RICE LEAF DISEASE DETECTION USING DEEP LEARNING

B. Jagadeesh[1], A. Umesh Chandra[2], G. Uday Sankar Reddy[3], G. Satish[4], Md. Shakeel Ahmed[5]

[1,2,3,4]*Department of Information Technology, VVIT, AP, India*
[5]*Associate Professor, Dept. of Information Technology, VVIT, AP, India*

---***---

Abstract-

Rice, a vital staple crop globally, confronts significant threats from various leaf diseases, adversely impacting yield and agricultural sustainability. In response, our project endeavors to develop an efficient rice leaf disease detection system using deep learning models. The study utilizes a comprehensive dataset encompassing images of rice leaves afflicted with four prevalent diseases: bacterial blight, blast, tungro, and brown spot. Leveraging diverse deep learning architectures, including Simple CNN, ResNet, Inception, and LeNet, we train and evaluate models to accurately classify these diseases. Through meticulous experimentation, we identify the model exhibiting the highest accuracy on the validation dataset. Deploying the selected model with the Streamlit library, we construct a user-friendly frontend interface facilitating seamless interaction. This interface empowers users to upload rice leaf images, enabling real-time disease prediction and identification. By integrating advanced deep learning techniques with accessible user interaction, our project offers a practical solution for farmers and agricultural experts to swiftly diagnose and address rice leaf diseases. This initiative holds promise for enhancing crop management practices and bolstering agricultural productivity.

Key Words: Deep Learning, Image classification, Simple CNN, LeNet, ResNet, Inception, Bacterial Blight, Blast, Tungro, Brownspot

1.INTRODUCTION

Rice leaf diseases pose significant threats to crop yields worldwide, necessitating faster and more reliable detection methods. Current approaches relying on textual datasets and traditional algorithms like SVM/KNN face challenges with image complexity, potentially leading to suboptimal classification. Recent technological advancements in image processing have opened avenues for automated disease detection. Our project aims to enhance the accuracy and efficiency of rice leaf disease prediction by integrating deep learning techniques, particularly Convolutional Neural Networks (CNNs). By directly tackling the pressing issue of rice leaf diseases, our system offers a practical tool for farmers to improve disease management and minimize crop losses. Designed to be user-friendly, our system provides farmers with a convenient means of predicting and managing rice leaf diseases. The integration of CNN models not only addresses rice leaf diseases but also underscores the potential of deep learning in resolving complex agricultural challenges.

2. EXISTING SYSTEM

Existing systems for rice leaf disease detection often rely on text datasets and machine learning algorithms, such as Support Vector Machine (SVM) or K-Nearest Neighbors (KNN). These systems typically suffer from limitations in handling image complexity, potentially leading to suboptimal classification results. Some existing systems may utilize only one algorithm, which can further limit their accuracy and robustness. Despite their contributions to disease detection, these systems are often slower and less efficient compared to more advanced techniques like deep learning. Hence, there is a pressing need to explore and implement more sophisticated approaches to enhance the effectiveness of rice leaf disease detection systems.

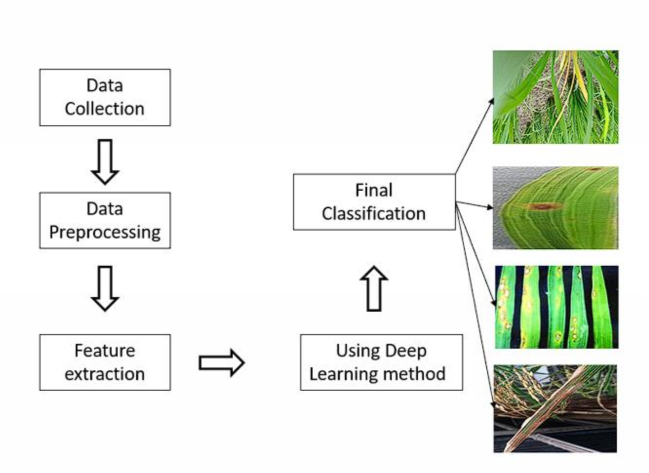


Fig: Existing System Architecture

3. PROPOSED SYSTEM

The proposed system for rice leaf disease detection leverages the power of deep learning models, including Simple CNN, ResNet, LeNet, and Inception, to enhance classification accuracy. Unlike existing systems, which often rely on text datasets and traditional machine learning algorithms, our approach utilizes image datasets, enabling more effective analysis of the complex visual features present in rice leaf images. Through rigorous experimentation and comparison of model accuracies, we identify the most optimal deep learning architecture for disease classification. This approach not only improves accuracy but also demonstrates the versatility and effectiveness of deep learning in tackling agricultural challenges. By harnessing the capabilities of various deep learning models, our proposed system offers a robust and efficient solution for rice leaf disease detection.

