

**RICE DISEASES RECOGNITION SYSTEM USING CONVOLUTION
NEURAL NETWORK**

Shams Shahriar Bhuiyan

ID: 181-15-11073

Rifah Tasnia

ID: 181-15-11320

Arafaht Anam

ID: 181-15-10922

This Report Presented in Partial Fulfillment of the Requirements for the
Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Aniruddha Rakshit

Senior Lecturer

Department of CSE

Daffodil International University

Co-Supervised By

Ms. Farah Sharmin

Senior Lecturer

Department of CSE

Daffodil International University



DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

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APPROVAL

This Project titled “ **Rice Diseases Recognition System Using Convolution Neural Network**”, submitted by ***Shams Shahriar Bhuiyan*** , ***Rifah Tasnia*** and *** Arafah Anam *** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on
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BOARD OF EXAMINERS



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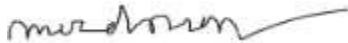
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Assistant Professor

Department of CSE

Faculty of Science & Information Technology

Daffodil International University

Internal Examiner



Md. Ohidujjaman Tuhin (MOT)

Assistant Professor

Department of CSE

Faculty of Science & Information Technology

Daffodil International University

Internal Examiner



Shah Md. Imran

Industry Promotion Expert

LICT Project, ICT Division, Bangladesh

External Examiner

DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Aniruddha Rakshit, Senior Lecturer, Department of CSE**, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:



Mr. Aniruddha Rakshit

Senior Lecturer

Department of CSE

Daffodil International University

Co-Supervised by:



Ms. Farah Sharmin

Senior Lecturer

Department of CSE

Daffodil International University

Submitted by:

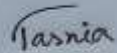


Shams Shahriar Bhuiyan

ID: 181-15-11073

Department of CSE

Daffodil International University



Rifah Tasnia

ID: 181-15-11320

Department of CSE

Daffodil International University



Arafah Anam

ID: 181-15-10922

Department of CSE

Daffodil International University

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ABSTRACT

Our farmers provide food for the entire planet. However, they face a wide range of obstacles in agriculture, which they are unable to manage, including from illnesses to insect infestations. Crop losses are caused by a number of diseases, and diseases are a part of our normal life. Using a computer based automatic system or approach, like image segmentation for disease recognition systems or approaches. It is really beneficial to us. For this most worthwhile apparatus is deep learning in convolution neural network CNN. This paper proposes some methodology to detect 3 types of rice diseases with U-Net architecture. We worked on pre-processed data with three trained models(60:40; 70:30; 80:20). In our research we segmented RGB image to grayscale output using semantic segmentation. We also used the Grid Search algorithm for comparing six types of optimizer. We used Adam optimizer to run this model. We developed a U-Net architecture model with added layers and successfully got more than 93% accuracy respectively which is more efficient for future deep learning and also the agricultural sector. This research work is incredibly good and should be developed as a real-time system for future farmers to u

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CHAPTER 1

Introduction

1.1 Introduction

Rice is just an essential meal for about 1/2 of the country's population, covering almost all of East and Southeast Asia; humans consume 95 percent of the world's rice production. Rice may be cooked in a variety of ways, such as by boiling it or grinding it into flour. Across Asian, Middle Eastern, as well as other cuisines, it is served alone or in a wide range of salads, side dishes, and main entrees. Planted rice is an annual herb that reaches a height of around 1.2 meters (4 feet). The hollow stalks carry the long, flattened leaves.

1.2 About Rice Diseases

Rice, although is among the most important agricultural products, is plagued by a variety of illnesses. Throughout Bangladesh, 32 rice disorders have been identified. Rice Leaf Blast (RB), Brown Spot, Hispa are among the several illnesses. Rice blast is the most dangerous of these infections. During today's environment, it is critical for farmers to employ contemporary technologies to manage their crops efficiently. Rice is cultivated twice a year in Bangladesh. Due to fungus, bacteria, and viruses, majority rice growers confront several challenges when producing the crop. They are frequently unable to meet their financial obligations.










Table 1 : Table of disease production loss

No	Disease Name	Production Loss
1	Rice Leaf Blast	80%
2	Brown Spot	45%
3	Hispa	20%

1.3 Motivation

In this investigation, we employed a unique dataset of our own that included photos of diseased rice leaves obtained from several sources. We collected our dataset from kaggle which was a pre-processed dataset. The consistency and efficiency of our suggested technique were justified after evaluating its performance on three independent datasets. We're utilizing three different diseases, and 80% of the data is for training and 20% is for testing. Label the photographs of three distinct classes accurately. Those classes are (a)Brown Spot; (b)Hispa; (c)Leaf Blast. A total of 1200 photos for training and 369 images for testing were taken.

Table 2 : Table of sample dataset

Brown Spot			
Hispa			
Leaf Blast			

These have been demonstrated which we can train utilizing better significant data and extremely strong accuracy for each illness type. During this are segmented to use the most

details about the illness symptoms by separating impacted sections of the leaves rather than complete leaf pictures in this experiment.

In this paper, we propose three significant contributions to rice disease detection in this study. We have a kaggle dataset to work with. We have trained 80% and 20% tested data of three different types of rice diseases. We have segmented these data from this dataset. In this case input data is in RGB format and output image is in grayscale. This is because input images are segmented by semantic segmentation.

We have made a change in U-Net architecture, normally U-Net architecture has 5 layers. In our Architecture, we increased a layer which will get more accuracy. It starts from 32x32 pixels. We develop an U-Net architecture that will be useful in the deep learning industry. Our dataset has been trained for classification but not segmented prior to working on it. To get greater accuracy, we pre-trained this dataset for segmentation.

We also trained 70% and 30% tested data and 60:40% data to get the ROC. For these we have made a comparison between trained datasets.

We did a comparison by using the Grid Search algorithm of 6 different types of optimizers. Convolutional Neural Networks performed well in simpler picture segmentation challenges, but not so well in more difficult ones. This is where U-Net plays its part. U-Net was created with several types of image segmentation in mind for rice diseases. Result shows that, Everything just produced good results that it applied to a variety of different disciplines. Segmentation process is a significant issue. Daily basis, a new study article is released. U-Net made a huge contribution to this research paper. U-Net has influenced a lot of innovative architectures. But there's still so much to discover. Because there are so many variations of this design in the business, it is vital to understand them all. Understanding the first one to have a greater understanding of the others. A convolutional network is referred to as a u-net. Framework for picture segmentation that is quick and accurate. U-net architecture (32x32 example pixels at the absolute lowest resolution).It produced such positive results that it was later applied to a variety of other disciplines.

However, some researchers have discovered that the traditional U-Net model is still quite simple, and that node convolution may be improved. Another noteworthy feature is that U-Net employs a new loss weighting system for each pixel, with a greater weight towards the segmented object's edge. In this research, we use U-Net, which has been enlarged with just minor alterations to the CNN design. It was created to cope with crop photos in which the goal is to not only assess whether or not there is a disease, but also to locate the infective region.

