Disease Identification in Rice Plant using Machine Learning and Deep Learning Models

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Abstract

Rice, a staple food for more than half of the world's population, is highly susceptible to various diseases that significantly affect yield and quality. Traditional methods of disease identification are often manual, time-consuming, and prone to human error. This study explores the application of Machine Learning (ML) and Deep Learning (DL) approaches for accurate, automated detection of rice plant diseases using image data. Classical ML models such as Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbors (KNN) are employed with handcrafted features derived from color, texture, and shape descriptors. In parallel, state-of-the-art DL architectures including VGG19, DenseNet201, MobileNetV2, CNN, and NasNet are utilized for end-to-end learning from raw images. The paper further investigates hybrid models, combining CNNs with SVM and Random Forest, as well as transformer-based MLCNN classifiers to enhance performance. Experimental results reveal that DL and hybrid models consistently outperform traditional ML classifiers, achieving accuracy levels exceeding 95% in several cases. Evaluation metrics such as precision, recall, F1-score, and per-class accuracy confirm the robustness of these models. The study concludes that deep and hybrid models hold significant promise for real-time, scalable deployment in agricultural monitoring systems, contributing to early disease diagnosis and improved crop management.

Keywords: *Machine Learning, Deep Learning, VGG19, DenseNet201, MobileNetv2, CNN*

I. Introduction

Machine Learning (ML) and Deep Learning (DL) techniques have revolutionized the field of plant disease detection by providing highly accurate, automated classification models. Machine Learning models, such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forest (RF), rely on handcrafted features extracted from plant images to classify different diseases. On the other hand, Deep Learning models, particularly Convolutional Neural Networks (CNNs), can automatically learn complex features from raw images, significantly improving classification accuracy.

The work focuses on the integration of ML algorithms, and advanced DL architectures to develop an efficient hybrid framework for rice plant disease detection. The proposed methodology begins with image preprocessing using color space transformations (HSV and LAB), segmentation using K-means clustering, and feature extraction to highlight diseased regions. Subsequently, deep learning models such as VGG19, DenseNet201, and Multi-Layer CNN (MLCNN) are compared with traditional machine learning classifiers. Furthermore, hybrid models combining CNN with SVM and CNN with Random Forest are explored to enhance classification performance.

The analysis of these approaches highlights the effectiveness of deep learning-based techniques in achieving higher classification accuracy compared to conventional ML models. Additionally, the study evaluates model performance using key metrics such as accuracy, precision, recall, F1-score, and confusion matrices to determine the best-performing approach. The findings of this study demonstrate the potential of deep learning and hybrid models in developing an automated, real-time rice plant disease detection system that can aid farmers and agricultural experts in early disease diagnosis and effective crop management.

II. Literature Survey

The paper [1] presents a rice leaf disease detection system using machine learning approaches. Three of the most common rice plant diseases: leaf smut, bacterial blight, and brown spot—are targeted. The proposed system utilizes image processing techniques to extract features from leaf images, which are then classified using machine learning algorithms. The system achieved an accuracy of 95%, demonstrating its potential for effective disease detection.

The study in the paper [2] explores the use of Convolutional Neural Networks with an attention mechanism (CNNAM) to detect diseases in rice plants. The reliability of CNNAM in image identification tasks is leveraged to classify various rice diseases, contributing to precision agriculture by enabling timely and accurate disease management.

The authors of paper [3] propose a machine learning technique that allows for the precise categorization and detection of a wide variety of rice leaf diseases, achieving an accuracy of 98.8%. The methodology involves feature extraction from leaf images followed by classification using advanced machine learning algorithms.

The paper [4] discusses the use of computer vision and machine learning methods for classifying and detecting diseases in rice plants. The study emphasizes the importance of automated systems in agriculture to improve disease management and crop yield.

The authors of the paper [5] develop an automated approach to detect paddy diseases using a deep learning model based on the SMOTE-ENN resampling technique. This method addresses class imbalance in the dataset and enhances the model's ability to accurately detect diseases.

The work of [6] examines the performance of various machine learning models to identify an efficient model for diagnosing crop diseases in the early phase. The study aims to enhance early detection and management of rice plant diseases.

