A Resource efficient Method to Detect Rice Leaf Diseases

MSc Research Project
Data Analytics

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A Resource efficient Method to Detect Rice Leaf Diseases

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Abstract

Rice leaves related diseases affect many farmers globally, posing a threat to the sustainable production of rice. There are several diseases that affect the rice leaf, including bacterial, viral, and fungal infections. Leaves, nodes, panicles, and collars of flag are affected by the fungus. Depending on the part of affected plant the disease is called as leaf blast or rotten neck. Brown Spot, Leaf Blast and Hispa are some common diseases during the growth of rice. The yeild of rice crops can be decreased by 20 to 100 with the increased diseases in rice.A wide variety of machine learning, deep learning and image processing techniques are currently being developed to detect diseases, though these require a great deal of computational power and are not suitable for mobile devices. The development of machine learning models for mobile devices that have limited space and speed is challenging. This research proposes a method Based on mobile devices that require less resources. My proposed framework uses MobileNet architecture which is a light weight neural network and are created for mobile devices. A combination of multiple datasets with 3,336 images is obtained from kaggle and is used to train the model with 4 classes of rice leaf diseases namely hispa, leaf blast, brownspot and healthy. The MobileNetV3, DenseNet169, and InceptionV3 models are trained using data augmentation and transfer learning. Results of the three models are presented in this paper based on accuracy, loss and size. This research proposes a resource efficient model to implement of mobile devices.

1 Introduction

As rice cultivation has evolved over the years to increase yields, simple methods have given way to more advanced methods Yu et al. (2012). The majority of recent yield increases have been driven by high-yielding varieties that require more fertilizer, water, and other inputs, leading to disease outbreaks as well Khush et al. (1989). Diseases caused by bacterial infection such as leaf blight, brown spots, leaf blasts, and hispa are common during the rice growing season Ou (1985). The yield loss from a single pest outbreak would be more than 2 million tons, resulting in a total loss of 22 million tons, equivalent to 12 percent of crop's production Liu et al. (2016). The development of plant diseases (epidemics) depends on three main factors. A mixture of susceptible cultivar, virulent pathogen, and favorable environmental factors of fungus can result in severe disease epidemics, if all three factors are present for a considerable period of time. Disease will be less severe or nonexistent if one of the factors is missing or if all three are not sustained for long enough Wamishe et al. (2013). Leaves, nodes, panicles, and collars of flag are affected by the fungus. Depending on the part of affected plant the disease is called as leaf blast or rotten neck. Some researchers have proposed ML and DL methods like randomn forest, CNN, Densenet, etc. for predicting rice leaf diseases Rukhsar and Upadhyay (2022).However the main drawback is these models are not resource effecient to deploy them on mobile devices. In developing countries, Given that the majority of farmers have limited internet connectivity, these automated systems should be convenient and simple to operate. Therefore, a mobile application capable of detecting rice leaf diseases is a great necessity.

The Aim of this research is to propose a resource efficient method to detect rice leaf diseases. The major contribution of this research is to predict rice leaf diseases using resource efficient method which can be deployed on mobile devices. A Minor contribution of this research is to increase dataset size using data augmentation. In order to identify the resource efficient deep learning model this research compares MobileNetV3, Efficient Net, and InceptionV3 based on accuracy, size and loss.

In this paper, there are six sections, with section 2 discussing related work and its findings. The methodology of research is discussed in section 3. In section 4, we discuss design specifications. The implementation and results are discussed in section 5 and section 6. In section 7, conclusions and future work is discussed.

2 Related Work

Rice leaf disease detection helps reduce the impact on rice yeild. Bhartiya et al. (2022) and Mekha and Teeyasuksaet (2021) proposes disease detection using machine learning and image processing techniques. Dataset is obtained from UCI dataset[1] which has 120 images of 3 classes. Different machine learning algorithms like Random forest, Decision tree, Gradient Boosting, Naive Bayes with knime image processing are applied by Mekha and Teeyasuksaet (2021) and random forest has highest accuracy of 69.44 percent. Bhartiya et al. (2022) uses algorithms like linear SVM, Cubic SVM, Ensemble subspace KNN, Kernel Naive Bayes with mean shift segmentation and got highest accuracy of 81.8 percent for quadratic SVM. Bhartiya et al. (2022) indicates the future research should include deep learning approach which will increase the performance further.