CHAPTER 2

Literature Review

2.1 Introduction

A literature review examines books, academic papers, and any other sources related to a certain subject, field of study, or theory, and gives a description, summary, and critical assessment of these works in connection to the research problem under consideration. Literature reviews are meant to provide readers an overview of the sources you utilized to explore a certain topic and to show them how your findings fit into a larger field of study.

2.2 Literature Review

[1] (Wan-jie Liang et al.,2019)In this paper, They present a new rice blast identification algorithm based on CNN in their research. CNN model is trained and They findings of the study reveal that increased extracted features by CNN are more selective and productivethan typical hand-crafted features such as binary patterns histograms (LBPH) Furthermore, quantitative evaluation results show that CNN with Fully connected layers and CNN with support vector machine (SVM) perform similarly to LBPH plus an SVM as the classifier with higher accuracy, larger area under curve (AUC), and effectively aspects involved distinctive (ROC) curves. Since their approach of automated rice blast detection has shown good results, but they need much more effort is required to increase its accuracy level.

[2] (Parul Sharma et al.,2019) proposed a methodology for detecting 10 types of tomato plant's diseases and compared the performance of training a convolutional neural network (CNN) model using segmented images (S-CNN) and full images (F-CNN). They had applied multiple convolution and pooling steps and introduced nonlinearities using a Rectified Linear Unit (ReLU) to automatically learn the decision boundaries for classifying the images. The average accuracy of the S-CNN model was 98.6% as compared to 42.3% of the F-CNN model. The authors also evaluated the quantitative analysis of self-classification confidence of the two models and showed that

82% of the test dataset showed higher confidence resulting from S-CNN than F-CNN model.

[3] (Yang Lu et al.,2017) In this paper, they provide a comprehensive rice disease detection approach based on deep convolutional neural networks (CNNs) techniques. CNNs are trained using a dataset of 500 real photos of damaged and healthy rice leaves and stems taken from a rice experimental field to recognize ten common rice illnesses In the ten-fold they suggested CNNs-based model, as well as the integral approach technique reaches a 95.48 overall accuracy. The outcomes can be achieved using a 10-fold cross-validation technique to train and test, and evaluate mean-pooling, max-pooling, and stochastic pooling. It shows that probabilistic pooling did best. Additionally, observe the diameters of the 5 convolutional filters. As can be seen, different convolutional filter sizes have distinct effects. Outcomes of the BP technique and the support vector were compared. Optimization algorithm with the support vector machine (SVM) approach is also observed.

[4] (Monzurul Islam et al.,2017) In this paper, they offered a method for identifying illnesses using leaf photos that combines image processing and machine learning. Picture segmentation using multiclass SVM is used to automate an easily accessible system.

It intends to add a larger number of illnesses from diverse plant species to the system. The use of a segmentation method and a support vector machine resulted in a 95 percent accuracy in illness categorization across 300 photos.

[5] (K. Padmavathi et al.,2019)In this paper, they analyzed and compared two types of photos, Grayscale and RGB images, and provided a comparison result. Applying picture methods like pre-processing and analysis, they evaluated and examined the Grayscale and RGB images. For identifying leaf diseases, segmentation and clustering are used. Color has a role in spotting diseased leaves. crucial factor for determining the severity of the illness Grayscale and RGB photos were analyzed, and the median filter was utilized. Image enhancement and segmentation are employed to remove the sick region of the image, which is then utilized to identify the illness. The RGB image provides a clearer, noise-free image that is suited for detecting sick leaves .

[6] (Monishanker Halder et al., 2019) In this paper, they examine several illness classifications. There are a variety of procedures that may be used to identify plant leaf disease detection, image processing, K-means clustering, SVM, ANN algorithm. This study provides an overview of alternative disease categorization strategies that may be utilized for plant leaf disease detection, as well as an algorithm for automated detection using picture segmentation. The best outcomes were achieved with very little computing effort.

[7] (Srdjan Sladojevic et al., 2016) In this paper, Between picture collection for training and validation to image preprocessing and augmentation, they eventually used the technique for training and fine-tuning the deep CNN model. Various experiments were carried out to evaluate the performance of the newly generated model and ANN architecture. Every image from the validation collection was put to the test. The deep CNN training was carried out using a deep learning framework built . For independent class examinations, the experimental findings on the constructed model obtained accuracy between 91 and 98 percent, on average 96.3 percent.

[8] (Shradha Verma et al., 2020) In this paper, they implemented three CNN models, namely, AlexNet, SqueezeNet and Inception V3, to determine the severity of Tomato Late Blight illness. The photos were chosen from the Plant Village collection and divided into three disease severity phases. The CNN architectures were developed in two modes: transfer learning and feature extraction (where the extracted feature set was used to train a multiclass SVM). AlexNet outperformed the other two networks in both ways, with accuracy of 89.69 percent and 93.4 percent.

[9] (Md. Al-Amin et al., 2019) This paper developed a CNN-based model for forecasting different rice leaf diseases that is 97.40 percent accurate.

Using a dataset of over 900 photos of diseased and healthy leaves using the 10-fold cross validation approach, researchers were able to identify illnesses and healthy leaves. The model was taught to recognize four different rice illnesses.

[10] (Prajapati et al., 2017) In this paper based on photos of sick rice plants, a prototype system for detecting and classifying rice illnesses has been developed. This prototype system was created following a thorough investigation of the various approaches utilized

in image processing. They looked at three diseases that affect rice plants: Bacterial leaf blight, Brown spot, and Leaf smut.. They used a digital camera to collect photos of diseased rice plants in a rice field. They put four background removal approaches and three segmentation techniques to the test. They presented centroid feeding based K-means clustering for segmentation of disease sections from a leaf picture to enable accurate feature extraction. For multi-class classification, they employed Support Vector Machine (SVM). On the training dataset, they were 93.33 percent accurate, and on the test dataset, they were 73.33 percent accurate. They ran 5 and 10-fold cross-validations and got 83.80 percent and 88.57 percent accuracy.

[11] (Nunik Noviana Kurniawati et al.,2009) In this paper, The purpose of this study is to create a model system that can detect paddy illnesses such as Blast Disease (BD), Brown-Spot Disease (BSD), and Narrow Brown-Spot Disease (NBSD) (NBSD). The procedure entails capture of photos, conversion of RGB images to binary. That used an approach based on automated thresholding method created this image. The method is to employ a morphological algorithm applying the area filling approach to eliminate noise. Then comes the color of a spot and the color of a split paddy leaf are taken by photos of paddy leaves As a result, using the output rule Using this technology, 94.7 percent accuracy of paddy infections may be identified. To discover the right result in evaluating ninety-four paddy leaf photos, two thresholding approaches were used. Two techniques that employed an algorithm to reduce cutoff had the highest accuracy.

[12] (Peng Jiang et al.,2019)This research proposes a deep learning strategy for real-time detection of apple leaf diseases based on upgraded convolutional neural networks (CNNs). The apple leaf disease dataset (ALDD), which was made up of laboratory photos and complicated images taken in the field, was initially created using data augmentation and image annotation tools in this work. By incorporating the GoogLeNet Inception structure with Rainbow concatenation, a novel apple leaf disease detection model based on deep-CNNs was suggested. Finally, the proposed INAR-SSD model was trained to identify these five prevalent apple leaf illnesses using a dataset of 26,377 pictures of sick apple leaves in the hold-out testing dataset. The INAR-SSD model achieved a detection performance of

78.80 percent mAP on ALDD, with a high-detection speed of 23.13 FPS, according to the results.