The study of paper [7] provides a comprehensive understanding of current rice plant illnesses and the deep learning approaches used to detect such diseases. The authors discuss various machine learning techniques, including Convolutional Neural Networks (CNNs), for the accurate identification of diseases affecting rice plants. The paper emphasizes the importance of early detection in preventing significant crop losses and enhancing yield. The study also highlights the challenges in implementing these technologies in real-world scenarios and suggests potential solutions.

The study of [8] explores the application of Artificial Intelligence (AI), specifically Convolutional Neural Networks (CNNs), for detecting rice plant diseases using resource-optimized models suitable for real-time applications on embedded devices. The authors developed lightweight CNN architectures that maintain high accuracy while reducing computational complexity, making them ideal for deployment in resource-constrained environments. The models were tested on a dataset of rice plant images, achieving high accuracy in disease detection, thereby demonstrating their potential for practical use in agriculture.

In the review paper [9], the authors focus on image processing techniques using machine learning (ML) and deep learning (DL) models related to multi-scale rice diseases. They analyze various studies that have employed these technologies to predict and diagnose diseases at different growth stages of rice plants. The review highlights the advancements in precision agriculture and the role of ML and DL in enhancing the accuracy and efficiency of disease detection, thereby contributing to better crop management and yield.

The comparative study in paper [10] evaluates various plant disease detection and classification techniques, focusing on the three most frequent rice crop diseases: brown spot, leaf smut, and bacterial leaf blight. The authors compare traditional machine learning methods with deep learning approaches, assessing their performance in terms of accuracy, computational efficiency, and practicality for real-world applications. The study provides valuable insights into selecting appropriate techniques for effective disease management in rice cultivation.

The authors of paper [11] explore the use of machine learning classifiers to analyze images of rice plants and determine their health status. They experiment with various algorithms, including Support Vector Machines (SVM), Decision Trees, and ensemble methods, to classify diseases based on visual symptoms. The study demonstrates that machine learning can effectively identify and classify rice crop diseases, providing a foundation for developing automated disease detection systems to assist farmers in timely decision-making.

This paper [12] presents a hybrid approach combining machine learning techniques with Internet of Things (IoT) systems for rice crop disease detection. The authors integrate IoT devices to collect real-time data from rice fields and apply machine learning algorithms to analyze the data for disease detection. The study highlights the potential of combining IoT and ML technologies to create efficient and scalable solutions for monitoring crop health and improving agricultural productivity.

The paper [13] presents a rice plant disease detection method using transfer learning techniques on images captured from drones. The authors leverage pre-trained deep learning models and fine-tune them on a dataset of rice plant images to detect diseases accurately. The use of drone imagery allows for large-scale monitoring of rice fields, enabling early detection of diseases and timely intervention. The study demonstrates the effectiveness of transfer learning in adapting existing models to specific agricultural applications.

Benos et al. [14] presented a review of various works aimed at exploring ML in agriculture. Initially, they described the four basic categories in which ML algorithms are involved. Crop management is subdivided into five categories (yield prediction, disease detection, weed detection, crop recognition, and crop quality), water management, soil management, and livestock management. They performed an extensive search on various search engines and selected articles for the period from 2018 to 2020. Finally, they concluded that: (i) a large percentage of research articles were about crop management, (ii) ANNs were the most effective
ML models, (iii) the most investigated crops in the papers were maize, wheat, rice, and soybean, and finally, (iv) the most utilized input data was mainly RGB images and then weather, soil, water, and crop quality.

In [15] the author proposed a VGG16 (Convolutional Neural Network) with transfer learning to identify rice plant diseases. In this classification task, the authors used 4 classes of images for training and achieved an accuracy of 92.4% for VGG16. In [65] the author suggested a convolutional neural network as an effective system for identifying diseases in varieties of plants such as apple, tomato, maize and grape. Totally the dataset contains 15210 leaf images belong to 10 classes which were used for training and testing the model. The proposed convolutional neural network obtained an accuracy of 86%. In [66] the author has used a ResNet50 CNN model for detecting the diseases in the tomato leaf images. There are 3000 images in the dataset corresponding to 3 classes. The accuracy of this model is 98.0%.

