WHEAT LEAF DISEASE CLASSIFICATION USING DEEP LEARNING

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

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APPROVAL

This Project/Thesis titled **"Wheat Leaf Disease Classification Using Deep Learning"**, submitted by Md. Sazid Parvez Rasel, ID No: 211-25-008 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 M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 19-01-2021.

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DECLARATION

We hereby declare that this thesis work has been done by me under the supervision of **Md Zahid Hasan, Assistant Professor & Coordinator MIS,** Daffodil International University. We also declare that neither this work nor any part of this work has been submitted elsewhere for award of any degree and diploma

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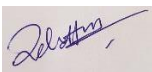

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Abstract

Human kind's one of the main food sources is wheat. That secure the food supply for a large amount of people. Which requires a large scale wheat cultivation in the largest planting area. As we plant these much amount of wheat, major part of this plantation putrefied due to the various disease. At present, we discovered more than two dozen of wheat diseases that are dangerous to the wheat corps. This research introduces an efficient way to detect wheat leaf disease by using deep learning model. Which will detect two types of wheat leaf disease stripe rust and Septoria and healthy leaf just from an image. Three different algorithms CNN, ResNet and Inception V3 are used for the research. These algorithms are trained with around 4k image data set. That gives us the highest accuracy up to 94.96% of accuracy. Thus, we can monitor our crop fields for these two diseases at a large scale by automation. Which in result, will allow us enough time to protect our crops by taking proper action.

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Chapter 1

Introduction

1.1 Introduction

Plants can be seen in each and every corner in our world. We have nearly around 4 lac species around us. Plants are one of the most vital natural resource for us. We all of us who breath rely on the trees for the oxygen without this we couldn’t survive in the world. Along with this plants give us the food, shelter. Plants has so many diversity in its characteristics which gives the scope to select from thousands of options

Wheat is a kind of plant grown throughout the world for its majorly nutritional and usable grain. It's one of the top most produced crop in the world, along with rice and corn [1]. Civilization of wheat over times and likely originates in the rich field, along with other stable crops. This disease leads the wheat to a huge reduction in the volume and quality of the product.

One in every 10 people suffers from severe malnutrition because of the failure in the food supply system due to the effect of the disease according to the UNFAO (United Nations Food and Agriculture Organization). There is a huge difference in the per hectare grain production in developing and developed countries. It is because of the use of advanced tools and the ways of the cultivation in the fields. At present we are in the era of technological revolution. Artificial intelligence, machine learning. IOT, cloud computing are playing a vital part in the agriculture sector. These technologies performing well in reducing the resource destruction and increased grains.

1.2 Motivation

Mortal life is quite dependent by the quality of the food grains. In the developing countries especially in the Asia and Africa has a noticeable food deficit which is leading the people into the hunger combat with malnutrition. So many families are affected by the low crop product.

Visually observable pattern of the wheat plant disease is preferable to understand the disease of plant splint trial effectively [2]. For the successful civilization of crop in any farm leaf disease monitoring is necessary. Before the technological era, wheat experts monitors the wheat complaint manually. For this, the experts must be trained on the wheat disease and has to be enriched with deep knowledge of the field along with the experience of the disease condition symptoms and the reason behind the disease. In the developing countries farmers has to travel a long distance to consult an expert which cost them with money and their valuable time. Sometime they couldn’t get the chance to meet the expert. Later after the development of the automatic wheat condition. Automatic discovery of wheat conditions is a salutary exploration as it help to cover a massive crop field, and automatically descry the manifestation of conditions incontinently on appearing wheat leaves [3]. Guarding plants from conditions is pivotal by perfecting the quantity and the quality of the crops. That’s why primary discovery and picking out the marked disease is more helpful by selecting appropriate treatment and preventing the complaint from spreading [4]. The goal of this research is to introduce an approach to classify wheat leaf disease by deep learning from the wheat leaf images.

1.3 Problem Statement

Wheat has variety of diseases. Some of them are internal and some of them are external. Most common is the leaf disease problems. Among them Stripe Rust and Septoria is the worst-case scenario. When wheat got affected with these diseases then the production reduced in a significant number. That brings a huge loss to the farmer in addition to the world food supply. Also, if an area got affected with this diseases then nearby area is also affected. In most cases farmer depends on their primary farming experience. But that is not enough to prevent this disease. Because they don't know which disease is this exactly? As a result, they couldn't apply proper treatment to their field. So, if we can bring a solution that will detect the disease with maximum accuracy then they can take right decision against the disease.

1.4 Research Question

Our main target for this research is, how to classify wheat leaf disease using deep learning?

1.5 Research Objectives

Our main target is to classify wheat leaf disease so, from this question and previous discussion we get a clear list of our main objective for the research. They are as follows,

1. To train a deep learning model using image data to detect the disease.
2. Identify the disease with highest accuracy to get the best result.
3. Show information about the disease and specialist contact to the farmer to prevent the disease.

1.6 Research Scope

Currently we don't have much research or technology regarding this problem. There has very few related works on this. But they are not feature proof. Especially they are not dedicated to this particular problem. Instead of this they generalized for a variety of domains. That means we have a huge scope to explore this field, learn about this problem, do research on it and finally enrich this sector with our quality research.

1.7 Paper Outline

This paper is distributed into 5 sections. Which will help the reader to read and understand the paper easily. They are as follows,

- Introduction: Describe about the project background, introduction, research scope, research objectives etc.
- Literature Review: Shows the related work of this field, project scope and the challenges to implement.
- Methodology: Briefly describe about the working procedure, mathematical calculations, algorithms used in the project, algorithm hyper parameters.
- Result Discussion: Summary of the results of the algorithms, result interpretation
- Conclusion and Recommendation: Interpret the result along with its limitations, stretch any significant insights, future work.

