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AI and Neural Network-Based Approach for Paddy Disease Identification and Classification

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Abstract: The purpose of this work is to use the artificial intelligence features of the ResNet50 architecture to provide a novel method of paddy disease identification. Farmers face numerous problems in raising paddy as its yield is affected by various factors like changing biodiversity, environment, weather pests, and disease. Traditional methods combined with smart farming, innovation, tools, and technology are needed for the mass production of food Here we develop a model using a convolutional neural network, ResNet50 that identifies disease in paddy leaf. The proposed model paddy disease identification model will give more precise results. The paddy disease identification model may be transformed into TensorFlow Lite (TFLite), which can be used for Android phones and drone applications, among other things. The Paddy model in this article obtained a training accuracy of almost 99% and a test accuracy of 92.83% when it was trained on 13,876 well-defined datasets. The loss function of 0.0014 at 100 epochs demonstrated that the model was effectively trained using ResNet50.

Keywords: Paddy Model, Paddy CNN, Drones, Leaf Classification, Smart farming.

1. Introduction

Changing environmental conditions, drought, changing weather conditions, disease, and insect attacks on plants will impact agricultural production, yield quality, and nutrition [1]. The increase in the carbon dioxide (CO_2) in the air causes global warming, climate fluctuations will result in new races of pathogen development [2]. In recent years, agricultural production has faced numerous problems like over-exploitation of natural resources, and changes in biodiversity [3]. Rice is the basic food for about half of the global people. Challenges in production are addressed by modern tools and techniques [4]. A drone, also known as an unmanned aerial vehicle (UAV), is guided by on-board computers or by a person on the ground via remote control. Drones (unmanned Ariel vehicles) are used nowadays in smart farming. For ages, People with experience in the agricultural field use their knowledge in detecting, and monitoring plants. This kind of observation may lead to mistakes. Putting smart farming, and precision agriculture into practice means using technology to effectively monitor and improve crop management, which raises agricultural production [5]. Due to the incorporation of technological advancements, agriculture activities have changed from manual labor to automated labor.

1.1 Problem Statement and Objectives

Paddy is the preferred common food that most people in the world take. Diseases like false smut, brown spots, rice blasts, and bacterial leaf streaks all had an impact on the paddy's yield. Farmers will be able to take additional precautions to prevent crop loss, production loss, and financial loss with the aid of early disease diagnosis. Various conventional and modern methods, tools, and processes are used to diagnose the diseases. A significant role of conventional neural networks (CNNs) is played in numerous real-time object detection applications. Numerous CNN approaches, such as Alex Net ResNet and Inception v3, are effective in object detection.Several variables, including soil, water, environment, pests, and diseases, influence the yield. For ages, farmers have employed their skills, and crop management practices to address paddy plant illnesses by visual inspection, perhaps resulting in mistakes. Building a model to monitor plant illness using state-of-the-art technology, predicting the kind of disease inpaddy plants, and taking preventive action to avoid crop loss.

In this work, the researchers pre-trained the model using ResNet50 and attached the classifier to the top of the layer. The model is frozen. Only the weights from the classifier get updated at the time of training.

Table 1. Paddy Plant Diseases

Reference	Name of the disease	Scientific name
[6]	Bacterial Leaf Blight	Xanthomonas oryzae pv. oryzae
[7]	Bacterial Leaf Streak	Xanthomonas vasicola pv. vasculorum
[8]	Bacterial Panicle Blight	Burkholderia glumae
[7]	Rice blast	Magnaporthe oryzae
[7]	Brown spot	Helminthosporium oryzae

The base layer of the convolution finds all the characteristics associated with the paddy disease type like, rice blast, and paddy leaf streak. Performance is enhanced with new data and is fine-tuned. Weights are tuned for feature characteristics according to the dataset. By using deep learning techniques to classify images of paddy leaves, crop diseases may be precisely identified and diagnosed, which improves the overall effectiveness of agricultural disease identification and control. The authors developed a paddy disease identification model to analyze and apply deep learning algorithms using convolutional neural networks, ResNet50 to employ images of paddy plants to identify five diseases in paddy plants mentioned in Table 1

1.2 Benefits of the Paddy Disease Identification Model

The Paddy Disease Identification Model has several paybacks for farmers and agricultural managers. By applying this model, paddy plant diseases can be promptly detected, enabling farmers to better manage their harvests. Early problem detection is crucial for resolving issues and enabling the cultivation of healthier, more productive crops. Moreover, the concept can be used with drone technology to address farmers' navigational issues, offering a comprehensive and practical solution. The model can be converted into tflite, wide, and can be used in a wide range of devices like drones, Android devices, and Raspberry Pi

2. Literature Review

Sethy, *et. al.,* set itself apart in the particular setting of paddy leaf disease identification by using an innovative and thorough methodology [9]. This required integrating SVM (Support Vector Machine) for accurate classification, k-means clustering for pattern recognition, fuzzy logic for addressing uncertainty, and approaches for processing advanced analysis. It obtained an impressive accuracy of 86.35% with this creative combination of approaches, demonstrating how well this strategy works to expand the precision, and trustworthiness of identifying disease in plants.