Current research into Rice leaf disease detection are implementing deep learning models to improve perfomance such as Convolutional Neural Network (CNN), Zippier S-Method Daniya and Vigneshwari (2021) , AlexNet Zakzouk et al. (2021) , inception V3 Teja et al. (2021). Kaur et al. (2021) reviews the literature related to rice leaf disease detection from 2012 to 2020 and provided comparison on basis of accuracy, dataset and method. From the comparision it is seen that most of the authors have used small dataset and various ML, DL techniques are used. Compared to other approaches, deep learning methods with large datasets achieve better accuracy. So in our research we will be considering the deep learning methods and with larger dataset.

Rukhsar and Upadhyay (2022) detects rice leaf diseases such as blight, blast and tungro using transfer learning models.The dataset is obtained from kaggle and it contains 24 images with 80 images in each class. Densenet201 model is used to detect the rice leaf disease. Rukhsar and Upadhyay (2022) acheives an training accuracy of 96.09 percent and testing accuracy of 94.44 percent. In this paper AlexNet Zakzouk et al. (2021) got the dataset from Kaggle that contains 16,000 images and was divided into 4 groups

[1]https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases

namely, Brown Spot, Healthy leaf, Bacterial Leaf blight and Leaf Smut . The images are preprocessed and trained using alexnet.Parameters like 50 epochs, 0.01 learning rate and 45 batch size are used to increase accuracy.The proposed alexnet model achieves an accuracy of 99.71 percent.Teja et al. (2021) uses a mix of optimization technique into InceptionV3 and transfer learning. The dataset is obtained from UCI which has 120 images. The input is pre-processed using InceptionV3 based on the picture. A combination of machine learning models and image inputs produced good results in this study, but the best results came from an inceptionV3 and transfer learning mixture with an accuracy of 99 percent. From the above studies it is evident that transfer learning models are perfoming well as they are pretrained on image net dataset which has over 1 million images.however these models require a lot of computational power. We also observered that the datasets used in these papers are small.Zakzouk et al. (2021) uses dataset with 16000 images but it contains augmented images.In our research we will be using pretrained model to obtain better perfomance.

Krishnamoorthi et al. (2021) uses image augmentation and convolutional neural network for identification of maize leaf diseases. The dataset is obtained from kaggle which has 4149 images of 9 classes. These images are converted into 256 by 256 pixel images.Then data augmentation is applied to increase the size of dataset using techniques like cropping, rotation, padding , transposing and so on. Then augmented images are split into test and train datasets. GoogleNet model is used for classification of maize leaf diseases. It has obtained an accuracy of 99.87 percent and 98.55 percent for training and testing. CNN models need larger datasets to get better accuracy so we will be using image augmentation to increase the size of dataset.

In this paper Anh and Duc (2021) uses most popular models like MobileNets, MnasNet , EfficientNets Lite, InceptionNets and ResNets and compare which model is suitable for deployment on edge devices. The dataset is obtained from plant village[2] which consists of 5430 images divided into 30 classes.Then they used pretraining using imagenet weights. The input images were resized and normalized to 224 by 224 by 3.MobileNetV3 had the highest accuracy of 96.58 percent after training and comparing the results with EfficientNet, who had the lowest accuracy of 96.3 percent. Despite using only 4972 MB in initialization and 7.4 MB total in 1GB RAM, MobileNetV3 outperformed other architectures. Training hyperparameters used are 5 train epochs, 32 batch size, 0.005 learnign rate,0.9 momentum, 0.2 dropout and 0.0001 l2 regularizer.From the results we can see that mobilenet is suitable model for mobile devices.

