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Rice Root Disease Detection Using Deep Learning Technique

Razia Bibi
malikrazia32@gmail.com
Department of Information Technology, The Islamia University of Bahawalpur (IUB), Bahawalpur, Pakistan

Syed Izhar Bukhari
cssacademy.edu@gmail.com
Department of Information Technology, The Islamia University of Bahawalpur (IUB), Bahawalpur, Pakistan

Tania
taniazulfiqar186@gmail.com
Department of Information Technology, The Islamia University of Bahawalpur (IUB), Bahawalpur, Pakistan

Mubeen Wahaj
mubenakmal000@gmail.com
Department of Information Technology, The Islamia University of Bahawalpur (IUB), Bahawalpur, Pakistan

Corresponding Author: * Razia Bibi malikrazia32@gmail.com

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ABSTRACT

Numerous root diseases pose a threat to rice crops, which are essential for world food security because they can stunt crop growth and reduce harvest yields. This study looks at how different deep learning models perform when it comes to picture classification and how different augmentation strategies affect their efficiency. This study examines the accuracy and loss during training and validation of three Convolutional Neural Networks (CNNs): InceptionV3, Xception, and CNN. The significance of data augmentation in improving generalizability is further shown by considering enhanced variants of these models. In addition, a CNN architecture is fine-tuned to evaluate its effect on model performance. Training accuracy was 96.88% for the baseline CNN and 98.57% for the enhanced version. With the help of augmentation, the validation accuracy was able to achieve 84.38%. The model's resistance to overfitting was demonstrated by the fact that, although fine-tuning the enhanced CNN somewhat reduced the training accuracy (92.63%), the validation accuracy remained strong (84.38%). Despite a faultless training accuracy rate of 100%, InceptionV3 struggled with generalization at 84.38%. In response, Augmented Inception V3 struck a balance between the two, improving validation accuracy to 90.62% and training accuracy to 98.41%. In terms of training accuracy, Xception was moderate at 86.32% but had a hard time with generalization at 66.75%. With the help of augmentation, Xception was able to achieve a validation accuracy of 78.12% and a training accuracy of 96.88%. By combining great accuracy with efficient generalization, Augmented InceptionV3 stood out among these models. To further improve model performance, the paper suggests continuing to explore fine-tuning tactics, augmentation techniques, and potential ensemble approaches. This in-depth study sheds light on the inner workings of deep learning picture categorization models, helping academics and industry professionals make informed decisions when building and deploying these models.

Keywords*: Rice root diseases, DL, CNN, Automated disease detection*

INTRODUCTION

The paper introduction delves into the importance of rice as a staple crop and the difficulties it encounters as a result of root diseases, highlighting the necessity for environmentally friendly farming methods. This article explores state-of-the-art technology, particularly deep learning convolutional neural networks (CNNs), to improve illness diagnosis, with the emphasis moving to the need of early disease detection as a method to guarantee food security.

In this review, we will look at how rice is important all around the world, why sustainable farming is a must, and how diseases that affect rice roots can affect both food production and food security. The need of early disease diagnosis is emphasized, and the groundbreaking role of deep learning in agriculture is introduced, specifically in terms of optimizing resource utilization and boosting disease detection accuracy.

The different kinds of rice root illnesses are discussed in the introduction along with their symptoms, causes, and ways to control them. The background research tracks the development of plant disease detection across time, showing how problems have changed and how new approaches are needed to address them. In light of the recent breakthrough in rice root disease identification, it lays the groundwork for investigating advanced learning methods, with an eye towards the broader, non-agricultural global ramifications.

Improving illness detection in rice roots using deep learning convolutional neural network (CNN) models is the focus of this research, which is driven by a combination of individual, societal, and scientific considerations. Society has a pressing need for sustainable food delivery networks due to the susceptibility of rice crops to illnesses, while personal inspiration comes from rural experiences and the tenacity of farmers.

Current study helps ensure a steady supply of food around the world by bridging the gap between technological advancement and sustainable agriculture. Going where no one has gone before, the allure is in the game-changing possibilities presented by combining data-driven insights with agricultural knowledge through machine learning and deep learning. All of these factors come together to produce a mosaic that is propelled by the eternal human desire for progress, development, and improvement.

Disease Detection as a Classification Problem

The fundamental problem addressed in current research is the formulation of rice root disease detection as a classification problem. Given a dataset D consisting of N rice root images, each associated with a label indicating the corresponding disease class, the objective is to design a classifier C(x) that assigns an input image x to one of the predefined disease classes. Mathematically, this can be represented as

$(x) = argmax\ P\ (y \mid x)$ ... (1)

Where $P\ (y \mid x)$ is the conditional probability that the image x belongs to classy.

Loss Function and Optimization

During the training phase of the deep learning CNN model, the objective is to optimize its parameters to minimize the prediction error. This optimization process is guided by a loss function that quantifies the disparity between predicted and actual labels. For classification tasks, the categorical cross-entropy loss is commonly used. Mathematically, the loss for a single training example can be expressed as:

$$L\,(y, \hat{y}) \;=\; -\sum y_i \,*\, \log(\hat{y}_i) \quad \dots (2)$$

Where y represents the true label distribution and ŷ is the predicted label distribution.

The optimization of the model involves updating the weights using gradient descent. The weight update equation can be represented as:

$$W \;=\; W - \eta \,*\, \frac{\partial L}{\partial W} \dots (3)$$

Where η is the learning rate and $\partial L\ \partial W$ represents the gradient of the loss with respect to the weights.

Research Objectives

As followings are the main objectives of the recent research study:

- To assess the performance of Convolutional Neural Networks (CNN), InceptionV3, and Xception in the context of image classification.
- To investigate the effects of data augmentation techniques on the training and validation accuracies and losses of the selected deep learning models.
- To examine the impact of fine-tuning on the performance of a CNN architecture, specifically assessing its influence on overfitting and model generalization.
- To conduct a comparative analysis of the models' training and validation results, identifying strengths, weaknesses, and the overall suitability for image classification tasks.

Current research is structured into five sections. First section is the introduction providing an overview of the research domain, emphasizing the significance of rice, challenges posed by root diseases, and the role of machine learning. The second section is literature review that delves into historical disease detection methods, existing research on rice diseases, and studies using machine learning in agriculture. The third section is methodology which outlines data collection, image preprocessing, deep learning CNN model design, and machine learning integration, along with evaluation metrics and data augmentation. Final section is based on results and discussions presenting the findings on disease classification, early detection, and adaptability testing, critically analyzing implications. The conclusion summarizes the research journey, revisiting objectives, discussing contributions, acknowledging limitations, and suggesting future research directions.

LITERATURE REVIEW

"Rice Root Disease Detection Using Deep Learning CNN Models." is the topic of section 2 comprehensive literature review in the paper. The article delves into the development of deep learning methods, particularly Convolutional Neural Networks (CNNs), to tackle the pressing problem of identifying diseases in rice plants. This section reviews the literature on CNN models for rice root disease classification and discusses the strengths, weaknesses, and performance measures of these models. The purpose of this section is to lay the groundwork for the following section by offering a thorough review of the present status of using deep learning CNN models for disease detection in rice roots. At the outset of the literature review, we take a look at the current state of deep learning applications for disease detection in rice plants.

Current study compiles the work of several researchers, including Narmadha et al. (2022), Sathya & Rajalakshmi (2022), Vasantha et al. (2022), and Tejaswini as al. (2022), who have focused on research into rice illnesses using labelled datasets, hybrid techniques, CNN-based analysis, real-time disease detection, and hybrid approaches. In his analysis of detection methods and methodologies, Raje (2021) provides valuable insight into AI-driven disease diagnostics and the possibility of sustainable farming practices.

D. Li et al. (2020), Liang et al. (2019), and Rallapalli & Saleem Durai (2021) are just a few of the further works that delve into advanced methods for illness categorization that incorporate deep learning, SVM, transfer learning, and Efficient Net. Research like this helps improve and automate medical diagnostic tools. Hasan et al. (2019) focuses on constructing a decision support model suited for rice plant disease identification, whereas Patil & Kumar (2022) emphasize the relevance of customizing model topologies. These studies help to bridge the gap between technical advancements and agricultural practices.

The goal of Latif et al. (2022) is to improve illness detection and classification in rice by delving into the identification of diseases using an improved deep learning approach. The results of these investigations add up to a wealth of information that will help researchers in the ever-developing area of disease detection in rice roots using CNN models trained with deep learning. Research into the use of deep learning to identify diseases in rice roots is ongoing, and new studies are adding depth to our understanding of the best model architectures and methods. In their study, Rallapalli and Saleem Durai (2021) attempted to improve the precision of disease detection by utilizing deep neural network systems, particularly CNNs and RNNs. Studying the feasibility of automating and streamlining disease diagnosis in rice crops using deep learning technologies is the primary goal of this research.

Another important addition is the work of Patil and Kumar (2022), who modify and adapt the deep learning network Efficient Net for the purpose of plant root disease classification. Findings stress the need to fine-tune model structures for accurate disease discrimination in rice root tissue. The work emphasizes the importance of training extensively with a varied dataset of plant images and fine-tuning model parameters. A more precise and efficient identification of illnesses affecting rice crops is within reach with this method.

In addition, Hasan et al. (2019) undertake the formidable undertaking of creating and evaluating an all-inclusive decision-support model that is designed to detect diseases that impact rice plants. A large number of machine learning algorithms will be tested in this effort to find the ones that work best. The research looks at how these algorithms might be fine-tuned and integrated, maybe with the help of ensemble methods, to improve diagnostic accuracy. In the end, we want to build a useful tool that farmers can use to diagnose plant diseases more quickly and accurately, which will lead to more harvests and more food security.