Chen, *et. al.,* used a unique technology approach to achieve an accuracy of 89.4% in the field of rice leaf illness detection [10]. This method was different from traditional approaches since it used state-of-the-art technology such as spore germination analysis, Convolutional Neural Network, and the IOT (Internet of Things). CNN was utilized to effectively extract features from images of paddy leaves, and IoT enabled real-time data gathering and monitoring.

Shrivastava, *et. al.,* made a significant contribution to the field of rice leaf disease detection by implementing cutting-edge techniques [11]. This required the use of SVM (Support Vector Machine) for efficient classification, transfer learning to make use of prior knowledge, and the MatConvNet toolbox for simplified implementation. Deep CNN (Convolutional Neural Network) was used for complex image analysis. The remarkable accuracy rate of 91.37% that resulted from the synergistic integration of different practices highlights the substantial contribution to the advancement of the accuracy and efficiency of paddy leaf illness detection techniques.

Islam *et. al.,* demonstrated remarkable proficiency in paddy leaf disease identification, with an astounding accuracy rate of 92.68% [12]. The use of advanced architecture like like Inception-ResNet-V2, ResNet101, and VGG-19, highlights the need for sophisticated model frameworks in improving performance. In the framework of paddy agriculture, these deep learning models recognize variety of infections in the paddy. Brown spot, blast, leaf smut, and bacterial leaf blight are common paddy diseases that are the focus of this study.

Using 636 thermal pictures, Bharanidharan *et. al.,* analyzed five paddy illnesses and extracted 14 statistical variables from each image [13]. The classifiers, which use four machine learning techniques, perform below 65% balanced accuracy at first. However, performance is greatly enhanced by using a feature transform based on Modified Lemurs Optimisation, which results in a noteworthy 90% balanced accuracy for the K-Nearest Neighbour classifier.

Naga Swetha, *et. al.,* split 120 images of diseased rice plants into 75% training data set and 25% testing data set [14]. Based on the collected data, the researchers used SVM and k-nearest Neighbor classifiers to categorize paddy crop diseases. In disease classification, the accuracy of the Support Vector Machine (SVM) was 91.23%, higher than the k-nearest Neighbor algorithm's 89.54% accuracy.

Biradar, *et. al.,* the authors created Paddyleaf15, a customized deep learning model, by changing the architecture of pre-trained CNNs and employing transfer learning. In the classification experiment, Paddyleaf15 outperformed established models like VGG16 and Inception V3 with an astonishing 93% accuracy [15].

The CNN model, which was specifically constructed for rice leaf images, obtained a stunning accuracy of 91.4% on a heterogeneous dataset in Abasi, *et. al.,* [16]. This performed better than Transfer Learning EfficientNet-B2 and Transfer Learning Inception-v3.

Researchers used SVM (Support Vector Machine) and CNN to identify and categorize illnesses in paddy plants in Haridasan, *et. al.,* [17]. The combination of these strategies, combined with the application of relu and soft-max functions, yielded an amazing accuracy of 91.45%, demonstrating the efficacy of this strategy in automated disease identification in rice crops.

The authors of Senan, *et. al.,* used a Kaggle dataset of 3355 paddy images to discriminate between healthy leaves and those damaged by brown spots, leaf blasts, and hispa. One convolutional layer, one pooling layer, and three fully connected layers were integrated to create a 5-layer convolutional neural network (CNN), displaying a well-organized architecture for efficient feature extraction and classification, reaching an astonishing 93% accuracy in detecting and categorizing varied paddy leaf states [18].

3. Materials and Methods – Training, Validation, and Testing Data

3.1 Data set

An extensive collection of plant leaf images is necessary for the identification of illnesses affecting rice plants. The rice leaf images used in this study were from eight separate web datasets related to paddy diseases. The obtained paddy plant leaf images were subjected to several pre-processing procedures, such as resizing, labeling, tagging, and augmentation, to guarantee the accuracy of the classification model. Parameterizing the model and using regularization methods are essential for enhancing its performance and avoiding overfitting.

During training, the model gains knowledge from the training dataset. The training dataset is diverse, consisting of 10407 images that we used to assess our Convolutional Neural Network (CNN) model. These images include 1764 healthy leaves, 479 bacterial leaf blight, 380 bacterial leaf streak, 337 bacterial panicle blight, 1738 blast, 1442 dead heart, 620 downy mildew, 1594 hispa, 1088 tungro, and 965 brown spots. The 3,469 images in the test data are an aggregation of every image of sick leaves that were used in the testing process.