[13] (Jayme Garcia Arnal Barbedo et al.,2016) In this paper, Based on image modifications, statistical features, and a new and improved categorization system, this research provides a technique for illness plant detection. A big collection including photos of diseases was used to assess its efficiency. There are 82 distinct biotic and abiotic stressors that impact the plants of 12 various plants. Their initial job was to eliminate the backdrop by segmenting the leaf holding the symptoms. The challenge is simple if the leaf is separated from the backdrop by some form of screen, but this was not the case for many of the photographs utilized in this project. The method's accuracy level for common beans was 50%, which is a decent result considering there were 12 potential illnesses to examine.

[14] (Chunshan Wang et al.,2021)In this paper, for cucumber leaf disease severity classification (DUNet) in complicated backdrops, this work developed a two-stage model that combined DeepLabV3+ and U-Net. This model utilizes DeepLabV3+ to segment leaves from complicated backgrounds in the first step. After segmentation, the pictures of leaves were utilized as input for the second step. U-Net was utilized in the second step to segment the sick leaves and acquire disease spots. The average disease severity classification accuracy was 92.85 percent, the Dice coefficient of disease spot segmentation was 0.6914, and the leaf segmentation accuracy was 93.27 percent.

[15] (Liyang Cao et al.,2021) this research proposes an enhanced U-Net segmentation network and reconstructs the U-Net model by improving the model framework, activation function, and loss function. It was used to do automated segmentation and extraction of key feature parameters from plant leaf photos. The modified model can produce consistent segmentation results for a variety of leaf sizes, lighting settings, backdrops, and plant leaves, according to experimental results. The accuracy of pixel-by-pixel segmentation was 0.94. This network performed robust and high-throughput picture segmentation when compared to standard approaches.

[16] A similar work was conducted by (Anam Islam et al.,2021) which applied local threshold-based segmentation to extract the disease affected spots on the rice leaves precisely. A novel dataset of both disease-affected and healthy rice leaves was created from

different sources along with two online repositories and several image preprocessing as well as image segmentation techniques were applied before passing it to the three CNN architectures VGG, ResNet and DenseNet. The paper had applied hold-out and 10-fold cross-validation on the datasets and the results validated that ResNet50 performed lower than other VGG and DenseNet for all three datasets and accuracies for segmented leaf images (94.64%) are better than that for non-segmented leaf images (91.99%). This work achieved 91.67% accuracy which was higher than that of K-means clusterization segmented model.

[17] In (R Vijaya Saraswathi et al., 2021) paper, the CNN model is used to recognize 12 different types of leaf diseases of pepper, potato and tomato plants and to suggest remedies for the corresponding diseases. Color co-occurrence algorithm was used to extract features from plant images and Adams optimization algorithm was used to optimize network weights. For configuring the CNN model, a convolutional layer of 32 filters, a 3x3 kernel and ReLU activation function were utilized and obtained optimum efficiency of 96% for leaf disease detection.

[18] (Chowdhury R. Rahman et.al, 2020), introduced a novel two-stage small CNN architecture, called Simple CNN for detecting diseases and pests from rice plant images. They had collected a total of 1426 images of rice diseases and pests from paddy fields of Bangladesh Rice Research Institute (BRRI) and demonstrated the effectiveness of five CNN architectures (VGG16, InceptionV3, MobileNet, NasNet Mobile and SqueezeNet). The authors also compared their proposed simple CNN model with the above five CNN architectures and found that the proposed model is memory efficient and accuracy of the model is 93.33% consisting of only 0.8 million parameters for identifying nine classes of rice diseases and pests.

[19] (Chowdhury Rafeed Rahman et al.,2020)This paper is used for detecting rice diseases, i.e., detecting rice disease and treating them properly can reduce the paddy losses. An algorithm was used for the data and to find out the accuracy using deep learning algorithms. Convolution neural networks(CNN) ,train VGG16 model and small CNN architectures to get better accuracy and build the prediction models. The data set was from

Bangladesh Rice Research Institute (BRRI). The result, combining CNN and VGG16 and simple CNN algorithms achieved the highest accuracy of 97.12%.

[20] (Dr. K Venkata Nagendra et al.,2019) this paper is for awareness of rice leaf disease, i.e., rice leaf disease is reducing the rice production and this hampered the rice demand. Here an algorithm was used to filter the data image and calculate the accuracy of leaf disease using deep learning algorithms. In addition, convolutional neural networks (CNN) and training VGG16 model to improve the accuracy and construct prediction models. The dataset is from KAGGLE. In the result, combining CNN and VGG16 algorithms achieved the highest accuracy of 95% .

[21] (Santosh Kumar Upadhyay et al.,2021) this paper is for rice plant diseases recognition, i.e., rice plant diseases destroy the paddy plant and decrease the rice production. An algorithm was used for the data image recognition using deep learning algorithms. Convolution neural network(CNN) and convolution layers were used to find the highest accuracy and construct the model. The data set was collected from kaggle. The result , Convolution neural network (CNN) achieved the highest accuracy of 99.7% .

[22] (Achmad Ramadhanna'il Rasjava et al.,2020) this paper is for the condition of rice plants, i.e rice plants are affected by some diseases and that reduces productivity . An algorithm was used for the data images and getting better accuracy using deep learning algorithms. Convolution neural networks (CNN) and the convolution layers of CNN model to improve the accuracy of the model. The data was from <https://archive.ics.uci.edu>. The result, CNN with CNN layers achieved the highest accuracy of the model is 100% for training data and 86.67% for testing data.

[23] (S. Poornam et al.,2021) this paper is for detecting the plant leaf diseases, i.e., detecting the leaf diseases which help to produce good crops. Early detection helps to produce the paddy quality and quantity. An algorithm was used for the data image and the accuracy using deep learning algorithms. Convolution Neural network(CNN) and Convolution layers were used to improve the accuracy. The dataset was collected from Image Net Database. CNN algorithms achieved the highest accuracy of 98.32%.

[24] (Norhalina Senan et al.,2020) this paper is for the rice leaf and pest diseases, i.e, early detection of leaf and pest diseases is very important to improve the quantity and quality of

rice production. In addition, an algorithm was used for the image classification using deep learning algorithms. In addition, Convolution neural network(CNN) and all the convolution layers were used to improve the accuracy and construct prediction models. The dataset was collected from kaggle repository. In the result, combining CNN and CNN layers to achieve the highest accuracy of 96.60%.

[25] (B. Baranidharan et al.,2021) this paper is for identifying the rice leaf diseases, i.e Identification of rice leaf diseases helps to take the proper steps to increase the crops production. Here an algorithm was used to identify the data images and calculate the accuracy of leaf diseases using deep learning algorithms. In addition , Convolution neural network(CNN) and pre-trained AlexNet, VGG16 model to improve the accuracy and construct the prediction models. The data set was self collected. Here SGD and Adam optimizers were used. In the result, combining CNN , AlexNet and VGG16 algorithms to achieve the highest accuracy 81.25%.