In [16] the author has proposed a methodology for detecting the diseases in coffee leaf using the techniques such as Fuzzy Logic Based Expert System, Radial Basis Function Neural Network, CNN with Data augmentation, and CNN with data augmentation and transfer learning (using Inception V3 architecture). This work is carried out using two types of datasets and they are original leaf images and selected symptom's part from leaf images. Each of the datasets contains 5 categories of leaf images. The IncepionV3 model gave a good result of 97.61%.

In [17] the author has proposed a machine learning algorithms such as SVM, K-NN, and decision trees for classifying the diseases in the plant leaves. They used feature extraction method to segment the diseased part from the leaf image which process involves several stages like convert RGB image to Lab color space model, K-means clustering for grouping the color pixel values of leaf, histogram and fast fourier transform used for color feature extraction, scale-invariant feature transform used for shape feature extraction, principal component analysis used for lessening vector size. The above-mentioned algorithms are used for classification and SVM gave a better result than other two methods.

In [18] the author has applied a VGG16 model with transfer learning approach for detecting the disease in millet crop. This work collected 124 leaf images and split into mildew diseases and healthy categories. The VGG16 model obtained an accuracy of 95%.

In [19] the author has applied a random forest classifier used for recognizing the diseases of bacterial spot, early blight, late blight in the plant leaves. In image segmentation, HSV-Herpes Simplex Virus technique was used to partition the diseased portion and healthy portion of the leaf and gray level co-occurrence matrix operated for feature extraction. This model attained 98% accuracy.

In [20] the authors conducted a systematic literature review, analyzing 82 high-quality articles published since 2017 on deep learning approaches for rice leaf disease detection. The review highlights the effectiveness of techniques such as Transfer Learning, Ensemble Learning, and Hybrid approaches in addressing challenges associated with traditional detection methods. The study also discusses model architectures, hyperparameter settings, fine-tuning techniques, and performance evaluation metrics utilized across various studies.

III METHODOLOGY

The major issue is the lack of continuous monitoring of the plants. Sometimes farmers are unaware of the plant diseases and its occurrence period. Generally, diseases can take place at any time on any plant. However, a disease infection can be prevented by continuous monitoring. As rice is one of the important food in India, the automatic disease detection and infection to the rice plant can be prevented by applying the concepts of machine learning and image processing on it. Any plant can be infected by any diseases like bacteria, fungi, and virus. Bacterial leaf blight, Brown spot, Leaf smut, Leaf blast, and Sheath blight are one of the most common type of diseases in rice plant [4]. The infected part of the rice plant can be given as an input to image processing operations. However, different rice plants showcase different symptoms of diseases. Different color variations can be observed like diseases may have brown color or yellow color. Each disease defines its own unique characteristics. Different shapes, size, color can be observed for different diseases. Some of the diseases might have the same color, but different shapes; while some have different colors but same shapes. Due to the lack of knowledge and confusion, farmers are not able to select proper pesticides for the appropriate diseases. One of the best way to reduce plant disease detection is to capture image of the diseased plant and extract information from that image. In order to capture images, cameras can be placed at an appropriate location from where the images can be captured. These images can be processed and given as an input to machine learning algorithm and relevant pesticides can be suggested. Hence, the system should automatically identify the diseases. The general system to detect rice plant disease is shown in Figure 1. The system comprises of four different modules: Image Pre-Processing, Image Segmentation, Feature Extraction and Classification.