In this study Elfatimi et al. (2022) proposes bean leaf classification by Testing the accuracy and training times of MobileNetV2 architecture under controlled conditions. We obtained this dataset from github, which has been annotated by the National Crops Resources Research Institute (NaCRRI). The images were captured with a smart phone in the field, and they were resized to 128 by 128 pixels to meet MobileNet's input requirements. A variety of TensorFlow architectures and optimizers were used to train MobileNet models, including adagrad, nadam, SGD, RMSprop, and the Adam optimizer with asyncronous gradient descent. All criteria were used under the same conditions in order to compare different architectures. Compared to the rest, Adam's optimizer and SGD's optimizer performed the best in terms of accuracy. Adam's optimizer reached 100 percent accuracy, while SGD's optimizer reached 99.94 percent accuracy. Adam optimizer training at 0.001 learning rate with 32 batch size has the highest accuracy. This study had 94.74 and 98.50 percent minimum validation and training accuracy.

[2] www.plantvillage.org

Noon et al. (2021) present a low cost and efficient solution for classification of cotton crop diseases.The images of dataset is collected from the internet and from the fields of Punjab region in pakistan. They have used pretrained models of efficient net and mobilenet architectures. from the evaluation we observed that mobilenet has less trainable parameters and acheived accuracy close to EfficientNet. Elhassouny and Smarandache (2019) presents a eficcient mobile application based on deep learning to recognize tomato leaf disease. To classify tomato leaf diseases, the model was inspired by the MobileNet CNN. They are 7100 images in the dataset . Dataset has been used to train MobileNet model, but desired results have not been received. In order to increase MobileNet's accuracy, the adapted model was tested with optimization methods such as stochastic gradient descent, Adam, adagrad, adagradDA, momentum, adadelta optimization, proximaladagrad, Ftrl, and RMSprop optimization. In their study, they achieved 90.3 percent accuracy with learning rate 0.001 by using proximal gradient descent.

There are 3600 images in this paper Sun et al. (2021)that are categorized into five categories: daisy, tulip, sunflower, rose, and dandelions. This dataset is used to train both convolutional neural networks and MobileNet. Each image is resized to 224 by 224 pixels and the batch size is set to 16. Normalization and modification are applied to both models. As part of CNN model, the zeros and ones between 0 and 255 are unified to 0 and 1. The MobileNet model is optimized using the Adam algorithm and the cross entropy method is used to calculate the loss function. CNN and Mobilenet achieve accuracy of 66 and 88.3 percent, respectively. This dataset with 2400 images was obtained from Kaggle by Arfan et al. (2021). MobileNet model was trained using transfer learning. To acheive more accuracy the model has been fine tuned with following parameters training epochs = 25, learning rate = 0.01 and they got 94 percent accuracy.

In conclusion, the state of the art indicates some of the best deep learning, machine learning, image processing techniques are implemented for rice leaf disease detection and there is a need for through experimentation to identify the resource efficient model for use in rice disease classification. Current research indicates that mobilenetV3 model is a resource efficient model which is giving good accuracy and less in size.In addition when compared to other models it takes less computational power which makes perfect model to deploy on mobile device.current research also indicates that data augmentation helps in increasing the size of data which in turns increase the performance.This research proposes a resource efficient method to detect rice leaf disease that uses data augmentation and pretrained MobilenetV3 model.We will compare the perfomance of the model with inceptionV3 and densenet169.we will also use quantization to optimize the model for deployment on edge devices.

3 Methodology

The research methodology consists of five steps namely data gathering, data pre-processing, data transformation, data modelling and fine tuning, evaluation and results as shown in Figure 1

The first step, Data Gathering involves obtaining dataset from kaggle which contains images collected from different sources. [3][4]

The second step, Data Pre-processing involves image re-classification to ensure a clean