[26] (Syed Md. Minhaz Hossain et al., 2021)this paper is for paddy leaf recognition, i.e, early recognition of rice leaf diseases helps to increase the production. An algorithm was used for the leaf image recognition using deep learning algorithms. Convolution neural network(CNN) was used to get the highest accuracy and construct the prediction models. The dataset was a novel independent dataset. In the result, Convolution neural network (CNN) achieved the highest training accuracy of 99.78% and validation accuracy of 97.35%.

[27] (S Praveen Kumar et al.,2020)this paper is for detecting the paddy diseases, i.e, improving the agriculture and reducing the crops quality and quantity ,it is very important. Here an algorithm was used to detect the diseases and the accuracy of paddy diseases using deep learning algorithms. Convolutional neural network (CNN) and Convolution layers were used to improve the accuracy. The dataset was self collected from the field. In the result, CNN algorithm achieved the highest accuracy of training 100% and testing accuracy is 80%.

[28] (Shreyasi Bhattacharya et al.,2020)this paper is for recognition and control of rice leaf diseases, i.e., timely recognition of rice leaf diseases helps to control the growth of rice leaf diseases and increase the productivity of rice. An algorithm was used for compiling

the image and getting the accuracy using deep learning algorithms. Convolution neural network(CNN) was used to find out the accuracy. The dataset was collected from KAGGLE. CNN algorithms achieved the highest accuracy of 94%.

CHAPTER 3

Overview of Methodology

3.1 Introduction

The U net was initially designed and being used for visual identification in the agriculture sector. Its design is roughly divided into parts: an encoder network and a decoder network. Unlike classification, where the final result of the process is the classification, classification is a process where the end result is The only thing that matters is the deep network, although semantic segmentation is also significant. Some requires pixel-level discrimination as well as a way to project the results discriminative characteristics encoded into the pixel at various stages of the encoder space. In the architectural diagram, the encoder is the first half. It's generally a pre-arranged meeting. VGG/ResNet is a trained classification network that uses convolutional neural networks.to encode the input picture into blocks, followed by a max-pool downsampling. It is a typical supervised learning method.

3.2 Architecture of U-Net

The U-shortcut Net's connection is intended to address the challenge of data leakage. The U-net being structured in such a way where encoder and decoder nodes are present. The above encoder components transmit respective extracted characteristics to its matching decoder blocks, establishing a U-net architecture. Up to this point, we've learnt that now the picture's size decreases as it goes through into the cnn architectures. That was because it max-pools layers at the same time, which implies data is lost as a result. Through convolving high-level characteristics with low-level ones, this design allows the program to collect precise data and present additional data. U-net is capable of providing sharper and much more consistent data by appending knowledge from several nodes. We added an extra layer to get more accuracy in U-net. Normally the U-net method has 5 layers ,and in our architecture we added an extra one layer which starts from 32 and it has 6 layers.

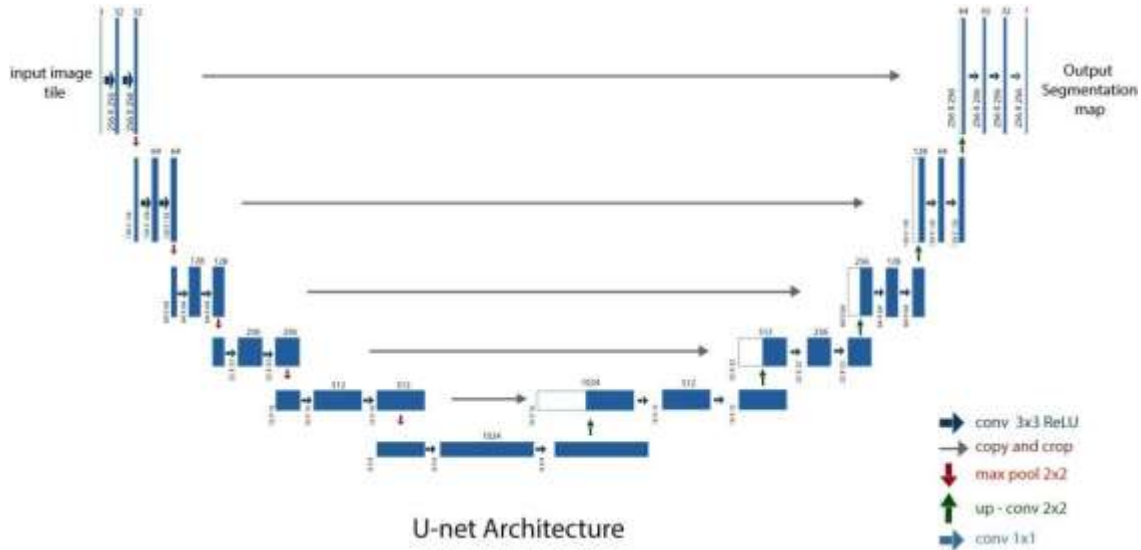


fig 1: U-Net Architecture

Here is our U-Net Architecture figure we have encode and decode layer, where we added an extra layer. Our input image is RGB format which is 3 filters and the size is 256X256. Then we add relu and converted to 256X256X32, after this we have made 5 layers with concatenate to decode the layers for up-Conv. And we have got the output segmented image in grayscale which is 256X256X1 with very goof accuracy. We have made a new U-net architecture model, which is more efficient in future. We explained an equation chart in below to understand the model.

