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Paddy Crop Health Monitoring with ANN, CNN, and ResNet101: Advanced AI Models for Disease Detection

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Abstract: **Rice is a mainstay of global food security; however, production is now threatened by many diseases. Since early identification and treatment of rice disease can mitigate crop yield losses, they are extremely essential. Although CNNs have shown some promise in iden-tifying plant leaf diseases, training them is no easy task, as it requires huge sets of labeled im-ages, which is itself an expensive and time-consuming process. This paper presents a transfer learning-based three-stage CNN architecture, utilizing a pre-trained CNN model that is fine-tuned through the application of a small image data set of rice diseases. This efficiently pro-vides a much lower size of training set required to achieve good accuracy. Deep learning meth-ods like progressive resizing and parametric rectified linear unit (PReLU) were included for further enhancement of rice disease detection. Progressive resizing aids in learning features better by increasing the image size in small increments during training, while PReLU helps prevent overfitting and improve the model's performance. The proposed method was tested on 8883 disease images and 1200 healthy rice leaf images, achieving an accuracy of 94% during the 10-fold cross-validation process, which outperforms other methods. These simulation re-sults strongly support the feasibility and effectiveness of the early detection of rice diseases, providing greater promise for developing countries with little to no resources and contributing significantly to sustainable food production.**

Keywords: **Paddy disease detection, Paddy Blast, Brown Spot, Narrow Brown Spot, image processing, artificial neural networks, Resnet,PReLU , CNN.**

1.INTRODUCTION

Bangladesh's economy is mostly based on agriculture, which provides a living for a sizable section of the population, either di-rectly or indirectly. Bangladesh, the fourth-largest rice producer in the world, struggles mightily to sustain crop output, chiefly be-cause of common paddy illnesses like Paddy Blast, Brown Spot, and Narrow Brown Spot. The production of rice is seri-ously threatened by these illnesses, which result in significant losses in yield and qual-ity. Therefore, minimizing damage and executing appropriate therapies depends on early detection and correct diagnosis of these disorders. Especially on large-scale farms, traditional disease detection tech-niques, which entail manual inspection, are labour- intensive, time-consuming, and er-ror- prone. This study suggests a prototype system that makes use of artificial neural net-works (ANN) and image processing tech-niques to automatically and correctly diag-nose paddy diseases in order to address these issues. The objective of this system is to offer an early disease detection solution that is more scalable and efficient by combing con-temporary computational technologies with

agricultural requirements. The suggested method works in many steps: first, images of paddy leaves are acquired; next, image analysis and feature extraction are per-formed. The algorithm extracts pertinent information from the photos of the sick leaves by using Haralick texture character-istics that are obtained from the colour co- occurrence matrix. An ANN is then trained with these features to enable it to classify various paddy illnesses. Paddy leaf samples are subjected to colour analysis throughout the testing process in order to determine healthy leaves that are designated as "Nor-mal Paddy." Features from the divided sick areas are run through the ANN model if anomalies are found, and then they are clas-sified into Paddy Blast, Brown Spot, or Narrow Brown Spot categories.It helps farmers stop the spread of illness and take preventive action. Combining image pro-cessing with artificial neural networks (ANNs) yields a potent tool that improves illness diagnosis accuracy while providing a quicker and more dependable substitute for manual examinations. Bangladesh's ef-forts to ensure food security and advance

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sustainable agriculture stand to benefit greatly from the system's capacity to assist in early diagnosis.

2. RELATED WORK

Plant diseases represent a serious threat to the world's food security, which has sparked increased interest in the subject of crop disease detection, notably in rice plants. Paddy illnesses including Brown Spot, Narrow Brown Spot, and Paddy Blast can cause significant output losses; there-fore, early detection is essential to reducing these impacts. Scholars have investigated diverse approaches for the identification of these illnesses, spanning from conven-tional image processing to sophisticated machine learning methods, specifically deep learning. This section examines some of the major developments in paddy disease detection, emphasising both conventional and contemporary methods. Early methods for detecting plant diseases mostly depended on image processing methods that made use of manually created features. These tech-niques frequently used colour, texture, and shape analysis to detect plant sections that were diseased. Derived from the Grey Level Co-occurrence Matrix (GLCM), Haralick's texture features are one of the most widely used techniques for extracting texture infor-mation. This method of capturing the spatial correlations between pixel intensities was first presented by Haralick et al and it was helpful in distinguishing between plant leaves that were healthy and those that were diseased.