[3]https://www.kaggle.com/datasets/shayanriyaz/riceleafs

[4]https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases

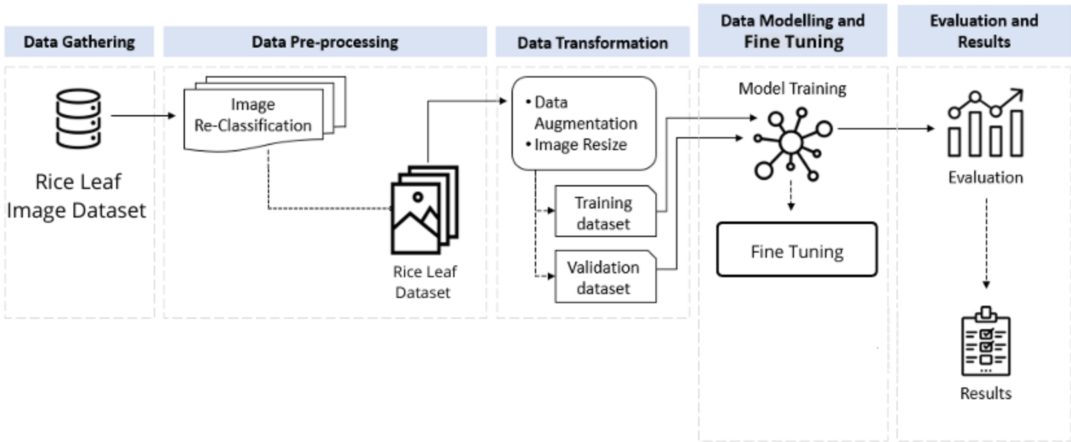

Figure 1: Research Methodology

image dataset.From the EDA we observed that many images were misclassified and some images have more than one disease. All the rice leaf images were checked manually.. These misclassified images were reclassified accordingly and images with more than one disease are removed. some blurred images which cannot be seen were also removed. After pre-processing the riceleaf dataset contained 3347 rice leaf images.

The third step, Data Transformation involves data augmentation, image resizing and splitting the dataset into train and validation datasets. During data augmentation, the dataset is reshaped and reconfigured in preparation for modeling. The riceleaf dataset contained 4 classes of leafs namely Brownspot with 515 images, Healthy with 1488 images, Hispa with 565 images and leaf blast with 779 images. TensorFlow ImageDataGenerator was used to augment the rice leaf dataset. These included vertical flip = True, horizontal flip = True, zoom range = 0.2,rotation range = 30 , colour mode = “rgb” (3 – channels), batch size = 32 , width shift range = 0.1 and height shift range = 0.2. Depending on the model, the target size is either (224, 224) or (48, 48). In order to train and validate the augmented riceleaf dataset was split into ratio of 80:20.

The fourth step, Data Modelling involves model training and fine tuning. We have used three pretrained models namely MobilenetV3, InceptionV3 and Densenet169 with imagenet weights. MobileNetV3 was trained with an image shape of (32, 224, 224, 3). InceptionV3 and DenseNet169 were trained with an image shape of (32, 48, 48, 3). To the pre-trained model a classifier is added with global average pool, dense layer with relu, dropout layer and dense layer with softmax activation function. After freezing the feature extraction layers we train the model with rice leaf dataset with 30 epochs, early stopping criteria of 5,learning rate 0.1, SGD optimizer and categorical cross entropy as loss.Then the model is fine tuned by unfreezing the feauture extraction layers with SGD optimizer, Learning rate 0.005 and 20 epochs. TensorFlow Lite was then used to convert the trained models into mobile-compatible formats. A small-sized model was obtained by applying post-training quantization while maintaining its performance.

The fifth step, Evaluation and Results involves evaluating each deep learning model’s performance according to its accuracy, precision, loss, and size. These results of these models are compared and visualized power BI to find the resource efficient model.

4 Design Specification

The resource efficient method architecture combines data augmentation and deep learning image classification model as shown in Figure 2

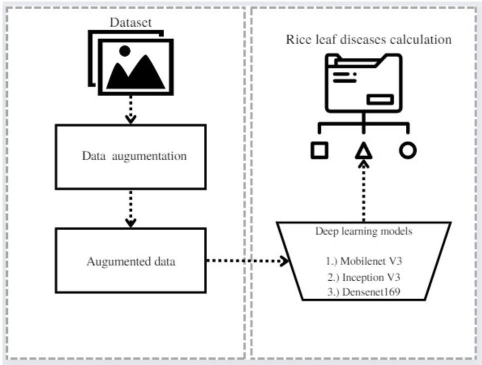

Figure 2: Resource Efficient Deep Learning Architecture

4.1 Data Augmentation

For a deep learning model to be effective, data augmentation is a process of expanding an existing dataset.This will also increase the overall efficiency of model.An image data augmentation process can help expand datasets for use in training learning models.In general, augmentations include geometric transformations, flipping, color space transformations, cropping, rotation, translation, adding blue and noise to images.A variety of techniques are used here, such as rotation, zoom, enhancing contrast, shifting, rotation, and flipping.