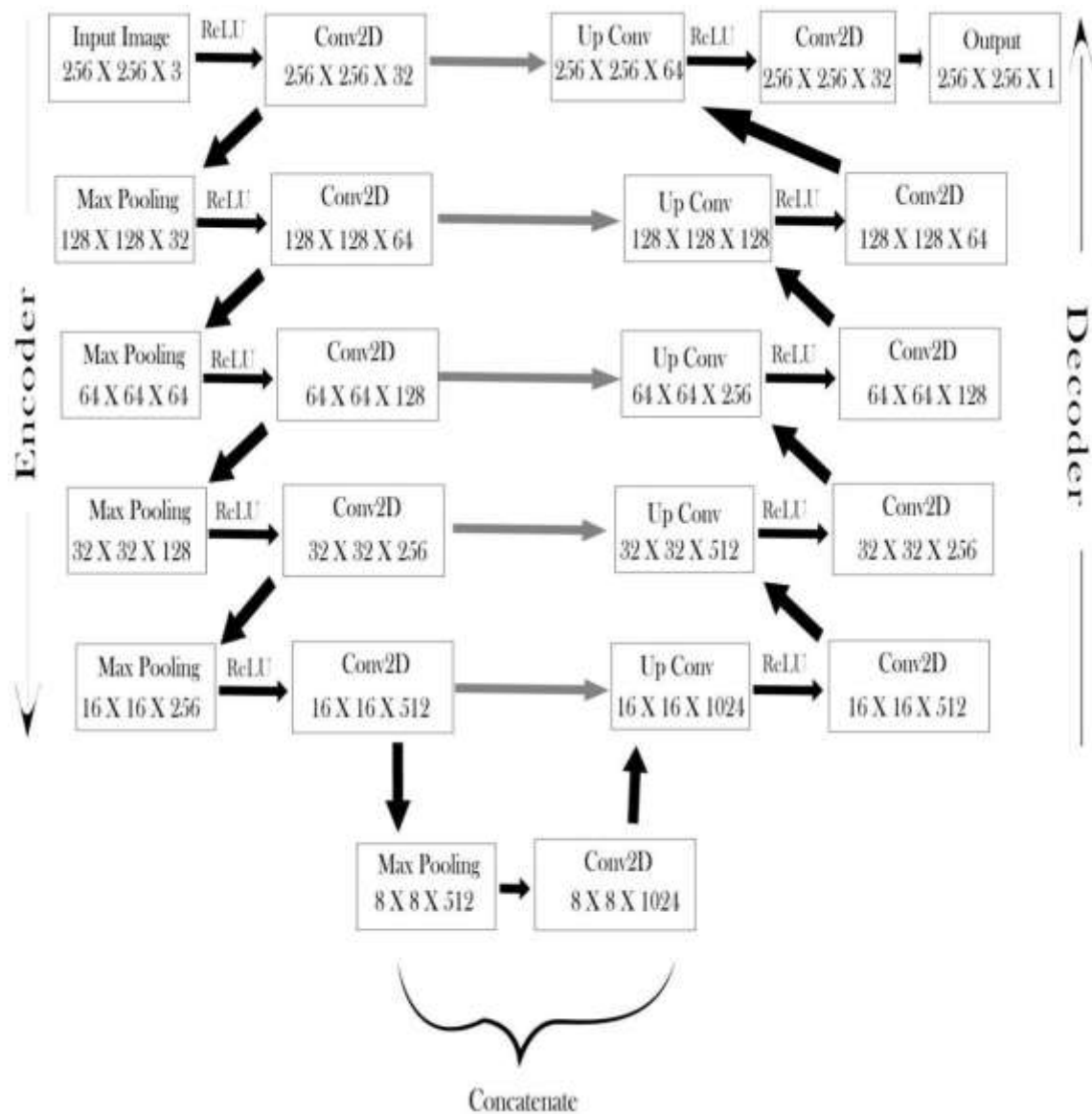


fig 2 : Equation Chart CNN

3.3 Pooling

One basic goal behind pooling is really to lessen the difficulty of convolution layers by down sampling. This is comparable to in the image recognition area. The performance is being reduced. The increase in prevalence by pooling is unaffected. A set of classifiers. Among the most prevalent kinds of pooling is max-pooling. The Technique of pooling is, It divides the picture into subregions. It also only provides the highest value of the boundaries, and it only gives the full value of the rectangles. The fundamental addition of U-Net in this regard is that, when up sampling inside the system, we also concatenate the greater resolution feature maps from the cnn model with the extract features data in order to develop better descriptions with greater resolution feature maps. For properly illustrate the translation, we used data from previous phases. Also we have to have an efficient upsampling algorithm because it is a dense process.

3.4 Relu

The rectified linear activation function(ReLU) is a nonlinear and semantic function which outputs zero if the input is negative. We use this activation function in CNN. Even though a model that employs it is quicker to train and delivers high results, this has become the standard perceptron for several machine learning algorithms. The benefit of employing the ReLU function above all other training algorithm is that it does not simultaneously stimulate all of the neurons. And the result, using ReLU helps in avoiding the fast increase of the compute needed to run the neural network. The higher cost of adding more ReLUs ratio increases as the length of the CNN grows.

3.5 Optimizer

Our model has been trained using Adaptive Moment Estimation (Adam). This is a probabilistic conjugate gradient extension (sgd). With all value updates, stochastic gradient descent sustains a preset learning algorithm.

In addition, the pace of training rate. Throughout instruction, it does not alter. However, Adam's learning rate fluctuates independently. It provides a unique combination of

benefits. Adam seems to be unquestionably one of several greatest deep learning optimization methods, and its demand is rapidly expanding.

It is an adaptive learning rate approach that calculates individual learning rates for various parameters. Its name is derived from adaptive moment estimation, and it is so named because Adam adapts the learning rate for each weight of the neural network using estimations of first and second moments of gradient descent.

$$m_n = E[X^n]$$

Adam additionally preserves a mean of previous slopes that decays gradually, which is comparable to the concept of speed. Adam acts like such a thunderstone with roughness, preferring smooth optimum on the error surface, while speed functions like such a ball moving downslope. We used the Greed Search algorithm for getting the comparison accuracy of 6 different optimizers which is (Adam, SGD, Nadam, RMSProp AdaDelta & AdaGrad) . We get Adam which performed better than all of these optimizers.

CHAPTER 4

Result Analysis and Comparison

4.1 Introduction

A variety of experiments and our results are presented in this section to demonstrate the performance of the proposed rice disease recognition framework using selective models of deep neural networks. In our tests, we were able to detect three different forms of rice illnesses and obtain more precise results. Three sorts of percentage models can be contrasted here, which is our expectation that we should be able to obtain better result.

4.2 Precision & Recall

The sensitivity of the algorithm indicates how effectively it predicts disease detection. Sensitivity is defined as the ability to successfully decide Leaf Disease instances, and is defined as follows:

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

4.3 Precision & Recall graph

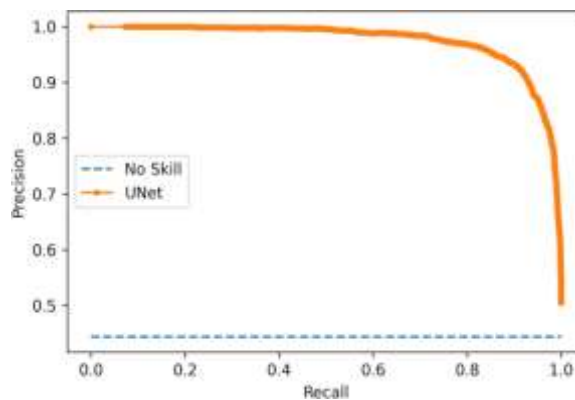


Figure 3 : Precision Recall Curve

4.4 Accuracy

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

4.5 ROC & AUC Curve with comparison

The AUC (Area Under Curve) is a higher-level statistic that combines the true positive rate (TPR, which is the same as sensitivity) and the false positive rate (FPR = FP/FP+TN), which reflects how well a classification system distinguishes between positive and negative classifications. It's tough to identify if a classification method has been overfitted with positive reports (high scores). Because specificity and sensitivity are employed independently, they might cause overfitting with negative samples.

As a result, the AUC is proposed as the ultimate metric for determining the effectiveness of a campaign. There are several positive and negative classification systems. When the criterion for categorization is reached AUC is the area under a Roc Curve curve that changes. TPR and FPR are mixed together in various ways. AUC is a measure of how well a person knows what they are talking about.

