternative classifiers.

References

[1] N.S. Patil, E. Kannan, Identification of Paddy Leaf Diseases using Evolutionary and Machine Learning Methods, Turkish J. Comput. Mathe. Educ. 12 (2) (2021) 1672–1686.

[2] B. Geraldin, C. Dela, Nitrogen Deficiency Mobile Application for Rice Plant through Image Processing Techniques, Int. J. Eng. Adv. Technol. 8 (6) (2019) 2950–2955, https://doi.org/10.35940/ijeat.f8721.088619.

[3] P.S. Jitesh, B.P. Harshadkumar, K.D. Vipul, A survey on detection and classification of rice plant diseases, in: IEEE International Conference on Current Trends in Advanced Computing (ICCTAC), 2016, https://doi.org/ 10.1109/icctac.2016.7567333.

[4] J. Yang, W. Gong, S. Shi, L. Du, J. Sun, S. Song, B. Chen, Z. Zhang, Analyzing the performance of fluorescence parameters in the monitoring of leaf nitrogen content of paddy rice, Sci. Rep. 6 (1) (2016), https://doi.org/10.1038/srep28787.

[5] J. Yang, L. Du, W. Gong, S. Shi, J. Sun, B. Chen, J.-S. Jeon, Potential of vegetation indices combined with laser-induced fluorescence parameters for monitoring leaf nitrogen content in paddy rice, PLoS ONE 13 (1) (2018) e0191068, https://doi.org/10.1371/journal.pone.0191068.

[6] K.B. Nalini, K.R. Amiya, K.B. Santi, Image Processing Techniques for Diagnosing Rice Plant Disease: A Survey, Procedia Comput. Sci. 167 (516) (2020) 530, https://doi.org/10.1016/j.procs.2020.03.308.

[7] V. Praveena, P. Chinnasamy, P. Muneeswari, R. Ananthakumar, Bensujitha, Detection and Categorization of Plant Leaf Diseases Using Neural Networks, Eur. J. Mol. Clin. Med. 7 (4) (2020) 2438–2445.

[8] Robert Mendel, David Rauber, Luis A. de Souza, João P. Papa, Christoph Palm,Error-Correcting Mean-Teacher: Corrections instead of consistency-targets applied to semi-supervised medical image segmentation,Computers in Biology and Medicine,Volume 154, 2023, 106585, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2023.106585.

[9] Guangju Li, Dehu Jin, Qi Yu, Meng Qi,IB-TransUNet: Combining Information Bottleneck and Transformer for Medical Image Segmentation,Journal of King Saud University - Computer and Information Sciences,Volume 35, Issue 3,2023,Pages 249-258,ISSN 1319-1578,https://doi.org/10.1016/j.jksuci.2023.02.012.

[10] Marco Trombini, David Solarna, Gabriele Moser, Silvana Dellepiane,A goal-driven unsupervised image segmentation method combining graph-based processing and Markov random fields,Pattern Recognition,Volume 134,2023,109082,ISSN 0031-3203,https://doi.org/10.1016/j.patcog.2022.109082.

[11] Pedro Bocca, Adrian Orellana, Carlos Soria, Ricardo Carelli,On field disease detection in olive tree with vision systems,Array,Volume 18,2023,100286,ISSN 2590-0056, https://doi.org/10.1016/j.array.2023.100286.

[12] Ansam A. Abdulhussien, Mohammad F. Nasrudin, Saad M. Darwish, Zaid Abdi Alkareem Alyasseri,Feature selection method based on quantum inspired genetic algorithm for Arabic signature verification,Journal of King Saud University - Computer and Information Sciences,Volume 35, Issue 3,2023,Pages 141-156,ISSN 1319-1578,https://doi.org/10.1016/j.jksuci.2023.02.005.

[13] Khabir Uddin Ahamed, Manowarul Islam, Ashraf Uddin, Arnisha Akhter, Bikash Kumar Paul, Mohammad Abu Yousuf, Shahadat Uddin, Julian M.W. Quinn, Mohammad Ali Moni,A deep learning approach using effective preprocessing techniques to detect COVID-19 from chest CT-scan and X-ray images,Computers in Biology and Medicine,Volume 139,2021,105014,ISSN 0010-4825,https://doi.org/10.1016/j.compbiomed.2021.105014.

