

**RECOGNIZING BANGLADESHI AGRICULTURAL INSECTS USING MACHINE  
LEARNING**

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## APPROVAL

This Project/Thesis titled “Recognizing Bangladeshi Agricultural Insects using Machine Learning”, submitted by Tapsara Akter, ID No: 221-25-124 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 17-01-2023.

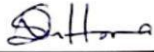
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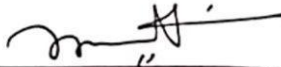
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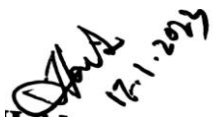


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## DECLARATION

I hereby declare that this thesis has been done by us under the supervision of **Sheak Rashed Haider Noori, Professor & Associate Head, Department of CSE**, Daffodil International University. I also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

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## ABSTRACT

Recently, some work has been done on agricultural insect recognition. But a limited number of works is done on Bangladeshi agricultural insects. Pests decimate crops on a massive scale each year. To achieve high crop output, pest detection and identification are necessary. For efficient pest control management, early pest detection in photographs is absolutely essential. Therefore, it has been difficult to identify the pest in the picture. I gathered the dataset for this study from a variety of sources. To achieve the greatest results in this study, I combined deep learning and transfer learning. I used some Deep Neural Networks here (DNN). ResNet50 and VGG16 produce the greatest results out of all of them. The model's output demonstrated 96.4% accuracy on the testing dataset, which is superior to other previous works.

Keywords — Convolutional Neural Network, Transfer Learning, Bangladeshi Agricultural insect Recognition, Bangladeshi Agricultural insects.

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# CHAPTER 1

## INTRODUCTION

### 1.1 Introduction

In Bangladesh, 77% of the labor force resides in the backcountry, and in the most rural homes, 87% of farmers rely on the agricultural industry for their primary source of daily income[1]. Though, our agricultural industry is confronting terrifying obstacles and urgently needs development. The goal of agriculture is to reduce plant illnesses while boosting food production and food quality. Plant diseases result in significant losses. Bangladesh has achieved commendable strides in the rural economy, where agriculture in particular is emerging as a key factor in reducing poverty. Agriculture has been around forever and continues to advance, but because of the negative consequences of climate change, pest diseases are now at an all-time high. Closer examination, nonetheless, refutes the exaggerated claim that agriculture is a manifestation field for many sciences and a robust production system. Farmers typically identify insects, and zoology and biology are the two head ecosystems that demand complex understanding of nature. But occasionally they are unable to accurately identify the pest. As is well known, agriculture in Bangladesh does not advance at the same rate as the rest of the nation or its technological advancements. The primary cause of it is a pest that spreads infections. The majority of diseases are unknown to farmers, who are also unfamiliar with modern technologies in our nation. The aim of this work is to recognize the plant's pest, which will help to increase the harvest's profit. An ordinary agricultural scientist in Bangladesh finds a new pest, and they are developing a remedy for the issue. However, the farmer is completely ignorant of the pests. When they are dealing with a pest infestation in their harvest land, they are unable to resolve the issue. Consuming leaves Pests damage plants quickly and eat through stalks, fruit, and roots. A harvest can also be dangerously infected by a virus or fungus. The majority of this work focuses on agriculture that can recognize the insect from a separate perspective or location. If an insect is on a fruit, the ground, a leaf, or anywhere else, it can be detected. And in future work, it can provide insight into the pest and the diseases that can affect plants or fruits, as well as a better remedy for the pest.



Figure 1.1.1 Bangladeshi agricultural insects

## 1.2 Motivation

Currently so much research work has been done on agricultural insect identification. But still limited researchers are attempting to work with Bangladeshi agricultural insects.

- This work will help to identify and understand agricultural insects. In this work a model will be proposed that can more accurately recognize and understand insects than previous existing works.
- This work will be beneficial for farmers and people who work with agriculture when they need to identify any pest. Because of this component, the system will be able to identify insects more easily and deal with them more successfully.
- Helpful for recognising Bangladeshi agricultural insects.

## 1.3 Rationale of the Study

Enough work has been done on agricultural pest identification. Compared to other countries' agricultural insect recognition, there has not been so much research work of Bangladeshi agricultural insects recognition and understanding. There is hardly any work that has been done on Bangladeshi agricultural insect recognition. So currently it becomes essential to work on Bangladeshi agricultural insects. The aim of this work is, using annotated photos of insects to train deep neural networks. Using this model will be capable of recognizing the photo of agricultural insects.

## **1.4 Research Questions**

1. What is the best approach to identify agricultural insects in Bangladesh? How might deep neural networks (DNNs) be used to identify agricultural insects in Bangladesh? And how does it work?
2. How can the proposed model's accuracy be measured? Which Deep Neural Network (DNN) model offers the highest level of accuracy for evaluating data implementation?

## **1.5 Expected Output**

In this work, the proposed model can accept one or more photos as input. And for each of those photographs, the model will automatically determine the type of insect. This means that either a single photo or a number of photos can be generated at once. But there needs to be one insect in that image.

## **1.6 Report Layout**

The structure of this report is as follows:

The backdrop of the research, including relevant works, an overview of the research, and problems, will be discussed in Chapter 2. I'll talk about the work methodology in chapter 3. The explanation of the research experiment's experimental findings will continue in Chapter 4. The overview, conclusion, and limitations of the research will be covered in Chapter 5.

## CHAPTER 2

### BACKGROUND

#### 2.1 Preliminaries

In this thesis work I am working with Bangladeshi agricultural insects recognition. Major macroeconomic goals including job creation, the development of human resources, poverty reduction, food security, and other social and economic forces are significantly impacted by the agricultural sector's success. Agriculture is the primary source of income for most Bangladeshis[2]. Any insect that belongs to the phylum Arthropoda, the biggest animal phylum overall, and specifically the class Insecta, which is the largest class within it. Insects make up around 85% of all animal species that have been scientifically identified to date; entomologists believe that there may be more than 10,000,000 insect species that have not yet been discovered[3]. My database, which I compiled for my thesis work, has information on 14 different types of agricultural insects.

Table 2.1.1 contains those 14 classes of agricultural insects:

Table 2.1.1 types of agricultural insects available in database

Number of types	Types of Insect
1	ArmyWorm
2	Beet ArmyWorm
3	Black CutWorm
4	Blister Beetle
5	Field Cricket
6	Flea Beetle
7	Jute Stem Weevil
8	Mole Cricket
9	Pieris Canidia
10	Spilosoma Oblique
11	Tarnished Plant Bug

12	Thrips
13	WireWorm
14	Yellow Mite

This project is a little machine learning undertaking (ML). Without employing a pattern or explicit instructions, the main goal of machine learning is to make predictions while using computer systems to perform certain tasks. Machine learning algorithms create models using datasets based on training data from those datasets. Email filtering, computer vision, and other uses of machine learning algorithms are common.