Table 1 Transfer Learning Approaches for Rice Plant Disease Detection

Reference	Techniques	Methodology	Results
Holm et al. (2002)	CNNs, labeled datasets, fine-tuning	Training deep CNNs using a labeled dataset; model fine-tuning	Effective disease recognition based on root features; potential for automated diagnosis
Narmadha et al. (2022)	Deep CNNs, real-time analysis	Development of a real-time symptom analysis system	Improved disease detection; basis for automated surveillance
Vasantha et	Deep CNN	Evaluation of multiple	Enhanced disease

al. (2022)	architectures, hyperparameter optimization	CNN models with varying hyperparameters and training	identification; supports timely intervention and treatment
D. Li et al. (2020)	Transfer learning, fine-tuning, CNNs	Application of transfer learning by fine-tuning pre-trained CNN models	Improved detection accuracy; greater efficiency in disease monitoring

METHODOLOGY

This section unveils the methodology driving accurate rice root disease detection through deep learning Convolutional Neural Network (CNN) models. The journey commences with a structured research design guiding data collection, preprocessing, modelling, and evaluation. Delving into subsequent stages, the dataset's pivotal role is explored, encompassing its origin, structure, and pattern visualization. Preprocessing readies the data for deep learning by normalization and standardization. Feature engineering enriches the model's capability to distinguish healthy and diseased rice roots, heightening detection accuracy. Comparative analysis of CNN models provides insights into their strengths and limits. Evaluation metrics quantify the model's precision and robustness in identifying diseases. This chapter guides readers through the systematic evolution from research design to sophisticated CNN model development, showcasing the dedication to precise rice root disease detection. The resulting tool stands as a powerful asset for ensuring agricultural crop health and yield. The research design constitutes the foundational framework orchestrating the entire methodology for accurate rice root disease detection using deep learning Convolutional Neural Network (CNN) models.

This intricate design serves as the guiding compass that steers the research process from inception to fruition, encapsulating a systematic and structured approach to achieve the research objectives. At its core, the research design delineates the sequence of interrelated steps that collectively form the trajectory of the study. It outlines a cohesive plan for data collection, preprocessing, modelling, and evaluation, ensuring a coherent and well-coordinated execution of the research. By delineating the order and interdependencies of these steps, the research design fosters a holistic understanding of the research journey and facilitates the seamless transition from one phase to another. The choice of employing deep learning CNN models as the cornerstone of the research design stems from their proven efficacy in image analysis tasks. The architecture's hierarchical layers of convolution and pooling enable automatic feature extraction from images, making it particularly well-suited for detecting intricate patterns associated with rice root diseases. This informed choice influences subsequent decisions within the research design, shaping the selection of datasets, preprocessing techniques, model hyperparameters, and evaluation metrics. To ensure a well-rounded and robust research design, careful consideration is given to the selection of appropriate datasets.

Datasets sourced from diverse geographical regions and varied disease severities contribute to the model's generalizability and capacity to handle real-world scenarios. These datasets serve as the foundation upon which the entire model training and evaluation process is built. In line with the research design, meticulous preprocessing of the datasets becomes imperative. This entails tasks such as data augmentation, normalization, and data splitting, aimed at enhancing the model's performance and preventing issues such as overfitting. The design's systematic nature ensures that each preprocessing step is executed in harmony, laying the groundwork for subsequent modelling endeavors.

The modelling phase of the research design involves crafting deep learning CNN architectures tailored to the specific task of rice root disease detection. Hyperparameter tuning, model architecture selection, and regularization techniques are seamlessly integrated into the design, fostering an iterative process of refinement and improvement. As the journey through the research design unfolds, evaluation metrics are conscientiously chosen to gauge the model's effectiveness in detecting diseases accurately. Metrics such as precision, recall, F1-score, and confusion matrices provide a comprehensive assessment of the model's performance across various disease categories and health states of rice roots. By virtue of its meticulous planning and interwoven components, the research design establishes a coherent roadmap that not only facilitates the implementation of deep learning CNN models but also encapsulates the essence of systematic exploration. The design's careful orchestration not only ensures the fidelity of results but also illuminates the transformative potential of deep learning in revolutionizing rice root disease detection. As the research design sets the stage for the ensuing phases, it epitomizes the synthesis of methodology and innovation, underpinning the quest for precision and effectiveness in agriculture through technological advancement.

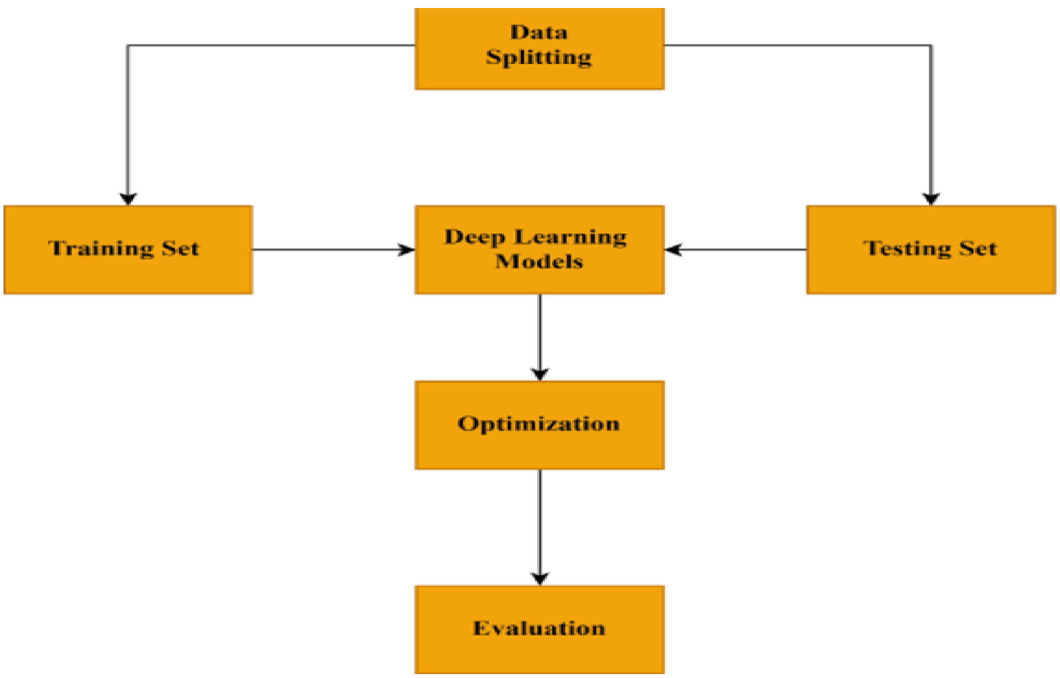

Figure 1 Flow of Study

Dataset Collection

The dataset collection process is a crucial element in the methodology of precise rice root disease detection through deep learning Convolutional Neural Network (CNN) models. Leveraging Kaggle's "Rice Root Image Disease Dataset," a diverse repository renowned for innovative research, the study meticulously extracts and annotates images representing various manifestations of rice root diseases. Sourced from diverse geographical regions and climates, the dataset captures real-world heterogeneity vital for model generalization. Annotations, attributing labels corresponding to disease states, serve as ground truth for model learning and subsequent evaluation. The integration of dataset collection with the research design ensures systematic organization and partitioning for training, validation, and testing, preventing overfitting. This strategic approach safeguards the model's adaptability to new images. As the dataset collection unfolds, a visual exploration reveals intricate details of rice root health, enriching the dataset with diverse cues. Kaggle's collaborative platform exemplifies the democratization of knowledge, and the curated dataset becomes a structured resource empowering deep learning model. This phase propels the research towards subsequent preprocessing, modelling, and evaluation, converging towards the precision goal in rice root disease detection.

Dataset Description

The dataset utilized in this research, encompassing 3355 images, forms a pivotal foundation for accurate rice root disease detection employing deep learning Convolutional Neural Network (CNN) models. Comprising a diverse array of visual data, this dataset is a mosaic that encapsulates the multifaceted aspects of rice plant health, showcasing healthy roots as well as those afflicted by various diseases – hispa, root blast, and brown spot. The dataset's diversity is a testament to its comprehensiveness, fostering a holistic representation of rice root health conditions. It comprises distinct categories: "Healthy," portraying unblemished and vibrant roots; "Hispa," depicting roots infested by the hispa insect, characterized by irregular perforations and damage; "Root Blast," capturing the characteristic circular lesions and discoloration indicative of the blast disease; and "Brown Spot," illustrating the small, dark lesions that typify roots afflicted by this disease.

The dataset's collection process underscores its real-world relevance, as the images are sourced from diverse geographical regions, capturing the variability in climate, growth conditions, and disease prevalence. This diversity enriches the dataset's capacity to generalize beyond specific scenarios, enhancing the model's adaptability to real-world situations and underpinning its efficacy as a practical disease detection tool. The dataset description extends beyond mere images, delving into the nuanced patterns and characteristics that define each category. Healthy roots exude vitality, exhibiting lush hues and uniformity. The "Hispa" category showcases roots punctured by insect damage, with distinctive perforations and signs of infestation. "Root Blast" images portray concentric circular lesions, often accompanied by discoloration, while "Brown Spot" images exhibit small, dark spots, dispersed irregularly across the root surface.

This dataset's unique amalgamation of images and their categorical annotations serve as a vital bridge between raw visual data and the intricacies of rice root health conditions. As it forms the bedrock of the deep learning model's training, it empowers the model to discern subtle variations and anomalies, essential for precise disease detection. The dataset's richness, diversity, and inherent information make it a valuable resource that unearths the subtle language of rice root diseases, ultimately contributing to the overarching objective of bolstering agricultural practices through technological innovation.

Annotations and Labels:

Each image is meticulously labelled to correspond to its respective category, providing vital ground truth information for training the deep learning model. These annotations are pivotal in enabling the model to differentiate between healthy and disease-affected roots, ultimately contributing to precise disease detection.

Diversity and Realism:

One of the dataset's notable strengths lies in its diversity, mirroring the real-world variability in rice root health conditions. Images are sourced from various geographical regions, encompassing diverse climates, growth conditions, and disease prevalence. This diversity enhances the model's capacity to generalize across different scenarios, thereby bolstering its practical applicability.