The Receiver Operator Characteristic (ROC) curve is a binary classification task found cognitive. This is a probabilistic graph that displays that TPR to against FPR at different minimum level, thereby separating the signal as from 'background.' The AUC indicates how well the machine distinguishes across positive and negative classes.

Train & Test (80:20)

When we used 80% train data to check true positive rate and false positive rate to find out the ROC AUC. We get 97.8% ROC AUC by using 80% training data and 20% testing data. Which is very good percentage rate. We have also a ROC AUC curve of (80:20) data . And we have trained our dataset into 80:20 data to run our project. We have already made a comparison by using accordingly (80:20), (70:30) and (60:40) datasets to get better accuracy. And (80:20) did better which got 97.8%. Also in (70:30) we got 96.3% and when we ran (60:40) data we got 95.4%. Here is the all ROC AUC curve below:

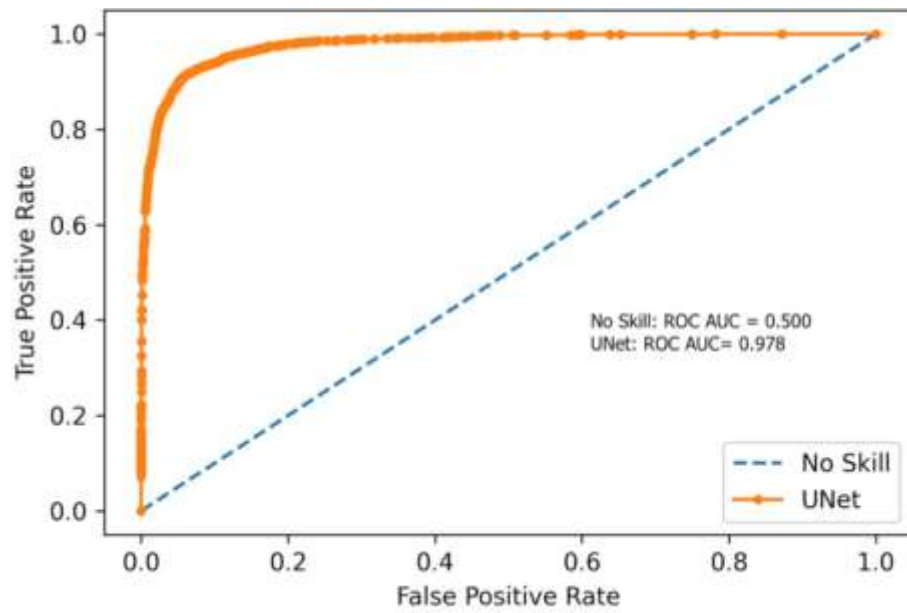


fig 4 : ROC AUC Curve (80:20)

Train & Test (70:30)

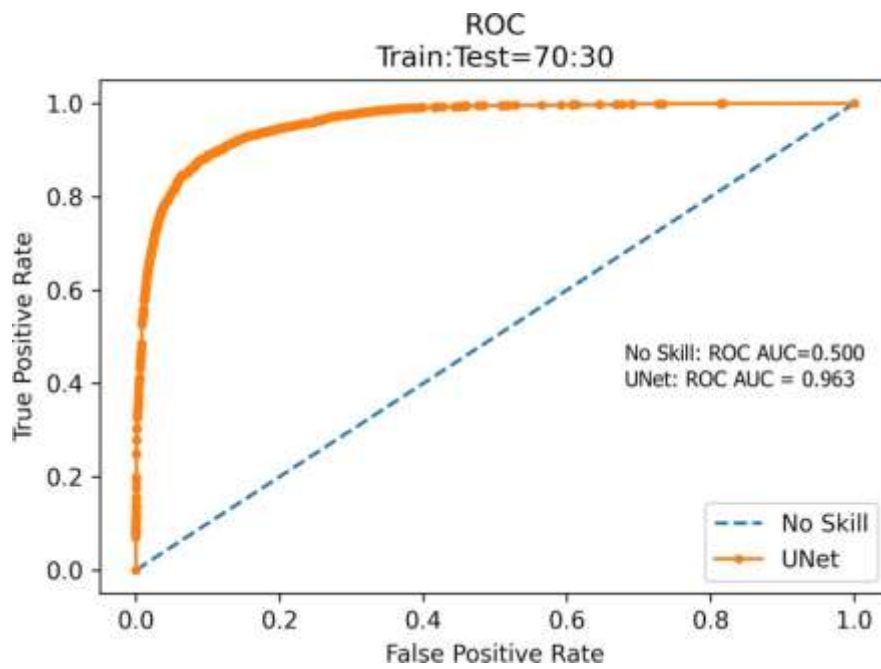


fig 5 : ROC AUC Curve (70:30)

Train & Test (60:40)

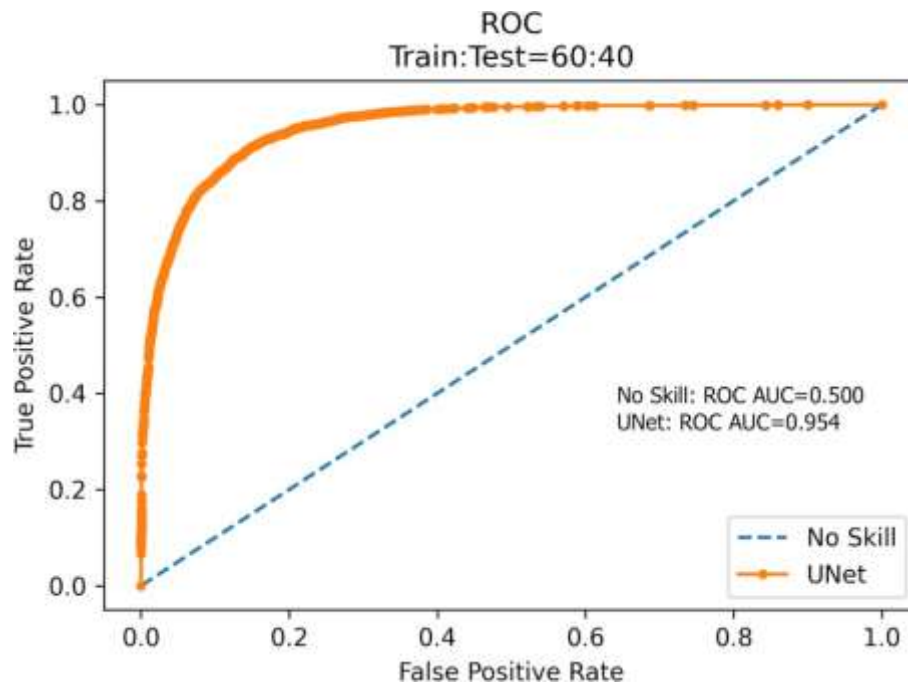


fig 6 : ROC AUC Curve (60:40)

4.6 Optimizer Comparison

We have also made a comparison using Greed Search Algorithm between 6 algorithms. Firstly we have optimize our project using ADAM. Which gets better performance than 5 optimizers. We also made a comparison to find out better training accuracy, training loss, validation accuracy and validation loss. Adam performed better than Nadam, SGD, RMSProp, Adadelata and AdaGrad.