Chapter 2
Literature Review

2.1 Related Works

Azimi et al. used statistics and machine learning methods to study the correlation between wheat head blight (FHB) and morphological and biochemical characteristics [1]. Septoria, Leaf Rust, Powdery Mildew, Speer, Zymoseptoria Tritici Rob are most known pathogens in world wide. They are seen in the pathogen widely in the grain crops. These causative agents damage the grain crops by 20% and if proper treatment like fungicide used in time, then it can be controlled [5]. The yellow color of epiphytes and the consequences of stem rust disease lead to more than 30% food shortages. In general, losses of grain yield vary from 15% to 30% that is depend on the seasonal conditions and the region [6, 7]. The most convenient and effective way to fight with these situations is to take timely defensive behaviors [7, 8, 9]. In the reality this strategy is quite impossible. Because we don't have any timely and correct pathogen opinion. In this situation, we have to identify the condition at the seedling stage, because by time while the growth of the pathogens the resistance has also increased [10]. As a result the similar diagnoses effectiveness depends massively on the resource intensity, labor intensity and their accuracy.

Across the history of the wheat cultivation, visual assessment of the affected wheat leaf condition has been using as one of the main working systems [11]. This process requires the quality full training for specialists in the phytopathology along with a strict routine work. Where they have to keep a book to record, do statistical process of compliances. In the recent years, molecular and spectral styles prediction by analyzing digital image of affected leaf have appeared and using worldwide [11, 12]. These procedures are different in the labor intensity, along with its cost and delicacy. The styles obtained from the digital RGB image analysis is predicted by determining the changes in the texture, color and the shape of the vital organs which arise as an output of changes in their color composition from the influence of the vital exertion of pathogens [13-16]. The main advantages of this analogous styles are the quite low cost of covering the outfit along with the high monitoring speed. On the other hand, low perceptivity is the main disadvantage.

Nowadays, the factory complaint prediction by digital RGB images technology have developed very well due to the improvement of the machine learning and neural network algorithms. Where a deep learning technology or neural network algorithm works like as human brain. Where the coming sub caste uses the information from the former layer as an input data to generate prediction regarding to the normalized objects [17]. For making this prediction some of the successful methods are Convolutional Neural Network, where it used several architecture options. AlexNet and VGG were the first type of CNN armature [18]. Day by day these methods developed to ameliorate the convergence of the offered algorithms, reducing the number of parameters ameliorate model training results because of the adaptive recalibration of responses across channels [19, 20]. At present they proved themselves by demonstrating remarkable success on factory phenotyping of complex problems [21].

2.2 Scope of the problem

Wheat leaf diseases like stripe rust, septoria, speer damage the corps by around 20 to 30%. To prevent this, we need a lot of specialists with a routine work in the field. That requires a lot of man power and a huge amount of cost. In this circumstance if we can automate this process by using AI with the help of deep learning it will be a game changer. Which will significantly reduce the cost and hard work.

2.3 Challenges

To achieve the solution of this problem we have some challenges that is quite hard to overcome. Some of the challenges as follows,

1. Finding proper image data set.
2. Finding the best combination of parameters to train the model.
3. Implement the model in the field at large scale.

Chapter 3
Research Methodology

3.1 Introduction

There are several ways to apply deep learning. We have plenty of algorithms, techniques etc. But most of the computer vision algorithm follows the same framework to identify the image. Figure 3.1 shows our primary methodology to execute our research.

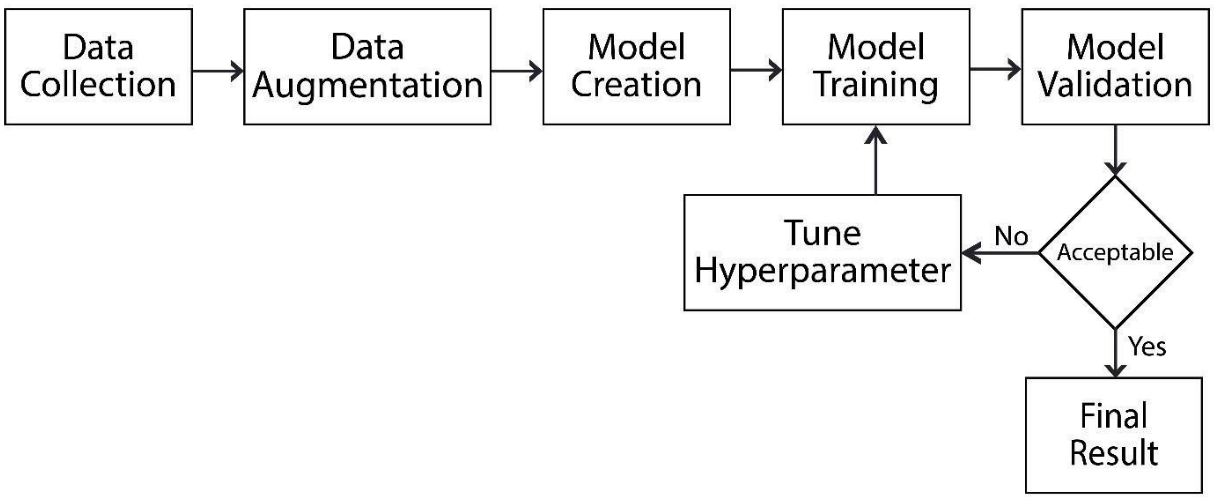

Figure 3.1: Research Methodology

At first we will collect the data set later on which we will apply data augmentation preprocessing. The next step is to create the model which we will train with our processed data set to detect the image. Then we will evaluate the model with test data if we get satisfactory result then we will take that otherwise we will retrain the model with some new parameters.

3.2 Data Collection

Before starting any machine learning or deep learning process the first task is to collect related data set from trustable source. Because this data set plays the most vital role in this process. If we train our model with non-related data or biased data set then the model won't be able to work perfectly. The result won't be independent. It will be affected by the wrong data set.