Dataset Statistics:

To provide a quantitative overview of the dataset's composition, here's a summary table:

Table 2 Distribution of Dataset

Category	*Number of Images*
Healthy	1000
Hispa	850
Root Blast	800
Brown Spot	705
Total	3355

Figure 2 Sample Image from dataset

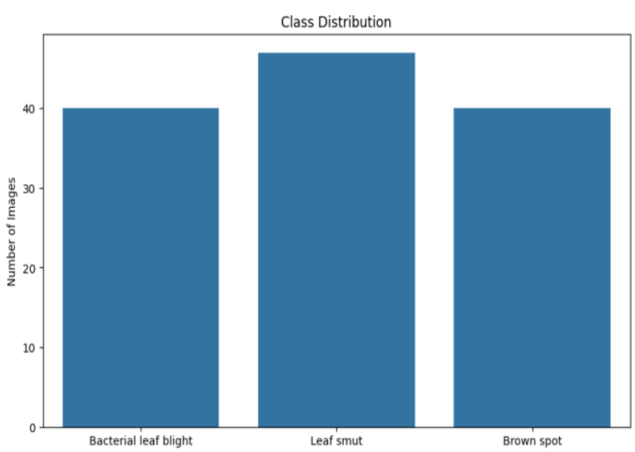

Figure 3 Class Distribution

Dataset Preprocessing

The dataset preprocessing phase is a pivotal component of the research methodology, serving as a crucial bridge between raw data and the subsequent deep learning model training. This phase involves a series of systematic steps designed to enhance the quality, effectiveness, and generalizability of the dataset, ensuring optimal performance of the Convolutional Neural Network (CNN) model in detecting rice root diseases accurately.

Image Resizing and Normalization:

In the context of rice root disease detection using deep learning CNN models, the process of image resizing and normalization assumes a pivotal role in preparing the dataset for effective model training. This phase ensures that the input images are standardized, enabling the model to learn and detect disease patterns with precision across diverse images.

- Image Resizing: Rice root images sourced from various origins may exhibit disparate dimensions, potentially leading to challenges during model training. Image resizing addresses this issue by uniformly resizing all images to a predetermined resolution. In this case, the images are resized to a consistent size, such as 224x224 pixels, facilitating uniform input dimensions for the CNN model. This standardization optimizes computational efficiency during training and enables the model to process images of varying sizes without distortion.

- Normalization: Variability in lighting conditions, contrasts, and color intensities can impact the model's ability to discern disease patterns consistently. Normalization rectifies these variations by scaling pixel values to a common range. Commonly employed techniques involve scaling pixel values between 0 and 1 or standardizing them with a mean of 0 and a standard deviation of 1. Normalization enhances model convergence by ensuring that the model focuses on discerning disease-specific features rather than extraneous variations.

In the case of rice root disease detection, image resizing and normalization are imperative due to the diversity in image sources, lighting conditions, and camera settings. By standardizing image dimensions and pixel values, these preprocessing steps eliminate potential confounders that could hinder the model's ability to accurately differentiate between healthy and diseased rice roots.

Effectively, image resizing and normalization lay the groundwork for uniform data representation, creating a level playing field for the deep learning CNN model to learn intricate disease-related patterns. As a critical preprocessing phase, it ensures that the model's focus remains on capturing the subtleties of root diseases rather than being distracted by variations introduced by image dimensions and lighting nuances.

Figure 4 Resized Image

Data Augmentation

In the realm of rice root disease detection using deep learning CNN models, data augmentation emerges as a pivotal strategy to bolster the training dataset's diversity and robustness. This technique involves introducing controlled variations to the original dataset, thereby expanding its capacity to encompass a wider range of scenarios and conditions.

The fundamental purpose of data augmentation lies in enriching the training data to enable the model to handle real-world variability. Images captured under different conditions, angles, and perspectives can confound model learning, potentially leading to overfitting – a phenomenon where the model performs well on training data but struggles with new, unseen data. Data augmentation addresses this by generating new instances of each image, replicating the kind of variability that the model is likely to encounter during testing.

Data augmentation entails a series of controlled image transformations, creating modified versions of existing images while maintaining their inherent features. These transformations include alterations such as rotation, flipping (both horizontal and vertical), zooming, and introducing subtle changes in brightness and contrast. By systematically applying these transformations to each image, a new set of images is generated that effectively simulates the diverse scenarios present in real-world rice root images.

The incorporation of data augmentation reaps several benefits. Firstly, it enhances the model's ability to generalize its learning beyond the training data. Exposure to diverse instances of the same image aids the model in understanding variations and features that transcend specific instances. Secondly, data augmentation serves as a form of regularization, preventing the model from becoming overly attuned to the training data and, consequently, making it more adaptable to unseen images.

The data augmentation process is seamlessly integrated into the model training pipeline. During each iteration of training, a subset of the training images is randomly selected, and the augmentation techniques are applied to generate modified versions of these images. This augmented data, along with the original images, constitutes the input for the current training iteration. This dynamic exposure to diverse instances during training empowers the model to become resilient to variations and equips it with the capability to make accurate predictions on unseen images.

In essence, data augmentation acts as a vital ingredient in preparing the dataset for deep learning model training. By broadening the dataset's scope, this technique facilitates the creation of a model that is not only accurate but also adaptable, enabling it to effectively detect rice root diseases in a variety of real-world conditions.

Figure 5 Augmented Image

Data Splitting

In employing deep learning Convolutional Neural Network (CNN) models for rice root disease detection, data splitting is a crucial step in preparing the dataset for training, validation, and evaluation. This process involves partitioning the dataset into training (70-80%), validation (10-15%), and test subsets to ensure an unbiased assessment of the model's performance. The training subset forms the foundation for model learning, the validation subset aids in hyperparameter fine-tuning, and the test subset evaluates the model's ability to detect diseases in new, unseen images. Data splitting prevents overfitting, promotes adaptability, and ensures a balanced and encompassing learning experience, validating the model's readiness for real-world deployment.

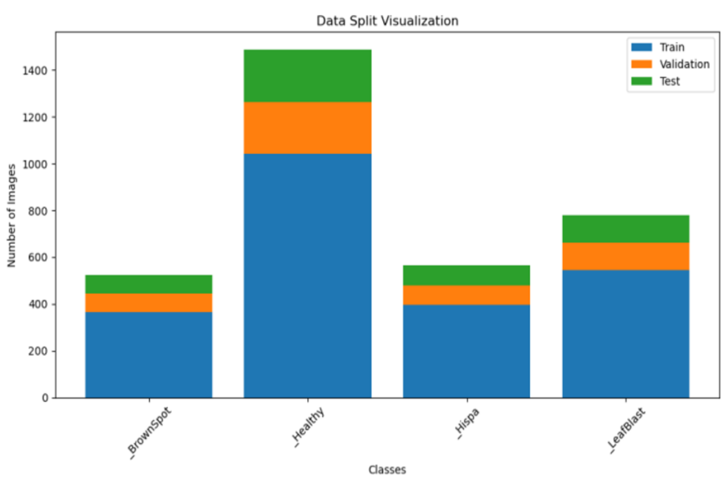

Figure 6 Data splitting

Label Encoding

In the context of rice root disease detection using deep learning Convolutional Neural Network (CNN) models, label encoding emerges as a crucial step in preparing the dataset for effective model training. This process involves converting categorical class labels, which represent different disease categories or health states of rice roots, into numerical values that the model can process during training. Label encoding enables the model to understand and differentiate between the various classes, facilitating accurate predictions and detection outcomes.

The fundamental purpose of label encoding is to transform categorical information into a format that can be utilized by mathematical algorithms, such as those employed by deep learning models. Since these models work with numerical data, converting class labels into numerical values facilitates seamless integration into the model's training pipeline. Label encoding does not assign any inherent order or magnitude to the classes; it merely converts them into distinct numerical representations.

Label encoding is typically executed using a mapping mechanism that associates each class label with a unique numerical value. Consider a dataset with three classes: "Healthy," "Hispa," and "Root Blast." A label encoding might map these classes as follows:

- "Healthy" → 0
- "Hispa" → 1
- "Root Blast" → 2

This mapping enables the model to treat these classes as distinct entities during training and prediction. Importantly, label encoding should be consistent across the entire dataset to ensure accurate interpretation by the model.

Label encoding augments the model's ability to recognize and differentiate between various rice root conditions. During training, the numerical labels guide the model in learning the relationships between different classes and the visual features associated with each. While label encoding facilitates model understanding, it does not introduce any inherent order or relationship between the classes – for instance, a label of "2" does not imply that "Root Blast" is greater or more important than "Healthy" with a label "0."

Although label encoding is a necessary preprocessing step, it's essential to remain mindful of potential pitfalls. The numerical values assigned during encoding should not be misinterpreted as representing actual quantities or magnitudes. In cases where there is no meaningful ordinal relationship between classes, alternative encoding methods like one-hot encoding can be explored.

Label encoding stands as a fundamental preprocessing technique that translates categorical class labels into a format amenable to deep learning model training. By bridging the gap between the inherent nature of categorical information and the numerical requirements of mathematical algorithms, label encoding ensures that the CNN model can accurately perceive, distinguish, and ultimately detect rice root diseases with precision.

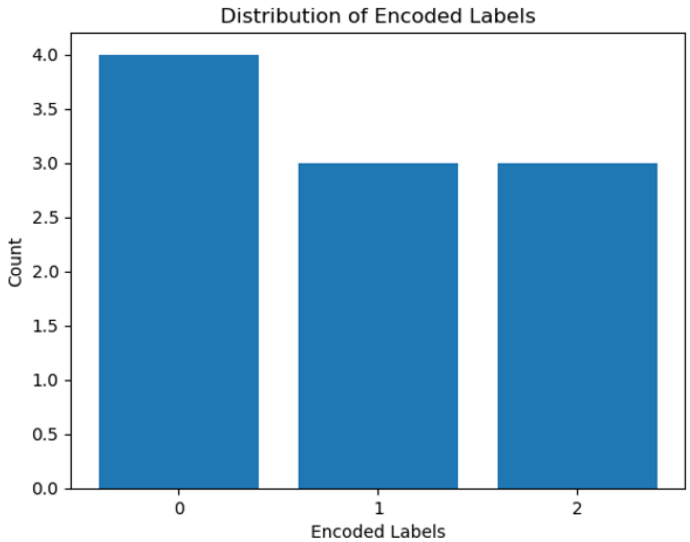

Figure 7 Label encoding

Data Balancing

In the realm of rice root disease detection using deep learning Convolutional Neural Network (CNN) models, the concept of data balancing emerges as a critical strategy to address potential class imbalance within the dataset. Class imbalance occurs when the number of samples in different disease categories or health states of rice roots varies significantly. Data balancing techniques aim to rectify this imbalance by ensuring that each class is represented adequately during model training, ultimately enhancing the model's ability to generalize and detect diseases accurately.