The test dataset is essential for validating and confirming the model's capacity to accurately predict or identify paddy diseases. A complete dataset for robust model training and evaluation is provided by classifying leaves as either diseased or normal.

4. Frequently Arising Paddy Leaf Disease

In Paddy, several diseases appeared. Table 2 lists the top four most common diseases.

4.1 Rice-Leaf Fungal Infections

The primary cause of the rice blast in crops of rice is a magnaporthe oryzae (fungus disease). It affects the entire crop, the left neck, leaves, and nodes. [19].

Leaf Blast: When the seedling's young leaves are primarily infected by the fungus, a leaf blast occurs. Later, it destroys the spindles by expanding in the yellow region, changing the color of the spots on the further mature leaves from purple to brown [20].

Panic Attack and Neck Rot: Triangular lesions form as the panicle blast travels through the crop's younger neck, and the panicle itself may collapse [21].

Table 2. Taxonomy of Rice Leaf Diseases

Brown spot	Blast	Bacterial Leaf Streak	Blight
			

Rot Collars: Brown lesions form at the sheath as a result of the infection collar rot, which can occasionally destroy the whole plant [21]. Node Blast: The brown-to-black color of the grain tissues is triggered by a lesion that develops on the node stem [21].

Rice Disease Sheath Blight: This fungus can endure for more than two years in the soil. Sheath blight symptoms include oval or originally oval green/gray symptoms on the sheath of a leaf. These lesions will continue to develop and enlarge until they reach the tops of the leaves. Sheath blight is infectious simply by coming into contact with diseased leaves [22].

False Smut: The disease is caused by the ustilaginoideavirens species. Once regarded to be a minor ailment, this illness has since become serious due to its global scattering since 2001 [23].

Brown Spot: The fungal pathogen Cochliobolusmiyabeanus is the cause of the rice disease that produces brown spots. From the very beginning to the very end, it has an impact on the plant. On the coleoptile, Yellow or brown lesions start to occur [24].

Grain Discoloration of Rice Leaf: Markings in dark brown or black begin appearing on the grains as a result of the spikelet’s color changing into brown or black due to grain degradation [25]. Bacterial Blight. This infection is caused by the xanthomonas oryzae.pv. Oryza species enter by way of the cut wounds in leaf tips. Affect the growth of the plant leaves change into yellow, drying of leaves, and death of seedlings. The plant becomes straw-yellow-colored within a few days [26].

5. Meta Architecture Paddy Disease Identification Model

5.1. Gathering of Images

5.1.1 Compilation of Pictures

First, build an extensive dataset with images of paddy leaves and disease representations. [27]

5.1.2 Pre-Processing

Here the image is enhanced by resizing, improving color clarity, brightness, rotations, and image smoothening, unwanted image background is eliminated [28].

5.1.2 Segmentation of Images

Segments of paddy leaves are used to identify and categorize crop diseases. To find pertinent data for feature extraction, it examines the paddy picture [29]. Labeled data includes relevant tags and is utilized in supervised learning. For unlabeled data, the K-means clustering technique was used to divide the dataset into distinct groupings [30].

5.1.3 Finding Features

It is necessary to concentrate on the unique characteristics to extract the necessary information for paddy plant infection finding and categorizing. The disease's color, texture, and shape are used to help with classification and detection. It's vital to remember that distinct diseases display distinct symptoms, and paddy crop symptoms might also differ [31].

5.1.4 Classification

Diseases in rice plants can be effectively predicted and classified using a variety of machine-learning techniques. CNN is an important tool for classifying leaf diseases [32]. Deep learning CNNs are used to achieve accurate illness classification. Pooling techniques are used to extract disease features from paddy plant leaves from images [33]. The model used for training is the ResNet50.

5.2. Architecture of Paddy Disease Identification Model)

The largest dataset for the model has an overall of 13,876 images, with 10,407 chosen to train, 3,469 images intended aimed at testing, 75% train dataset, and 25% test dataset. The paddy leaf of eight diseases is loaded into the neural network for training and the results of the outcomes are used for model weights. The model learned about the disease images of the leaf. Unwanted paddy image backgrounds are trained during the training and when it comes to real-time predictions performance is reduced. To overcome fine-tuning is done, to retain the information acquired during the first training while updating the model's weights based on fresh data to increase performance. The Paddy model takes the trained dataset as input. The test data set is used for validation and verification of the model to find that the model predicts/categorizes paddy disease correctly.