Deep learning is a part of machine learning that uses ANNs (Artificial Neural Networks). Deep learning is capable of being unsupervised, semi-supervised, or supervised.

Convolutional neural networks, the most widely used subclass of deep neural networks (CNN). In at least one of their layers, convolutional neural networks substitute convolution for general matrix multiplication.

In the experimental field of machine learning known as transfer learning, an issue is solved, the knowledge gained is stored, and the knowledge is subsequently applied to further, connected problems.

## 2.2 Related Works

Being able to recognize pests is a really difficult task. Numerous publications outlining various methods for employing image processing to detect pests or diseases in agricultural crops have been published. In this part, some earlier experiments had been reviewed in the relevant article. CNN image processing is highly powerful for image recognition and pest identification. In order to identify the pest, researchers are utilising image processing and other researchers found success using a different algorithm for this kind of labor.

In this study [4], to do image recognition, they introduce a Convolutional Neural Network (CNN) model, and the method offers the best architecture for image recognition with validation accuracy of 93.46% on 1600 images of Bangladeshi agricultural insects. Around 1200 images are used for training and 400 images are for the testing purpose. This work was done on six insect classes. They are Caterpillars, Henosepilachna,

Lawn\_Grubs, Rice\_Bug, eastern\_tent\_caterpillar, grasshopper. Limitation of this work is, they have worked with a low number of images.

In Study [5], where Akter et al. worked with both useful and harmful insects and introduced a beetle detection system of the farming field of Bangladesh. They had established their system on two scenarios, classification & learning and recall process. At first, DSS and ANN methods were used for learning procedures. With the help of ANN, they sub-classified the harmful beetle and stored those classified data into a dataset. Then they applied FCN as a detection tool for estimated image samples. At last SVR a regression technique was applied to predict the useful and harmful insects with more than 90% accuracy. They have used a dataset of 2351 samples that had been collected by them. They have also estimated the possibilities ratio of production quantities and future situation of target cropland based on their experimental results.

Thenmozhi et al. [6], authors present an algorithm that is capable of detecting the insects for Wang, Xie, Deng, and IP102 datasets. This work was done on nine and 24 insect classes of Wang and Xie dataset. They use artificial neural networks (ANN), k-nearest neighbors (KNN), naive bayes (NB), support vector machine (SVM) and convolutional neural network (CNN) models. First, they collect a dataset and divide it into a 70-30% test-train ratio. For the training set they use a dataset that contains 1296 images of Wang and 6280 images of xie. Then from the insect images shape features were extracted and ANN, KNN, SVM, and NB algorithms were applied for classification. And CNN based insect classification applied for comparison performance. From the RBF kernel SVM classifier the classification accuracy was 79.9% and 71.8% for 5 and 9 classes of insects observed with nine shape features. And For CNN model the accuracy was 93.9% and 91.5%.

In this paper[7], they developed a system that included color-based image segmentation and image preprocessing. They improve the image's quality, convert it to grayscale, and modify the contrast during preprocessing. Following the conversion of the image's colors from RGB to  $L^*a^*b$ , k-means clustering is applied to the image.

Xiaoping Wu et al. [8], authors work with a dataset named IP102 that includes more than 75000 images of 102 species. With their results, they demonstrate that current handcrafted feature methods and deep feature methods cannot yet handle the pest recognition well.



Meanwhile, in this study [9], they present a model that can automatically identify insect specimen images at the order level. They worked with 29-38 insect orders. They gather a collection of 225 specimen photos from nine orders and sub-orders, with 25 photographs from each order, for that purpose. For pattern recognition, they use Artificial neural network (ANN) and Support vector machines (SVM). After Applying Artificial neural networks (ANN) and Support vector machines(SVM), they get better performance for SVM.

The research can provide a strong basis to back it up. The entire literature review paper in this area discusses how to identify pests, and various scholars have another way to identify the bug. The key objective of this paper is to identify the insect and offer a piece of improved knowledge for farmers. The purpose of this work is related to literature surveys.

### **2.3 Comparative Analysis and Summary**

In this work, I'm going to discover a technique to identify agricultural insects. Insects come in a wide range. It can be really challenging to understand some of them at times. Now that there are so many different insect image patterns, it is difficult for me to select a model that can identify insects. This is why I've implemented

- Sequential Convolutional Neural Network (CNN)
- And some architectures of CNN like ResNet50, VGG16, InceptionV3.
- Sequential mode is superior to the applied transfer learning model.
- ResNet50 performs best.

### **2.4 Scope of the Problem**

1. Users of this model can submit input photographs to determine which insect is in the image. The input image should only contain a single bug.
2. I focused on single insect recognition for this research. No image may be used in this project to identify insects.
3. This initiative will only be useful for identifying agricultural insects in Bangladesh.

### **2.5 Challenges**

1. An issue with determining the image's size before resizing it.
2. Choosing appropriate classification techniques.
3. Using Python to implement those categorization techniques. because running the models took a long time

## **CHAPTER 3**

### **Research Methodology**

#### **3.1 Research Subject and Instrumentation**

Due to the great range of insect visual patterns, identification of insects is challenging. In this work, I need to create a dataset in order to create this model, and I also need to know what kind of work I am doing. I have fourteen classes at work. Our brains serve as the model for neural networks. Just as neurons in human brains connect various regions, the network's layers are made up of individual nodes.

A weight will be assigned to the inputs to the nodes in a single layer, modifying that parameter will change the outcome of the forecast. Each node could be influenced by various weights because the weights are allocated on the links between the nodes.

The input layer of the neural network contains all of the data which are training. The values are then transformed depending on the weights at every node as the data is then sent through the hidden layers. A value from the output layer is then returned. Here I use CNN and some of its architecture for finding the best accuracy result. Because in the input image, design elements like gradients, lines, circles, or even faces and eyes are extremely successfully picked up by CNN. Each of the numerous convolutional layers that make up CNN is capable of identifying more complex shapes. These layers are stacked on top of one another. And CNN architecture has more layers. That's why the output result is better than the classic CNN model.

In this work, I tried to build an effective model by trying some Deep Neural Network (DNN) such as sequential convolution Neural Network (CNN), some architecture of CNN like InceptionV3, ResNet50, VGG16. I'll compare the outcomes after putting these algorithms into practice. I will briefly discuss all the terms of work in the proposed methodology section.