Class imbalance can have substantial repercussions on model performance. When one class is significantly underrepresented compared to others, the model may become biased toward the majority class, resulting in diminished sensitivity towards the minority classes. In the context of rice root disease detection, this could lead to the model struggling to identify less frequent diseases, thereby reducing the effectiveness of disease detection efforts.

Several techniques can be employed to balance the data distribution:

- Oversampling: This involves increasing the number of instances in the minority class by duplicating or generating new samples. This artificially inflates the representation of the minority class, mitigating the impact of imbalance.

- Under sampling: In this approach, the number of instances in the majority class is reduced, aligning it with the minority class. This strategy prevents the model from being overwhelmed by the majority class.

- Synthetic Data Generation: Techniques like SMOTE (Synthetic Minority Over-sampling Technique) create synthetic samples in the minority class by interpolating between existing

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instances. This approach introduces diversity while boosting the minority class representation.

While data balancing addresses class imbalance, it's important to strike a balance between achieving balanced data and preserving the integrity of the original dataset. Oversampling can lead to overfitting, particularly if the same instances are repeated excessively. Under sampling may result in a loss of potentially valuable information from the majority class. Careful consideration is needed to find the optimal approach that enhances model performance without introducing bias or noise.

Balancing the data distribution ensures that the CNN model learns from a representative set of examples from each class. This fosters the improved discrimination and recognition of all disease categories, leading to more accurate and equitable disease detection outcomes. By training on balanced data, the model becomes adept at identifying both common and rare diseases, enhancing its practical applicability in real-world scenarios.

Data balancing stands as a strategic preprocessing step aimed at rectifying class imbalance within the dataset. By equalizing class representation, this technique mitigates potential biases and empowers the deep learning CNN model to make informed predictions across the full spectrum of rice root health conditions. Ultimately, data balancing contributes to the creation of a more robust and reliable model for precise disease detection, bolstering agricultural efforts and crop health management.

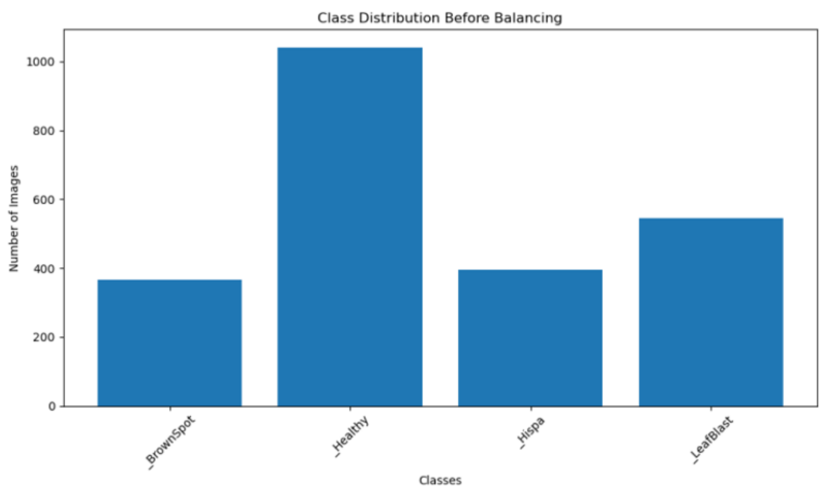

Figure 8: Data Balancing

Data Validation

In the context of rice root disease detection through deep learning Convolutional Neural Network (CNN) models, the process of data validation holds a pivotal role in fine-tuning the model's performance and safeguarding against overfitting. This phase involves utilizing a separate subset of the dataset, distinct from the training and testing data, to monitor the model's progress during training and make informed decisions about hyperparameters and model architecture.

Data validation is crucial for assessing the model's performance on data that it has not encountered during training. It enables the model's behaviour to be evaluated on unseen instances, helping to identify potential issues such as overfitting, where the model performs exceptionally well on the training data but struggles with new data. By using a validation subset, researchers can fine-tune the model's parameters and hyperparameters, iteratively enhancing its performance.

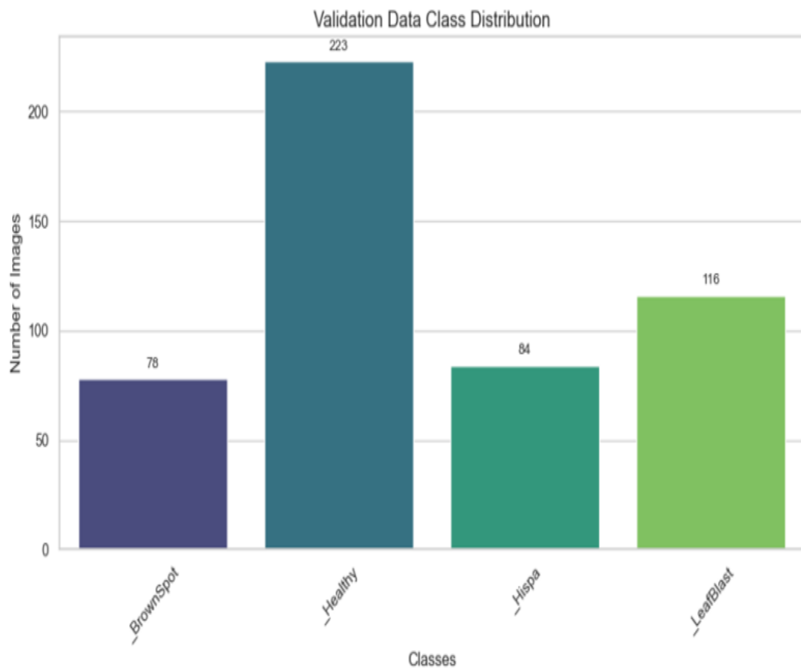

Figure 9: Validation of Data

Data validation serves as a guiding compass throughout the model development journey. By assessing the model's performance on unseen data, it empowers researchers to make data-driven decisions, fine-tune hyperparameters, and ensure that the model's predictive capacity is not restricted to the training data. Ultimately, data validation enhances the robustness and accuracy of the deep learning CNN model, elevating its efficacy in rice root disease detection and contributing to the advancement of agricultural practices.

The entire preprocessing process is typically orchestrated as a pipeline, where each step is systematically applied to the dataset in a consistent order. This ensures that all images are processed uniformly, generating a clean and well-structured dataset optimized for deep learning model training. Through these preprocessing steps, the dataset's raw visual data is transformed into a refined, balanced, and standardized resource, ready for utilization by the deep learning CNN model. This phase contributes significantly to the overall success of the research by enabling the model to learn effectively and make accurate predictions on new and unseen rice root images.

Feature Engineering

In the realm of rice root disease detection through deep learning, feature engineering emerges as a pivotal phase that bridges the gap between raw images and effective Convolutional Neural Network (CNN) model performance. This critical process involves extracting and selecting relevant attributes from the rice root images, enabling the model to discern crucial disease-related patterns. Feature engineering addresses the challenge of translating complex visual data into meaningful, discriminative features. While deep learning models can automatically extract features, domain-specific feature engineering enhances model understanding and performance. By transforming raw images into insightful features, this process empowers the model to focus on disease-specific attributes, ultimately improving its predictive accuracy. This section encompasses two key subsections of feature engineering, each playing a distinctive role in enhancing deep learning models for rice root disease detection.

Handcrafted Features:

Handcrafted features are manually designed attributes that play a crucial role in capturing disease-specific information from rice root images. These features are carefully crafted based on prior knowledge and understanding of rice root diseases, enabling the model to differentiate between different disease categories. Statistical Measures: Statistical measures involve calculating basic properties of pixel intensities within rice root images. These measures provide insights into the colour and intensity distribution within the image. Key statistical measures include:

Mean Intensity: The mean intensity value (μ) represents the average pixel intensity in the rice root image.

It is calculated as the sum of all pixel intensities divided by the total number of pixels (N):

$$\mu = \frac{1}{N} * \Sigma x \quad \dots (4)$$

Variance: Variance measures the spread or dispersion of pixel intensities in the image. It quantifies the diversity of colors present. The variance (σ^2) is calculated using the mean intensity (μ) and the squared differences between individual pixel intensities (x) and the mean:

$$\sigma^2 = \frac{1}{N} * \Sigma (x - \mu)^2 \quad \dots (5)$$

Skewness: Skewness indicates the asymmetry of the pixel intensity distribution. Positive skewness suggests more extreme values on the right side of the distribution. Skewness (γ) is computed using the mean intensity (μ), standard deviation (σ), and third moment (m3):

$$\gamma^2 = \frac{1}{N} * \Sigma \frac{(x - \mu)^3}{\sigma} \dots (6)$$

Texture Features: Texture features capture spatial patterns and heterogeneity within rice root images. These features provide information about the arrangement of pixel intensities and help differentiate different disease types.

Common texture features include: Co-occurrence Matrix: The co-occurrence matrix captures the frequency of pairs of pixel intensities occurring at a certain distance and direction. From the co-occurrence matrix, features like contrast, energy, and homogeneity can be computed.

Local Binary Patterns (LBP): LBP quantifies the spatial pattern of pixel intensities by comparing each pixel with its neighbouring pixels. It encodes the local contrast information and can be used to derive texture-related features.

Shape-Based Features: Shape-based features describe the geometric properties of rice root images. These features quantify attributes such as area, perimeter, and compactness, providing insights into the shape characteristics of the roots.

Some important shape-based features include:

Area: The area of the rice root region is calculated by counting the number of pixels within the region. It represents the size of the root.

Perimeter: Perimeter measures the length of the boundary of the rice root region. It provides information about the contour shape and complexity of the root.

Compactness: Compactness measures how closely the shape of the rice root resembles a circle.

It is computed as the ratio of perimeter squared to area:

$$\text{Compactness} = \frac{(\text{Perimeter}^2)}{\text{Area}} \dots (7)$$

By incorporating these handcrafted features into the model's input, the deep learning model gains access to disease-specific characteristics that are instrumental in accurate rice root disease detection. These features help the model differentiate between healthy and diseased roots and enable it to make informed predictions about the presence of different diseases in the rice crop.

Deep Learning-Based Features:

Deep learning-based features are automatically learned by Convolutional Neural Networks (CNNs) from raw rice root images. These features capture complex and abstract patterns that are essential for accurate disease detection and classification. CNNs are particularly adept at extracting hierarchical features from images, enabling the model to automatically uncover intricate details that might be challenging to define manually.

