Multi-Model Deep Learning Rice Crop Disease Prediction

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ABSTRACT

Rice diseases remain a major concern for farmers worldwide, posing a serious threat to food security and causing significant crop losses. The ability to identify and predict the consequences of these diseases can safeguard yields to a significant extent. One of the major challenges that motivated this research is the lack of timely and accurate disease diagnosis systems for rice crops in rural and resource-limited areas. Farmers often rely on manual inspection, which is error-prone and delayed, leading to significant yield losses and food insecurity. This gap highlighted the need for an automated, accessible, and high-accuracy solution that can assist in early disease detection and yield loss prediction using Deep Learning. This research presents a Deep Learning (DL) based approach utilizing Convolutional Neural Network (CNN) to detect six prevalent rice diseases: leaf blast, brown spot, narrow brown spot, neck blast, sheath blight and sheath rot. The models were trained on 2,237 images sourced from the Vishweshwar Aiah Canal region in Mandya, Karnataka. The result shows DenseNet121 demonstrated the best performance, achieving 99.5% validation accuracy. Furthermore, the proposed system estimates disease severity and considers different environmental factors to predict potential yield losses. To support farmers further, a multilingual, easy-to-use mobile application has also been developed, offering localized management suggestions to help farmers protect their crops.

Keywords: Rice Disease, Deep Learning, Convolutional Neural Network, Disease Detection, Yield Prediction.

1. INTRODUCTION

Rice is a vital staple crop that serves as the primary food source for more than half of the global population. It is cultivated predominantly in tropical and subtropical regions, with countries such as India, China, Indonesia and the Philippines leading in production. In addition to its role in food security, rice is a key economic driver, providing livelihoods for millions of small-holder farmers reliant on cultivation [1]. According to reports [26], India is a major rice producer and exporter, with an estimated 138 million metric tons produced in 2024 and a significant portion of the global rice trade. In 2024, India had an estimated 47.6 million hectares of land area for rice cultivation. However, rice farming faces several challenges with plant diseases being among the most significant threats to yield and profitability. If not detected and managed in time, this disease can cause substantial economic losses [2][44].

Rice plants are highly susceptible to fungal, bacterial and viral infections, complicating disease management. Some of the most prevalent and damaging diseases include leaf blast, sheath blight, brown spot, narrow brown spot, sheath rot and neck blast [6]. These diseases target different plant parts, such as leaves, stems and grains, each causing unique adverse effects. For example, leaf blast weakens photosynthesis by forming lesions on leaves, whereas sheath blight compromises stem strength, leading to lodging and reduced grain yield [3]. Without effective disease control, the entire rice field can be devasted, exacerbating food insecurity and financial hardship, particularly for smallholder farmers [4].

Traditionally, rice disease diagnosis has relied on manual visual inspection by farmers or agricultural experts. However, this approach is often ineffective, prone to error, and constrained by the limited availability of trained professionals, particularly in rural regions [51][45]. Some diseases, such as sheath blight, often remain undetected until severe damage has already occurred [12]. The varying intensity of infections across large fields further complicates disease management, highlighting the urgent need for technological intervention to enable early disease detection and rapid response [4].

Advancements in Machine Learning (ML) and Computer Vision (CV) present promising solutions to these challenges. CNN, a type of ML model, has demonstrated high accuracy in rice disease identification through image analysis [27][43]. By training these models on large datasets containing images of both healthy and diseased rice plants, automated systems can precisely detect infections from images [8]. The final classification layer of the CNN employs a SoftMax activation function, which converts logits into class probabilities, enabling accurate multiclass disease prediction. Integrating these AI-driven systems into mobile applications enables farmers with real-time disease detection capabilities using only a smartphone [17]. This approach enhances disease management efficiency, reduces dependence on agricultural specialists, and ensures broader accessibility to timely diagnosis, ultimately mitigating crop losses and improving agricultural sustainability [31][32].

1.1 DISEASE DETECTION AND YIELD PREDICTION: AN INTEGRATED APPROACH

Although early detection of diseases is vital, it represents just one aspect of the answer. After a disease is recognized, it is essential for farmers to obtain advice on management approaches that consider the disease's severity, as well as elements such as environmental conditions and the development stage of the crop. This demands an all-encompassing system that not only identifies illnesses but also provides preventive strategies, treatment suggestions, and chemical or organic and agricultural methods to aid in controlling disease spread. For example, if leaf blast is identified early, the use of a suggested fungicide is recommended [6][49]. Nevertheless, in more serious situations, more extensive measures might be necessary, such as a combination of chemical treatments and improved agronomic practices to mitigate further spread [52][41].