Some time we can't collect data directly from the field. We have to rely on some data provider source. In this matter Kaggle is one of the most reliable data sources out there. So, we take our data set from Kaggle. As we will work on wheat leaf disease, we just focus on this data only. We took 3 types of image data they are as follows,

1. Healthy
2. Stripe Rust
3. Septoria

There we have two types of disease image and one healthy image. Figure 3.2 shows a snap of our data set.

Figure 3.2: Sample Images from Data Set

3.3 Data Augmentation

At this step we did the data augmentation technique to increase the number of our data along with data preprocessing.

Firstly, we augmented the data set. This process contains the below step;

- **Rescale:** Rescale the image to a new shape

Figure 3.3: Rescaled Image

- **Rotation:** Rotate the image to a random range

Original Rotated

Figure 3.4: Rotated Image

- **Width Shift:** Shift the image width

Original Width Shift

Figure 3.5: Width Shifted Image

- **Height Shift:** Shift the image height

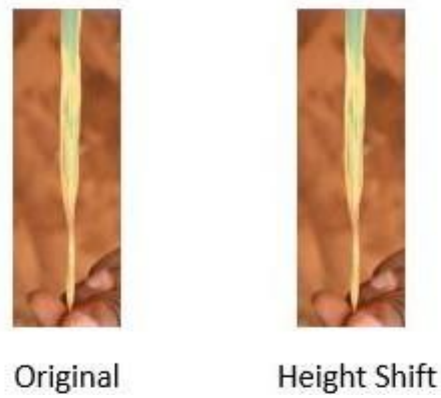

Figure 3.6: Height Shifted Image

- **Shear:** Image is distorted along the range

Figure 3.7: Sheared Image

- **Flip:** Image is flipped by horizontal or vertical

Figure 3.8: Flipped Image

- **Zoom:** Image is zoomed to a new range

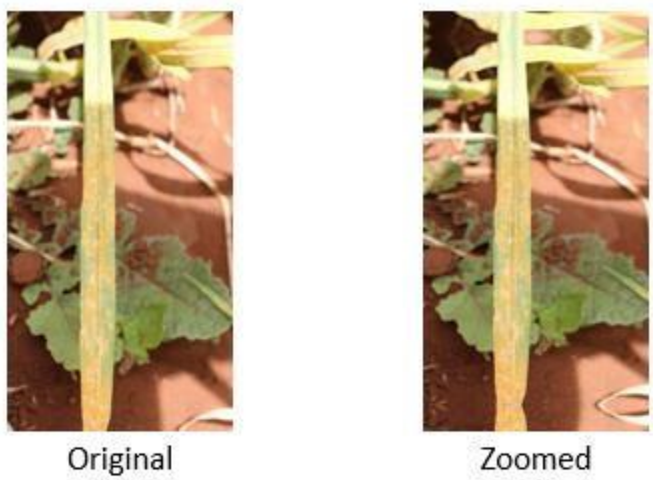

Figure 3.9: Zoomed Image

Image processing is also following the same step along with Image resizing that resize all the image into a fixed shape. Also, we rgb color mode that is the colored version of our image to train our model.

3.4 Model Creation

After processing the image data, the next step in the computer vision algorithm framework is to select some algorithm and create a model on them. That will be used to train the and catch the right label for the image.

For our model we took three different algorithms. They are CNN, ResNet and Inception V3. We can use any types of algorithms for the model but this algorithm has some advantages than the other algorithm.

CNN

Convolutional Neural Network in short CNN is feed forward neural network that is divided into 3 layers. They are as follows;

- Input Layers
- Hidden Layers
- Output Layers

Where the Input layer is an input tensor. Which shape is (input numbers) x (input height) x (input width) x (input channels).

Suppose we will feed an image into the CNN algorithm which shape is 256 x 256 and it is a colored image then the input tensor shape will be (1 x 256 x 256 x 3).

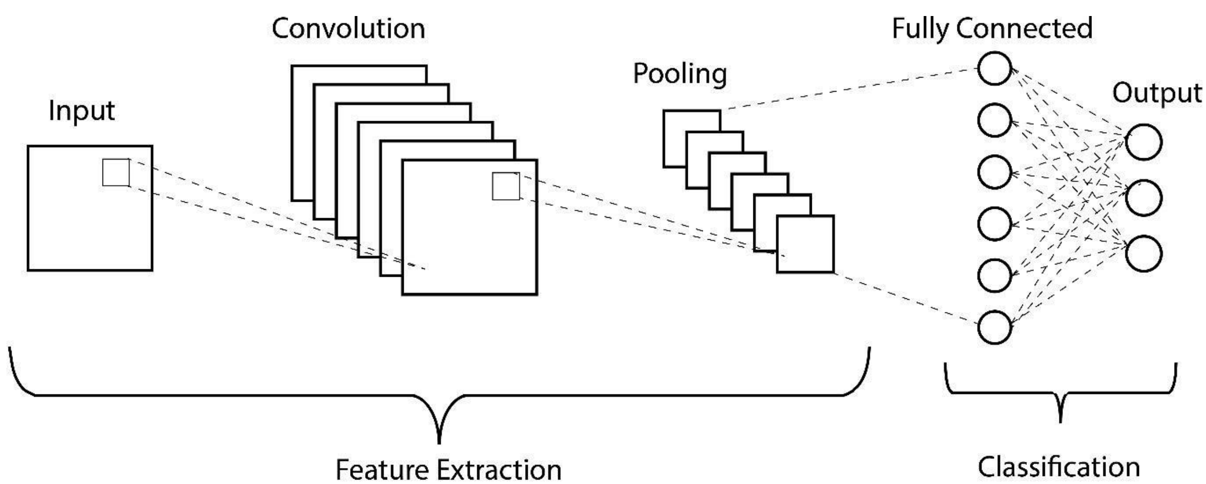

Figure 3.10: CNN basic architecture

CNN architecture is mainly divided into 2 main parts. They are

- Feature Extraction
- Classification

Feature Extraction is a process where a convolutional tool extract various feature from the image for the analysis.