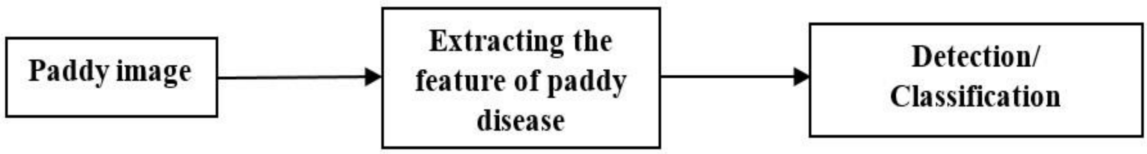

Figure 1. Architecture - Paddy Model

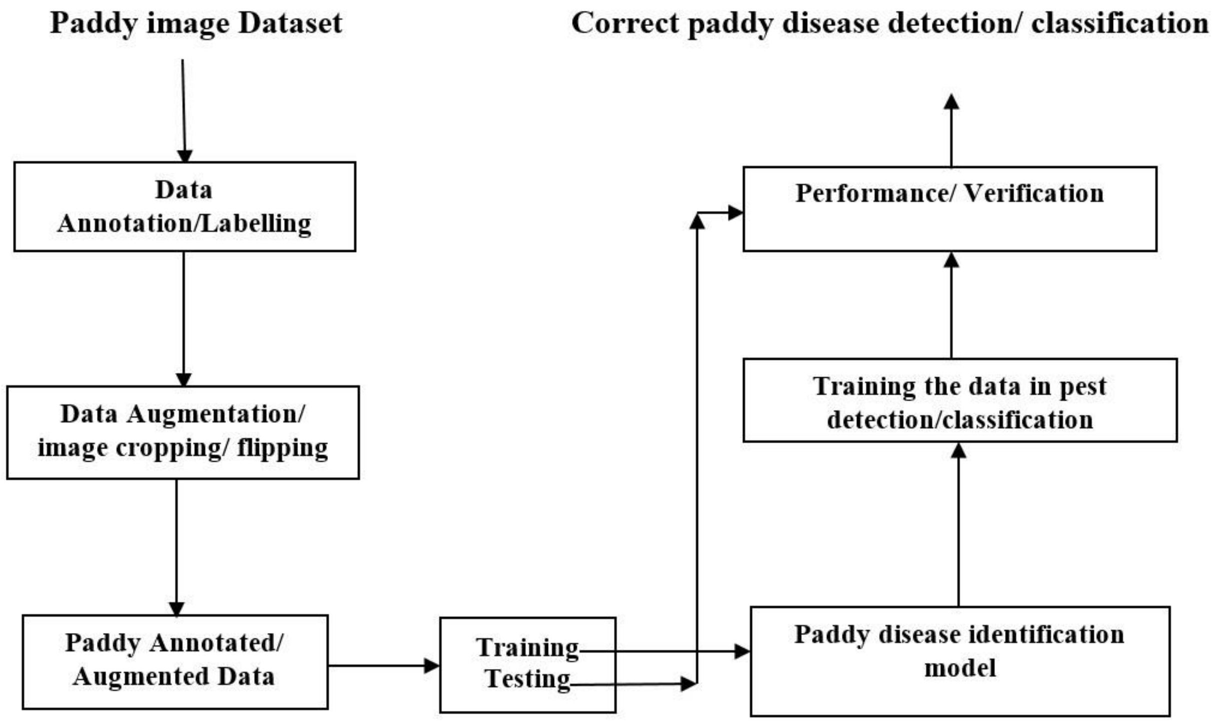

Figure 2. Paddy model for identifying the classification of disease using CNN ResNet50

As shown in Figure 1. The paddy leaf image captured by the camera is loaded into our system. The system will detect whether it is a rice blast, bacterial streak, or any other disease. Our system performs various processes by our neural network feature extractor and classifier.

Figure 2 depicts the six essential processes in the methodology, which range from dataset gathering to model training and performance evaluation.

5.2.1 Gathering Paddy Image Dataset

The authors used Paddy leaf disease datasets from several sources, such as https://paddydoc.github.io/dataset, free public plant disease datasets, and https://www.kaggle.com/c/paddy-disease-classification/, to carry out the usual procedure of plant disease identification. Making use of a variety of sources guarantees a complete and trustworthy gathering of information about illnesses that affect paddy leaves. This method strengthens the process of identifying plant diseases and increases its efficacy and accuracy, laying a strong basis for future studies.

5.2.2. Data Labeling/Annotation

Annotate or label the acquired dataset accurately, indicating the disease-affected locations. During model training, this phase is critical for supervised learning.

5.2.3 Data Augmentation/ Cropping/ Clipping

Using data augmentation techniques like cropping or clipping to upsurge the diversity of the dataset, allowing for greater model generalization.

5.2.4 Paddy Annotated/ Augmented Data

Here, the dataset has been enlarged, refined, and annotated to provide a broad and diverse set of instances from which a model can be trained and trained to generate predictions. To guarantee that the model experiences a wide range of scenarios during training and can effectively generalize to new, unknown data during inference, it is intended to be given a large and diverse set of cases. The model's overall performance and adaptability are enhanced by this procedure.