#### **3.2 Data Collection Procedure**

First, I gathered my data for my intended work. I've gathered photos of agricultural insects from a variety of sources. The total dataset contains 14 classes of insects. I gathered a total of 7890 images of Bangladeshi agricultural insects. In this project

- The internet is used to gather certain images.

● And some other data images were collected with the help of my family and friends. My working dataset has 910 images of Army Worm, 193 images of Black Cutworm, 793 images of Mole Cricket, 485 images of Pieris Canidia, 686 images of WireWorm, 250 images of Field Cricket, 250 images of Jute Stem Weevil, 250 images of Spilosoma Obliqua, 250 images of Yellow Mite, 787 images of Flea Beetle, 1134 images of Beet ArmyWorm, 378 images of Tarnished Plant Bug, 828 images of Blister Beetle, 696 images of Thrips.

### 3.3 Statistical Analysis

Table 3.3.1 each class's statistical analysis:

Table 3.3.1 For statistical analysis

Bangladeshi Agricultural Insect	Class Label	Total Data	Training Data	Testing Data
ArmyWorm	0	910	728	182
Beet ArmyWorm	1	1134	907	227
Black CutWorm	2	193	154	39
Blister Beetle	3	828	662	166
Field Cricket	4	250	200	50
Flea Beetle	5	787	630	157
Jute Stem Weevil	6	250	200	50
Mole Cricket	7	793	634	159
Pieris Canidia	8	485	388	97
Spilosoma Oblique	9	250	200	50
Tarnished Plant Bug	10	378	302	76
Thrips	11	696	556	140

WireWorm	12	686	548	138
Yellow Mite	13	250	200	50

### 3.4 Applied Mechanism

Because there are so many different insect image patterns, it is difficult to recognize insects. In this study, I've tried to create a model that offers superior recognition results. Convolutional neural networks (CNN) and various CNN architectures have been used in my attempt to construct a model that can identify agricultural insects. Utilizing the Convolutional Neural Network and various additional CNN designs, including ResNet50, VGG16, and InceptionV3, and comparing the results across them using 14 distinct image classes. Which has some phases that are following in below Figure 3.4.1:

- Data collection.
- Splitting data
- ImagePreprocessing.
- Training models.
- Testing models.

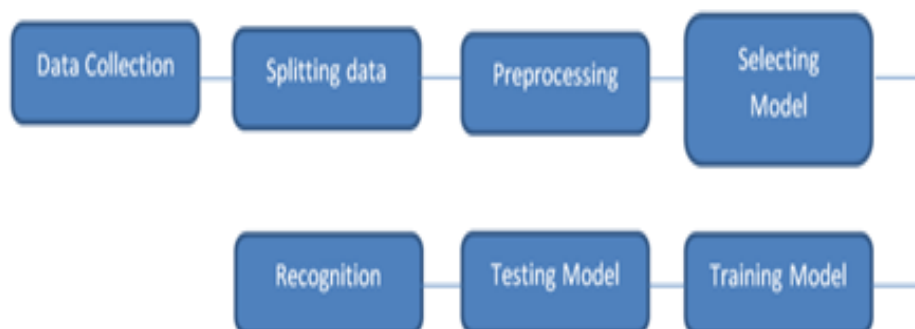


Figure 3.4.1 Block diagram of work methodology

### Experiment Data Set:

This dataset consists of almost eight thousand images that contain 14 classes. The majority of the photographs were taken in fields and around trees in this dataset, while other images were retrieved from the internet. This dataset was produced in order to test a theory about image recognition. There are approximately 7890 photos in this dataset, of which 6312 are used to train and the remaining images are used for testing the model. There are fourteen classes of train data sets and tests in the study. For training purposes, 907 to 200 photographs have been discriminated against, and for testing purposes 50 to 227 images are chosen for each class.



Fig. 3.4.2: Images From Collected Dataset

### Splitting Data:

I initially divided my insect dataset into a test set and a training set in order to test and train my model. I divided the dataset into a train set that made up 75% of the sequential convolutional neural network (CNN) and a test set that made up 25%. Additionally, the split size for another architecture was 20% in the test set and 80% in the train set.

### Image preprocessing:

To acquire the right outcome, preprocessing is carried out. I scale each chosen image from my target dataset to 400\*300 pixels for sequential CNN. Then I turned the RGB image to a grayscale one. Then I clean out the noise and name the pictures. I used the ImageDataGenerator function for CNN's other architecture.