Yield forecasting is another crucial element that must be included in disease management. Diseases have a direct impact on crop yields by impairing plant health, making it crucial for farmers to recognize how a disease could influence their harvest. By integrating disease detection with predictive analytics, farmers can assess possible yield losses according to the intensity of infection [7][42]. This method assists farmers in making educated choices regarding resource distribution and planning for the harvest. It enhances value by providing farmers with a better understanding of possible results and the actions they can undertake to reduce yield loss [25][46].

1.2 TECHNOLOGICAL LANDSCAPE FOR DISEASE DETECTION AND YIELD PREDICTION

Technology in agriculture, or "agritech," encompasses a wide range of tools and techniques, including computers, robotics, Internet of Things (IoT) and software aimed at improving agricultural output and efficiency [16]. For example, Artificial Intelligence (AI) and ML, particularly CNN, have advanced agricultural applications, especially in plant disease detection. CNN excel at identifying subtle visual differences between healthy and diseased plants across various crops [28]. For rice disease detection, CNN are trained on diverse datasets, via techniques such as data augmentation and class weights to improve accuracy and address imbalanced data [9][48]. Advanced yield prediction models incorporate historical data, environmental factors, and disease severity to forecast potential yields. Integrating disease detection and yield prediction provides farmers with a comprehensive, data-driven farm management solution [25][33].

1.3 SIGNIFICANCE OF RESEARCH

This research could greatly improve rice disease management in farming communities by providing a real-time, accessible tool for disease detection, enabling farmers to act swiftly and independently without relying on experts [17][39]. The yield prediction feature adds value by helping farmers anticipate the effects of diseases on harvests, which is crucial for areas where rice is a primary food and income source. It advances agricultural technology by showcasing the practical use of ML and mobile apps for real world challenges. An open-source approach also encourages widespread adoption, further innovation, and collaboration across the agricultural sector [40][47].

1.4 DEVELOPMENT OF AN OPEN-SOURCE MOBILE APPLICATION FOR FARMERS

This research aims to develop an open-source mobile app for farmers that uses ML to detect rice crop diseases and predict yields. The key features include the following:

1. Disease diagnosis through image analysis
2. Tailored disease management recommendations
3. Yield prediction to estimate disease impact
4. Offline mode for areas with limited internet access
5. Intuitive interface for users with minimal tech skills
6. Multi-language support for localized information

The app will run on any smartphone, promoting accessibility and innovation in agricultural technology. This tool will help farmers make informed decisions about crop management, even in remote areas.

2. RELATED WORKS

Haridasan *et al.* proposed a CNN-based deep learning system for detecting and classifying five paddy plant diseases. The model incorporated preprocessing and a hybrid CNN-SVM architecture, achieving an accuracy of 94.5%, thus showcasing the effectiveness of deep learning in agricultural diagnostics. However, the system was primarily tested on curated datasets and lacked validation in real-field conditions. The absence of disease severity estimation and limited deployment scalability present critical gaps that our proposed system aims to address. [10]

Sethy *et al.* conducted a comprehensive review of image processing techniques for diagnosing rice plant diseases, focusing on traditional Machine Learning models. The study emphasized the effectiveness of classifiers like Support Vector Machine (SVM) and K-Nearest Neighbour (KNN) when combined with feature extraction methods such as color and texture analysis. The survey, based on papers selected for their relevance to rice disease identification using image-based ML approaches, reported that SVM achieved accuracies of up to 85%. However, the review highlighted key limitations, including reliance on manual feature extraction and a lack of deep learning integration, indicating the need for more automated and scalable solutions. [11]

Upadhyay *et al.* proposed a CNN-based approach for classifying three common rice plant diseases using image-based feature extraction, achieving a high accuracy of 96.4%. Their model significantly outperformed traditional Machine

Learning techniques such as SVM and KNN, emphasizing the effectiveness of Deep Learning in plant disease classification. However, the study was limited to a few disease classes and lacked aspects such as severity estimation, real-time applicability, and multilingual support, indicating the need for more comprehensive and deployable solutions [12].

Sharma *et al.* explored Machine Learning and Deep Learning techniques for rice disease detection, using transfer learning with various pretrained CNNs. InceptionResNetV2 achieved the highest accuracy, validating the effectiveness of deep models. However, the study focused solely on classification accuracy and lacked considerations for real-time deployment, severity estimation, and usability in field conditions [13].

Jackulin *et al.* conducted a comprehensive survey of AI-based plant disease detection methods, selecting papers primarily focused on disease identification using ML and DL models over the past decade. Their review emphasized CNN architecture and hybrid techniques, evaluating performance across various crops and datasets. They highlighted key challenges such as limited generalizability, lack of real-time application, and absence of severity estimation. This survey underscores the need for robust, scalable, and field-deployable systems, thereby justifying the development of our proposed solution [14].