5.2.5 Splitting Training and Testing

The aim is to evaluate a model's capacity for prediction and generalization using fresh, untested data. To train the model, the dataset is split into two subsets: a training set and a testing set. Normally, the model is trained on around 75% of the data, with the remaining 25% set aside for assessing the accuracy of the model using untested data. This division helps to produce a more accurate assessment. This division also contributes to a more accurate assessment of the model's efficacy by ensuring that it is not just learning to memorize the training data but also developing the ability to make predictions for previously unobserved cases.

5.2.6. Model Training and Pest Detection/Classification

The dataset is used to educate the machine to recognize and categorize paddy leaf diseases during the training phase using the ResNet50 model.

5.2.7. Model Performance Verification

Model performance verification entails measuring the model's efficiency in disease detection and classification using a predefined testing dataset. This includes evaluating the model's capacity to reliably and properly identify paddy illnesses in samples that have never been observed before. The evaluation encompasses an in-depth examination of the model's classification ability, employing accuracy and loss metrics to offer a thorough understanding of its functioning.

5.2.8. Final Performance and Verification

Conduct a thorough examination of the capacity of the model performance, taking into account metrics like accuracy and loss. This stage assures that the model will be reliable and effective in real-world

6. Results and Discussion

The dataset has 3,469 data for testing and 10,407 entries for training in the Paddy disease identification model. After 100 epochs, the model demonstrated an excellent accuracy of almost 99% training accuracy and 92.83% test accuracy, with a low loss function of 0.0014. This suggests that the ResNet50 architecture was used to train the model successfully. As shown in Figures 3, 4, and 5, the dataset was divided into three categories: diseased-wise, age-wise, and rice variety-wise the dataset's images were shrunk to 224 by 224 pixels. This resizing was probably carried out to guarantee consistency and lower computational complexity, which would facilitate the model's efficient processing of the paddy leaf images.

The model's design is illustrated in Figure 6, which shows that there are 24,124,126 total parameters. 57,728 of these factors are non-trainable, and 24,066,398 of them are trainable. This arrangement shows a balanced model that got up the ability of accurate illness predictions. Accuracy and loss were the main metrics used to assess the performance of the model. The results show that the accuracy of the model and the size of the training dataset are positively correlated, as predicted.