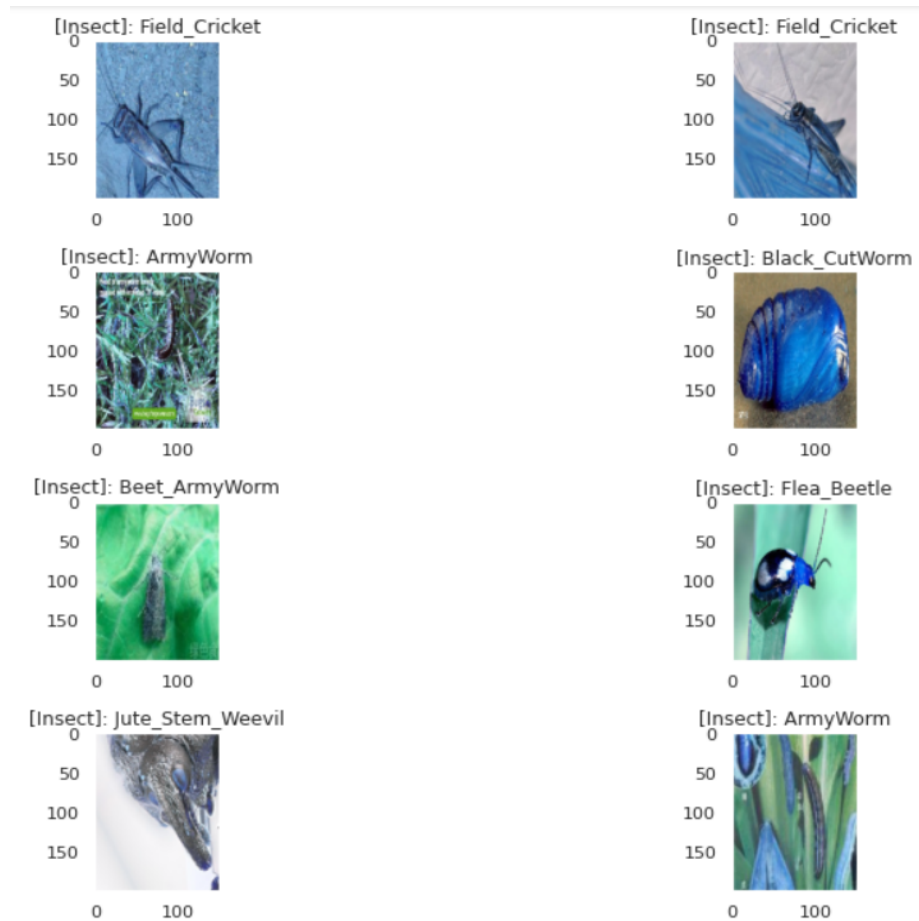


Fig. 3.4.3: Image preprocessing

### Selecting model, Training model, testing model:

To achieve the best possible result, I'll use Convolutional Neural Network (CNN) and a few different CNN architectures, including ResNet50, VGG16, DenseNet121, and MobileNet.

### Sequential Convolutional Neural Network (CNN):

- Convolutional Neural Network (CNN)[10]

The model has two completely connected layers and is meant to identify pests from any location. It comprises four convolutional layers and two fully connected layers. A Batch normalisation includes a completely connected layer. a number of thick and dropout which can assist in utilising the model. The input layer is the first convolution layer. Layer with a kernel size of 3 and an RGB input shape of 32x32. The filter size is 32 and the color mode is. The layer that employs ReLU (1) Strides (1) activation, with the same padding attribute.

When a positive value is supplied as an input, the ReLU function outputs that same value. If the value is negative, it returns 0.

$$f(x)=\max (0, x) (1)$$

Convolution layer 2 receives the output of convolution layer 1 as an input.

The first layer with maximum pooling Binning sub-regions is a method of separating them. Max-pooling is a technique for minimising the number of parameters in a program, and it's used here. In the maximum pooling layer, pool size 2 with strides 2.

The filter size in the second layer is 64, with a kernel size of 3 and a stride of 1. This layer uses batch normalisation to regularise the vanishing gradient convolutional network during training, resulting in improved performance and reduced training time. Batch normalisation is used to speed up the learning process and allow for a faster learning rate. The second convolution layer's output is linked to the next pooling layer. The layer also has a pool of two and strides of two.

With the exception of the 128 filter size, strides, layer 3's kernel size and batch normalisation characteristics are identical to those of layer 2. The output from layer three is related to the 3rd pooling layer and the two-stride pool size.

Layer 4 has a filter size of 256 and includes the same features as layer 3. However, a 25% dropout was applied in this layer to increase the model's stability throughout training, albeit this can become overly regimented.

Following this four-layer structure, there are two thick layers that symbolize matrix-vector multiplication. There are 256 concealed units in the first dense layer, and the activation value causes a 25% drop off. The overfitting dropout technique is utilised here to combat the problem. The dense is 6 without drop out in the second dense layer to normalise the model, and sigmoid activation is present. The model is constructed in this way.

After adding all of these layers to the model, the output becomes smooth and noise-free, and for improved classification performance, an additional two completely linked dense layers are added, including batch normalisation and property dropout. A sigmoid will then be used to translate the data into probabilities for each class. A sigmoid function-  $(z)=1/(1+e^{-z})$

For problems involving binary classification, the loss serves as a loss function, is defined with the help of the binary cross-entropy. Since this is a classification problem, the optimizer will assist with gradient descent and the metrics will set accuracy. The structure of the model's summary is depicted in Figure 3.4.4: -

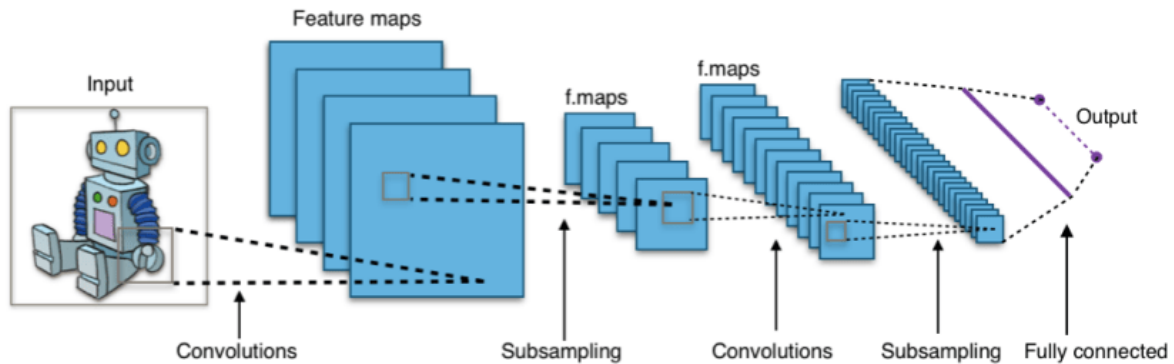


Fig. 3.4.4 Model Summary Representation

## Architectures of Convolutional Neural Network (CNN):

### • VGG16 [11]:

Convolution neural network (CNN) architecture VGG16. I initially loaded all the required libraries to start putting this architecture into practice. similar to OS, NUMPY, and KERAS, which I'll need to use with VGG16. From KERAS, I also imported ImageDataGenerator. After that, I need preprocessing so I can quickly import data with labels into the model. Then using the KERAS program I import the VGG16 architecture. As soon as that is done, I make an object called ImageDataGenerator for training and test data, passing the folder containing the training data to the object trdata and the test data to the object tsdata. Each folder's contents will automatically be labelled with the same padding thanks to the ImageDataGenerator. After initialising the model, I add

- using the same padding and two convolution layers of 64 channels by three kernels
- 2x2 pool size, 1x maximum layer, and 2x2 stride
- using the same padding and two convolution layers with 128 channels in
- 2x2 pool size, 1x maximum layer, and 2x2 stride



- 256 channel, 3x3 KERNEL, 3x3 convolution layer, and identical padding
- 2x2 pool size, 1x maximum layer, and 2x2 stride
- 512 channel, 3x3 KERNEL, 3x3 convolution layer, with identical
- 2x2 pool size, 1x maximum layer, and 2x2 stride
- 512 channel, 3x3 KERNEL, 3x3 convolution layer, with identical padding
- 2x2 pool size, 1x maximum layer, and 2x2 stride

Rectified Linear Unit (ReLU) activation is also added to each layer. This prevents all negative values from being sent to the following layer.

I flatten the vector that results from the convolutions after constructing the full convolution before passing the data to the dense layer.