Bari *et al.* utilized Faster R-CNN with a region proposal network (RPN) to detect rice leaf diseases, achieving 99.25% accuracy. Their survey focused on CNN-based models for disease identification using annotated image datasets. While the method ensured precise localization of affected areas, it highlighted a major research gap—its high computational cost restricts real-time deployment, underscoring the need for lightweight and field-adaptable solutions [15].

Ahmad *et al.* reviewed 70 studies on Deep Learning applications in agriculture, focusing on plant disease diagnosis and severity estimation. The survey selected papers based on their relevance to DL-based disease identification across diverse crops and imaging techniques. A major finding was the inconsistency in defining disease severity, which hinders model generalizability and cross-dataset performance. The authors emphasize the need for standardized evaluation metrics and annotated benchmarks to enhance the robustness and real-world applicability of DL models in agriculture [16].

S. Tyagi *et al.* proposed a lightweight CNN-based rice disease detection system enhanced by CLAHE for image preprocessing and a hybrid HSV-K-means clustering method for segmentation, achieving 99% accuracy. While effective in controlled environments, the model's dependency on handcrafted segmentation techniques restricts its adaptability to diverse crop types and real-world field conditions [17].

Agrawal *et al.* conducted a comparative analysis of CNN architectures—VGG19, XceptionNet, DenseNet,

SqueezeNet, and ResNet50—for rice disease classification, with ResNet50 achieving the highest accuracy of 97.5%. The study emphasizes the strength of Deep Learning models in plant disease detection but lacks consideration for real-time deployment, resource efficiency, and user accessibility—key factors necessary for practical, field-level applications [18].

T. Daniya *et al.* conducted a model-centric survey emphasizing hybrid AI techniques for rice disease detection, particularly focusing on neuro-fuzzy systems integrated with optimization algorithms. Their review prioritized studies employing Deep Learning, soft computing, and bio-inspired optimizers for image-based disease identification. While existing models demonstrated promising accuracy, gaps such as limited real-time applicability, lack of generalizability, and absence of multilevel classification pipelines were evident. These insights justify their proposed hybrid deep neuro-fuzzy network with RHGSO, which achieved 93.04% accuracy, though at the cost of increased model complexity [19].

Hasan *et al.* developed a lightweight CNN model that achieved 97.9% accuracy on a test dataset of 630 images, focusing on rice disease classification through mobile integration. The survey methodology centered on recent AI-based models, particularly CNNs, selected based on their relevance to plant disease identification and practical deployment potential. The study highlights the model's suitability for resource-limited environments due to its simplicity and efficiency. However, the limited dataset size and lack of environmental diversity in testing reveal a key research gap in model generalizability—justifying the need for robust, scalable systems adaptable to varied agricultural conditions [20].

Z. Chu *et al.* proposed the BBI model, integrating BPNNs and IndRNNs to predict rice yield by capturing both spatial and temporal dependencies in agricultural data. The study focuses on Deep Learning-based yield forecasting rather than disease identification and reflects the growing trend of hybrid AI models in agriculture. While the model shows improved prediction accuracy, its high computational demands and limited scalability highlight the need for more efficient and deployable solutions in real-time field environments [21].

Nishant *et al.* employed advanced regression methods, including kernel ridge and elastic net, for yield prediction, further enhancing performance through stacking regression. While their ensemble approach effectively captured complex yield patterns, the model relied solely on tabular data without considering disease factors or image-based features, limiting its applicability for holistic agricultural modeling [22].

Cao *et al.* integrated satellite imagery, meteorological data, and soil properties to predict rice yields up to two months before harvest using LASSO, Random Forest, and LSTM models. Their approach highlights the effectiveness of multi-source data and Machine Learning in early yield forecasting. However, the study does not consider disease-related factors, limiting its scope in modeling real-world agricultural variability [23].

Zhou *et al.* analyzed CNN, ConvLSTM, and CNN-LSTM models for rice yield forecasting using remote sensing data, concluding that the CNN-LSTM hybrid best captures spatial and temporal dependencies. While the study demonstrates the effectiveness of Deep Learning in yield prediction, it does not consider disease-related variables, revealing a gap in integrating biotic stress factors for more accurate modeling [24].

Pankaj *et al.* employed Machine Learning techniques to estimate panicle area and predict rice yield using RGB images captured via DSLR. While the method demonstrated high accuracy at the plot level, its reliance on controlled imaging conditions limits its scalability for field-wide deployment. The study does not consider disease impact, highlighting the need for more adaptable and comprehensive models for real-world agricultural scenarios [25].

3. METHODOLOGY

The methodology for this study involves training multiple Deep-Learning models for image classification via transfer learning techniques. The dataset is structured into training and testing directories, with an 80-20 split for validation within the training set. Various pretrained CNN [38], including ResNet50[9], DenseNet121 [10], EfficientNetB0[11], InceptionV3[12], and VGG16 [13], these models were selected based on their proven performance in image classification tasks, their compatibility with transfer learning using limited agricultural data, and their architectural strengths in extracting complex visual features.