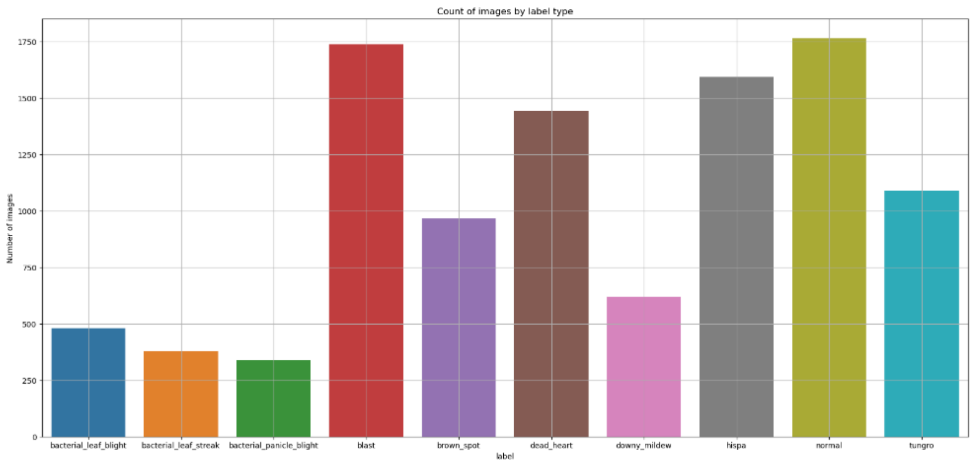

Figure 3. Paddy Diseased Images

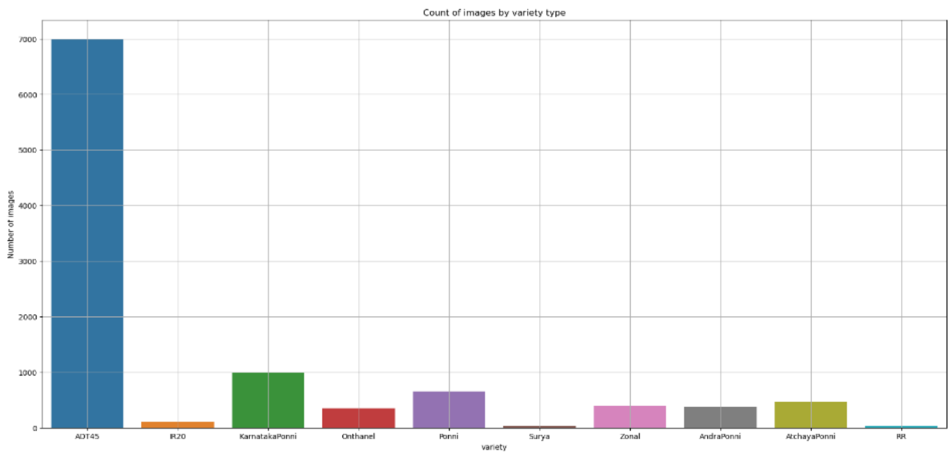

Figure 4. Paddy Rice Varieties

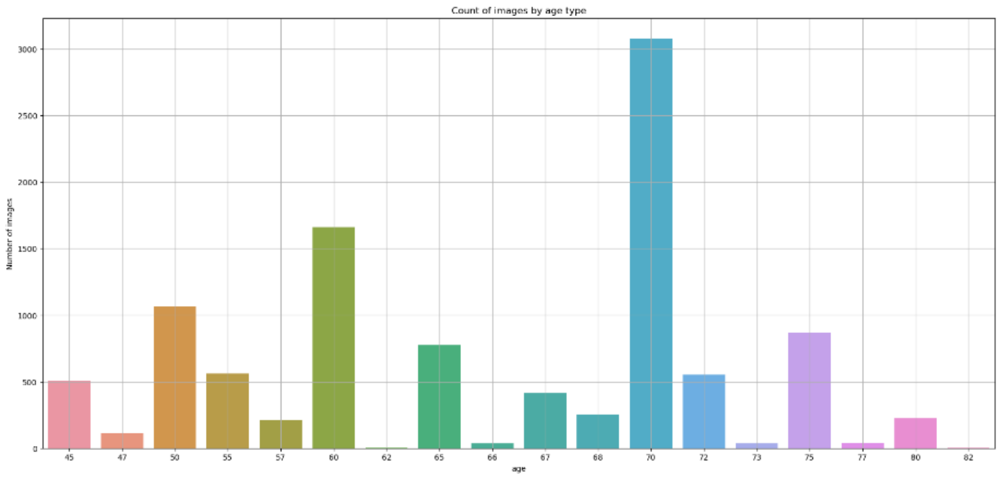

Figure 5. Paddy Images by Age Type

```
In [66]: model = build_resnet50()

Model: "model_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_8 (InputLayer)        [(None, 224, 224, 3)]     0

 conv2d_3 (Conv2D)           (None, 224, 224, 3)       84

 resnet50 (Functional)       (None, None, None, 2048)  23587712

 global_average_pooling2d_3   (None, 2048)             0
 (GlobalAveragePooling2D)

 batch_normalization_6 (Batc  (None, 2048)             8192
 hNormalization)

 dropout_6 (Dropout)         (None, 2048)              0

 dense_3 (Dense)             (None, 256)               524544

 batch_normalization_7 (Batc  (None, 256)              1024
 hNormalization)

 dropout_7 (Dropout)         (None, 256)               0

 root (Dense)                (None, 10)                2570

=================================================================
Total params: 24,124,126
Trainable params: 24,066,398
Non-trainable params: 57,728
```

Figure 6. ResNet50 Model

The accuracy increases and the loss lowers as the training dataset grows. This validates the model's capacity to generate precise forecasts as it gains knowledge from a larger and more varied collection of data.

6.1 Comparative Performance Analysis

We performed a Comparative Performance Analysis of paddy leaf detection models in our research work, concentrating on five unique diseases: Bacterial Leaf Blight, Bacterial Leaf Streak, Bacterial Pannicle Blight, Rice Blast, and Brown Spot. As shown in Table 3, previous research primarily focused on two to four diseases employing machine learning, deep learning, or computational intelligence. However, our study is unique in that it addresses all five diseases at the same time. Sethy *et al*, [9] used Fuzzy logic, computational intelligence, SVM, and k-means to achieve 86.35% accuracy. Chen *et al,* [10], on the other hand, used CNN, IoT, and spore germination to achieve an accuracy of 89.4%. Vimal [11] employed Deep CNN, SVM, transfer learning, and the MatConvNet toolkit to achieve 91.37% accuracy. Islam *et al* [12] used 844 images for training and 140 images for testing. 92.68% accuracy was achieved by using VGG-19, Inception-ResNet-V2, and ResNet-101 to identify leaf smut, leaf blast, bacterial leaf blight, and brown spot. With a 97% accuracy performance, Bharanidharan *et al* [13] used four machine learning techniques such as K-Nearest Neighbor, Random Forest, Linear Discriminant Analysis, and Histogram Gradient Boosting. At first, the classifiers achieve less than 65% balanced accuracy. However, performance is greatly enhanced by using a feature transform based on Modified Lemurs Optimisation, which results in a noteworthy 90% balanced accuracy for the K-Nearest Neighbour classifier. In this article the authors provide an enhanced ResNet50 Paddy Disease Identification Model that outperformed these benchmarks by almost 99% training accuracy and 92.83% test accuracy, with a low loss function of 0.0014 after 100 epochs and, demonstrating its usefulness in paddy leaf disease identification across several illnesses as depicted in figure 7, 8. The comparative analysis is given in Figure 9.