- 4096 units in 1x dense layer
- 4096 units in 1x dense layer
- 10 units of dense Softmax layer one

Following that, this model is finally ready. Now I need to put the model together. I'll employ Adam's optimizer. In order to arrive at the global minima when training the model, I will use the Adam optimizer. And the optimizer's learning rate is set in this example to 0.001 and will be specified after that. I can now use `model.summary()` to examine the model's summary. I'll import `ModelCheckpoint` and the `EarlyStopping` function from KERAS after building the model. I'll make an object that contains both a `ModelCheckpoint` and an `EarlyStopping` callback and feed it to `fit_generator`. Then, the model will begin to train, and I'll start to see the accuracy and loss of training and validation. I can now use `matplotlib` to visualise training or testing accuracy and loss. For VGG16, accuracy is 96.04%. Figure 3.4.5 demonstrates the VGG16 architecture.

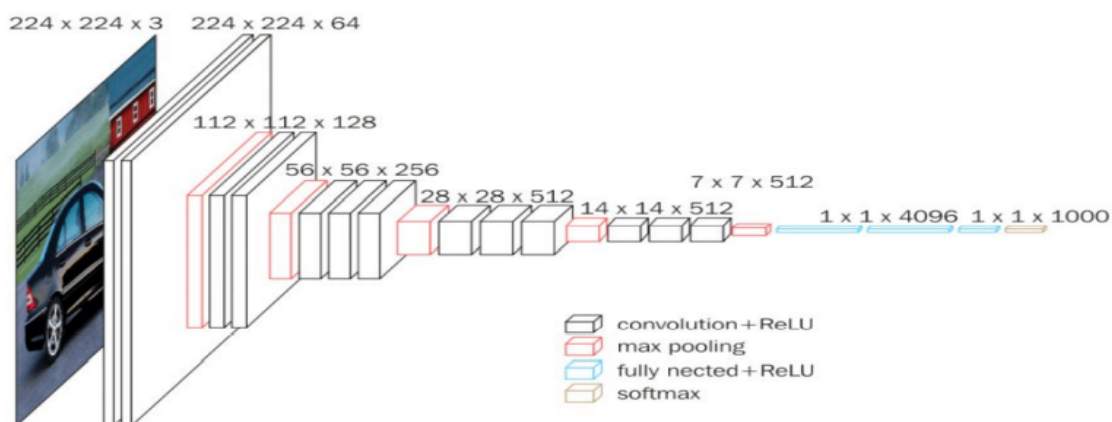


Figure 3.4.5 architecture of VGG16

- **ResNet50 [12]:**

Convolution neural net (CNN) architecture ResNet50. I initially loaded all the required libraries to start putting this architecture into practice. As an example, I will need to implement ResNet50 using KERAS, OS, and NUMPY. ImageDataGenerator was imported from KERAS. I then need preprocessing so I can quickly add labeled data to the model. I then use the KERAS application to import the ResNet50 architecture. As soon as that is done, For training and test data, I create an object named ImageDataGenerator and send the training data folder to object trdata and the test data folder to object tsdata. Each folder's contents will automatically be labelled with the same padding thanks to the ImageDataGenerator. Initialising the model, The following layers are used:

- 2x convolution layer of 64 channels of 3x3 KERNEL and use the same padding;
- 1x maxpool layer of 2x2 pool size and stride 2x2;
- 2x convolution layer of 128 channels of 3x3 KERNEL and use the same padding;
- 3x convolution layer of 256 channels of 3x3 KERNEL and use the same padding;
- 1x maxpool layer of 2x2 pool size and stride 2x2;
- and 3x convolution layer

Rectified Linear Unit (ReLU) activation is also added to each layer. This prevents all negative values from being sent to the following layer.

I flatten the vector that results from the convolutions after constructing the full convolution before passing the data to the dense layer.

- 4096 units in 1x dense layer
- 4096 units in 1x dense layer
- 10 units of dense Softmax layer one

Following that, this model is finally ready. Now I need to put the model together.

In order to arrive at the global minima when training the model, I will use the Adam optimizer. The optimizer's learning rate is set in this example to 0.001 and will be specified after that. I can now use model.summary() to examine the model's summary. I'll import ModelCheckpoint and the EarlyStopping function from KERAS after building the model. I'll make an object that contains both a ModelCheckpoint and an EarlyStopping callback and feed it to fit generator. Then, I'll start to see the loss and accuracy of training and validation as

the model starts to train. I can now use matplotlib to visualise training or testing accuracy and loss. For ResNet50 the accuracy is 96.4%. Figure 3.4.6 demonstrates the ResNet architecture.

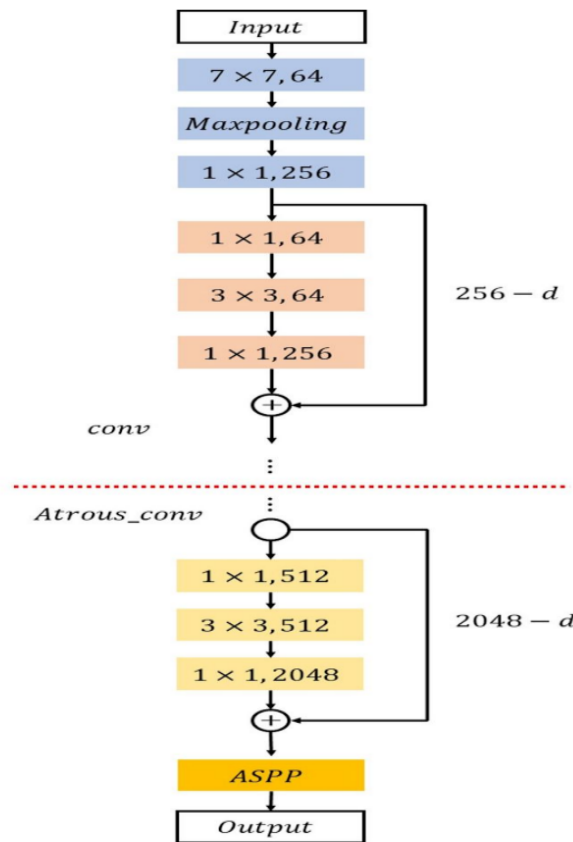


Figure 3.4.6 architecture of ResNet

### • InceptionV3 [14]:

Convolution neural net (CNN) architecture is used in InceptionV3. I initially loaded all the required libraries in order to put this design into practice. As an example, I will need to implement ResNet50 using KERAS, OS, and NUMPY. Also from KERAS, I imported ImageDataGenerator. Preprocessing is then required so that I can simply import data with labels into the model. I then import the KERAS application's InceptionV3 architecture. As soon as that is done, I make an object called ImageDataGenerator for training and test data, passing the folder containing the training data to the object trdata and the test data to the object tsdata. Each folder's contents will automatically be labelled with the same padding thanks to the ImageDataGenerator. Initializing the model first, I then add

- 2x convolution layer with the same padding and a 64-channel 3x3 KERNEL.
- 1x maxpool layer of 2x2 pool size and stride 2x2.