This comparative approach enabled us to identify the most efficient and accurate model — DenseNet121 — for deployment in a real-world rice disease prediction system. And these models are used as base models, initialized with ImageNet weights and fine-tuned for classification. Data augmentation techniques such as rotation, width and height shifts, shear, zoom, horizontal flipping, and brightness adjustment are applied to improve model generalizability [5][14].

The models are trained via categorical cross-entropy loss and optimized via AdamW with a learning rate of 1e-4 and a weight decay of 1e-5 which is acquired via empirical tuning of the model. Initially the models started with a learning rate of 1e-4. Class imbalance is addressed by computing class weights. The training process is guided by callbacks such as Model Checkpoint [29][34] for saving the best model, TensorBoard [19] for visualization, ReduceLROnPlateau [20][50] for dynamic learning rate adjustments, and early stopping to prevent overfitting. The models are evaluated on test data via accuracy, precision, and recall metrics, and the best-performing model is identified based on test accuracy. Finally, a confusion matrix and classification report are generated to analyze model performance, ensuring a robust assessment of the trained models [53][35].

3.1 DATA COLLECTION

The dataset for this study was collected from the Vishweshwar Aiah Canal Region in Mandya and is specifically curated for rice disease classification. It comprises images categorized into six primary disease types: brown spot, leaf blast, narrow brown spot, neck blast, sheath blight and sheath rot. Representative images for each category are provided below for reference *Fig 1.* The dataset contains a total of 2,237 images of which 1,792 are used for training with an 80-20 split to ensure accurate performance evaluation. Images were taken under a variety of ambient and lighting situations to improve the model's generalizability to real-world scenarios. Each image is labelled with a disease name, providing a solid foundation for supervised Machine Learning. This dataset supports the development of effective classification models capable of distinguishing multiple rice diseases based on their unique visual characteristics leading to early detection and improved disease management for farmers. *Table 1* presents the distribution of samples across the six disease category classifications.

Table 1: Disease and Number of Samples Collected from Mandya

Disease Class	Number of Training Images
Brown Spot	467
Leaf Blast	377
Narrow Brown Spot	443
Neck Blast	379
Sheath Blight	385
Sheath Rot	186

Brown Spot	Narrow Brown Spot	Sheath Blight

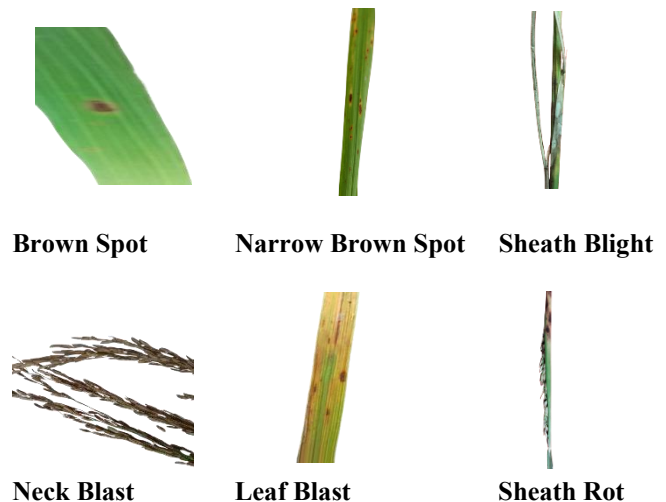| Neck Blast	Leaf Blast	Sheath Rot

Fig 1: Sample images of different rice crop leaf diseases collected from Mandya

3.2 TOOLS & TECHNOLOGIES

This study utilizes advanced Deep Learning (DL) and Computer Vision (CV) tools, with TensorFlow (TF) serving as the primary framework for model development. Multiple pretrained CNN architectures available in TensorFlow Keras Applications — including DenseNet121, ResNet50, InceptionV3, EfficientNetB0, and VGG16 — were employed with ImageNet weights for initial feature extraction and fine-tuning [30][37].

3.3 PRE-PROCESSING

To ensure data quality and maximize model performance, a comprehensive image preprocessing pipeline was implemented before training. All input images were resized to a uniform dimension of 244 × 244 × 3 pixels to ensure compatibility across various CNN architectures and standardize input dimensions. The pixel values were normalized to the [0, 1] range, which facilitated faster model convergence and reduced input variance. To improve image quality and highlight disease features, basic denoising techniques such as Gaussian blurring and contrast enhancement were applied to minimize background noise.

Additionally, images captured at varying angles were corrected for orientation using affine transformations and rotation adjustments, ensuring consistency in leaf alignment. To expand the diversity of training samples and mitigate overfitting, the ImageDataGenerator was employed to perform data augmentation, introducing variations such as random rotation, width and height shifts, shearing, zoom, horizontal flipping, and brightness modifications. This enhanced the model's ability to generalize across real-world scenarios. Furthermore, the dataset was carefully screened to detect and remove any missing or corrupted images, including those that were unreadable or excessively noisy, to preserve data integrity. Given the unequal distribution of images across the six rice disease classes, class weights were calculated and applied during training to ensure fair learning and reduce model bias toward overrepresented categories [54][36].