Table 3. Prior research on paddy disease comparison

References	Name of the disease	Tools/ Technologies used	Accuracy %
[9]	Blast, Brown spot, blight, leaf scald.	K-means, SVM Fuzzy logic, computational intelligence	86.35%
[10]	Blast	CNN, IoT, spore Germination	89.4%
[11]	blast, sheath blight.	Deep CNN, SVM, transfer learning, MatConvNet toolbox, AlexNet, NVIDIA GeForce 940M GPU	91.37%
[12]	leaf smut, blast, blight, brown spot	VGG-19, Inception-ResNet-V2, ResNet-101	92.68%
[13]	Brown spot, blast, bacterial leaf blight, leaf folder, hispa, and.	K-Nearest Neighbor, Random Forest, Linear Discriminant Analysis, Histogram Gradient Boosting, feature transform based on Modified Lemurs Optimisation.	90%
Proposed Paddy Disease Identification Model	Brown Spot, Blast, Leaf Streak, Blight	CNN, ResNet50	92.83%

```
Epoch 1/100
131/131 [==============================] - 1307s 10s/step - loss: 1.8347 - categorical_accuracy: 0.4738 - val_loss: 6.5829 - val_categorical_accuracy: 0.2805 - lr: 0.0010
Epoch 2/100
131/131 [==============================] - 1283s 10s/step - loss: 1.0382 - categorical_accuracy: 0.6864 - val_loss: 1.4977 - val_categorical_accuracy: 0.5408 - lr: 0.0010
Epoch 3/100
131/131 [==============================] - 1281s 10s/step - loss: 0.8810 - categorical_accuracy: 0.7392 - val_loss: 4.8502 - val_categorical_accuracy: 0.2695 - lr: 0.0010
Epoch 4/100
131/131 [==============================] - 1283s 10s/step - loss: 1.0106 - categorical_accuracy: 0.6959 - val_loss: 1.8543 - val_categorical_accuracy: 0.4837 - lr: 0.0010
Epoch 5/100
131/131 [==============================] - 1304s 10s/step - loss: 0.6390 - categorical_accuracy: 0.8065 - val_loss: 1.1336 - val_categorical_accuracy: 0.6523 - lr: 0.0010

Epoch 95/100
131/131 [==============================] - 1287s 10s/step - loss: 0.0095 - categorical_accuracy: 0.9984 - val_loss: 0.0015 - val_categorical_accuracy: 1.0000 - lr: 1.4211e-17
Epoch 96/100
131/131 [==============================] - 1290s 10s/step - loss: 0.0104 - categorical_accuracy: 0.9981 - val_loss: 0.0011 - val_categorical_accuracy: 1.0000 - lr: 1.4211e-17
Epoch 97/100
131/131 [==============================] - 1292s 10s/step - loss: 0.0120 - categorical_accuracy: 0.9976 - val_loss: 0.0011 - val_categorical_accuracy: 1.0000 - lr: 1.4211e-17
Epoch 98/100
131/131 [==============================] - 1293s 10s/step - loss: 0.0128 - categorical_accuracy: 0.9984 - val_loss: 0.0010 - val_categorical_accuracy: 1.0000 - lr: 3.5527e-18
Epoch 99/100
131/131 [==============================] - 1292s 10s/step - loss: 0.0105 - categorical_accuracy: 0.9978 - val_loss: 0.0012 - val_categorical_accuracy: 1.0000 - lr: 3.5527e-18
Epoch 100/100
131/131 [==============================] - 1291s 10s/step - loss: 0.0100 - categorical_accuracy: 0.9984 - val_loss: 0.0014 - val_categorical_accuracy: 1.0000 - lr: 3.5527e-18
```