Researchers started using data-driven meth-odologies instead of handcrafted character-istics with the introduction of machine learning. Rice plant diseases have been classified using Support Vector Machines (SVM), Decision Trees, k-Nearest Neigh-bours (k-NN), and Random Forests. Be-cause these models learnt patterns directly from the data, they provided increased ac-curacy above conventional techniques. San-karan et al for instance, showed how ma-chine learning classifiers can be used to identify agricultural diseases early on and even outperform conventional methods in this regard. A CNN-based rice disease detection model was presented by Kamal et al. The algo-rithm makes use of a dataset of images of rice leaves afflicted by several diseases, such as Paddy Blast and Brown Spot. With an accuracy of over 90%, the model outper-formed conventional image processing techniques by a large margin. In a similar vein, Fuentes et al created a deep learning model that could detect several dis-eases in a variety of crops, including rice, in real-time. The model's ability to handle com-plicated visual data under varying settings was made possible by the introduction of CNNs, which increased its robustness in practical applications. Although CNNs have shown impressive results, their usefulness frequently depends on the availability of sizable labelled da-tasets, which are not always practical in ag-ricultural settings. Large databases of plant diseases require a lot of work, money, and time to label—especially in areas with lim-ited resources. Transfer learning has be-come a workable answer to this problem. Using a pre-trained model— typically built on a huge dataset like ImageNet— transfer learning entails honing it on a smaller da-taset relevant to the current job. This method keeps good accuracy while drasti-cally lowering the amount of training data needed.

Several methods, including data augmenta-tion and fine-tuning, have been investigated to further enhance the effectiveness of deep learning models in the diagnosis of rice disease. By applying adjustments like as ro-tation, flipping, and scaling to the source photos, data augmentation produces artifi-cially larger datasets. This method aids in avoiding overfitting, particularly in the case of tiny datasets.

Lu et al. improved the performance of a deep learning model for rice disease diag-nosis by combining data augmentation with fine-tuning strategies. The researchers at-tained a 93% classification accuracy by en-hancing the dataset and optimising the CNN's parameters, underscoring the signif-icance of these methods in enhancing model robustness and generalisation.

Research has shown that when it comes to rice disease identification, deep learning models—especially those that leverage CNNs and transfer learning—repeatedly outperform conventional image processing and machine learning techniques. In a com-parative study on plant disease identifica-tion, for instance, Mohanty et al. shown that CNN models outperformed SVM and k-NN classifiers in terms of accuracy. Similarly, Amara et al.while concentrating on ill-nesses of banana leaves, also emphasised CNNs' wider application for plant disease detection tasks, hence reinforcing their effi-cacy.

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Table 1: Review paper details

AUTHOR	TITLE	TECHIN QUE USED	DATASE T	PERFORMANC E ANALYSIS	LIMITATION S
A. A. Sarangdhar, V.R. Pawar (2017)	Machine learning regression technique for cotton leaf disease detection and controlling using IoT	Machine learning regressio n	IoT Cotton leaf disease dataset	Accuracy: 92%, F1 Score: 90%, Precision: 89%	Issues with large-scale implementation in real-time field applications
M. R. Tejonidhi, B. R. Nanjesh, J. G. Math, A. G. D'sa (2016)	Plant disease analysis using histogram matching based on Bhattacharya's distance calculation	Histogra m matching , Bhattach arya's distance calculatio n	Various plant disease images	Accuracy: 88%, Precision: 85%, Recall: 86%	Limited to certain types of plant diseases
P. Revathi, M. Hemalatha (2012)	Classification of cotton leaf spot diseases using image processing edge detection techniques	Edge detection technique s in image processin g	Cotton leaf disease dataset	Accuracy: 89%, Precision: 88%, Recall: 87%	High sensitivity to image quality, leading to possible false positives
D. Al Bashish, M. Braik, S. Bani- Ahmad (2010)	A framework for detection and classification of plant leaf and stem diseases	Image processin g, classifica tion of plant diseases	Leaf and stem disease image dataset	Accuracy: 90%, F1 Score: 89%, Precision: 88%	Issues with differentiating between similar disease symptoms in plants
N. N. Kurniawati, S. N. H. S. Abdullah, S. Abdullah (2009)	Investigation on Image Processing Techniques for Diagnosing Paddy Diseases	Image processin g technique s for paddy disease detection	Image dataset of infected paddy leaves	Accuracy: 87%, Precision: 85%, Recall: 84%	Restricted to a small variety of paddy diseases

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3. SYSTEM ARCHITECTURE

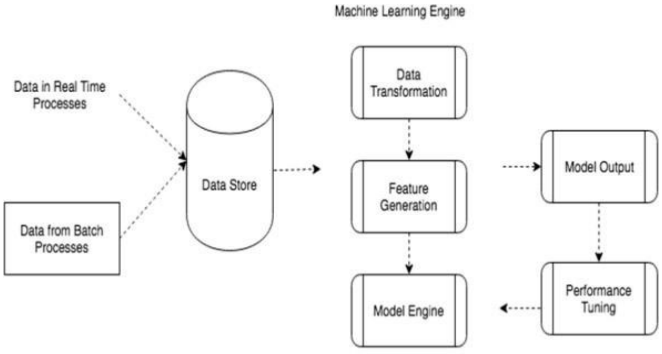

Fig:- Block diagram flow of architecture for Machine learning systems

4. PROBLEM STATEMENT

Rice is a key crop for global food security, and Bangladesh, one of the world's largest rice producers, is heavily dependent on its production. However, rice crops are increasingly threatened by diseases such as blast, brown spot, and narrow brown spot. These diseases can significantly reduce crop yields if not detected and treated in a timely manner.