3.4 MODEL DEVELOPMENT

The model development process begins with data preprocessing and augmentation via ImageDataGenerator, which applies transformations such as rotation, shifting, zooming, and brightness adjustments to increase dataset variability. The base model is loaded without its top layers to serve as a feature extractor. The input size is adjusted to the model requirements, ensuring compatibility with the pretrained architecture. The base layers remain frozen initially, allowing only newly added layers to learn. The model includes a GlobalAveragePooling2D layer to reduce dimensions, followed by batch normalization to improve convergence. Two fully connected dense layers with L2 regularization and dropout are added to prevent overfitting, followed by a SoftMax output layer for classification. The fine-tuning phase unfreezes specific layers of the pretrained

model, optimizing deeper layers to adapt to the dataset. This hybrid approach ensures that the model learns domain-specific features while benefiting from general-purpose feature representations.
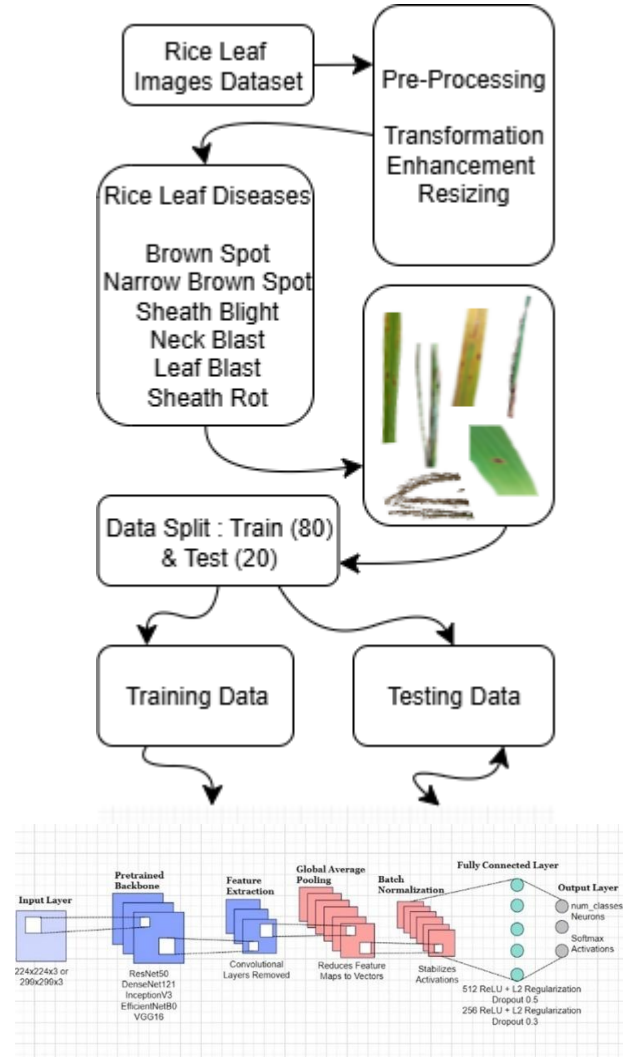

Fig 2: *The proposed architecture diagram and workflow for rice crop leaf disease classification*

Fig 2 presents a custom-designed diagram, developed from scratch to visually illustrate the workflow and training process of the proposed learning model. The model itself is based on transfer learning, utilizing pretrained architectures such as ResNet50, DenseNet121, InceptionV3, EfficientNetB0 or VGG16 as feature extractors. These models are modified by removing their original classification layers while retaining their learned feature representations. The extracted feature maps are passed through a global average pooling (GAP) layer, which reduces dimensionality by converting them into compact vector representation. Batch Normalization is applied to stabilize activation and improve convergence. The model includes two fully connected layers with 512 and 256 neurons, employing ReLU activation, L2 regularization, and dropout

rates of 0.5 and 0.3 to mitigate overfitting. The final layer consists of num_classes neurons with SoftMax activation for multiclass classification. This architecture efficiently integrates transfer learning with a custom dense layer, enhancing feature extraction and fine-tuning capabilities for robust image classification.

3.4.1 Mathematical modeling of the proposed CNN Architecture

The proposed CNN-based architecture incorporates a pretrained DenseNet121 backbone for hierarchical feature extraction, followed by a custom classification head. The forward pass of the network can be described using the following mathematical model:

Input:

Let $x \in R^{H \times W \times 3}$ be the RGB image, where H and W denote height and width, respectively.