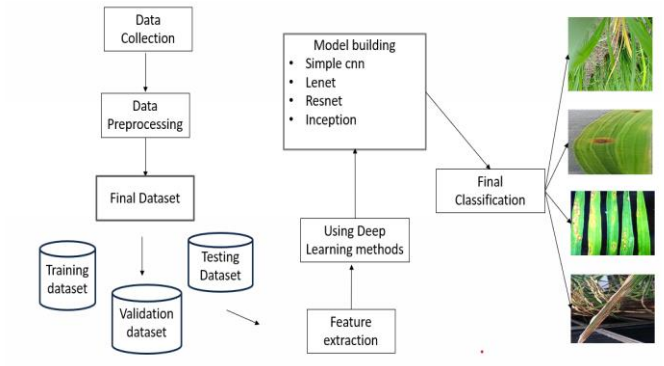


Fig: Proposed System Architecture

4. OBJECTIVES

1) **Early Detection with CNN Integration:** Utilizing Convolutional Neural Networks (CNN) to enable early and accurate detection of rice leaf diseases, enhancing agricultural disease prediction efficiency.

2) **Efficiency Enhancement:** Moving away from time-consuming visual inspection methods to achieve quicker and more efficient disease detection.

3) **Precision Improvement through Deep Learning:** Utilizing advanced deep learning techniques, particularly CNN models, to enhance disease prediction precision compared to traditional methods.

4) **Enhanced Disease Management Strategies:** Developing a predictive model capable of capturing detailed visual information for precise and reliable disease classification, contributing to improved disease management strategies in rice cultivation.

5) **Empowering System Use with Visual Information:** Integrating CNN models to effectively utilize visual information for disease prediction, showcasing significant advancements in precision agriculture and the potential of deep learning in agricultural applications.

5. METHODOLOGY

5.1 Dataset Collection and Preparation:

The project began with collecting a dataset containing images of rice leaves affected by four common diseases: bacterial blight, blast, brown spot, and tungro.

The dataset was organized into appropriate directories, ensuring compatibility with TensorFlow's image dataset loading utilities.

Preprocessing steps included resizing images to a uniform size and rescaling pixel values to the range [0, 1].

5.2. Data Augmentation:

To augment the dataset and enhance model generalization, data augmentation techniques were applied using TensorFlow's Sequential API. These techniques included random horizontal and vertical flipping, as well as random rotation.

5.3. Model Selection and Architecture:

Four deep learning models were selected for experimentation: Simple CNN, LeNet, ResNet, and InceptionV3.

Each model's architecture was defined using TensorFlow's Keras API, tailored to suit the characteristics of the dataset and the complexity of the task.

The models were compiled with appropriate loss functions (sparse categorical cross-entropy) and optimizers (Adam), and accuracy was chosen as the evaluation metric.

5.4. Model Training and Evaluation:

The dataset was split into training, validation, and test sets, with 80%, 10%, and 10% of the data allocated to each set, respectively.

Training was performed on each model using the training set, with validation performed on the validation set to monitor performance and prevent overfitting.

Training progress, including loss and accuracy metrics, was tracked over multiple epochs.

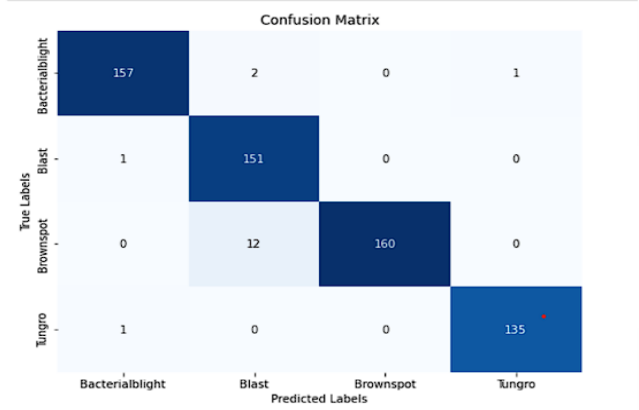
After training, the models were evaluated using the test set to assess their performance on unseen data.