Feature extraction process consists of several steps. At first in convolutional layer a convolutional mathematical operation is performed between the input image and a definite size of filter. Here the filter move over the image and take the dot product of the filter and the same position on the image. This is called feature map. This feature map includes several information about the image as like the corner, edge etc.

The next step in the feature extraction is the pooling step. Normally an image can consist of a huge amount of feature which can consume too much resources and time to learn. Here the pooling step decrease the feature map size and reduce the computation time by decreasing the connections between the layers. This operates on each map independently. There are several types of pooling operation. Average Pooling, Max Pooling, Sum Pooling.

In max pooling the pooling takes the largest element in the feature map. In the average pooling the pooling takes the average of the feature map elements. And finally in the sum pooling it takes the total sum of the feature map elements.

Classification is the process where the algorithm classify an image using the extracted feature from feature extraction process.

In classification part we have the fully connected layer at first. Here the classification task begin to start. This layer consists of neuron's weights and biases. It is mainly used to connect two different layers. In this layer the flattened input image vector from the previous layer is fed into the fully connected layer. Then it go in some more FC layer where the mathematical function operations are applied. Sometime a model can be over fitted so a drop out operation is applied after this. That reduce the over fitting probability as well as the model size.

After this the activation function comes. The main purpose of this function is to decide either an information should be passed to the end of the network or it should be fired. It works as like an information filter of the neuron. There are several types of activation functions available such as ReLU, Softmax, Sigmoid etc. Normally Sigmoid function is used in a binary class classification and softmax is used in a multi class classification. In general softmax is used.

ResNet 50

Residual Network also known as ResNet is a special neural network. It was first coming to limelight in 2015. There are so many variants of ResNet convolutional neural network algorithm where ResNet 50 is one of them. Where 50 in the name of the ResNet 50 name indicate that it has 50 layers means it has 50 deep layers. Here 48 layers are convolutional layers, 1 layer is a max pooling layer and another 1 layer is average pool layer.

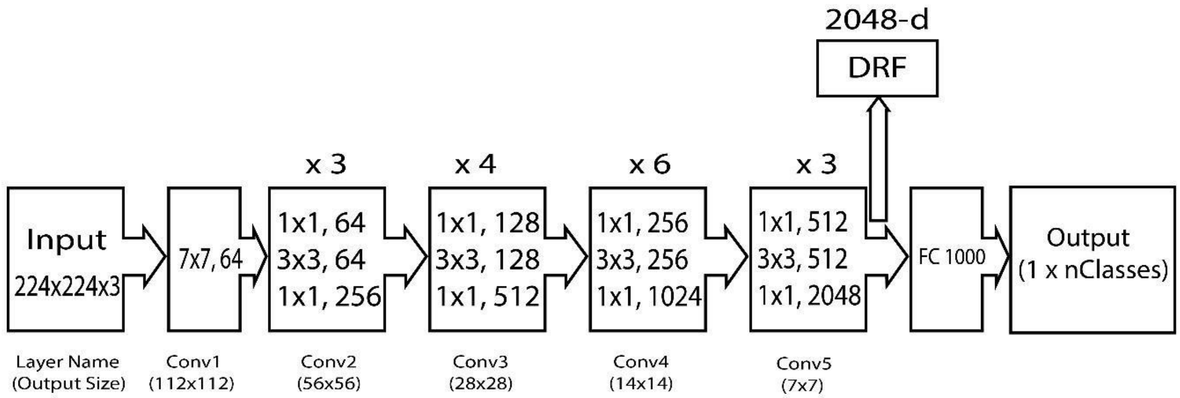

Figure 3.11: ResNet 50 architecture

ResNet-50 Architecture

Figure 3.11 shows us the basic architecture of the ResNet 50 but it has some variation in the production line. Here because of the time taken to train the layers the building block was modified into a bottleneck design. This procedure use 3 layer stack instead of 2 layer stack.

In this way, every 2-layer block from ResNet 34 is replaced by the 3 – layer bottleneck block while constructing the ResNet 50 architecture. Because of this changes ResNet 50 can achieve much higher accuracy than ResNet 34 model. This can be up to 3.8 by FLOPS

Inception V3

Inception v3 was derived for reducing the computational power from the original inception algorithm by modifying its architecture. It is a widely used model for image recognition where it achieved more than 78.1% accuracy on the ImageNet dataset. It is mainly the combination of many ideas from multiple researchers over years.

Generally, it is constructed by asymmetric and symmetric building blocks which contains max pooling, average pooling, fully connected layers, dropouts etc. Softmax is used for calculating the loss function by default. It is more efficient in computation than VGGNet, Inception Networks (Inception v1) in both generating the number of parameters and incurring in the memory and other resource cost. Incentive care is needed while making any changes in it to avoid the loss of the computational advantages. That’s why it is quite difficult to adapt the model for different use as it will become uncertain in the efficiency of the network as several techniques are used to optimize the network.