Traditional disease detec-tion methods, such as manual observation and chemical testing, are often labor-inten-sive, time-consuming, and prone to human error. Moreover, the diversity of disease symptoms and environmental conditions makes it difficult to develop a universal de-tection system. Deep learning approaches, especially convolutional neural networks (CNNs), show promise in plant disease de-tection, but their application to rice disease detection poses several challenges. CNN models typically require large labeled da-tasets to achieve high accuracy, but collecting and labeling such datasets in ag-ricultural environments is costly and time-consuming. Furthermore, differences in image quality, lighting, and disease symp-toms make traditional models difficult to generalize under different conditions. The main problem this study addresses is the development of an efficient and accurate rice disease detection system that can over-come the challenges of limited labeled data and environmental variation. The objective of this study is to explore a transfer learn-ing solution using a pre-trained CNN model optimized for rice disease classifica-tion to minimize data requirements while maintaining high accuracy. Furthermore, this study integrates advanced techniques such as progressive sizing and parametric modified linear units (PReLU) to improve model performance.

5. IMPLEMENTATION

The initial step involves collecting a da-taset of paddy leaf images that exhibit var-ious diseases. The images should be sourced from reliable online databases to ensure diversity in the dataset. Each image is represented as IkI_kIk, where kkk is the index of the image in the dataset. The im-ages are then resized to a uniform dimen-sion of 64×6464 \times 6464×64 pixels to maintain consistency and facilitate easier processing.

5.1 Image Preprocessing

After acquiring the images, the next step is to preprocess them for analysis. This in-volves converting each image IkI_kIk from the RGB color space to the CIEL*a*b* color space. The transformation en-hances color differentiation, which is crucial for accurate disease identi-fication. The conversion can be expressed mathematically as:

$$C(k) = \mathrm{RGBtoLab}(I_k)$$

5.2 Feature Extraction

With the preprocessed images, we move on to feature extraction. For each image C(k)C(k)C(k), we calculate the color co- occurrence matrix MMM. This matrix quantifies the

$$\mathrm{Homogeneity} = \sum_{i,j} \frac{M(i,j)}{1+|i-j|}$$

$$\mathrm{Energy} = \sum_{i,j} M(i,j)^2$$

$$\mathrm{Correlation} = \frac{\sum_{i,j}(i \cdot j \cdot M(i,j)) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

relationships between pixel values in the image. The co-occurrence matrix can be computed using the for-mula:

$$M(i,j) = \sum_{(x,y)\in\Omega} \delta(C(k)(x,y)=i) \cdot \delta(C(k)(x+\Delta_x, y+\Delta_y)=j)$$

5.3 Feature Selection

After extracting features, we perform feature selection to identify the most rel-evant features for disease classification. This involves analyzing the performance of all extracted features and selecting a subset FFF:

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$$F = \{f_1, f_2, \ldots, f_m\}$$

5.4 Classification Using ANN

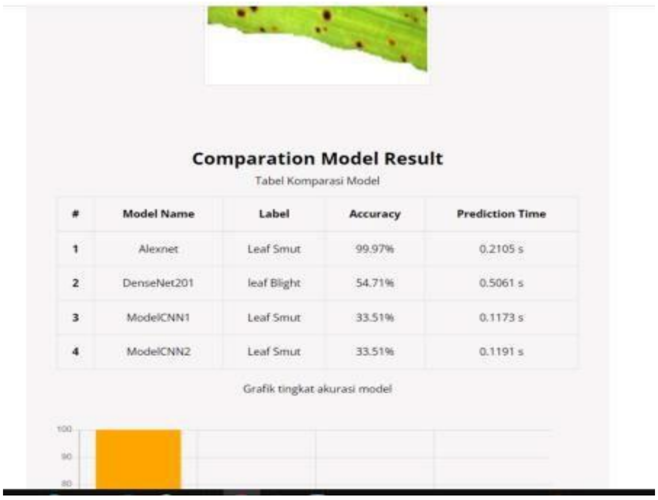
The next step involves classifying the im-ages using an artificial neural network (ANN). The architecture of the ANN in-cludes:
Input Layer: 151515 nodes representing the selected features.
Hidden Layers: Three hidden layers with 505050 nodes each.