5.6. Model Comparison and Selection:

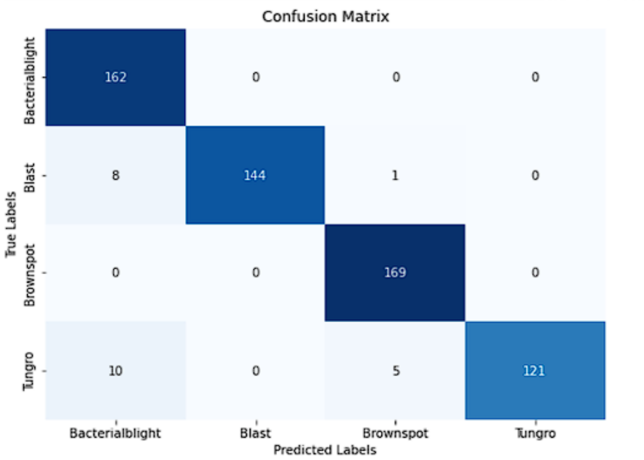
Performance metrics such as accuracy, precision, recall, and F1-score were computed for each model using the test set.

Confusion matrices were generated to visualize the models' classification performance across different disease classes.

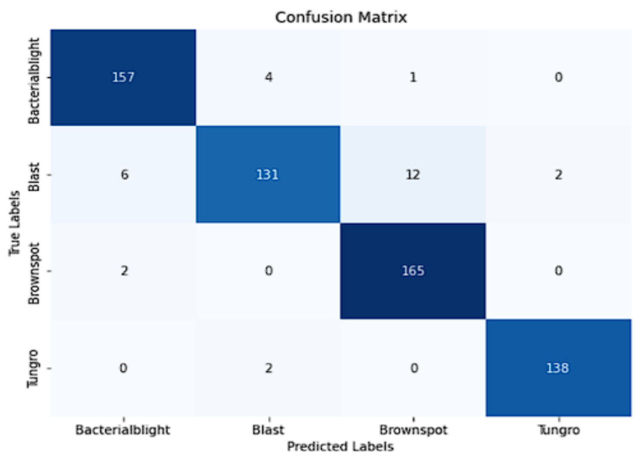
Based on the evaluation results, the model with the highest accuracy and most robust performance was selected as the optimal model for rice leaf disease detection.