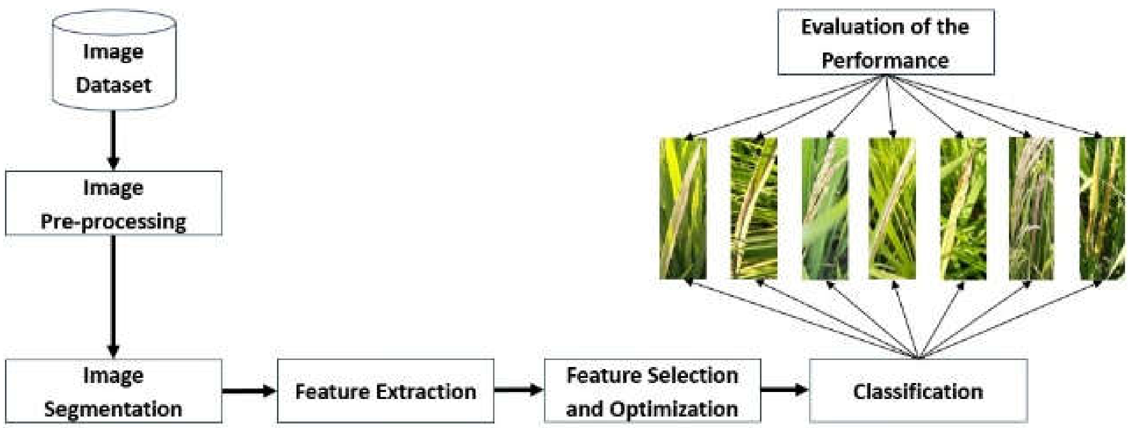

Figure 1: General System to Detect Rice Plant Disease

3.1 Image Pre-processing

Pre-processing is the initial step of the system. Image Processing comprises of four different modules: Image Acquisition, Image Resizing and Scaling, Color Space Conversion [5], Histogram Equalization and noise reduction filters [6].

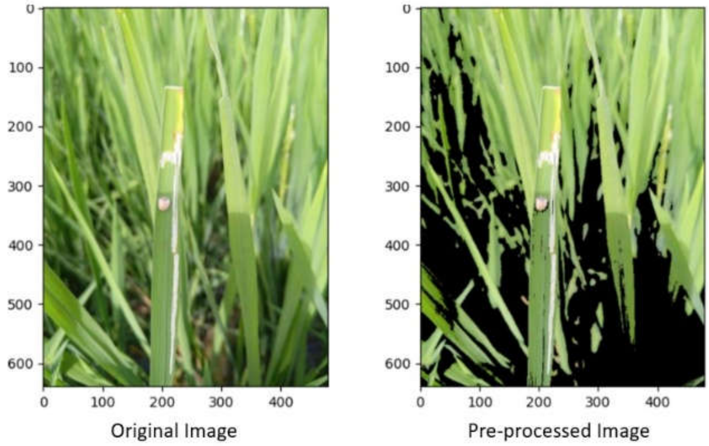

Figure 2: Conversion of Original Image to Preprocessed Image

3.2 Segmentation

Image Segmentation is the next step after image pre-processing. It generally involves dividing an image into segments in order to analyze specific region of interest (diseased area). The segmented regions are termed as objects, boundaries or relevant feature of image. Figure 3. shows different types of Image segmentation techniques.

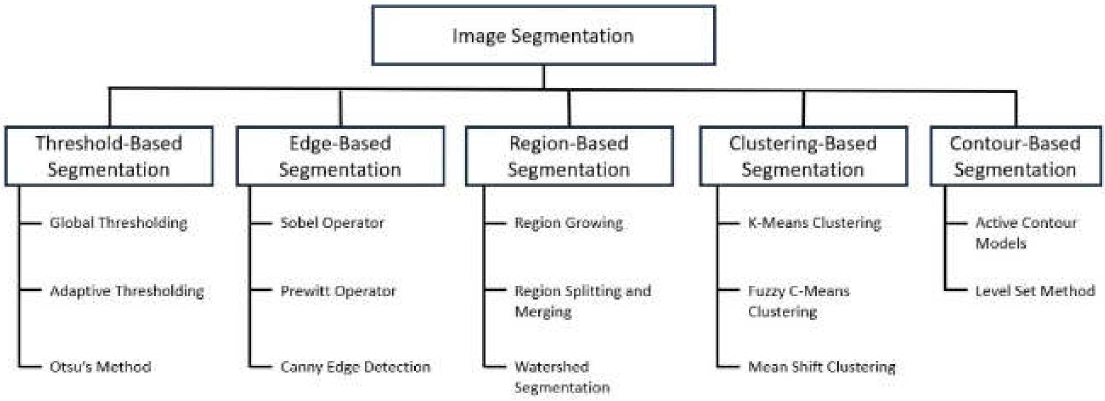

Figure 3: Image Segmentation Techniques

3.3 Feature Extraction

Feature extraction process involves the technique of identifying and extracting meaningful information or patterns from an image that can be used for classification, object detection, recognition and analysis. It plays a very important role in dimensionality reduction, performance improvement of the model, and focusing on more relevant information.