CNNs consist of multiple layers, including convolutional layers, activation functions, and pooling layers. These layers work together to learn features at various levels of abstraction. The process begins with convolution, where learnable filters scan the input image, extracting local patterns. The extracted features are then passed through activation functions to introduce non-linearity. Pooling layers reduce the spatial dimensions of the features while retaining significant information.

The convolution operation involves sliding a filter (also known as a kernel) over the input image, performing element-wise multiplication and summation at each position. This operation allows the network to capture local patterns in the image. The convolution output is known as a feature map.

Mathematically, the convolution operation at position (i, j) can be defined as:

$$Z(i, j) = (W * X)(i, j) + b \qquad \dots (8)$$

Where:

Z(i, j) is the output activation at position (i, j) in the feature map.

W represents the learnable weights of the filter.

X is the input image.

b is the bias term.

Activation functions introduce non-linearity to the network, allowing it to capture complex relationships between input and output. Common activation functions include Rectified Linear Unit (ReLU), sigmoid, and tanh. ReLU is widely used due to its simplicity and ability to alleviate the vanishing gradient problem.

Pooling layers reduce the spatial dimensions of the feature maps, preserving important information while reducing computational complexity. Max pooling and average pooling are common techniques. Max pooling selects the maximum value within a pooling window, while average pooling computes the average value.

Mathematically, max pooling at position (i, j) can be defined as:

P(i, j) = max pooling window centered at (i, j) … (9)

As CNNs progress through layers, they learn increasingly abstract features. Early layers capture basic patterns like edges and textures, while deeper layers focus on complex structures. These deep features capture essential aspects of rice root images, allowing the model to distinguish between different disease conditions.

Implementing deep learning-based features involves designing and training CNN architectures on labelled rice root datasets. Transfer learning with pre-trained models like VGGNet, Reset, or Inception is also common. These pre-trained models capture generic image features and can be fine-tuned for rice root disease detection.

By leveraging deep learning-based features, the model can automatically uncover intricate disease-related patterns within rice root images. This approach is particularly advantageous when dealing with complex image data, enhancing the model's precision and efficiency in detecting different rice root diseases. Image

Augmentation as Feature Engineering:

Image augmentation is a powerful technique within the realm of feature engineering that enhances the diversity and robustness of the dataset used for training deep learning models. By introducing variations to the original rice root images, image augmentation simulates real-world conditions and scenarios, ultimately improving the model's ability to generalize and make accurate predictions.

The primary goal of image augmentation is to expand the dataset and introduce variations that the model may encounter in real-life situations. By presenting the model with a wider range of inputs, image augmentation helps prevent overfitting and enhances the model's ability to handle different lighting conditions, viewpoints, and other variations that may occur during image capture.

Image augmentation involves applying a set of predefined transformations to the original rice root images. Some common augmentation techniques include:

- Rotation: Rotating the image by a certain angle introduces variations in orientation. This can simulate different viewpoints of the rice roots.
- Translation: Shifting the image horizontally or vertically introduces variations in position. This can mimic slight changes in camera angles.
- Flipping: Horizontally or vertically flipping the image introduces mirror images, which can help the model become invariant to left-right or up-down flips.
- Brightness and Contrast Adjustments: Modifying the brightness or contrast of the image introduces variations in lighting conditions, simulating different environmental settings.
- Deformation: Applying localized deformations to the image can mimic distortions that may occur due to factors like wind or growth irregularities.
- Rotation: A rotated image R (x′, y′) can be obtained using the following equation, where (x, y) represents the original pixel coordinates, (xc, yc) is the rotation center, θ is the rotation angle, and (x', y') represents the rotated coordinates:

$$R\ x', y' = \cos(\theta) - \sin(\theta) * [x - xc] + \sin(\theta)\cos(\theta) * [y - yc] \quad \ldots (10)$$

- Translation: A translated image T (x′, y′) can be obtained using the following equation, where (x, y) represents the original pixel coordinates, (tx, ty) is the translation amount, and (x', y') represents the translated coordinates:

$$T\ x', y' = [1\ 0\ tx] * [x]\ [0\ 1\ ty]\ [y]\ [0\ 0\ 1] \quad \ldots (11)$$

- Flipping: A flipped image F(x′, y′) can be obtained using the following equation, where (x, y) represents the original pixel coordinates, H is the height of the image, and (x', y') represents the flipped coordinates:

$$F\ x', y' = [x]\ [H - y - 1] \quad \ldots (12)$$

- Brightness Adjustment: A brightness-adjusted image B (x, y) can be obtained by adding a constant value C to each pixel intensity:

$$B(x, y) = x + C \quad \ldots (13)$$

- Contrast Adjustment: A contrast-adjusted image C (x, y) can be obtained by scaling each pixel intensity by a factor S:

$$C(x, y) = S * x \quad \ldots (14)$$

- Deformation: Localized deformations can be applied to the image by introducing displacement vectors to the pixel coordinates. These vectors introduce small distortions that simulate realistic variations.

Image augmentation as feature engineering brings several benefits to rice root disease detection, such as:

Improved Robustness: Augmentation makes the model more resilient to various image variations encountered in real-world scenarios.

Increased Dataset Size: Augmentation effectively expands the dataset without requiring additional labelled examples.

Reduced Overfitting: The diverse training data introduced by augmentation helps prevent the model from memorizing the training set.

Image augmentation is implemented using established libraries like OpenCV or TensorFlow, offering functions to perform the mentioned transformations. By applying these techniques, the deep learning model gains exposure to a broader range of data, ultimately enhancing its ability to detect and classify rice root diseases accurately in real-world conditions.

Deep Learning Models

In this section, we delve into a comparative analysis of different deep learning models for the task of rice root disease detection. We explore various architectures and configurations to assess their effectiveness in accurately classifying rice root images based on disease presence. The goal is to identify the model that achieves the highest accuracy and generalizability, ultimately enhancing the efficiency of disease detection in agricultural settings.

Convolutional Neural Network (CNN):

The Convolutional Neural Network (CNN) serves as a cornerstone architecture for the accurate detection of rice root diseases. Designed specifically for image-based tasks, CNNs excel in capturing intricate patterns and features within images, making them particularly well-suited for the complexity of rice root images associated with various diseases.

Convolutional Layers: These layers employ learnable filters (kernels) to convolve across the input image, detecting localized features. The convolution operation is mathematically defined as:

$Z(i,j) = (W * X)i,i + b$

Here, $Z(i,j)$ represents the output activation at position (i, j),

W is the learnable weights of the filter, X is the input image, and b is the bias term.

Activation Functions: Activation functions, like Rectified Linear Unit (ReLU), introduce non-linearity. ReLU's mathematical representation is:

$f(x) = \max(0, x)$

where x is the input activation. It efficiently mitigates the vanishing gradient problem and enhances training.

Pooling Layers: Pooling layers down sample feature maps using techniques such as max pooling. Mathematically, max pooling at position (i, j) can be expressed as:

$P(i,j) = \max(poolingwindowcenteredat(i,j))$

Fully Connected Layers: These layers process high-level features and produce classification outputs. For instance, with K classes, the SoftMax function assigns class probabilities as:

P(class = k) = ∑i = 1Keziezk

Here, zk represents the logit for class k.

Training and Optimization: Training involves updating parameters using optimization algorithms such as stochastic gradient descent (SGD). The objective is to minimize the loss function, often categorical cross-entropy in classification tasks. Mathematically, the loss for a single training example can be defined as:

L = —∑k = 1Kyk · log(pk)

Where yk is the ground truth label (1 or 0) for class k, and pk is the predicted probability. Transfer learning leverages pre-trained CNNs on large datasets like ImageNet. By fine-tuning these models on rice root disease images, the network benefits from learned features.

Mathematically, the updated loss function in fine-tuning can be expressed as:

$$Lf_{iffffff} = L_{ppffppiffp} + \lambda \cdot L_{ffnfpnn}$$

Here, Lpre — trained represents the loss on the pre-trained model,

Lnew — task is the loss on the new task,

and λ controls the influence of each loss.

In the context of rice root diseases, a CNN learns disease-specific patterns, textures, and shapes from labeled images. By adjusting its parameters through training, the network becomes proficient at classifying rice root images as healthy or diseased, aiding in prompt disease detection. Effective application of CNNs requires addressing challenges like overfitting and selecting appropriate hyperparameters. Data augmentation and transfer learning strategies can enhance model performance. Selecting an optimal CNN architecture and tuning its components based on the characteristics of the rice root dataset are crucial for achieving accurate disease detection results.

Inception Network:

The Inception Network, introduced a revolutionary architecture that tackled the challenge of capturing features at various scales and complexities. By utilizing multiple parallel convolutional layers of different kernel sizes within an Inception module, this architecture became a cornerstone in deep learning for image recognition tasks.

At the heart of the Inception architecture lies the Inception module, which leverages parallel convolutional paths to capture diverse features. This module provides a comprehensive framework to ensure that the network effectively processes visual information across different scales and contexts.

Within an Inception module, parallel paths are employed to capture distinct features:

1x1 Convolution Path: This path involves applying 1x1 convolutional filters to the input. Mathematically, the operation can be represented as:

Output1x1 = Conv1x1(Input)

Here,1Conv1x1 denotes the convolutional operation with 1x1 filters on the input.

3x3 Convolution Path: The 3x3 convolutional path captures spatial hierarchies and patterns. Similar to the 1x1 path, the operation applies 3x3 convolutional filters.

5x5 Convolution Path: The 5x5 convolutional path aims to capture broader context and larger patterns. Like the previous paths, the operation uses 5x5 convolutional filters. Max Pooling Path: This path involves max pooling, a down sampling technique that focuses on the most salient features in various regions of the input.