Training Accuracy Graph:

By using Greed Search Algorithm we made a comparison in training accuracy graph. Respectively we have find good training accuracy in ADAM and Nadam using 20 epochs. Adam and Nadam performed better than other optimizers. We have made a graph comparison of training accuracy. And also made a table chart on training accuracy of these optimizers.

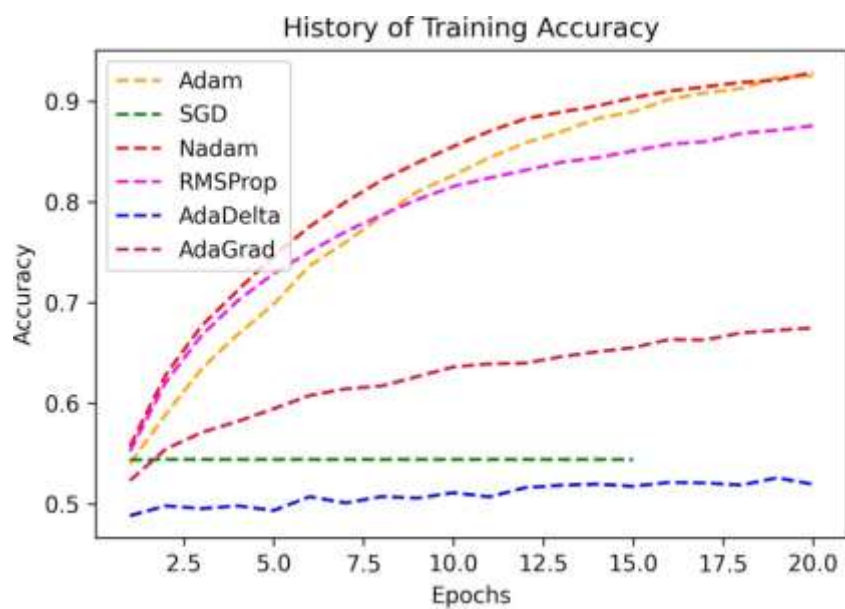


fig 7 : History of Training Accuracy Graph

Table 3 : Table of training accuracy

No	Optimizers	Accuracy	Epoch
1	Adam	0.943	20
2	SGD	0.523	15
3	Nadam	0.956	20
4	RMSProp	0.873	20
5	AdaDelta	0.510	20
6	AdaGard	0.645	20

Training Loss Graph :

Here is also a comparison of training loss graph. Respectively we have find good training loss in ADAM and Nadam using 20 epochs.

Adam performed better than Nadam and also other optimizers. We have made a graph comparison of training loss. And also made a table chart on training loss of these optimizers.

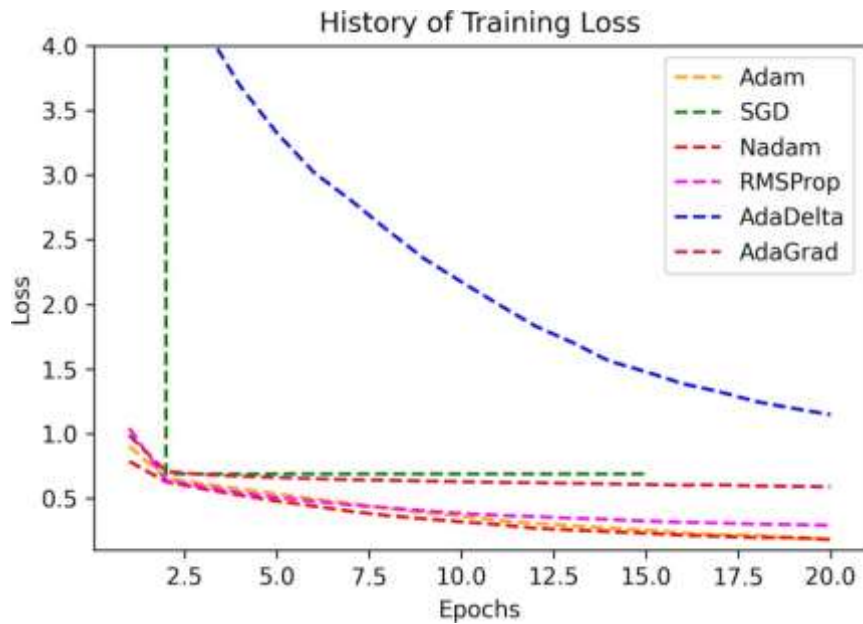


fig 8 : History of Training Loss Graph

Table 4 : Table of training loss

No	Optimizer	Loss	_Epoch
1	Adam	0.103	20
2	SGD	0.790	15
3	Nadam	0.110	20
4	RMSProp	0.250	20

5	AdaDelta	1.273	20
6	AdaGard	0.678	20

Validation Accuracy Graph :

We have also made a comparison in validation accuracy graph. Respectively we have find good validation accuracy in ADAM and Nadam using 20 epochs.

Adam performed better than other optimizers. We have also made a graph comparison of validation accuracy. And also made a table chart on validation accuracy of these optimizers.

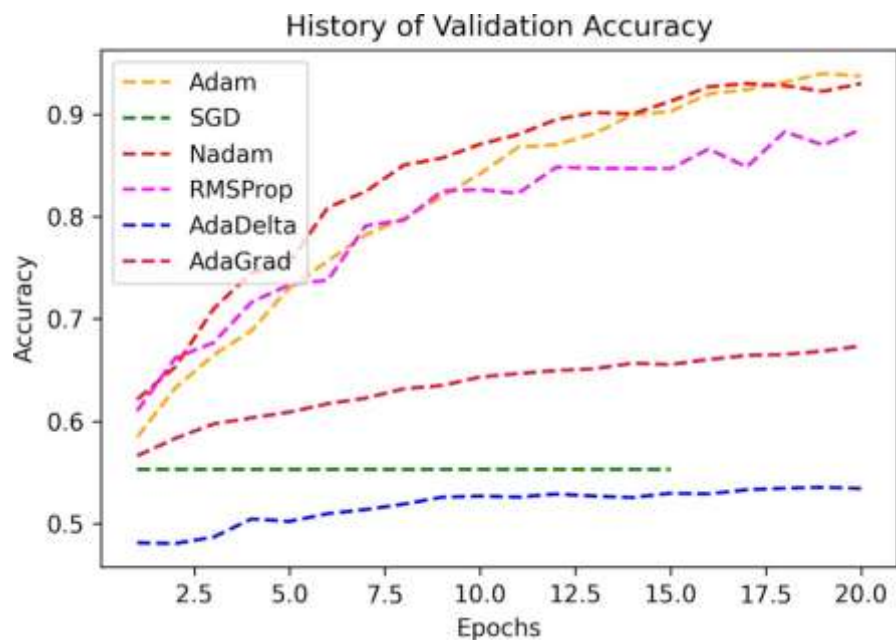


fig 9 : History of Validation Accuracy

Table 5 : Table of validation accuracy

No	Optimizer	Accuracy	_Epoch
1	Adam	0.973	20

2	SGD	0.559	15
3	Nadam	0.950	20
4	RMSProp	0.875	20
5	AdaDelta	0.542	20
6	AdaGard	0.678	20

Validation Loss Graph :

We have also made a comparison in validation accuracy graph. We have find good validation loss in ADAM and Nadam using 20 epochs.