Figure 7. Epoch Result

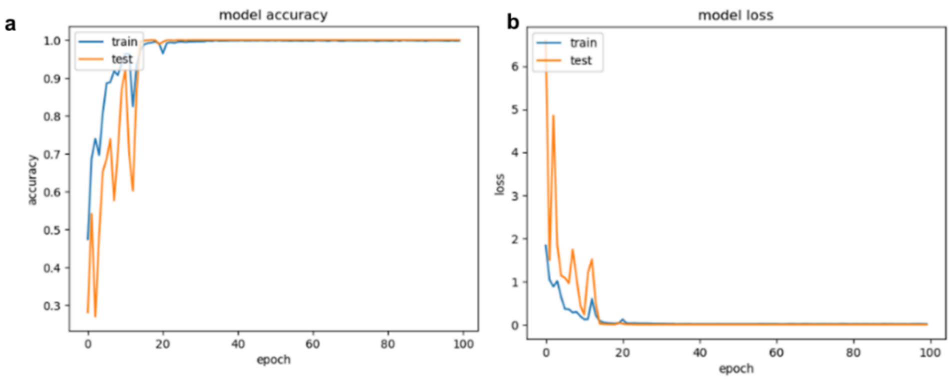

Figure 8. a) Model Accuracy and b) Model Loss

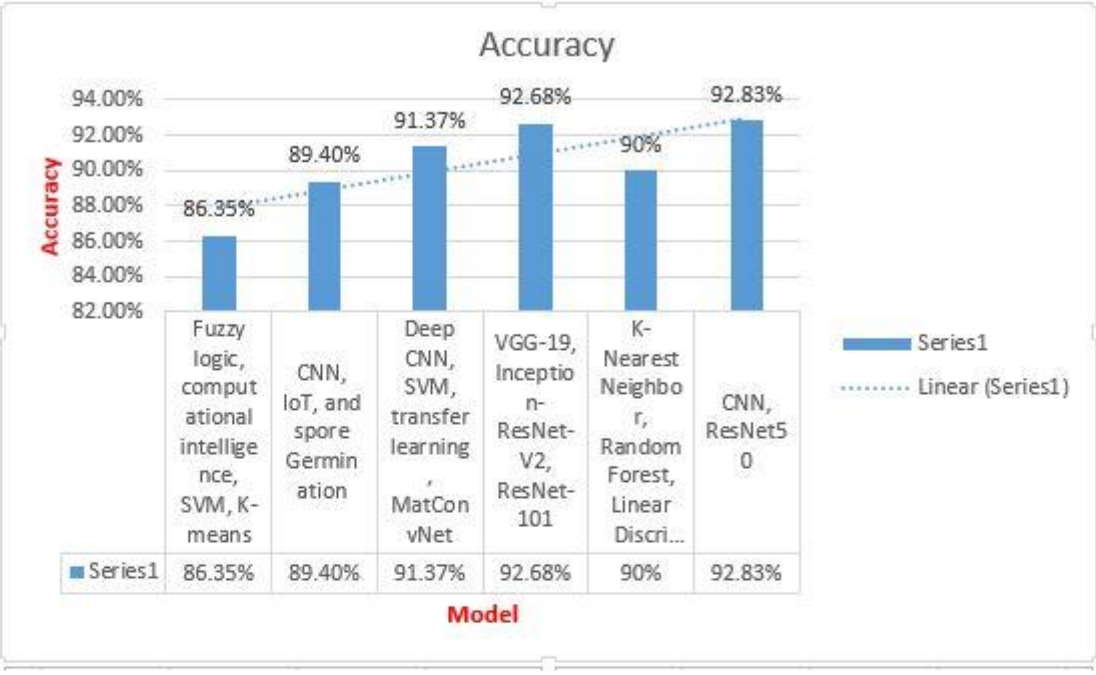

Figure 9. Comparative Performance Analysis

7. Conclusion

Finally, our paddy disease recognition model displayed extraordinary training accuracy, scoring 99% and test accuracy scoring 92.83% on a well-defined dataset of 13,876 paddy disease images. The training period, which used 10,407 images, and subsequent testing with 3,469 images, demonstrated the model's robustness and proficiency in dealing with various paddy illnesses. The model's capacity to improve its performance with a larger dataset is significant, as evidenced by the decreasing loss. Particularly, among the many tested models, ResNet50 outperformed competitors such as VGG-19, ResNet-101, and Inception-ResNet-V2. This demonstrates the accuracy with which our chosen architecture can recognize and classify paddy diseases. Our study not only adds a high-precision model for disease detection but also emphasizes the importance of dataset size and model selection in improving overall performance.

8. Future Work

In the future, the paddy disease identification model will be trained using drone-captured photos of paddy leaves, providing a thorough six-foot-altitude overhead view of rice fields. The model's efficacy will be increased by adding assessment metrics like accuracy, F1 score, precision, and recall. It is expected that this improvement will greatly enhance the model's ability to more effectively detect diseases over wider areas. This modification will improve the model's ability to detect diseases across greater areas more efficiently. The research model is optimized for mobile applications by converting it to a TensorFlow Lite (TFLite) format designed for Android platforms. The model can also be associated with drone applications utilizing Raspberry Pi, allowing for real-time forecasts. This potential development underscores our disease identification approach's realistic deployment and scalability across varied agricultural environments.

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Authors Contribution Statement

V. Sahasranamam - Conceptualization, Methodology, Data collection, Formal analysis, Writing - Original Draft, Writing - Review & Editing; T. Ramesh - Data collection, Writing - Review & Editing, D. Muthumanickam – Validation, Writing - Review & Editing, A. Karthikkumar - Validation, Writing - Review & Editing.

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Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

Data will be provided upon request

Has this article screened for similarity?

Yes