4.2 Deep Learning Image classification Model

4.2.1 MobileNetV3:

For the deep learning image classification we are using MobilenetV3. MobilenetV3 is the latest with MobilenetV2 and Mobilenet as previous versions.The main architecture of mobilenet uses depth-wise seperable convolutions. A linear bottleneck and shortcut connections between layers were two new features in MobileNetV2. The MobileNetV3 analyzes images through image analysis, which is available in dozens of popular mobile applications. MobileNetV3 contributes to finding the best solution through its use of AutoML.

4.2.2 InceptionV3:

The Inception-v3 algorithm has produced good results in a number of applications using transfer learning. Convolutional filters of different sizes are concatenated into a new filter in the inception model. Within the same module of the network, the inception module serves as a "multilevel feature extractor." by computing a 1 by 1, 3 by 3, and 5 by 5 convolution.This will help decrease the no of trainable parameters which will decrease the computational complexity.

4.2.3 Densenet169:

In high-level neural networks, vanishing gradients cause accuracy to decline. DenseNet was developed to solve this issue. As information travels longer paths between input and output layers, it vanishes before reaching its destination.DenseNet Architecture is composed of DenseBlocks. As an example, DenseNet-169 has layers of [6, 12, 32, 32].

5 Implementation

The resource efficient method was implemented as a combination of data augmentation and deep learning model for rice leaf disease detection.In this section we will discuss the steps followed for this implementation. We have used anaconda jupyter notebook to code in python since it is easy to install packages and capable of handling large process.Tensorflow 2.9 import the model and train it.we have also used libraries like pandas, numpy matplotlib, seaborn and plotly in our implementation. first we have identified the dataset on kaggle which was a combination multiple datasets availble at different sources.This dataset was of 8 gb and has 3347 images. We have performed EDA on this dataset by loading it into jupyter notebook to see if there is any misclassification or unclean data.The dataset was available in 2 folders as training and validation with random distribution and they were also misclassified. so we have merged the train and validation images according to the classes, reclassified them and was split into a ratio of 70:30 for training and testing.we have defined some parameters like image height , width, Learning rate, epoch, etc. We have taken preprocess input from keras application according to the model and performed image augmentation using image data generator.Then this data is split into 80:20 for training and validation using flow from directory using a batch size of 32. Pretrained mobilenetv3 model is imported from keras applications with imagenet weights. The dataset is trained on this model by freezing the feature extraction layers.Then it is again fine tuned by unfreezing the feature extraction layers. The accuracy, loss are evaluated using accuracy vs epoch and loss vs epoch. later the model is evaluated with testing data.confusion matrix and classification report are also used to compare the model performance. Tensorflow lite is used to convert the model in to an .tflite model which is an efficient format.This model can be used in mobile device to classify the disease.

6 Results and Discussion

6.1 Experiment 1: Exploratory Data Analysis

The aim of this experiment is to perform an exploratory data analysis on the rice leaf dataset.The dataset has 3355 images classified into 4 classes with 565 images of Hispa, 515 images of Brownspot ,1488 images of Healthy, 779 images of Leafblast. In EDA we have observed that some images are misclassified or have multiple diseases.so this data set has been manually checked and reclassified. Then the dataset is split into ratio of 70:30 for training and testing. The train and test data has distribution as shown in figure Figure 3.