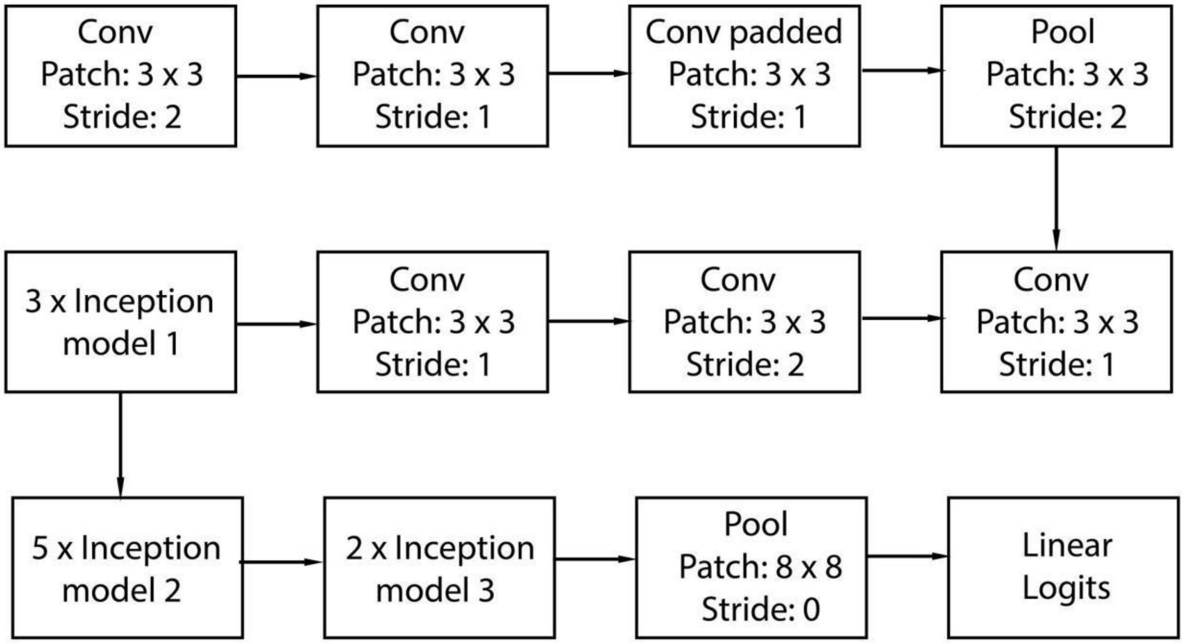

Figure 3.12: Inception V3 architecture.

Inception v3 Architecture

Inception v3 has a step by step architecture, they are explained below:

1. Factorized Convolutions: By reducing the number of parameters from a network it helps to get the best computational efficiency along with this it checks the network efficiency.

2. Smaller convolutions: Training time can be reduced by using the smaller convolutions instead of bigger convolutions. For example, a 5 x 5 has 25 parameters where a 3 x 3 has 9 parameters.

3. Asymmetric convolutions: It can use a 1 x 3 convolution followed by a 3 x 1 convolution instead of a 3 x 3 convolution.

4. Auxiliary classifier: Between the layers it can add an auxiliary classifier that is a small type of CNN and the raised loss is added to the main network loss

5. Grid size reduction: Pooling operations uses the grid size reduction.

Activation Function

Without an activation function a neural network is just a linear regression model. That's why activation function plays a vital role in deep learning model. In general, activation function is nothing but a function that is used to get the output of a node. This is also known as transfer function. Normally, it maps the resulting values from the output to 0 to 1 or -1 to 1 depending on the activation function. Which gives us the output result as either yeas or no.

There are two types of activation function;

- Linear Activation Function
- Non-Linear Activation Function

Linear activation function has a linear characteristics. If we apply linear activation function in any neural network and that has all linear layers then the final output will be the same as the input.

We can define the linear activation function by y = mx. Which has a range of $-\infty$ to $+\infty$. This function is normally used in the output layer.

Non-Linear activation function is the most used functions in neural network. It makes the model to adapt the variety of the data for differentiating the output.

For the activation function we used ReLU and SOFTMAX.

ReLU or Rectified Linear Unit is known as a non-linear activation function. It is a simple function but perform better than the sigmoid or tanh function. We can define the function by the following equation, f (x) = max (0,x). By this function this activation function return 0 if it get any negative value and for the positive value it returns the same value. Thus it has a value range from 0 to infinity.

The main advantage of this model is its simplicity. That's why it requires less time compared to the other activation functions. This little bit of extra time gives us huge benefits when we try to train a large data set. Also, it has sparsity. Which gives us the better predictive power and reduce the probability of over fitting or noise.

SOFTMAX function which is also known as exponential normalized function. This is a multinomial classification function. That is we can classify multiclass data set that has more than 2 class labels.

Softmax function can be define as follows;

$$\alpha(o_i) = \frac{e^{o_i}}{\sum_{j=1}^{n} e^{o_j}}$$

Softmax function normally used in the model's output layer. Which classify the inputs into multiple category.

For the optimizer we use ADAM. This is an extension of the stochastic gradient descent. It is a very straightforward to implement with a great amount of computation efficiency. It also consume very little memory. It is suitable for non-stationary objectives along with very noisy or sparse gradient problems.

We use Sparse Categorical Cross Entropy as our loss function. We fed the model in the training with a single integer label instead of the whole vector.

Along with this, we took 10, 15, 20 epochs where 15 epochs gave us the best result and a learning rate of 0.0001

3.5 Model Training

The next step is the model training part. Initially we had around 400 images. Later we increased this image data up to 4155 images by using the augmentation technique. We use this 4155-image data to train our model. Among this data set we have 3 classes where healthy has 1326, Stipe Rust has 1518 and Septoria has 1311 image data.

3.6 Model Validation

When we finish the model training it's time to validate the model. For the model validation we used around 1400 images from 3 classes.

Here at this point we have two ways, if the model gives us the satisfactory accuracy, then we can take that as final result otherwise we have to tune the hyper parameters until we get the appropriate accuracy.

3.7 Tune Hyper parameters

If we don't get the expected accuracy then we will have to tune the hyper parameters of the algorithm model to set the best combination that will give us our desire accuracy.

Chapter 4

Results and Discussion

4.1 CNN

We had around 2.2 million trainable prams in our model. Where we learned at the rate of 0.0001 for 15 epochs. Our first neural algorithm model was CNN. It performed pretty well. If we see at the figure 4.1 train vs. validation accuracy, we may see that train accuracy has an up trend line where the validation accuracy was also nearly same as the train accuracy. But gradually in the end it dropping from the train accuracy. Here we had highest accuracy 58.66% at 1st epoch and the lowest accuracy 92.57% at 14th epoch. At the end we got the average 79.92% accuracy from our CNN model.