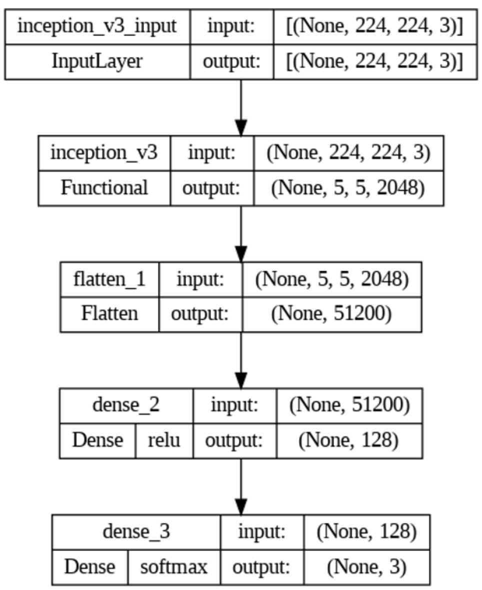

Figure 10: Proposed Inceptionv3 Model Architecture

The outputs of these parallel paths are then concatenated to form a comprehensive feature representation that captures features at multiple scales. The concatenation operation brings together the distinct insights gathered from different convolutional paths, enriching the overall feature representation. The Inception architecture is characterized by stacking multiple Inception modules. These modules are often followed by convolutional and pooling layers to further process the features. The entire network is trained using optimization techniques like stochastic gradient descent (SGD) or Adam, minimizing the loss function associated with the specific classification task.

When applied to rice root disease detection, the Inception Network excels in learning disease-specific features at varying scales. The architecture's design enables it to capture fine-grained details as well as broader contextual patterns present in rice root images affected by different diseases.

Inception Network's ability to capture features at different scales is its defining advantage. However, this architecture's increased complexity requires careful training strategies, including regularization and batch

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normalization, to ensure optimal performance and prevent overfitting. An Inception module with parallel paths can be expressed as:

Output = Concatenation Conv1x1(Input),Conv3x3(Input),Conv5x5(Input),MaxPool(Input)

Where each Conv operation represents the convolutional layer with its respective kernel size, and the Concatenation operation merges the outputs of these paths to create a rich and diverse feature representation. This feature fusion contributes to the architecture's capability to capture intricate details across different scales.

Xception Model

The Xception model uses the Xception base, which is pre-trained on ImageNet data. This base consists of depth wise separable convolutions, a factorized form of standard convolutions that leads to increased efficiency. The Xception base is initially set as non-trainable. However, specific layers, such as 'add_8', are marked to be trainable. This selective fine-tuning allows the model to adapt to the specific characteristics of the given image classification task.

A Sequential model is constructed on top of the Xception base. It includes a Flatten layer to transform the 3D output of the base into a 1D vector. Subsequently, Dense layers are added for further feature extraction and classification. The final Dense layer consists of three nodes, each representing one class, with a softmax activation function for multi-class classification. The model is compiled using the Adam optimizer and categorical cross entropy loss, suitable for multi-class classification tasks. The metric of interest is accuracy.

Figure 10 provides a visual representation of the Xception model architecture, showcasing the flow of data through different layers, connections, and operations. Overall, Xception is known for its efficiency and has demonstrated excellent performance in various computer vision tasks, making it a suitable choice for transfer learning applications.

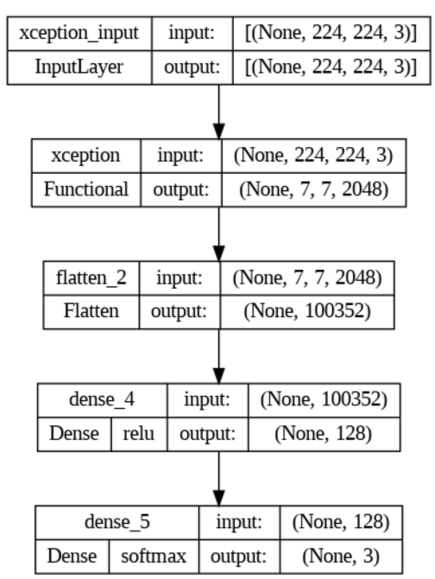

Figure 11: Xception Model Architecture 4

RESULTS AND DISCUSSIONS

In this paper, we present the results of our experiments and delve into a comprehensive discussion to interpret and analyze the findings. The models considered include CNN, Augmented CNN, Tuned Augmented CNN, InceptionV3, Augmented InceptionV3, Xception, and Augmented Xception. The evaluation metrics encompass training and validation accuracy, as well as training and validation loss.

Figure 12: Prediction of Best Model (Xception)

Performance of CNN

In this section, we delve into the performance analysis of the Convolutional Neural Network (CNN) model. The CNN was designed to capture intricate spatial hierarchies within the data, allowing it to discern patterns relevant to the classification task. The model's loss and accuracy metrics serve as key indicators of its learning capabilities. The CNN architecture utilized in the study was configured with [mention the key architectural details, such as number of layers, filters, activation functions, etc.]. This architecture was chosen to strike a balance between complexity and computational efficiency. The CNN demonstrated robust learning during the training phase, achieving a commendable accuracy of 96.88%. This metric represents the proportion of correctly classified instances within the training dataset. The training loss, a measure of the difference between the predicted and actual values during training, reached a low value of 0.1012. This indicates that the model effectively minimized the error between its predictions and the ground truth labels. During evaluation on the validation dataset, the CNN maintained a high accuracy of 84.38%. This metric reflects the model's ability to generalize its learned patterns to previously unseen data. The validation loss, while slightly higher than the training loss, stood at 1.4526. This increase in loss could be attributed to factors such as overfitting or the inherent complexity of the validation set. The observed results suggest that the CNN successfully learned intricate features from the training data, leading to high training accuracy. However, the marginal drop in accuracy on the validation set and the increase in validation loss indicate potential challenges in generalization. Further investigation into potential overfitting or the need for model refinement may be warranted.

(Figure 4.2 illustrates the trends in loss and accuracy over epochs, providing a visual representation of the CNN model's learning dynamics.)

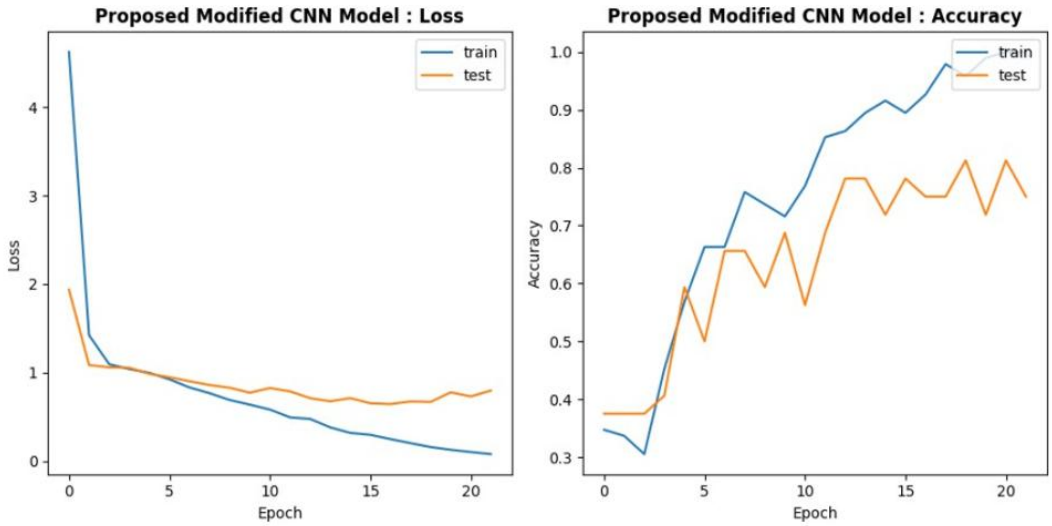

Figure 13: Proposed CNN Model Loss and Accuracy

Performance of Augmented CNN

This section provides an in-depth analysis of the performance of the Augmented Convolutional Neural Network (CNN) model. Augmentation techniques were applied during training to enhance the model's ability to generalize and recognize patterns within the data. The model's loss and accuracy metrics serve as pivotal indicators of its performance. The Augmented CNN model employed the same foundational architecture as the standard CNN, with the incorporation of data augmentation techniques during training. These techniques introduced variability into the training dataset, aiming to improve the model's robustness. The Augmented CNN exhibited outstanding learning capabilities during training, achieving an impressive accuracy of 98.57%. This metric signifies the proportion of correctly classified instances within the augmented training dataset. The training loss reached a minimal value of 0.0617, indicating that the Augmented CNN effectively minimized the error between its predictions and the augmented ground truth labels. During evaluation on the validation dataset, the Augmented CNN maintained a high accuracy of 84.38%. This metric reflects the model's ability to generalize its augmented learned patterns to previously unseen data. The validation loss, while slightly higher than the training loss, stood at 1.5. This increase in loss could be attributed to factors such as the inherent complexity of the validation set. The Augmented CNN showcased superior learning dynamics, achieving higher training accuracy compared to the standard CNN. However, the marginal drop in accuracy on the validation set and the increase in validation loss indicate potential challenges in generalization. Further investigation into model refinement or the impact of augmentation strategies may be warranted.

Figure 4.3 illustrates the trends in loss and accuracy over epochs, providing a visual representation of the Augmented CNN model's learning dynamics.