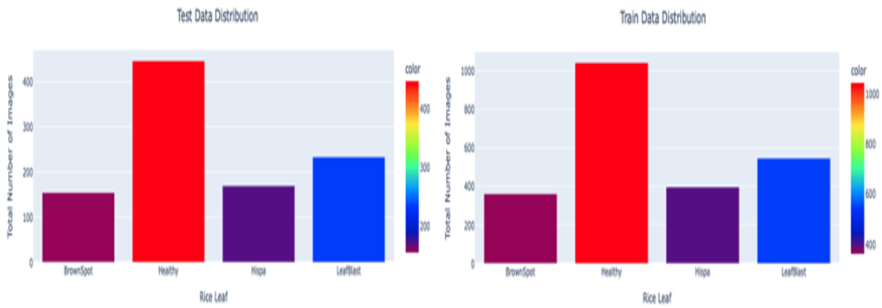

Figure 3: Data distribution of rice leafs dataset

6.2 Experiment 2: Replicate State of the Art

The aim of this experiment is to replicate the state of the art model Anh and Duc (2021) identified in literature review.The dataset used in this paper is for multi leaf disease not specific to rice leaf diseases. so we have used the dataset from kaggle.In the state of the art MobilenetV3 has acheived highest accuracy of 96.58 percent. First the images are resized into 224x224x3, then the pretrained mobilenet model is imported from keras and feature extractor later is freezed. To complete the model feature ectration layers is wrapped and to that they have added a fully connected layer, dropout layer with 0.2 value and softmax activation layer. hyperparameters are used in training process like train epochs = 5, learning rate = 0.0005, momentum = 0.9, batch size = 32, l1 regularizer = 0.0 and l2 regularizer = 0.0001. Stochastic Gradient Descent is used as optimizer and categorical crossentropy as loss function. units of dense layer are not mentioned in this paper.we have replicated this work and acheived 78 percent training and 59 percent testing which less compared SOA.we can see that the model has poorly performed in classification as shown in Figure 4 5

	precision	recall	f1-score	support
0	0.53	0.66	0.58	154
1	0.62	0.99	0.76	446
2	0.64	0.05	0.10	169
3	0.89	0.30	0.45	233
accuracy			0.62	1002
macro avg	0.67	0.50	0.47	1002
weighted avg	0.67	0.62	0.55	1002

Figure 4: Classification report of experiment 2 (Replicate state of art)

6.3 Experiment 3: Deep Learning image classification

The aim of this experiment is to fine tune the MobileNet Model from 6.2 to increase the performance of model. To fine tune the MobileNet Model we have tried different

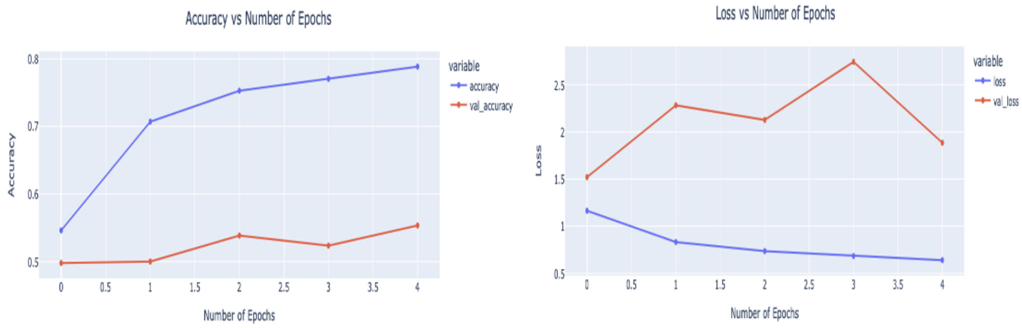

Figure 5: accuracy vs no of epochs and loss vs no of epochs of experiment 2 (Replicate state of art)

learning rates and optimizers like SGD and Adam which are shown in Table 1. we will also compare the model performance in terms of accuracy, size with other pretrained models like InceptionV3 and Densenet169. For training the model we have used SGD optimizer with learning rate of 0.1, 32 batch size and 0.0001 l2 regularizer. Then to fine tune the model we have used following parameters epochs 20, SGD optimizer and 0.005 learning rate.

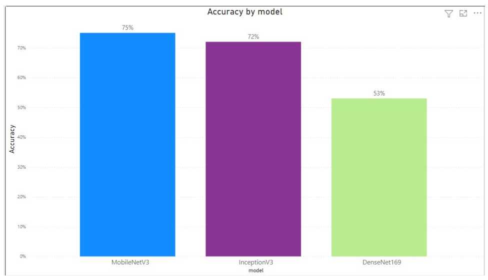

Figure 6: comparison of models by accuracy

Figure 6 shows the comparison of three models by accuracy. This result indicates that mobilenet model predict with an avg accuracy of 75 percent followed by inception with accuracy of 72 percent.