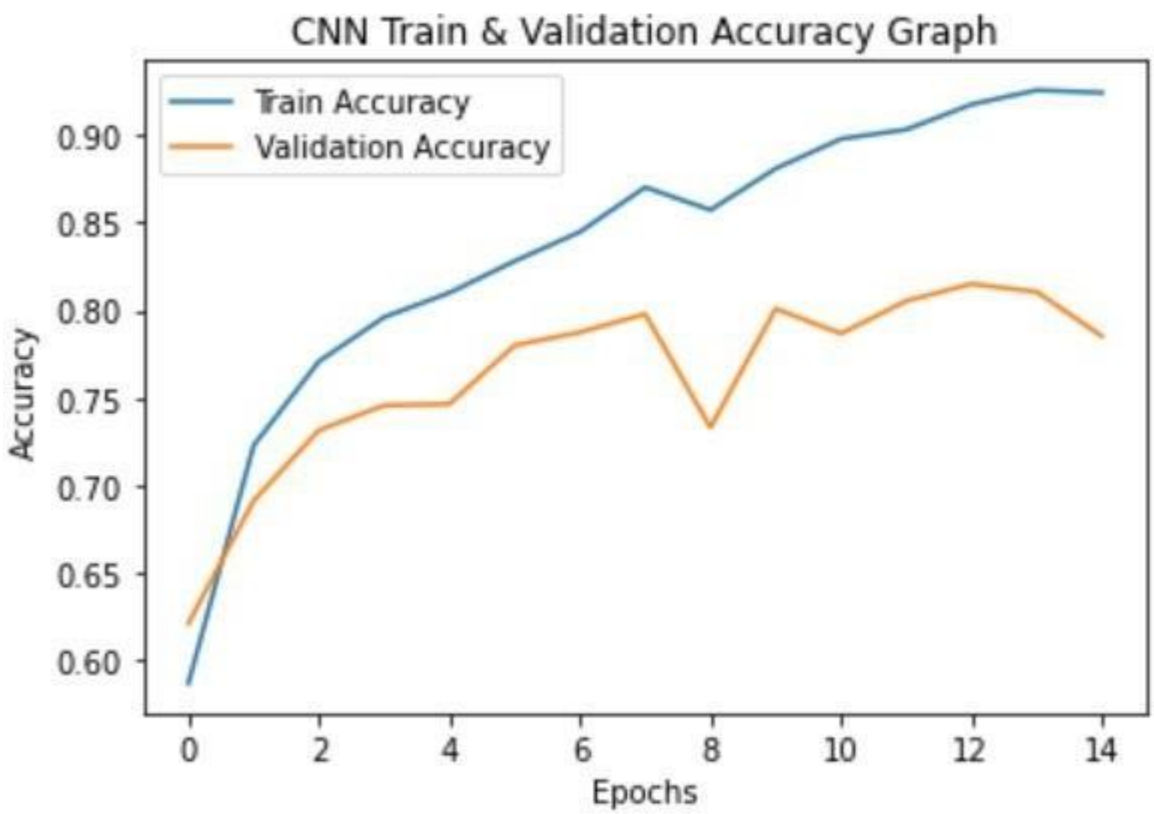

Figure 4.1: CNN Train vs. Validation Accuracy

4.2 ResNet 50

Our second model was ResNet 50. We run this model several times to get the best result. Where we got the highest average accuracy of 55.27%. Where the highest accuracy was 39.25% at 1st epoch and the lowest accuracy was 61.19% at 14th epoch. Figure 4.2 shows the train accuracy vs validation accuracy. We had a sudden drop at 7th epoch. This model perform better comparing train and validation accuracy then CNN model.