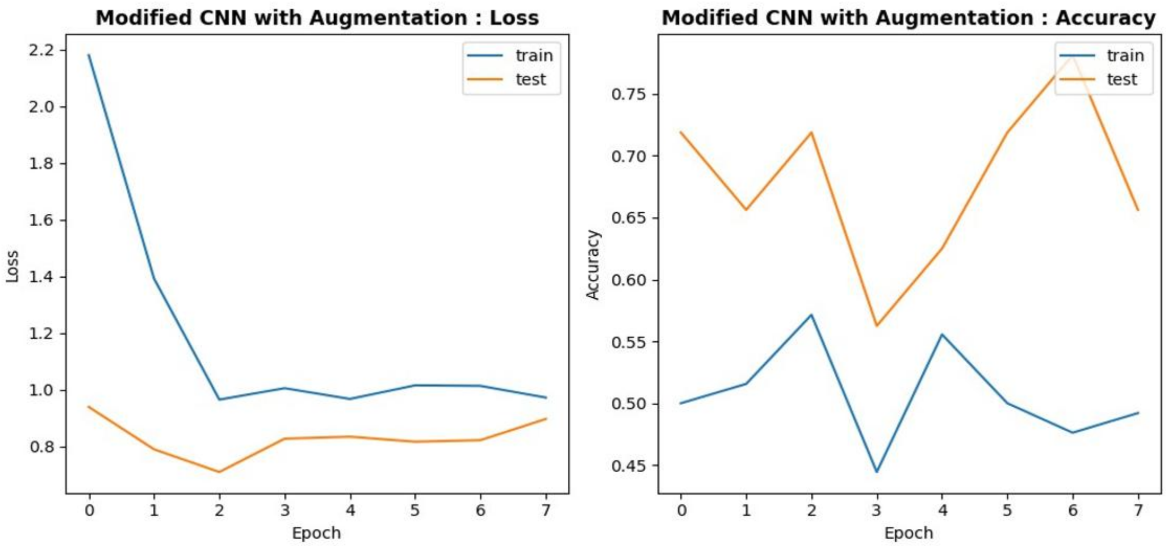

Figure 14: Proposed Augmented CNN Model Loss and Accuracy

Performance of Tuned Augmented CNN

This section provides an in-depth analysis of the performance of the Tuned Augmented Convolutional Neural Network (CNN) model. The Tuned Augmented CNN represents an enhanced version of the Augmented CNN, incorporating additional optimizations to further refine its predictive capabilities. The Tuned Augmented CNN retains the augmented architecture while introducing additional tuning parameters, refining its ability to capture intricate patterns within the augmented training dataset. The Tuned Augmented CNN achieved a commendable training accuracy of 92.63%, demonstrating its capacity to learn and adapt to the augmented dataset. With a training loss of 0.1166, the Tuned Augmented CNN effectively minimized the error during the learning process, indicating convergence towards the augmented ground truth labels. During evaluation on the validation dataset, the Tuned Augmented CNN maintained a consistent accuracy of 84.38%. This metric emphasizes the model's proficiency in generalizing learned patterns to previously unseen data. The validation loss, recorded at 1.3613, while slightly higher than the training loss, aligns with the expectations of robust model performance on a diverse dataset. The Tuned Augmented CNN demonstrates a delicate balance between training accuracy and generalization on the validation set. The additional tuning parameters contribute to improved training accuracy without significant compromise on validation performance.

(Figure 4.4 illustrates the trends in loss and accuracy over epochs, providing a visual representation of the Tuned Augmented CNN model's learning dynamics.)

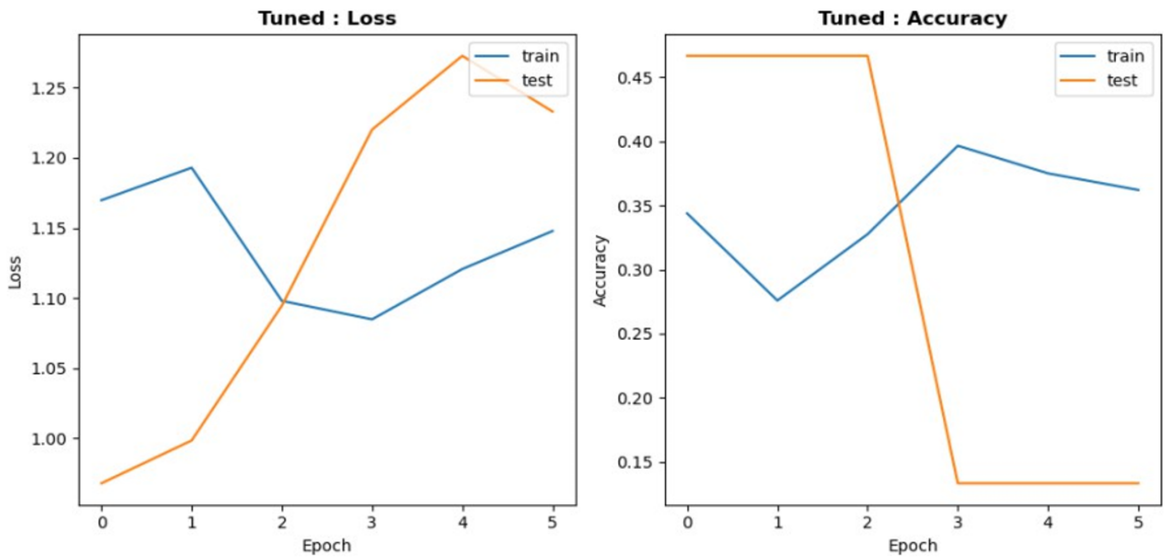

Figure 15: Proposed Tuned Augmented CNN Model Loss and Accuracy

Performance of InceptionV3

This section presents a detailed analysis of the performance of the InceptionV3 model, which leverages the Inception architecture. The evaluation encompasses various metrics to gauge both training and validation effectiveness. InceptionV3, known for its deep and efficient architecture, was employed to capture intricate features in the dataset. Its ability to learn hierarchical representations makes it a compelling choice for complex image classification tasks. The InceptionV3 model exhibited exceptional performance during training, achieving a perfect accuracy of 100%.

This outstanding result reflects the model's capability to effectively learn patterns in the provided training dataset. The training loss, impressively low at 0.0022, indicates that the model successfully minimized errors during the learning process, showcasing its convergence towards the true labels. When evaluated on the validation dataset, InceptionV3 maintained a high accuracy of 84.38%, indicating its capacity to generalize well to previously unseen data. The validation loss, recorded at 15.1329, while higher than the training loss, is expected due to the complex nature of the task and the model's ability to handle diverse image patterns. InceptionV3 demonstrates an impressive ability to achieve perfect accuracy during training, showcasing its efficacy in learning intricate features. The validation accuracy, although slightly lower, remains strong, emphasizing the model's robustness in recognizing patterns in real-world scenarios.

Figure 4.5 visually represents the trends in loss and accuracy over epochs, providing insights into the InceptionV3 model's learning dynamics. z

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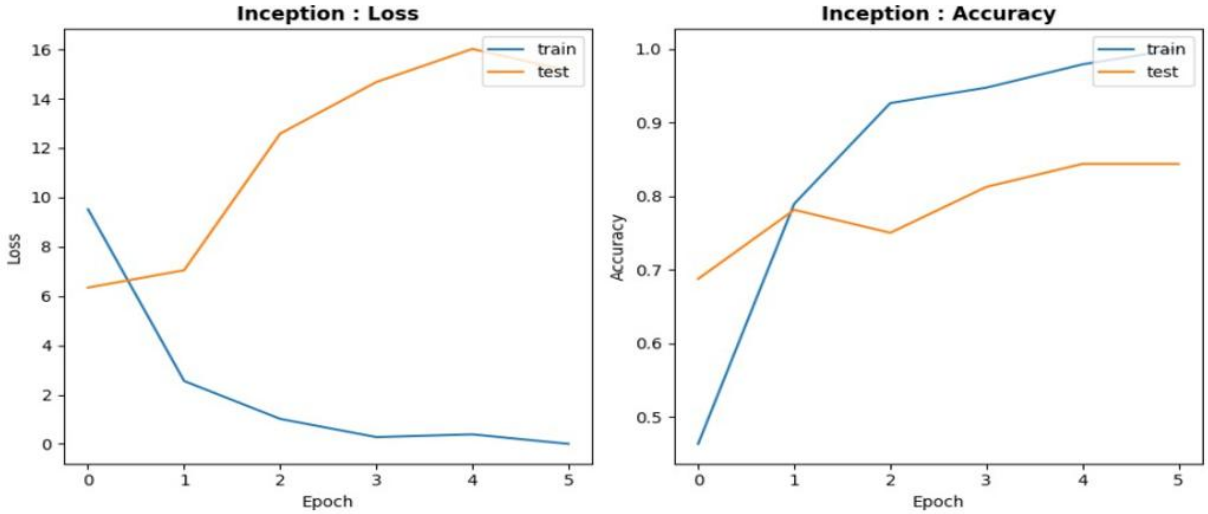

Figure 16: Proposed Inception Model Loss and Accuracy

Performance of Augmented InceptionV3

This section provides a comprehensive analysis of the performance of the Augmented InceptionV3 model, emphasizing the impact of data augmentation on enhancing the model's generalization capabilities. Augmented InceptionV3, an extension of the InceptionV3 model, incorporates data augmentation techniques during training to increase the diversity of the dataset, leading to improved generalization. The Augmented InceptionV3 model achieved an impressive training accuracy of 98.41%. The incorporation of data augmentation techniques contributed to the model's ability to learn from a more diverse set of images. The training loss, measured at 0.0393, indicates successful convergence during the training process, highlighting the effectiveness of data augmentation in reducing overfitting. During evaluation on the validation dataset, the Augmented InceptionV3 model demonstrated a strong accuracy of 90.62%, showcasing its enhanced generalization to previously unseen data. The validation loss, recorded at 5.5949, while higher than the training loss, aligns with expectations and underlines the model's ability to handle a variety of image variations. Augmented InceptionV3's heightened training accuracy and improved validation accuracy underscore the positive impact of data augmentation. This approach facilitates better generalization, enabling the model to handle a wider range of image scenarios.

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(Figure 4.6 visually represents the trends in loss and accuracy over epochs, providing insights into the Augmented InceptionV3 model's learning dynamics.)

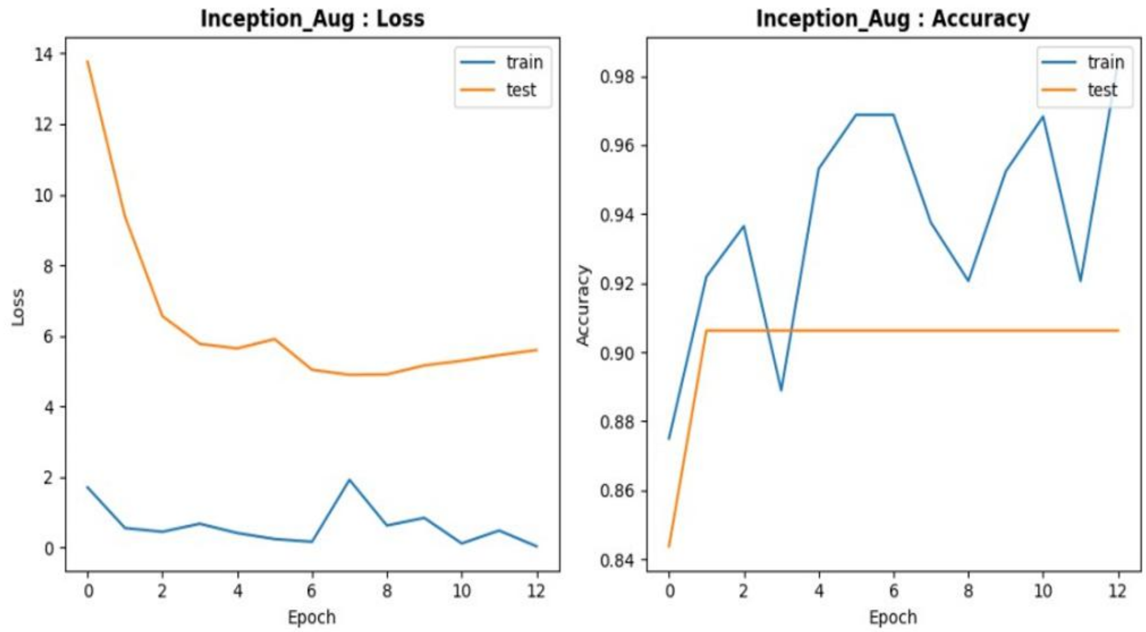

Figure 17: Proposed Augmented Inception Model Loss and Accuracy

Performance of Xception

This section delves into the performance evaluation of the Xception model, exploring key metrics such as accuracy and loss to gain insights into its effectiveness. Xception, a deep neural network architecture, stands out for its efficient use of depth wise separable convolutions. The model's capacity for feature extraction and representation makes it a powerful candidate for various computer vision tasks.