- 2x convolution layer of 128 channels of 3x3 KERNEL and use the same padding.
- 3x convolution layer of 256 channels of 3x3 KERNEL and use the same padding.
- 2x convolution layer with the same padding and a 64-channel 3x3 KERNEL.
- 3x convolution layer of 512 channels of 3x3 KERNEL and use the same padding.
- 2x convolution layer with the same padding and a 64-channel 3x3 KERNEL.
- 3x convolution layer of 512 channels of 3x3 KERNEL and use the same padding.
- 2x convolution layer with the same padding and a 64-channel 3x3 KERNEL.

Rectified Linear Unit (ReLU) activation is also added to each layer. This prevents all negative values from being sent to the following layer.

I flatten the vector that results from the convolutions after constructing the full convolution before passing the data to the dense layer.

- 4096 units in 1x dense layer
- 4096 units in 1x dense layer
- 10 units of dense Softmax layer one

Following that, my model is finally ready. I now need to put the model together. In order to arrive at the global minima when training the model, I will use the Adam optimizer. The optimizer's learning rate is set in this example to 0.001 and will be specified after that. I can now use `model.summary()` to examine the model's summary. I'll import the `ModelCheckpoint` and `EarlyStopping` methods from KERAS after building the model. I'll make an object that contains both a `ModelCheckpoint` and an `EarlyStopping` callback and feed it to `fit_generator`. After then, the model will begin to train, and I'll start to see the accuracy and loss of training and validation. I can now use Matplotlib to visualize training/testing accuracy and loss. The accuracy for InceptionV3 is 92.41%. Figure 3.4.7 depicts Inception's architecture.

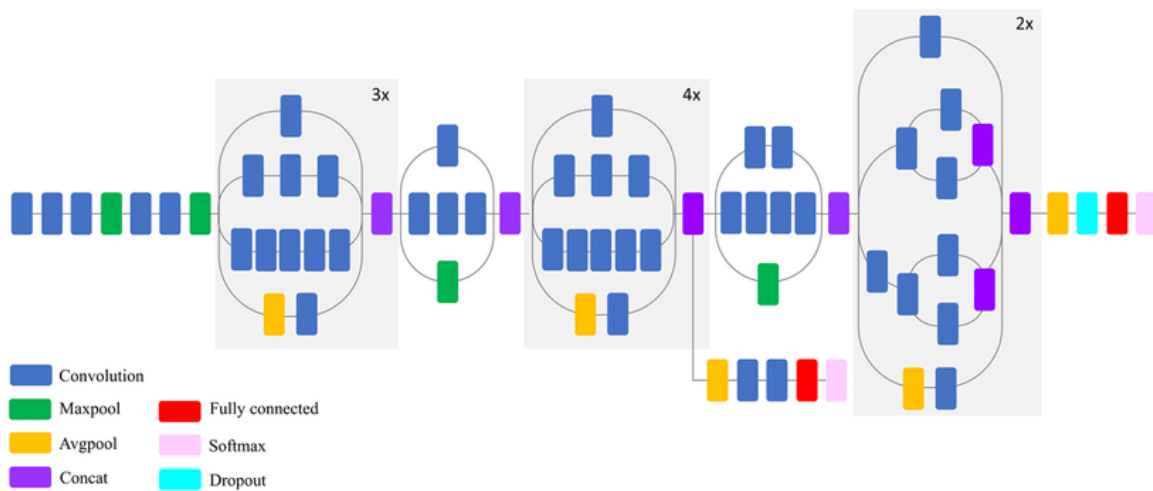


Figure 3.4.7 architecture of InceptionV3

### 3.5 Implementation Requirements

Here I am researching about Bangladeshi Agricultural Insect recognition. List of tools, devices, languages and programs that I used in my project are given below:

#### Tools and Advance Libraries:

1. Python (version 3.7.4)
2. Operating system: Windows 11 64 bit
3. Keras
4. Panda
5. Numpy
6. Tensorflow
7. Pillow
8. OpenCV
9. Sklearn

#### Software and Hardware:

1. Intel Core i5 8<sup>th</sup> gen integrated with 8GB ram
2. High Speed Internet Connection
3. Google Colab with 12GB GPU and 350GB ram

#### 4. 1 TB Hard Disk

Programming in Python is possible using both functional and object-oriented techniques. Numpy is a library for python. For matrix manipulation, calculations, and other scientific computing tasks, utilize Numpy. Additionally, multi-dimensional containers of common data are employed with Numpy. Another programming language library that is mostly utilized in real-time computer vision is called openCV. Tensorflow and other deep learning frameworks are supported by the OpenCV library. Tensorflow is used in the backend of this project for deep learning. Additionally used for image processing is OpenCV. Sklearn is a Python application that is comparatively easy to use and effective. I divide the dataset for my project into training and test sets using Sklearn. Another Python package that can function on top of TensorFlow in Keras. It is a human-designed API that offers concise and useful feedback in the event of user error. Panda is a library function that offers data that is adaptable, quick, and expressive. Additionally, it is used to read and write CSV files and process data.

## CHAPTER 4

### EXPERIMENT RESULTS AND DISCUSSION

#### 4.1 Experimental Setup

I'll talk about the experiment I ran in this chapter. Anyone can learn about the projected results of my project after reading this chapter, and they can also learn about the outcomes of the suggested model for identifying Bangladeshi agricultural insects based on each algorithm that was used in my research. In this work, I tried to build a model by trying some Deep Neural Network (DNN) such as sequential convolution Neural Network (CNN), some architecture of CNN like InceptionV3, ResNet50, VGG16.

#### 4.2 Experimental Results and Descriptive Analysis

- **Sequential Convolutional Neural Network:**

The accuracy rate for the sequential CNN model is 68.16%.