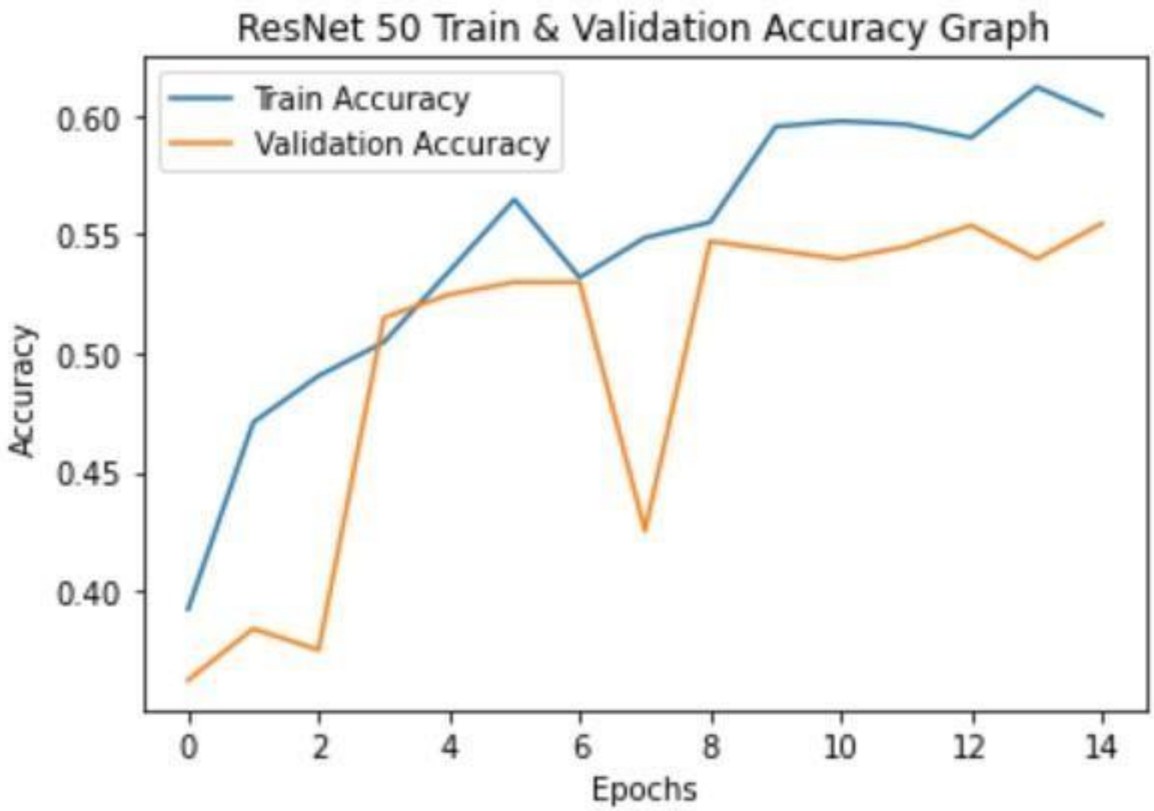

Figure 4.2: ResNet 50 Train vs. Validation accuracy

4.3 Inception V3

Our final model was Inception V3. This mode gives us the highest average accuracy of 94.04%. Where the highest accuracy was 99.81% at 11th epoch and lowest accuracy was 86.58% at 1st epoch. Figure 4.3 shows us the train vs. validation accuracy of Inception V3 model.

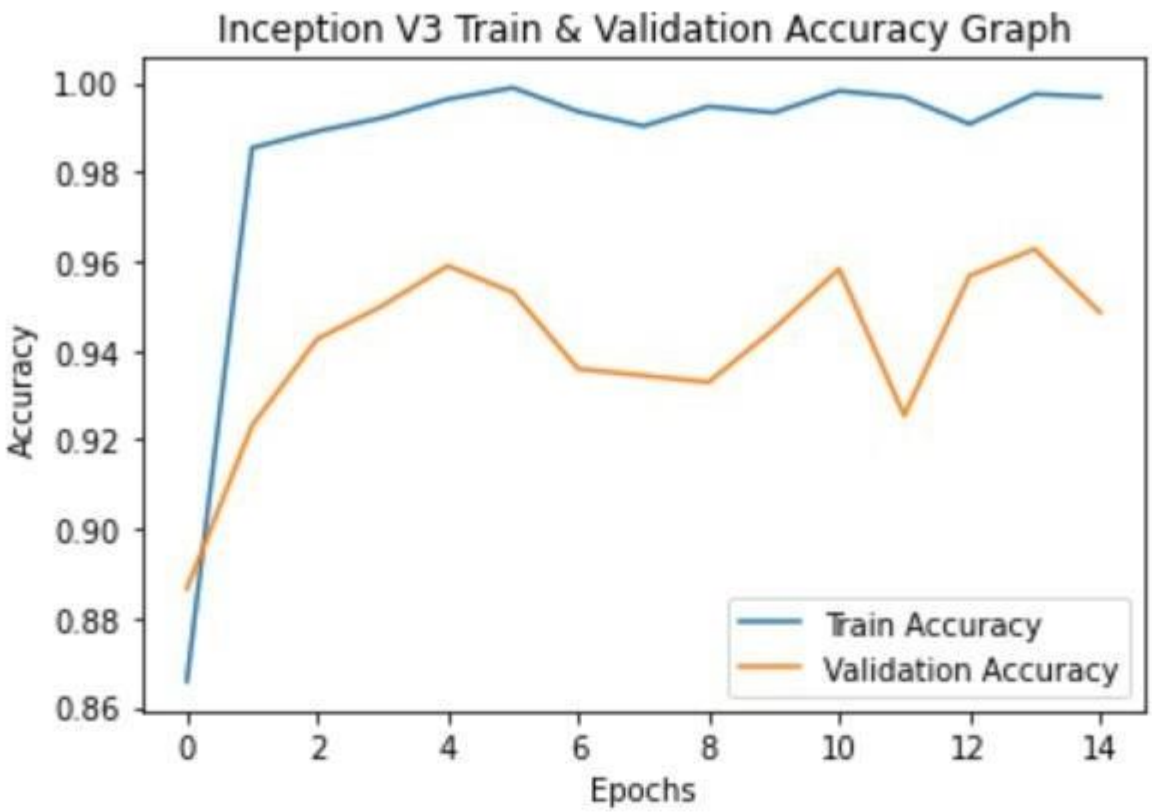

Figure 4.3: Inception V3 Train and Validation Accuracy

4.4 Confusion Matrix

For any classification problem if we want to deep dive into the classification performance then the best way is to use the confusion matrix. A confusion matrix is basically an N x N matrix. Where N is the number of the classes used in classification model. It shows the summary of the predictions from any classification model. Actual and predicted values are divided into respected classes. From here, we can find out the accuracy, f1-score, recall and the precision by calculating the true positive, true negative, false positive and false negative.

We had 166 of healthy, 161 of Septoria, 176 of Stripe Rust as unseen test data to find out the confusion matrix as well as the accuracy of the model along with the classification report.

Our first algorithm was CNN. Which did pretty well in our test data set. Below figure 4.4 shows us the confusion matrix of CNN.

		Prediction		
		Healthy	Septoria	Stripe Rust
Actual	Healthy	111	5	50
	Septoria	5	154	2
	Stripe Rust	30	9	137

Figure 4.4: CNN Confusion Matrix

From 166 healthy image CNN predicted 111 as healthy, 5 as septoria and 50 as stripe rust.

From 161 septoria test sample CNN predicted 5 as healthy, 154 as septoria and 2 as the stripe rust class.

From 176 stripe rust it predicted 30 as healthy, 9 as septoria and 137 as the stripe rust itself.

Our second algorithm was ResNet 50, which has very poor performance. Figure 4.5 shows the confusion matrix for ResNet 50.

		Prediction		
		Healthy	Septoria	Stripe Rust
Actual	Healthy	68	54	44
	Septoria	16	135	10
	Stripe Rust	37	64	75

Figure 4.5: ResNet 50 Confusion Matrix

Here we can see that, among the 166 healthy images it predicted only 68 as the correct healthy class, 54 for septoria and 44 for the stripe rust.

From 161 septoria images it could classify 135 samples as the septoria and 16 for healthy, 10 for the stripe rust.