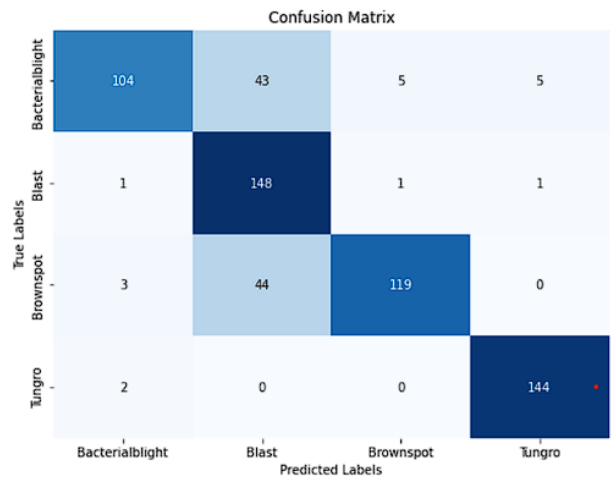
Simple cnn



Inception



Lenet Model



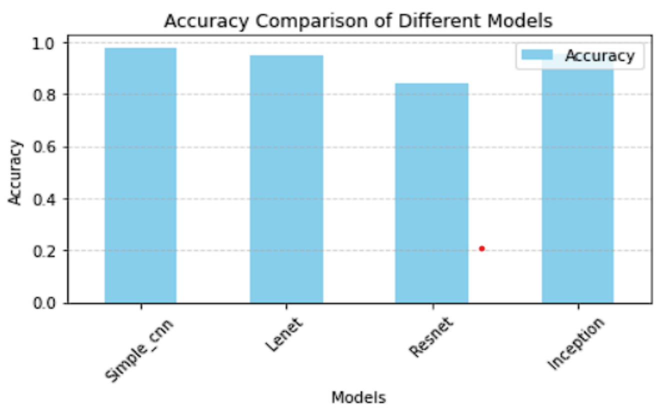
Resnet

Models	Precision	Recall	F1-Score	Accuracy
Simple CNN	0.973	0.974	0.973	0.972
LeNet	0.955	0.952	0.953	0.953
ResNet	0.871	0.836	0.834	0.830
Inception	0.966	0.957	0.960	0.961

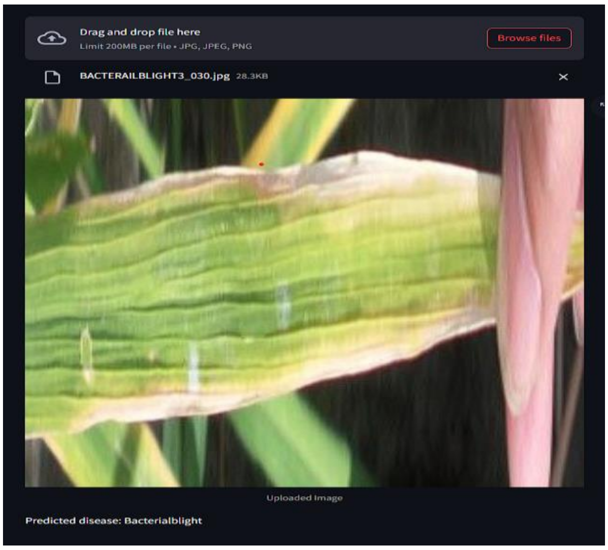
Table: Statistical analysis for different models

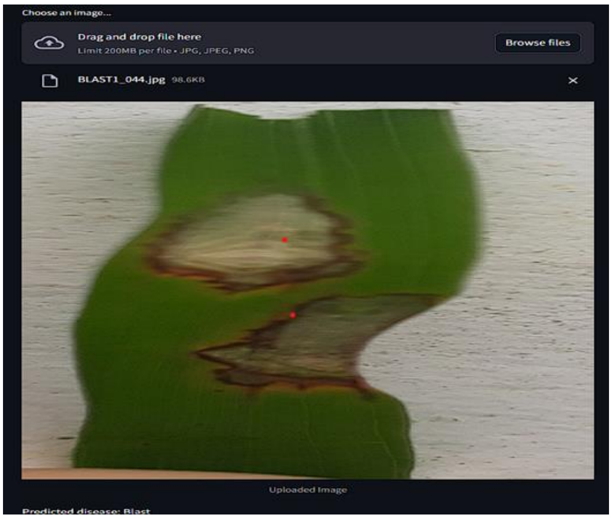
5.7. Model Deployment and Visualization:

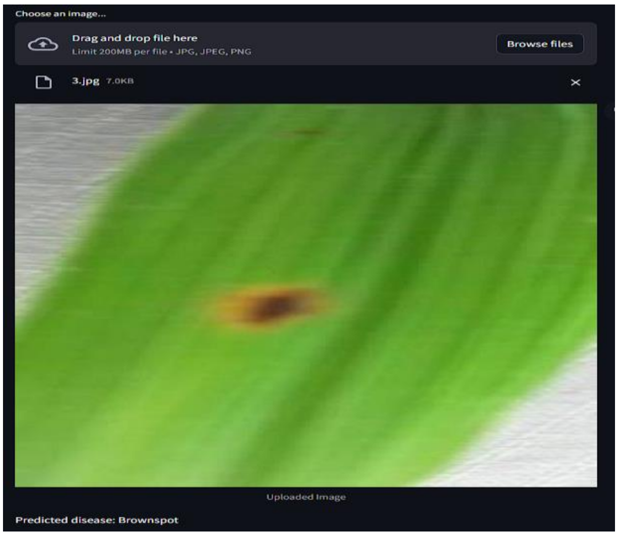
Deployed the selected model using the Streamlit library to create a user-friendly frontend interface for rice leaf disease classification. Integrated image uploading functionality to allow users to upload images for classification. Preprocessed the uploaded images for prediction by resizing them to the appropriate dimensions and normalizing them. Made predictions using the deployed model and displayed the predicted disease class on the frontend interface.