Graph:

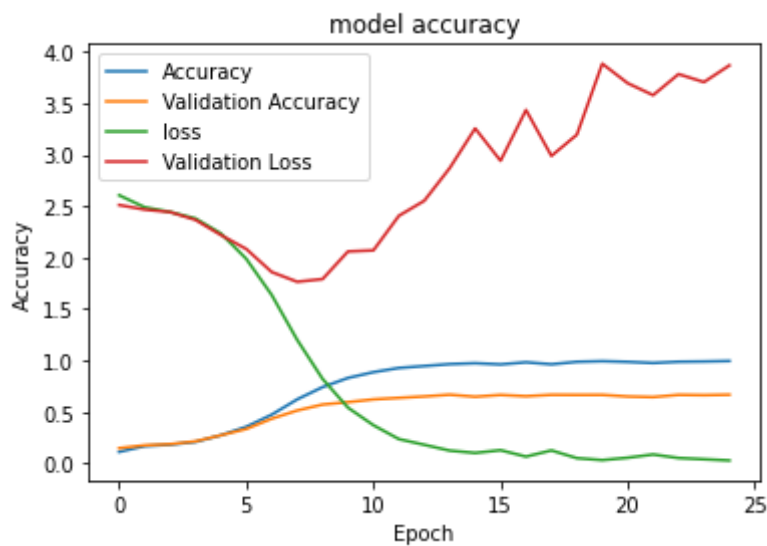


Figure 4.2.1 Model Accuracy Graph of CNN

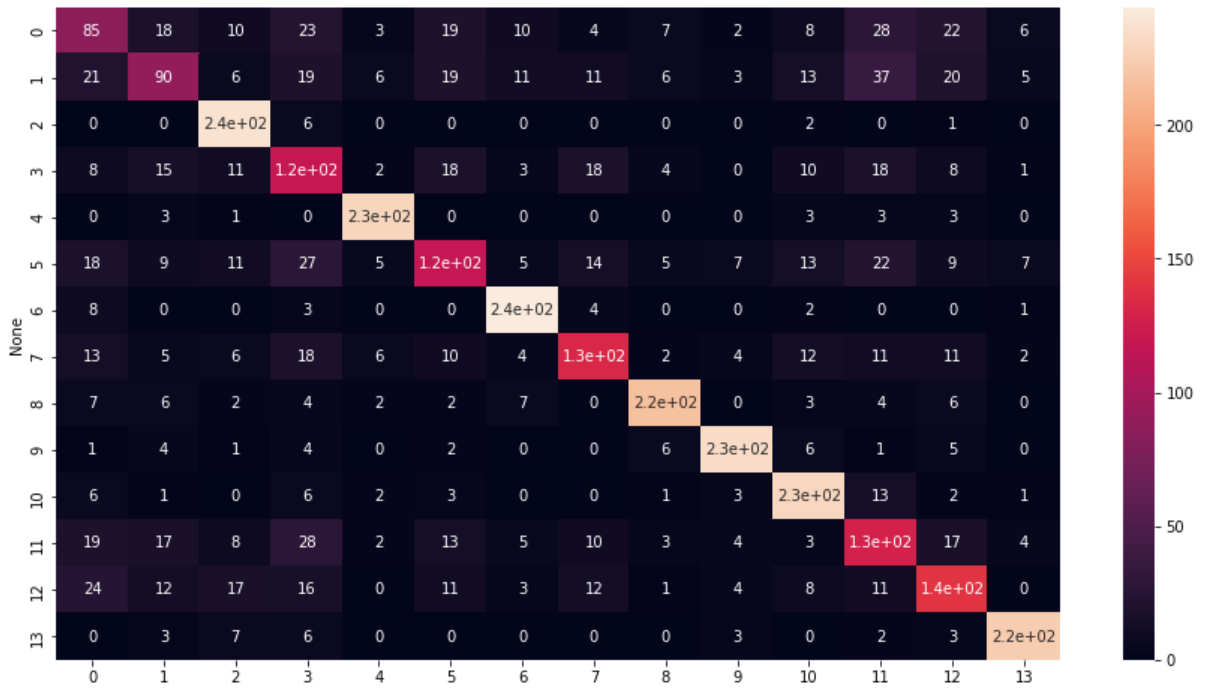


Figure 4.2.2 confusion matrix of CNN

- **Other Architectures of CNN :**

Table 4.2.1 Experimental outcomes using different architecture

Model	Size	Parameter	Depth	Training Accuracy	Training Loss	Testing Accuracy	Testing Loss
<b>VGG16</b>	528 MB	138,357,544	23	0.967	0.110	0.9604	0.06
<b>InceptionV3</b>	92 MB	23,851,784	159	0.9660	0.1052	0.9241	0.4
<b>ResNet50</b>	98 MB	25,636,712	-	0.9822	0.0587	0.9637	0.022



## VGG16

The graph's epoch value is represented by the X-axis, while the accuracy value is shown by the Y-axis.

Graph:

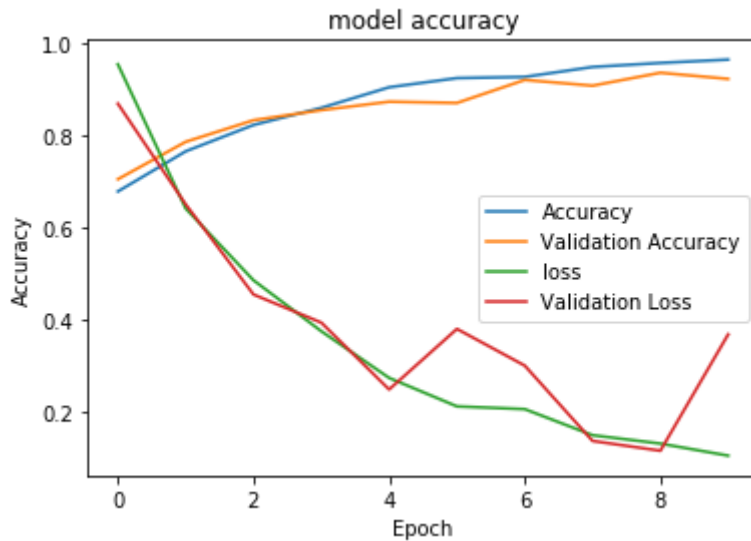


Figure 4.2.3 Model Accuracy Graph of VGG16

## InceptionV3

The graph's epoch value is represented by the X-axis, while the accuracy value is shown by the Y-axis.