Feature Extraction via Dense Connectivity:

In the DenseNet121 backbone, each layer l within a dense block receives feature maps from all previous layers via concatenation:

$$x_l = H_l([x_0, x_1, \ldots, x_{l-1}]) \tag{1}$$

Where:

$H_l(.)$ represents a composite function consisting of batch normalization, ReLU and a convolution operation:

$$H_l(x) = Conv_{3 \times 3}\left(ReLU\big(BN(x)\big)\right) \tag{2}$$

Transition Layers:

Between dense blocks, a transition layer performs spatial and channel-wise compression:

$$z = AvgPool2 \times 2\left(Conv1 \times 1\left(ReLU\big(BN(x)\big)\right)\right) \tag{3}$$

Global Average Pooling:

After the final dense block, the spatial dimension is removed via global average pooling:

$$x_{\text{pool}} = \frac{1}{H \cdot W}\sum_{i=1}^{H}\sum_{j=1}^{W} x_{i,j} \tag{4}$$

Fully Connected Layers:

The pooled feature vector is passed through two fully connected (dense) layers with L2 regularization and dropout:

$$h1 = Dropout0.5\big(ReLU(W1xgap + b1)\big) \tag{5}$$

$$h2 = Dropout0.3\big(ReLU(W2h1 + b2)\big) \tag{6}$$

Output Layer:

The final classification is done using a SoftMax layer over C classes:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}, \quad i \in \{1, \ldots, C\} \tag{7}$$

These equations formally describe the internal workings of the proposed model architecture, encompassing the stages of feature extraction using DenseNet121 densely connected layers, spatial and channel-wise compression via transition layers, and final classification through task-specific fully connected layers. The structural design and mathematical formulation of the backbone were inspired by the work of Huang et al. [51], who introduced DenseNet to improve gradient flow, enhance feature reuse and reduce the number of parameters in deep convolutional neural networks.

3.4.2 Optimization and Parameter

The AdamW optimizer was employed due to its improved generalization ability through decoupled weight decay. Unlike traditional Adam, AdamW applies L2 regularization directly to the weights rather than modifying the gradient, helping prevent overfitting in deep architectures.

The parameter update rule is defined as:

$$\theta_{t+1} = \theta_t - \eta \times (\hat{m}_t / (\sqrt{\hat{v}_t} + \varepsilon) + \lambda\theta_t) \tag{8}$$

where $\hat{m}_t$ and $\hat{v}_t$ are bias-corrected moment estimates, η is the learning rate, and λ is the weight decay coefficient. This optimizer proved effective in achieving fast and stable convergence across all evaluated CNN architectures.

3.5 FEATURE ENGINEERING AND SELECTION

By refining the input representation, feature engineering plays a vital role in enhancing model performance. Pretrained CNN models function as feature extractors, utilizing their learned representations from large datasets. Each model applies a specific preprocessing function, such as preprocessing input in ResNet50 to normalize the pixel values. Data augmentation techniques, including shear, zoom, rotation and horizontal flipping, introduce invariant features, improving model robustness to variations. The GlobalAveragePooling2D layer extracts features from the final convolutional layer reducing dimensionality while preserving critical information. Batch normalization stabilizes training. While preserving critical information. Batch normalization stabilizes training whereas L2 regularization mitigates overfitting. The dropout layer introduces noise during training, enhancing generalizability. Additionally, computes_class_weight address class

imbalance, preventing the model from favouring dominant class. By integrating pretrained networks with custom densest layers, the architecture effectively captures both general and task-specific features, ultimately improving the classification memory.

3.6 EVALUATION METRICS

Model performance evaluation involves multiple classification metrics to assess its effectiveness. The accuracy metric determines the overall percentage of correct predictions. Precision measures the proportion of true positive predictions among all positive predictions, ensuring fewer false positives. Recall evaluates the model's ability to identify all actual positive samples, reducing false negatives. These are crucial for applications where missing a positive case is costly, such as disease detection is costly. A classification report provides a per-class breakdown of these metrics. The confusion matrix visually represents misclassifications, which helps identify challenging classes. The ReduceLROnPlateau callback adjusts learning rates dynamically to optimize performance. Training and validation accuracy/loss curves reveal overfitting trends, guiding hyperparameter tuning. Finally, the best-performing model is selected based on the basis of test accuracy, ensuring its deployment readiness. ***Table 2*** shows the best-performing model results on classification of rice crop leaf disease.