[14] Sushreeta Tripathy, Tripti Swarnkar,Unified Preprocessing and Enhancement Technique for Mammogram Images,Procedia Computer Science,Volume 167,2020,Pages 285-292,ISSN 1877-0509,https://doi.org/10.1016/j.procs.2020.03.223.

[15] Larissa Ferreira Rodrigues, Murilo Coelho Naldi, João Fernando Mari,Comparing convolutional neural networks and preprocessing techniques for HEp-2 cell classification in immunofluorescence images,Computers in Biology and Medicine,Volume 116,2020,103542,ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2019.103542.

[16] Yiwei Fan, Chunyu Guo, Yang Han, Weizheng Qiao, Peng Xu, Yunfei Kuai,Deep-learning-based image preprocessing for particle image velocimetry,Applied Ocean Research,Volume 130,2023,103406,ISSN 0141-1187, https://doi.org/10.1016/j.apor.2022.103406.

[17] Kouta Hirotaki, Shunsuke Moriya, Tsunemichi Akita, Kazutoshi Yokoyama, Takeji Sakae,Image preprocessing to improve the accuracy and robustness of mutual-information-based automatic image registration in proton therapy,Physica Medica,Volume 101,2022,Pages 95-103,ISSN 1120-1797, https://doi.org/10.1016/j.ejmp.2022.08.005.

[18] Burak Tasci, Irem Tasci,Deep feature extraction based brain image classification model using preprocessed images: PDRNet,Biomedical Signal Processing and Control,Volume 78,2022,103948,ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2022.103948.

[19] Reewos Talla-Chumpitaz, Manuel Castillo-Cara, Luis Orozco-Barbosa, Raúl García-Castro,A novel deep learning approach using blurring image techniques for Bluetooth-based indoor localisation,Information Fusion,Volume 91,2023,Pages 173-186,ISSN 1566-2535,https://doi.org/10.1016/j.inffus.2022.10.011.

[20] Aashu Kumar, Peeta Basa Pati, Offline HWR Accuracy Enhancement with Image Enhancement and Deep Learning Techniques,Procedia Computer Science,Volume 218,2023,Pages 35-44,ISSN 1877-0509, https://doi.org/10.1016/j.procs.2022.12.399.

[21] Samuel Fernández-Menduiña, Fernando Pérez-González, Miguel Masciopinto,Source camera attribution via PRNU emphasis: Towards a generalized multiplicative model,Signal Processing: Image Communication,Volume 114,2023,116944,ISSN 0923-5965,https://doi.org/10.1016/j.image.2023.116944.

[22] Mahesh S Patil, Satyadhyan Chickerur, C Abhimalya, Anishma Naik, Nidhi Kumari, Shashank Maurya,Effective Deep Learning Data Augmentation Techniques for Diabetic Retinopathy

Classification,Procedia Computer Science,Volume 218,2023,Pages 1156-1165,ISSN 1877-0509, https://doi.org/10.1016/j.procs.2023.01.094.

[23] Ilknur Tuncer, Prabal Datta Barua, Sengul Dogan, Mehmet Baygin, Turker Tuncer, Ru-San Tan, Chai Hong Yeong, U. Rajendra Acharya,Swin-textural: A novel textural features-based image classification model for COVID-19 detection on chest computed tomography,Informatics in Medicine Unlocked,Volume 36,2023,101158,ISSN 2352-9148, https://doi.org/10.1016/j.imu.2022.101158.

[24] Tomé Albuquerque, Luís Rosado, Ricardo Cruz, Maria João M. Vasconcelos, Tiago Oliveira, Jaime S. Cardoso,Rethinking low-cost microscopy workflow: Image enhancement using deep based Extended Depth of Field methods,Intelligent Systems with Applications,Volume 17,2023,200170,ISSN 2667-3053, https://doi.org/10.1016/j.iswa.2022.200170.

[25] Tiwalade Modupe Usman, Yakub Kayode Saheed, Djitog Ignace, Augustine Nsang,Diabetic retinopathy detection using principal component analysis multi-label feature extraction and classification,International Journal of Cognitive Computing in Engineering,Volume 4,2023,Pages 78-88,ISSN 2666-3074,https://doi.org/10.1016/j.ijcce.2023.02.002.