Following are the few feature extraction techniques:
Texture Based Techniques: It generally focuses on pixel intensities of an image.

(i) Gray-Level Co-occurance Matrix (GLCM): It works for the relationships between pixels of an image. And also, helps to compute metrics like contrast, correlation, energy and homogeneity.
(ii) Local Binary Patterns (LBP): It compares the encoded texture of each pixel with the neighboring pixel.

Color-Based Technique: This technique extracts color histograms, mean values, and color space transformations for disease symptoms with distinctive color patterns.

(i) HSV and LAB Color Spaces: Extracting color information like hue, saturation, and brightness/contrast helps capture discoloration caused by disease.
(ii) Statistical Metrics: Mean, standard deviation, and histogram features from color channels provide quantitative descriptions of color intensity and distribution, useful for spotting color-based disease symptoms like yellowing or browning.

Shape Features: In shape feature extraction, features like calculating area, perimeter, aspect ratio, and circularity of disease spots are extracted.

(i) Contour Analysis: Extracts boundary information from affected areas, helping identify irregular shapes formed by lesions or infections.
(ii) Area, Perimeter, and Shape Descriptors: Quantitative descriptors, such as aspect ratio and compactness, are calculated from segmented areas to detect the shape characteristics of diseased spots.

IV Approaches and Result

Three types of approaches are experimented such as machine learning algorithms, deep learning algorithms and hybrid algorithms.

4.1 Approaches of Machine Learning Models for Rice Plant Disease Detection

Support Vector Machine (SVM) is a supervised classifier that effectively classifies diseased and healthy rice plants based on discriminative features extracted from images. This research work also applies image pre-processing such as segmentation in HSV and LAB color-space and features such as colored histograms are computed.
These features form a vector $x \epsilon \mathbb{R}^n$ and the SVM finds an optimal decision boundary that maximizes the margin between classes.
For binary classification, the SVM solves the following optimization problem:

$$\min_{\omega,b,\xi} \frac{1}{2}||w||^2 + C\sum_{i=1}^{N} \varepsilon_i$$

subject to,

$$y_i(\omega^T \emptyset(x_i) + b) \geq 1 - \varepsilon_i, \varepsilon_i \geq 0, i = 1, \ldots., N$$

where:

- ω and b define the hyperplane $\omega^T x + b = 0$,
- $y_i \in \{-1, +1\}$ represents the class label for the ith sample
- ε_i are the slack variables that allow for misclassification

- C is the regularization parameter controlling the trade-off between the maximizing the margin and minimizing the classification error.
- $\emptyset(x_i)$ is a feature mapping function, often implemented implicitly via kernel functions (e.g., the Radial Basis Function (RBF) kernel) to handle non-linearly separable data.

From the Figure 4

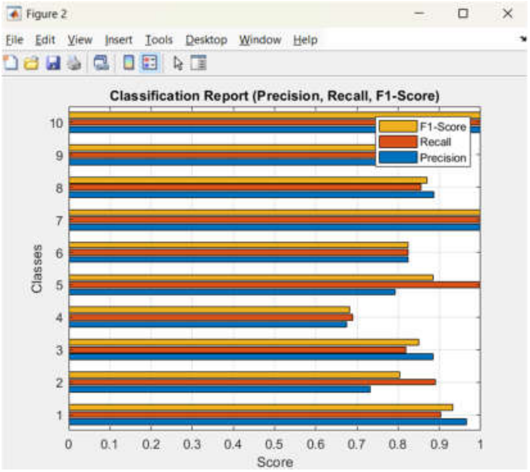

Figure 4: SVM Classification Report of 10 different Rice Plant diseases

Random Forest is an ensemble learning method that builds multiple decision trees during training and outputs the class of the classes predicted by individual trees. Features such as color, texture and shape are extracted from the rice plant images and is given as an input to Random Forest Classifiers.