Table 2: *Results of the best-performing mode.*

Disease Name	Precision	Recall	F1-Score	Support
Brown Spot	1.00	1.00	1.00	90
Leaf Blast	0.98	1.00	0.99	88
Narrow Brown Spot	1.00	1.00	1.00	77
Neck Blast	1.00	1.00	1.00	77
Sheath Blight	1.00	0.97	0.98	66
Sheath Rot	1.00	1.00	1.00	44
Accuracy				
Macro Avg.	1.00	0.99	1.00	442
Weighted Avg.	1.00	1.00	1.00	442

The confusion matrix in ***Fig 3*** illustrates the performance of the DenseNet121 model for rice disease classification. The matrix shows that the model correctly classified nearly all the test samples with diagonal values representing correctly predicted instances for each disease. Most classes have perfect classification (zero misclassifications), except for sheath blight, where 2 samples were misclassified as another class. This aligns with the classification report, where sheath blight had a slightly lower recall (0.97). Overall, the model demonstrates exceptional accuracy and robustness, with minimal misclassification and strong generalizability across different disease types.
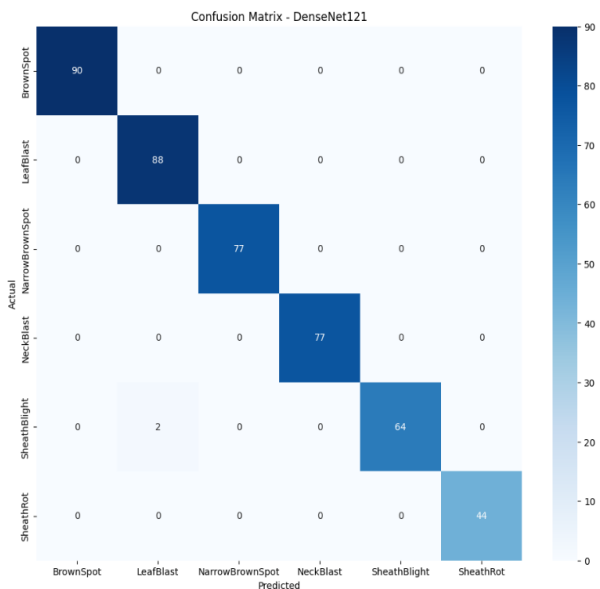

Fig 3: *Confusion matrix results for DenseNet121*

4. RESULTS AND DISCUSSION

The results of the model evaluation indicate that DenseNet121 outperforms the other architectures, achieving the highest accuracy of 99.55%, with a precision of 99.55% and recall of 99.32%. Among the tested models, ResNet50, EfficientNetB0, InceptionV3, and VGG16 demonstrated strong performance, with accuracies ranging from 96.61% to 98.64%. However, DenseNet121 consistently delivered superior metrics, across all the evaluation criteria. Unlike traditional CNN or even ResNet50, which use skip connections to add output from earlier layers, DenseNet121 introduces a dense connectivity structure, where each layer receives feature maps from all preceding layers. This enables effective feature reuse and enhanced gradient propagation, allowing the model to learn complex patterns more efficiently and generalize better for the given task. These factors contribute to DenseNet121's ability to capture intricate and fine-grained patterns in the data, which is especially valuable for tasks such as image-based disease classification.

Although EfficientNetB0 is widely acknowledged for its accuracy-efficiency trade-off in large-scale image classification tasks, the superior performance of DenseNet121 in this study can be attributed to the nature and size of the dataset. DenseNet121's dense connectivity structure allows each layer to receive inputs from all preceding layers, promoting feature reuse and mitigating vanishing gradient issues. This characteristic is particularly advantageous in smaller, domain-specific datasets like rice disease classification, where capturing subtle and localized patterns in the leaf texture is critical. Moreover, the model's ability to propagate fine-grained features through dense skip connections may have contributed to better generalization despite the relatively limited dataset. In contrast, EfficientNetB0, while efficient, is highly optimized for large-scale, well-curated datasets and may require more data or task-

specific fine-tuning to match DenseNet121's effectiveness in this context.

To validate the robustness of these results, a 95% confidence interval for DenseNet121's accuracy was calculated via the test set of 447 images. These resulting intervals, [98.41%, 99.2%], confirm the statistical reliability of the model's performance.

In addition to disease classification, the system estimates severity based on the infected leaf area Using HSV-based color segmentation, the system estimates disease severity based on infected leaf area and assigns a score from 1 to 10. Severity is then categorized as Low ($\leq$3), Moderate (4–5), High (6–7), or Extreme ($\geq$8). This analysis was performed on rice leaf samples collected from the Mandya region. Most cases were classified as Low to Moderate, with fewer falling under High and Extreme. This severity assessment supports targeted treatment planning and yield loss estimation. *Table 3* summarizes the evaluation metrics across all models, while *Fig. 4* visualizes their comparative performance.
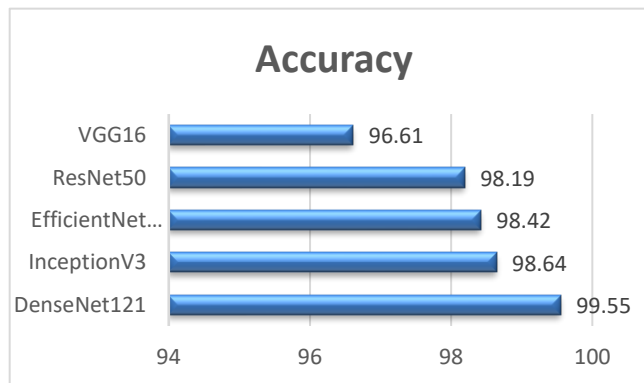