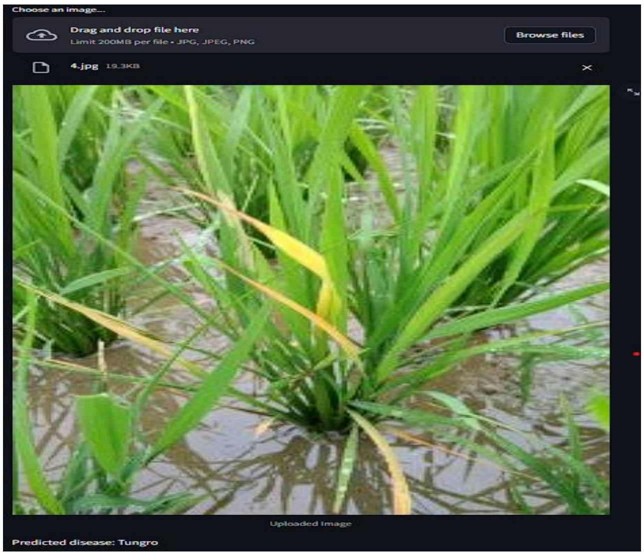


6.OUTPUT SNAPSHOTS









7.CONCLUSION

In conclusion, the integration of Convolutional Neural Networks (CNNs) in rice leaf disease detection represents a significant advancement in agricultural technology. Through rigorous experimentation and evaluation, our study demonstrates the superiority of deep learning techniques over traditional methods, achieving early and accurate disease detection. The deployment of a user-friendly frontend interface further enhances accessibility and usability for farmers, empowering them to manage rice diseases more effectively. Our project underscores the potential of deep learning in precision agriculture and offers a practical solution to mitigate crop losses. Moving forward, continued research in this field holds promise for further improving crop health and agricultural productivity.

8.FUTURE ENHANCEMENT

1) **Expansion of Disease Categories:** Expand the disease classification model to include a wider range of rice leaf diseases beyond the current categories, enhancing the system's capability for comprehensive diagnosis and management.

2) **Multimodal Data Integration:** Incorporate additional data sources such as weather patterns, soil conditions, and crop health metrics into the disease detection system, enabling a more holistic understanding of disease dynamics and facilitating targeted interventions.

3) **Integration with Precision Agriculture Technologies:** Integrate the disease detection system with precision agriculture technologies such as drones, satellite imagery, and IoT sensors, enabling precise and efficient disease monitoring and management at scale.

4) **Real-Time Monitoring and Alerts:** Implement real-time monitoring capabilities in the system, coupled with automated alert mechanisms to notify farmers of disease outbreaks or anomalies, enabling timely responses and interventions to mitigate crop losses.

REFERENCES

[1] Trébuil, G., 2011. Rice production systems in Asia: The constant presence of an essential cereal on a continent in mutation.

[2] Papademetriou, M.K., 2000. Rice production in the Asia-Pacific region: issues and perspectives. Bridging the rice yield gap in the Asia-Pacific region, 220.

[3] Bangladesh Rice Knowledge Bank, available at <>, last accessed on 25-11-2020, 08.40 am.

[4] Wikipedia, list of rice leaf diseases, available at <>, last accessed on 28-11-2020, 05.10 am.

[5] Mondal, M. H. (2010). Crop agriculture of Bangladesh: Challenges and opportunities. Bangladesh Journal of Agricultural Research, 35(2), 235- 245.

[6] Alamsyah D, Fachrurrozi M. 2019. Faster R-CNN with inception v2 for fingertip detection in homogenous background image. *Journal of Physics: Conference Series* 1196(1):12017'

[7] Arnal Barbedo JG. 2013. Digital image processing techniques for detecting, quantifying and classifying plant diseases. *SpringerPlus* 2(1):1-12

[8] Asfarian A, Herdiyeni Y, Rauf A, Mutaqin KH. 2014. A computer vision for rice disease identification to support Integrated Pest Management. *Crop Protection* 61:103-104