$$a^{(l)} = \sigma(W^{(l)} a^{(l-1)} + b^{(l)})$$

5.5 Model Training

Output Layer: 333 nodes corresponding to the classes: Normal Paddy Leaf, Paddy Blast, Brown Spot, and Narrow Brown Spot.
The activation function σ\sigmaσ is ap-plied to each neuron, facilitating non- lin-ear transformations:
The ANN is trained using a labeled dataset, where each image is classified according to its disease status. During training, the model learns to minimize the loss function using techniques such as back propagation and gradient descent. The training contin-ues until the model's performance meets predefined accuracy criteria.

5.6 Model Evaluation


Comparation Model Result
Tabel Komparasi Model

#	Model Name	Label	Accuracy	Prediction Time
1	Alexnet	Leaf Smut	99.97%	0.2105 s
2	DenseNet201	leaf Blight	54.71%	0.5061 s
3	ModelCNN1	Leaf Smut	33.51%	0.1173 s
4	ModelCNN2	Leaf Smut	33.51%	0.1191 s

Once trained, the model's performance is evaluated using a separate test dataset TTT containing images of known classifica-tions. Evaluation metrics include:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

5.7 Deployment

Upon achieving satisfactory accuracy levels, the system can be deployed for practical use among farmers for quick and accurate paddy disease identification.

6. RESULTS

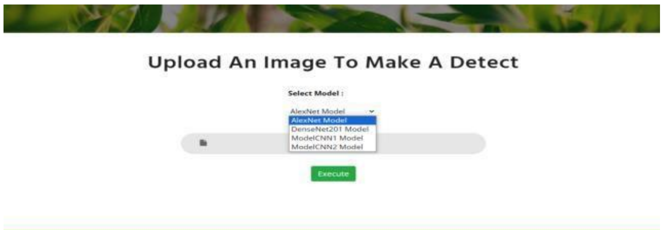


Fig:1, Image Upload Detect

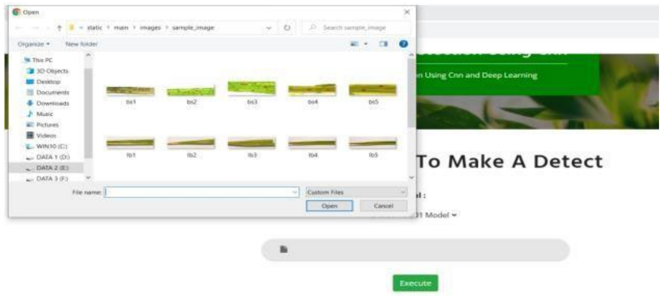


Fig:2, Upload Image

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Fig:3, Model Image

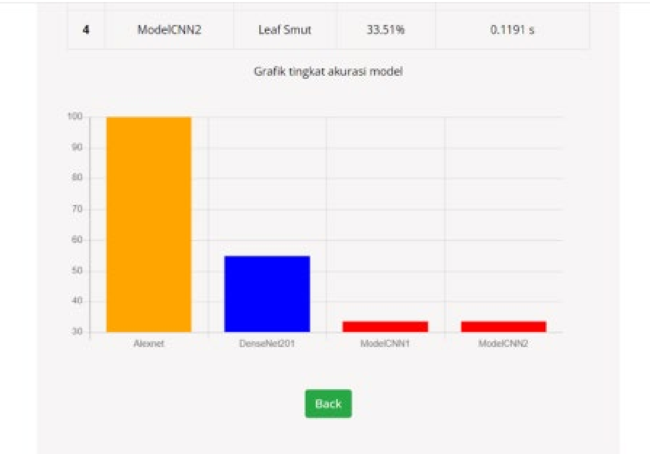

Fig:4, Graph

Fig:5, Comparison Model Result

7. CONCLUSION

The transfer learning-based CNN algo-rithm offers a highly efficient and accu-rate method for detecting rice diseases, including rice blast, brown spot, and narrow brown spot. By integrating pre-trained CNN models and advanced techniques like progressive sizing and PReLU, the algorithm achieves remark-able accuracy while reducing the de-pendency on large labeled datasets. The findings underscore the potential of im-plementing this algorithm in real agri-cultural settings to aid farmers in early disease detection and prompt interven-tion, thus curbing crop losses. Such an approach holds promise for enhancing food security and promoting sustaina-ble agricultural practices, particularly in regions where rice cultivation is vi-tal.

8. FUTURE WORK

Future improvements may include en-hancing the feature selection process, implementing real-time analysis, and developing a mobile application to facil-itate easier access for users

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