From 176 stripe rust sample it predicted only 75 as the correct class. Where it predicted 37 samples as healthy and 64 as the septoria class.

Our best performed algorithm is the Inception V3. Where it achieved the accuracy of 94.04%. Figure 4.6 shows the confusion matrix of Inception V3.

		Prediction		
		Healthy	Septoria	Stripe Rust
Actual	Healthy	149	0	17
	Septoria	2	152	7
	Stripe Rust	2	2	172

Figure 4.6: Inception V3 Confusion Matrix

We may see that it predicted 149 test samples correctly as healthy from 166 healthy samples. And just 17 is for the stripe rust.

152 samples predicted as septoria from the 161 septoria samples. Where rest 2 are as healthy and 7 as stripe rust.

Finally, 172 samples from the stripe rust were predicted as stripe rust perfectly and 2 for healthy, 2 for septoria only.

4.5 Classification Report

Classification report shows the in detail information about any model performance. This report is mainly based on the 4 parts. Those are Precision, Recall, F1 – Score and the Support Data.

Precision is how many predictions are right for a particular class prediction. We can define this precision by Precision = TP / (TP + FP). Here TP = True Positive and FP = False Positive.

Recall is out of all true value for a class how many right value we predicted from that. Recall can be define as Recall = TP / (TP + FN). Where TP = True Positive and FN = False Negative.

F1-Score is the measure of model accuracy. This is calculated by the help of precision and recall. We can write F1-score as F1-Score = 2 x (Precision x Recall) / (Precision + Recall)

Support is how many data is used to calculate the values for the model.

Here we have our classification report in figure 4.7. It shows the in detail summary of the three models that we used in our work.

		precision	recall	f1 - score	support
cnn	Healthy	0.67	0.76	0.71	146
resnet 50	Healthy	0.41	0.56	0.47	121
inception v3	Healthy	0.9	0.97	0.93	153
cnn	Septoria	0.96	0.92	0.94	168
resnet 50	Septoria	0.84	0.53	0.65	253
inception v3	Septoria	0.94	0.99	0.97	154
cnn	Stripe Rust	0.78	0.72	0.75	189
resnet 50	Stripe Rust	0.43	0.58	0.49	129
inception v3	Stripe Rust	0.98	0.88	0.92	196

Figure 4.7: Classification Report of CNN, ResNet 50 and Inception V3

Here we see that for the Healthy, Septoria and Stripe Rust Inception V3 perform very well separately. Where the ResNet 50 has the lowest score and CNN has the average score between these two model. Finally, from figure 4.8 shows the average accuracy comparison of these three models. Where we see Inception V3 is at the top with accuracy score 94.04%, CNN is in the middle with 79.92% and with 55.27% ResNet 50 is at the bottom. So, we can say that Inception V3 is the best model of our work

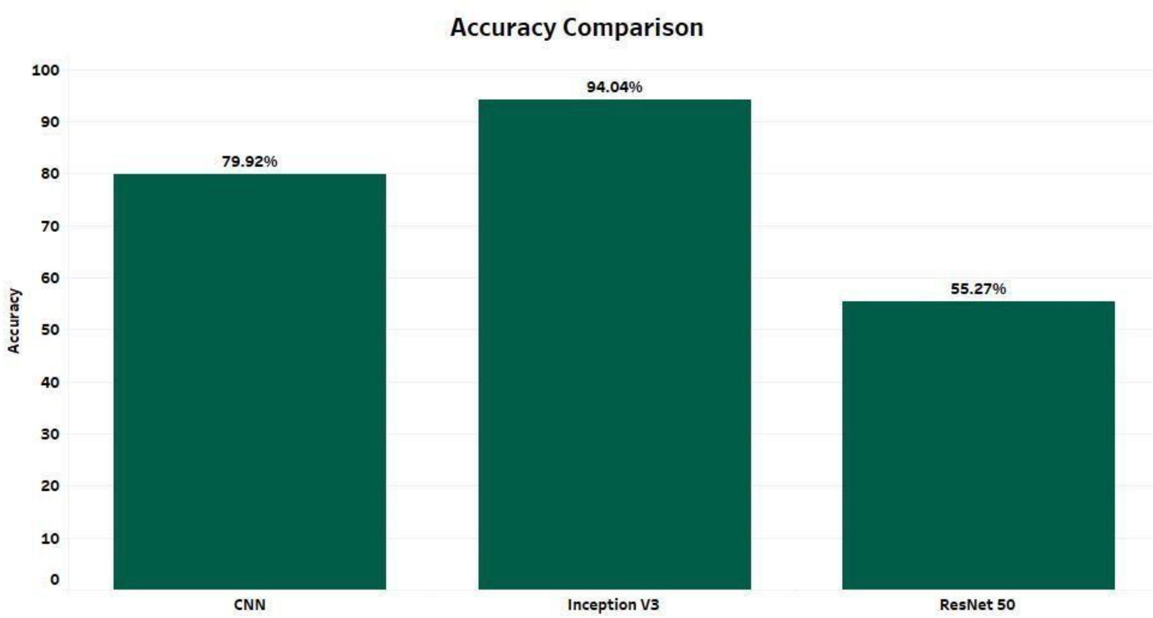

Figure 4.8: Accuracy comparison

Chapter 5

Conclusions and Recommendation

5.1 Findings and Contributions

In our experiment we found that, among CNN, ResNet and Inception V3 algorithm Inception V3 performance is best for the same amount of data set. Which can help many people to protect their crops by identifying the right disease of their plants. Thus, we hope that, we will be able to overcome the hunger problem one day.

5.2 Recommendations for Future Work

Although we got a good accuracy but there is chance that the model might be trained with biased data set. Or somehow it overfitted. As a result, we have this sustainable accuracy. Which can lead us to a wrong way. Also, we had little amount of data set that we later increased with augmentation technology which is a noticeable limitation.

In our future work, we will try to overcome these limitations and improve our work.

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