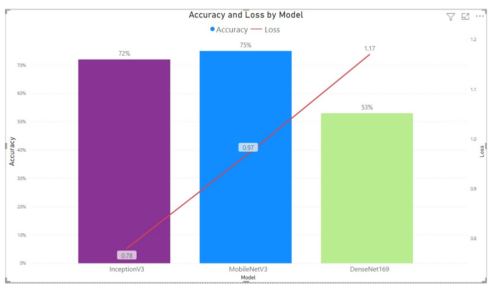

Figure 7: comparison of models by accuracy and loss

Figure 7 shows the comparison of three models by accuracy and loss. Loss is a measure of how well a model predicts after each optimization cycle. This result indicates that inceptionV3 has lowest loss with an accuracy of 72.

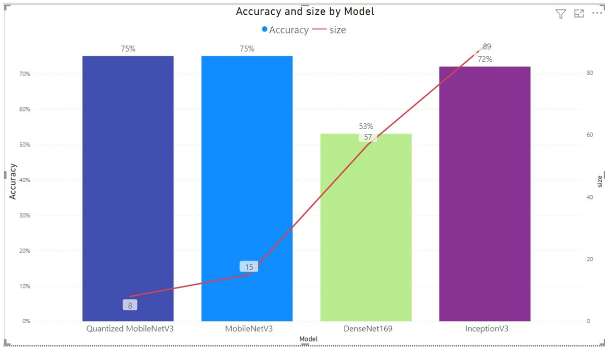

Figure 8: comparison of models by accuracy and size

Figure 8 shows the comparision of three models by accuracy and size. we can see that mobilenet after quantization has small size of 8mb which makes good model to deploy on mobile.

In Figure 9 , you can see the number of parameters for each model. MobileNetV3 has fewer parameters than other network architectures (3.2 million), performing better than InceptionV3 50 (23.9 million) and DenseNet169 (14 million). Figure 10 shows the accuracy of mobilenet model with different learning rates.

Model	MobileNetV3	InceptionV3	Densenet169
Number of parameters	3,275,780	23,905,060	14,351,940

Figure 9: comparison of models based on no of parameters

Learning rate	0.1	0.01	0.001	0.0005
Accuracy	75	71	68	64

Figure 10: Comparison of MobileNetV3 accuracy by learning rates

6.4 Experiment 4: Healthy/Unhealthy

The aim of this experiment is to classify the rice leaf disease as healthy or unhealthy instead of 4 class classification problem. This will still help farmers to detect if there is disease with higher accuracy.we have achieved an accuracy of 86 percent.

Figure 11: accuracy vs no of epochs and loss vs no of epochs of experiment 4 (Healthy/Unhealthy)

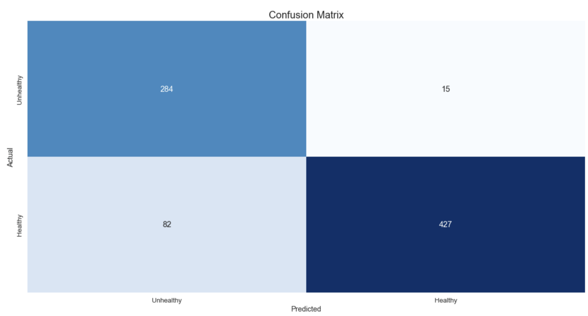

Figure 12: Confusion matrix of experiment 4 (Healthy/Unhealthy)

7 Conclusion and Future Work

The aim of this research was to propose a resource efficient method for detection of rice leaf diseases. In this paper we have proposed pre trained Mobilenetv3 model in combination with data augmentation increases the size of dataset and also increase the perfomance. Results demonstrate that MobilenetV3 has acheived highest accuracy of 75 percent. we also created .tflite model which can be deployed on mobile device and mobilenet has the small model size of 15 mb, followed by densenet with 57 mb and inceptionv3 with 89 mb.We also observed that mobilenet has less parameters of 3.2 million when compared to other models. This makes MobileNet the most efficient model to deploy on mobile devices. A limitation of this study is deployment of tflite model on mobile device and getting the stats.

This research can potentially enhance the detection of rice leaf diseases on mobile with limited resources, especially in developing countries.This work can be improved by optimizing the model by considering the statistics like intialization time, inference etc from a mobile device. The accuracy can also be increased by doing image segmentation which removes the background images. This work can further by extended by analysing panoramic images of fields which are captured using drones.

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