The Figure 5 presents a classification report in the form of a horizontal bar chart, illustrating the precision, recall, and F1-score for a multi-class classification model. The x-axis represents the score, ranging from 0 to 1, where 1 indicates perfect classification performance. The y-axis denotes different classes (1 to 10), suggesting that the model is classifying 10 different categories. The three-evaluation metrics—precision (blue), recall (orange), and F1-score (yellow)—are visualized for each class. Precision measures the proportion of correctly predicted instances out of all predicted instances for a given class, while recall determines the proportion of correctly identified positive instances from all actual instances of a class. The F1-score balances these two metrics, providing a harmonic mean of precision and recall.

From the visualization, it is evident that the performance varies across different classes. Some classes exhibit high precision, recall, and F1-scores, indicating that the model performs well in distinguishing those categories. However, certain classes—such as class 6 and class 4—show lower recall values, meaning that the model is missing actual cases, leading to higher false negatives. Similarly, some classes have relatively lower precision, suggesting higher false positives where incorrect classifications are being made. The overall classification performance appears strong, with most classes achieving scores close to 0.8 to 0.9, indicating a highly accurate model.

Figure 5: Random Forest Classification Report of 10 different Rice Plant diseases

K-nearest neighbors (KNN) is a straightforward yet effective algorithm for rice plant disease detection: after extracting relevant features from leaf images—such as color histograms, texture descriptors, and shape metrics—KNN classifies a new sample by comparing its feature vector to those of its closest neighbors in the training set. Essentially, it computes the distance (e.g., Euclidean) between the new leaf's features and those of known healthy or diseased samples, then assigns the class based on a majority vote among the k nearest neighbors. In the Figure 6, a classification report is shown where each horizontal bar represents a performance metric (precision, recall, and F1-score) for a particular disease class (labeled 1 through 10). Precision indicates how many of the samples predicted for a given class were actually correct, recall reflects the proportion of actual class samples correctly identified, and F1-score is the harmonic mean of precision and recall. Higher bars imply better performance; thus, if a certain class shows bars near 1.0, it means KNN performed well in distinguishing that disease from others. Conversely, shorter bars suggest that the algorithm may have confused that class with others, highlighting the importance of robust feature extraction and an optimal k value to ensure reliable detection of rice plant diseases.

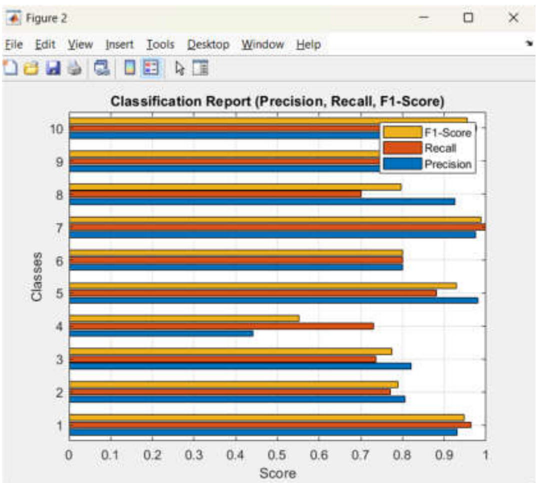

Figure 6: KNN Classification Report of 10 different Rice Plant diseases

4.2 Approaches of Deep Learning Models for Rice Plant Disease Detection

VGG19 is a deep convolutional neural network. VGG19 consists of 19 layers [16 convolutional layers + 3 fully connected layers] arranged with ReLU activations. VGG19 model is used to train 3000 images. Firstly, images are preprocessed (image size is considered as 256 X 256 X 3). Features such as edges, textures are extracted. The per-class accuracy Figure 7 demonstrates the classification of rice plant diseases effectively by achieving the accuracy of 90.23%.