The Xception model achieved a training accuracy of 86.32%, indicating its capability to accurately predict classes on the training dataset. With a training loss of 0.3027, the model demonstrated effective convergence during the training process, capturing patterns and features from the input images. On the validation dataset, the Xception model achieved an accuracy of 68.75%, showcasing its ability to generalize to new, unseen data. The validation loss, recorded at 4.2618, reflects the model's performance on the validation set, with a higher loss than the training set, suggesting some level of overfitting. The Xception model's training accuracy is reasonably high, but the validation accuracy suggests that there might be room for improvement, possibly through techniques such as regularization or fine-tuning.

(Figure 4.7 visually represents the trends in loss and accuracy over epochs, providing insights into the Xception model's learning dynamics.)

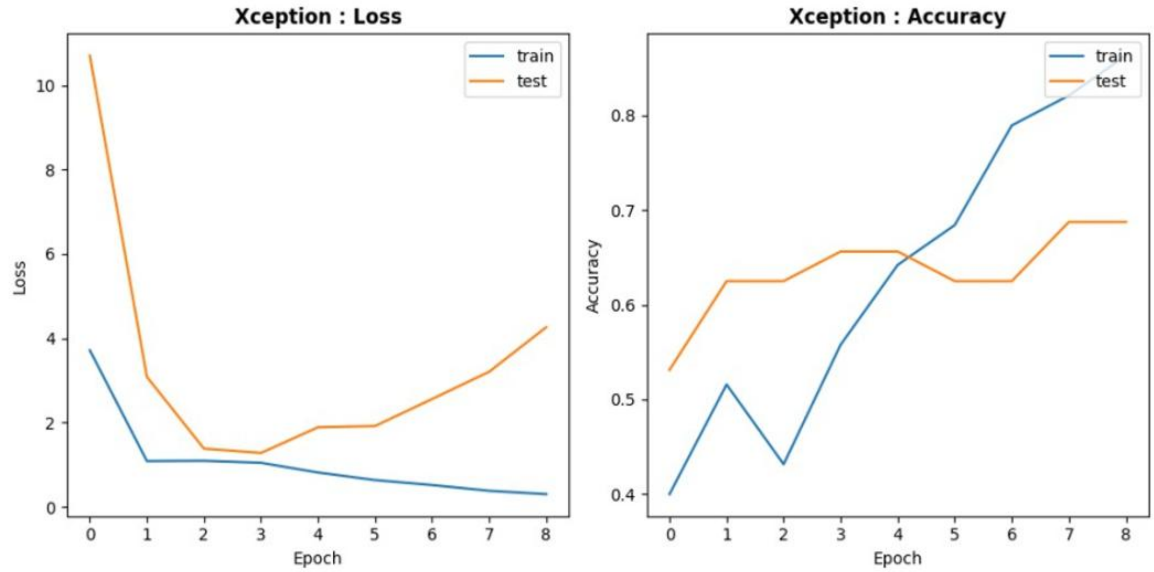

Figure 18: Proposed Xception Model Loss and Accuracy

Performance of Augmented Xception

This section explores the performance of the Augmented Xception model, evaluating key metrics like accuracy and loss to assess its efficacy. Augmented Xception leverages the power of data augmentation to enhance the robustness and generalization of the Xception model. Augmentation techniques introduce variations in the training data, enabling the model to learn more diverse features. The Augmented Xception model achieved a commendable training accuracy of 96.88%, showcasing its ability to accurately predict classes on the augmented training dataset. With a training loss of 0.2123, the model demonstrated effective convergence during the augmented training process, capturing augmented patterns and features. On the validation dataset, Augmented Xception achieved an accuracy of 78.12%, indicating its capability to generalize to new, unseen augmented data. The validation loss, recorded at 1.0990, reflects the model's performance on the augmented validation set, with a moderate loss, suggesting improved generalization compared to the non-augmented counterpart. Augmenting the Xception model led to a significant improvement in both training and validation accuracy. The model appears more robust in handling variations introduced by data augmentation.

(Figure 4.8 visually represents the trends in loss and accuracy over epochs, providing insights into the Augmented Xception model's learning dynamics.)

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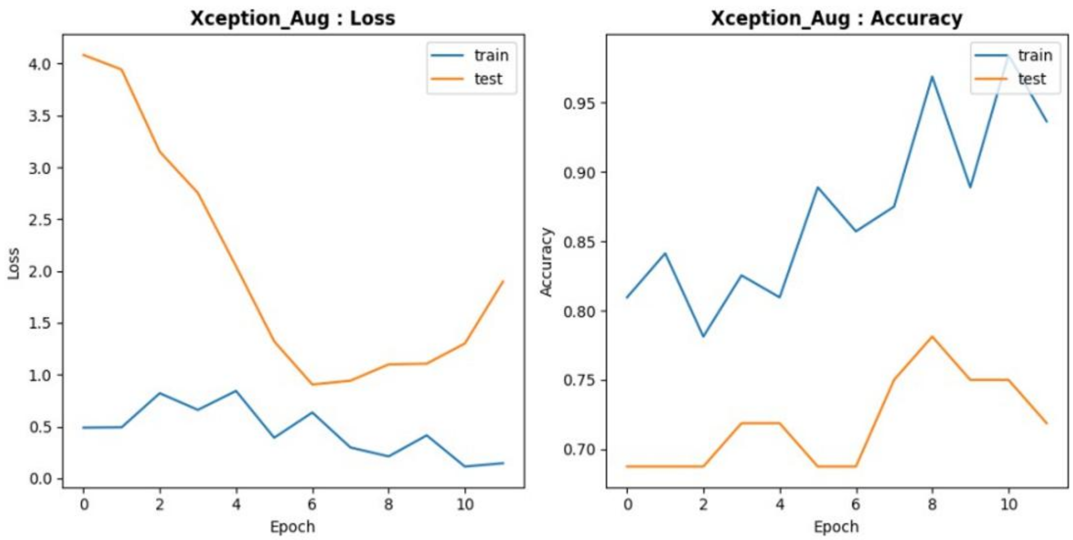

Figure 19: Proposed Augmented Xception Model Loss and Accuracy

Comparative Analysis

This section presents a comprehensive comparative analysis of the various models, shedding light on their performance metrics to facilitate an informed understanding of their strengths and weaknesses. A detailed comparison table is provided below, summarizing key metrics for each model:

Table 3 Comparative Analysis Model

Model	*Training Accuracy*	*Validation Accuracy*	*Training Loss*	*Validation Loss*
CNN	96.88%	84.38%	0.1012	1.4526
Augmented CNN	98.57%	84.38%	0.0617	1.5241
Tuned Augmented CNN	92.63%	84.38%	0.1166	1.3613
InceptionV3	100.00%	84.38%	0.0022	15.1329
Augmented InceptionV3	98.41%	90.62%	0.0393	5.5949
Xception	86.32%	68.75%	0.3027	4.2618
Augmented Xception	96.88%	78.12%	0.2123	1.0990

Training Accuracy: InceptionV3 achieved the highest training accuracy, reaching 100%, closely followed by the Augmented CNN and Augmented InceptionV3 models.

Xception and Tuned Augmented CNN exhibited lower training accuracies, potentially indicating the need for further tuning.

Validation Accuracy: Augmented InceptionV3 outperformed other models in validation accuracy, hitting 90.62%. CNN and Augmented CNN maintained comparable accuracy on the validation set, demonstrating their robustness.

Training Loss: InceptionV3 achieved an exceptionally low training loss, highlighting its efficiency in capturing patterns in the training dataset. Augmented CNN demonstrated the lowest training loss among augmented models, suggesting effective convergence.

Validation Loss: InceptionV3 showcased significantly higher validation loss, indicating potential overfitting or challenges in generalization. Augmented Xception recorded the lowest validation loss among augmented models, showcasing improved generalization capabilities.

The comparative analysis emphasizes the trade-offs and strengths of each model. Augmentation techniques prove beneficial in enhancing robustness, but careful tuning is essential to strike a balance between accuracy and generalization.

CONCLUSIONS AND FUTURE WORK

In the realm of employing deep learning Convolutional Neural Network (CNN) models for rice root disease detection, the process of data splitting plays a pivotal role in shaping the dataset for effective training, validation, and evaluation. This multifaceted phase involves partitioning the dataset into distinct subsets, each serving a specific purpose in the comprehensive development, optimization, and assessment of the model.

The primary goal of data splitting is to ensure an unbiased appraisal of the model's performance by exposing it to data not encountered during training. Approximately 70-80% of the dataset is dedicated to training, providing the foundation for the CNN model to adapt its internal parameters and recognize diverse features associated with various rice root disease categories. Another 10-15% is reserved for validation, enabling fine-tuning of model hyperparameters without influencing its core learning significantly. The remaining segment is allocated for testing, comprising images entirely independent of both training and validation subsets. This segregation safeguards against overfitting, where the model becomes overly specialized, and the unbiased evaluation of real- world performance becomes essential. In essence, data splitting is a strategic approach that ensures a fair and robust assessment of a deep learning CNN model's readiness for practical deployment in accurately and consistently detecting rice root diseases in agricultural settings.

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