Adam performed better than other optimizers. We have also made a graph comparison of validation loss. And also made a table chart on validation loss of these optimizers.

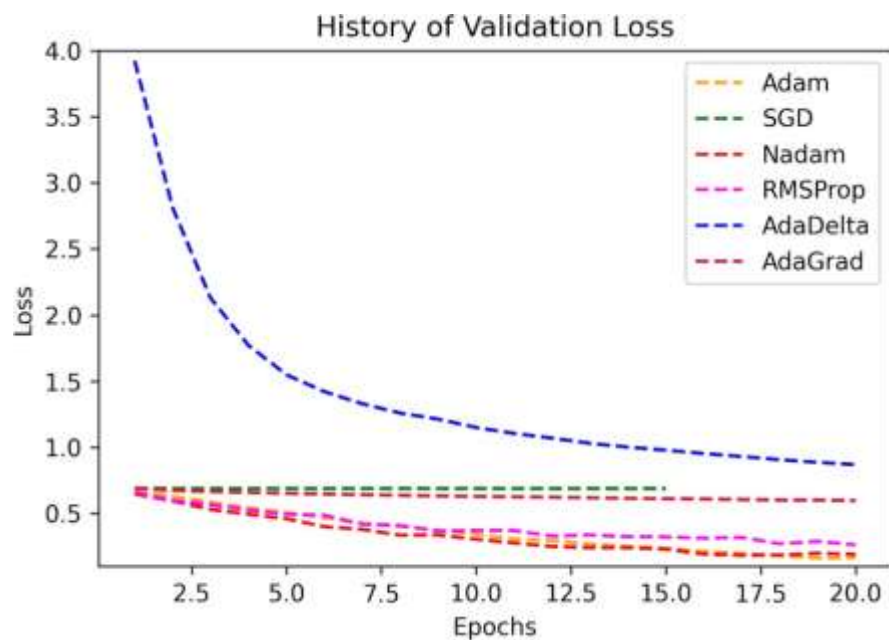


fig 10 : History of Validation Loss

Table 3 : Table of validation loss

No	Optimizer	Loss	_Epoch
1	Adam	0.067	20
2	SGD	0.459	15
3	Nadam	0.110	20
4	RMSProp	0.231	20
5	AdaDelta	0.885	20
6	AdaGard	0.448	20

4.7 Discussion

We employ the U-Net approach, which is the most common deep learning method. Agriculture sector uses this technology extensively. We achieve the correct result by utilizing this strategy. In terms of accuracy and sensitivity, the proposed technique exceeds existing classification algorithms. We were able to attain better results by employing the approach (Accuracy = 93.10%; F1 = 81.27%; Jaccard = 73.14%; Recall = 85.45% & Precision = 82.11%) using Kaggle Rice Diseases Image Dataset ISIC-2019 . We used 80% training data for segmentation.

Precision considers entire recovered materials, so it may alternatively be assessed using a cut-off rank that only considers the service's highest findings. It is combined with recall, which refers to the percentage of all necessary documents retrieved by a result. The F1 Score (or f-measure) is a combination of the two measurements that may be used to create a single measurement for a system. It's worth noting that the concept of "resolution" in the case of this research varies more than that of "accuracy" and "precision" in the other areas of technology.

CHAPTER 5

Segmented Images

5.1 Introduction

An objective of semantic segmentation is to provide a classifier to each pixel or character in a picture.

Semantic segmentation frequently necessitates the edge detection and models that may be used to deduce relevant relationships from the source images, thereby eliminating pollution. Semantic segmentation is an area of research that entails putting related elements of a picture into this kind of class.

In semantic segmentation three processes are necessary such as identifying localization and organizing pixels. Semantic segmentation is exactly the problem of categorizing a specific picture type then isolating this from the remainder of a place of greater emphasis through overlapping this with the procedures. We utilize semantic segmentation since that assigns a classification from each pixel. We've also added image sections that are similar in this sort of class. For this, the input layer is RGB, whereas the output layer is grayscale.

5.2 Segmented Images

Here we have segmented three types of rice disease images. Using semantic segmentation we have got grayscale output with very good result. These segmented output is shown below of three types of disease data.

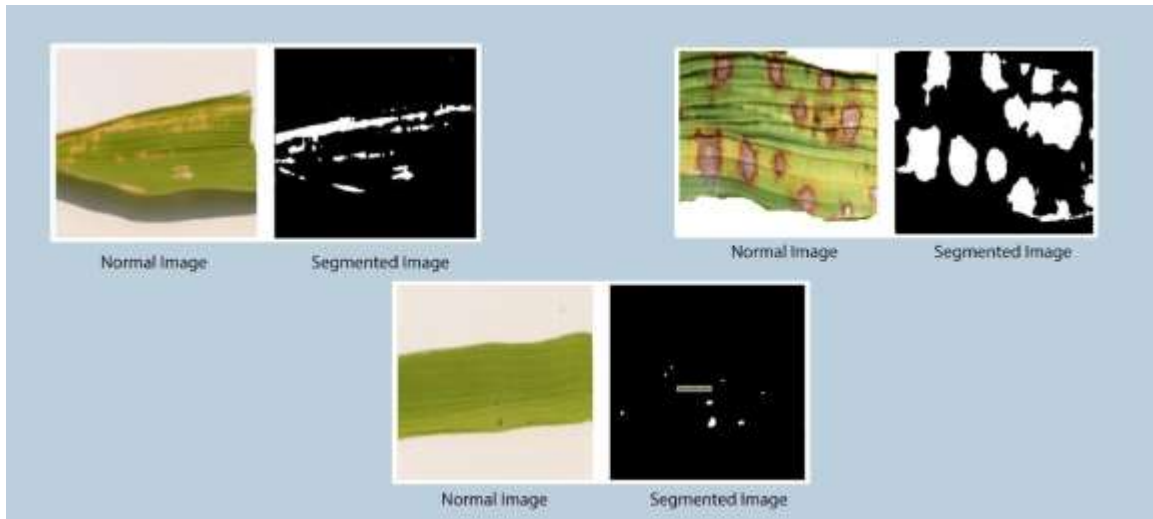


fig 11 : Segmented Images

CHAPTER 6

Conclusion

6.1 Conclusion

As applied to previously unseen real-world photos, most deep learning algorithms for autonomous illness identification problems are due. We show in this study that segmented pictures may be used to train a convolutional neural network (CNN) model with whole images. Our research examined how a deep learning technology may be used to analyse rice leaf diseases detection. With this sort of task, U-net is the ideal option and it results in an accurate output. In our paper, we propose to improve CNN U-Net architecture for image analysis and also detection. The main purpose of this work is there is any type of leaf diseases. To evaluate this work performance is very optimistic with more than 93% accuracy.

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