Fig 4: Graphical representation of the results summary for all the models

Table 3: Results summary of all the model performances

Model	Accuracy %	Precision %	Recall %
DenseNet121	99.55%	99.55%	99.32%
InceptionV3	98.64	98.64%	98.64%
EfficientNetB0	98.42	98.41%	98.19%
ResNet50	98.19	98.19%	98.19%
VGG16	96.61	96.61%	96.61%

4.1 DEPLOYMENT ON STREAMLIT

Streamlit-based web application designed for rice crop disease detection and severity estimation via a pretrained DenseNet121 model. The application loads a trained model and class indices from JSON files and provides a user-

friendly interface to predict plant diseases on the basis of uploaded images. The background image is set dynamically via base64 encoding. The application preprocesses the uploaded image, resizes it to 224x224 pixels, and normalizes it before feeding it into the model for classification. After prediction, the identified disease is mapped to severity levels based on the basis of the percentage of infected area, which is calculated via OpenCV's HSV-based color segmentation. The severity score is categorized into low, moderate, high, or extreme levels, and appropriate treatment recommendations are provided from a predefined dictionary. Additionally, the app estimates potential yield loss and growth based on the basis of the severity score, helping farmers make informed decisions. The integration of Google Translate allows for multilingual support, making the application accessible to a wider audience. The streamlit app was hosted locally on the computer, ensuring fast and efficient processing. In terms of inference time, the model takes approximately 30.0 s to process the image and generate the predictions. The *Fig 5* shows the streamlit-based web interface for a Rice Crop Disease Detection application. The interface allows users to upload images of rice crops for automated disease identification. It includes a language selection feature, making it accessible to diverse users. The description highlights the importance of early disease detection via AI, ML, and image processing for accurate and scalable monitoring. The drag-and-drop file upload feature supports image formats such as JPG, JPEG, and PNG, enabling easy user interaction. *Fig 6:* This interface enhances the efficiency of rice disease management by providing quick and precise diagnostics for farmers and researchers.

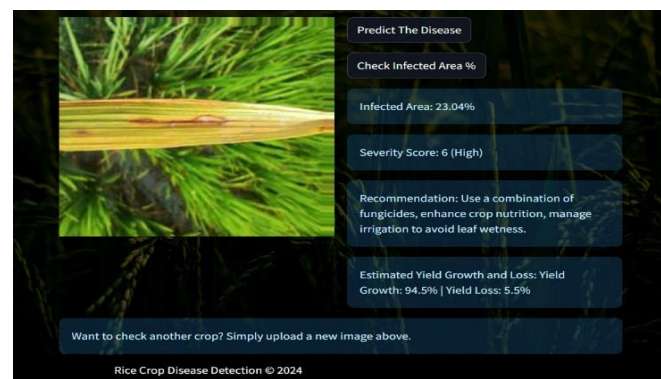*Fig 5: Stream lit UI (User Interface) on the Web-Application*

Fig 6: Detect, Prevent, and Protect: Rice Disease Analysis

5. CONCLUSION

This study demonstrates the efficacy of transfer learning for rice crop disease detection, via several Deep Learning models. This study explores the application of ResNet50, DenseNet121, EfficientNetB0, InceptionV3, and VGG16. The models were trained and fine-tuned on the dataset, and through experimentation, the study demonstrated that fine-tuning pretrained models can significantly improve performance, even with a limited dataset. DenseNet121 emerged as the best-performing model, achieving the highest accuracy and precision among the evaluated architectures. The findings highlight the power of deep learning techniques, particularly transfer learning, in solving real-world problems, such as crop disease detection, which can aid in more effective agricultural management and disease monitoring.

5.1 Future Work

To increase the effectiveness of the rice disease detection, future efforts should focus on mobile applications. The scalability of the application should be expanded by supporting more crops and diseases while integrating weather forecasting for better decision-making. A crucial next step is incorporating a farmer feedback system, enabling users to report the effectiveness of recommended treatments, thus refining the model over time. However, limitations such a small dataset size, data imbalance and scalability challenges must be addressed to improve the model's robustness. Furthermore, making the platform more accessible by optimizing it for low end devices and ensuring multilingual support will enhance adoption among smallholder farmers. The open-source nature of the app will drive continuous development, promote sustainable agriculture and improve resilience against crop losses in diverse agricultural settings.

5.2 ACKNOWLEDGEMENT

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