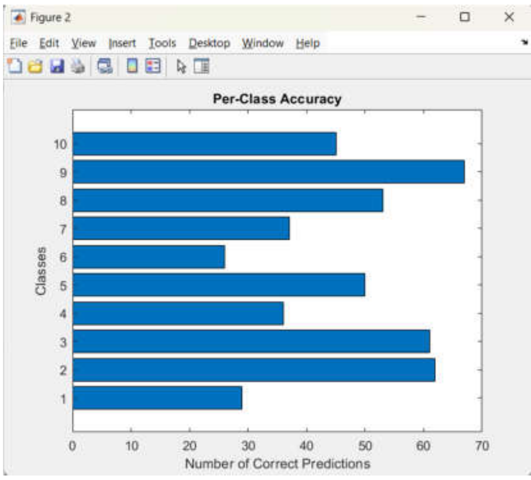

Figure 7: Per Class Accuracy of VGG19 for rice plant disease detection

MobileNetv2 is a lightweight convolutional neural network (CNN) architecture well-suited for resource-constrained environments, making it an attractive choice for rice plant disease detection on mobile or embedded devices. By employing depth-wise separable convolutions and inverted residuals, MobileNetv2 drastically reduces the number of parameters while preserving feature extraction capabilities, thereby enabling rapid inference and efficient memory usage. In the Figure 8, each horizontal bar indicates the per-class accuracy—specifically, the number of correctly predicted samples for each disease class (labeled 1 through 10). A longer bar means the model classified more samples correctly for that class, suggesting better performance; shorter bars reveal classes that the model struggled to identify consistently. Thus, if class 10 shows the longest bar (e.g., around 70 correct predictions), it implies MobileNetv2 was especially adept at recognizing that particular disease, while classes with fewer correct predictions may require further refinement, such as additional data or more targeted augmentation, to improve the model's overall accuracy in rice plant disease detection.

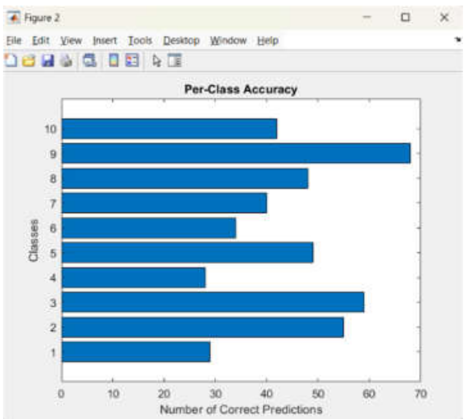

Figure 8: Per Class Accuracy of MobileNetv2 for rice plant disease detection

NasNet is a deep learning architecture discovered via neural architecture search (NAS), which systematically explores possible network configurations to maximize accuracy and efficiency. In the context of rice plant disease detection, NasNet automatically learns hierarchical features from leaf images, enabling it to distinguish among multiple disease classes with minimal manual design effort. NASNet stacks cells discovered by neural architecture search. Each cell has multiple input nodes B_j and a set of candidate operations Op_{ij}. The cell's output O_i can be written as:

$$O_i = \sum_{j\in I} \alpha_{ij} Op_{ij}(B_j),$$

where α_{ij} = are learnable coefficients weighting the chosen operations. Reduction cells decrease the spatial dimension, while normal cells preserve it.

In the Figure 9, each horizontal bar indicates the number of correct predictions for a given disease class (labeled 1 through 10), illustrating the per-class accuracy achieved by NasNet. Longer bars, such as for class 10 or class 9, signify that the model performed particularly well at identifying those diseases, whereas shorter bars for certain classes suggest areas where the model may require further training data or architectural fine-tuning. Overall, this chart demonstrates how effectively NasNet generalizes to different disease categories, while also highlighting classes that might benefit from additional refinement to further boost detection accuracy.

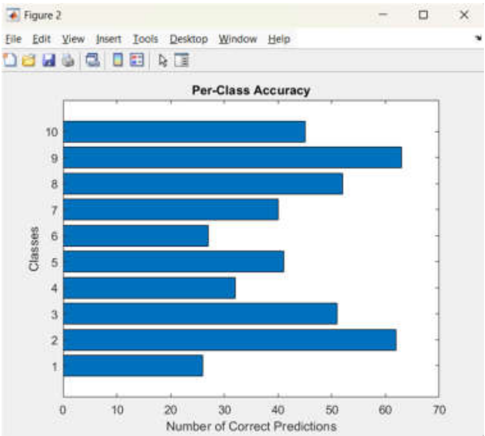

Figure 9: Per Class Accuracy of NasNet for rice plant disease detection

DenseNet201 is a deep convolutional neural network architecture that connects each layer to every other layer in a feed-forward fashion, promoting efficient feature reuse and stronger gradient flow. In rice plant disease detection, this design helps DenseNet201 learn both low-level and high-level patterns from leaf images, enabling it to identify diverse symptoms such as discoloration, lesions, and shape deformations with fewer parameters than many other deep models. A DenseNet block with L layers can be expressed as:

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

where, $[x_0, x_1, \ldots, x_{l-1}]$ denotes feature-map concatenation and $f_l(\cdot)$ is typically,

$$(\text{BN} \rightarrow \text{ReLU} \rightarrow 3 \text{ X } 3 \text{ Conv})$$

The growth rate k controls the number of output feature maps per layer.
Transition Layer: $x_{out} = g(x_{in}) = Conv(BN(Pool(x_{in})))$.

In the Figure 10, each horizontal bar represents the per-class accuracy for one of ten disease classes, showing how many samples of each class were correctly predicted by DenseNet201. Longer bars, like those for classes 9 and 10, indicate stronger performance on those diseases, whereas shorter bars for certain classes highlight areas where the network may benefit from additional data or targeted augmentation. Overall, this chart illustrates DenseNet201's capacity to discriminate among multiple rice diseases while also suggesting potential refinements to further enhance classification accuracy.

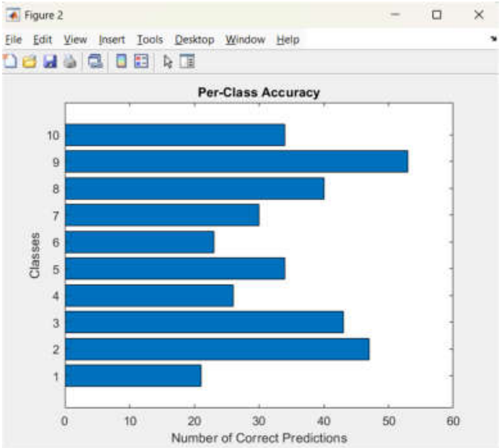

Figure 10: Per Class Accuracy of DenseNet201 for rice plant disease detection

From the Figure 11 with an accuracy of 79%, this CNN model provides a moderate performance level for rice plant disease detraction. The accuracy for different classes varies, indicating that some categories are classified more accurately than others. Classes 9 and 10 have the highest number of correct predictions, suggesting that the model is particularly effective in identifying these categories. Classes 4, 5, and 6 show significantly lower correct predictions, indicating that the model struggles to classify these classes accurately, leading to higher misclassification rates. Classes 1 and 6 have the lowest number of correct predictions. The mid-range accuracy observed for Classes 7 and 8 suggests moderate classification performance.

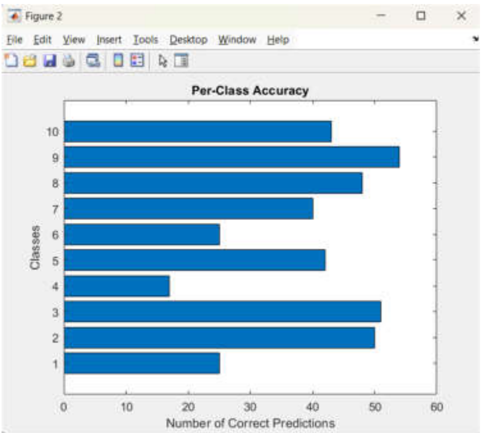

Figure 11: Per Class Accuracy of CNN for rice plant disease detection

V Conclusions

Machine learning and deep learning have significantly improved rice plant disease detection, enabling faster and more accurate classification compared to traditional manual methods. While traditional ML models such as SVM, Random Forest, and KNN rely on handcrafted features and perform well on small datasets, they struggle with complex image-based disease patterns. Deep learning approaches, particularly VGG19, NasNet, DenseNet201, CNNs, and MobileNetv2, automate feature extraction and achieve higher accuracy in image classification. Advanced hybrid models, such as SVM-CNN, Random Forest-CNN fusion, and MLCNN, integrate multiple techniques to further enhance performance, often surpassing 95% accuracy. However, challenges like class imbalance, computational cost, and real-time deployment persist. Future research should focus on efficient lightweight models, IoT-based real-time applications, and quantum-enhanced deep learning to further advance precision agriculture and improve global rice crop health.

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