Graph:

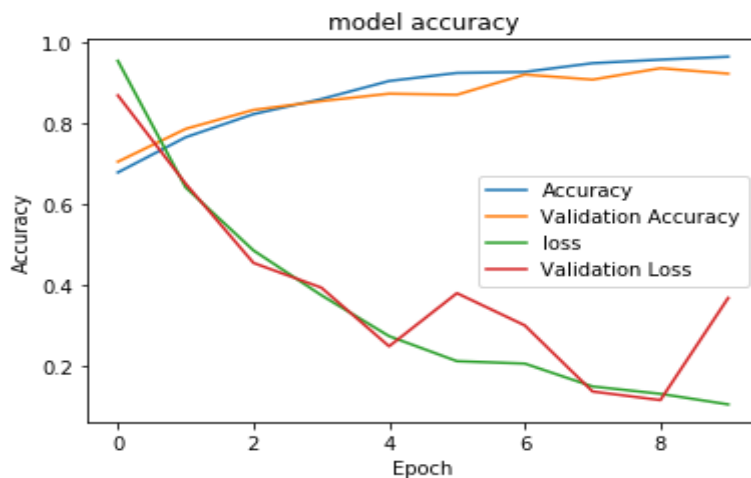


Figure 4.2.4 Model Accuracy Graph of InceptionV3

## ResNet50

The graph's epoch value is represented by the X-axis, while the accuracy value is shown by the Y-axis.

Graph:

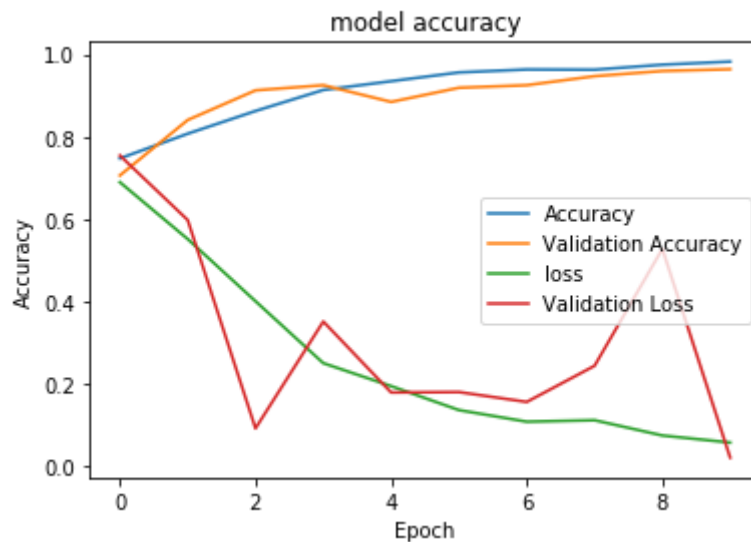


Figure 4.2.5 Model Accuracy Graph of ResNet50

For CNN accuracy visualization, I utilized a confusion matrix, and for other architectures, I plotted graphs. ResNet50 has an accuracy of 96.4% for VGG16, 96.4% for InceptionV3, 92.41% for CNN, and 96.4% for VGG16. Figure 4.2.6 evaluating the accuracy of various architectures I use 100 steps per epoch for all architecture, 10 steps for validation, and 10 epochs for all architecture. However, each model's output differs from the others. It occurred because the number of deep layers in each model varies. There are 19 layers in the VGG16 network. In the convolution layer, VGG16 always employs 3 x 3 filters with a stride of 1, and in the pooling layers, it employs the same padding (2 x 2) with a stride of 2. The input matrix for ResNet50 is computed using two linear transformations and the ReLU activation function. ResNet sums the result in the final relu function and directly duplicates the input matrix to the second transformation output. There are 100 layers in the ResNet network. The depth of the Inception network is 22 layers. Another model also performs well at identifying agricultural insects in Bangladesh.

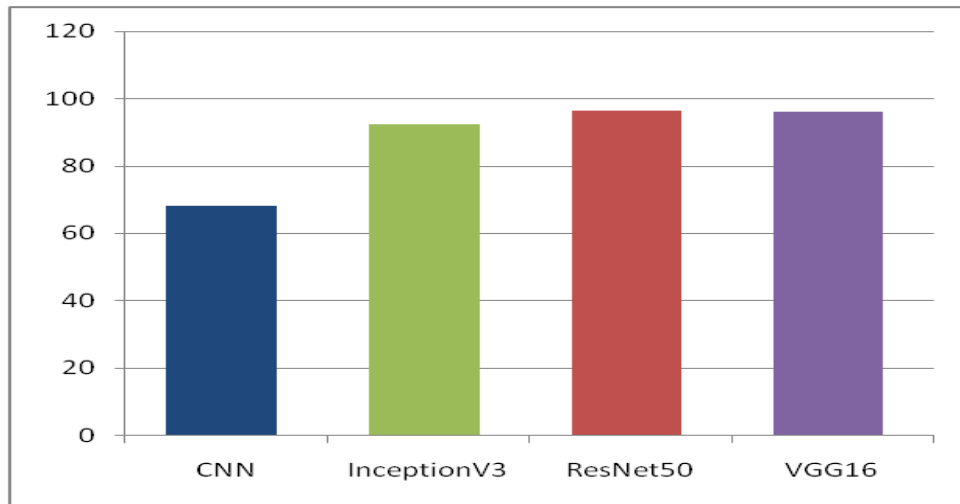


Figure 4.2.6 Accuracy for different architecture

A table 4.2.1 is given below that shows the comparative performance:

Table 4.3.1 Comparative performance

Reference	Model	Field	Accuracy
My work	ResNet50	Bangladeshi Agricultural Insect	96.4%
[5]	SVR	Bangladeshi Agricultural Insect	90%
[4]	CNN	Bangladeshi Agricultural Insect	93.46%

### 4.3 Discussion

After receiving the results, we can observe that the accuracy for VGG16 is 96.04%, for ResNet50 is 96.4%, for InceptionV3 is 92.41%, and for sequential CNN is 68.17%. ResNet50 is the model I'm suggesting because it has a higher accuracy rating than other models.

## **Chapter 5:**

### **Impact on Society, Environment and Sustainability**

#### **5.1 Impact on Society**

Agricultural sector has a massive impact on the economy of Bangladesh. That is the reason I have created this model so that anyone can easily identify insects that are harmful for the agriculture of our country. The insect identification will have a great effect in our society. The key objective of this paper is to identify the insect and offer a piece of improved knowledge for farmers. This work will help to increase our agricultural production, which can also improve our country's GDP rate and financial health.

#### **5.2 Impact on Environment**

It must have a significant impact on the environment as well because we anticipate that the work will be convenient and have a significant social impact. Because people create a society, and society is created by people. If those involved in agriculture have sufficient understanding of agricultural insects, then such insects will also predominate in their surroundings. As a result, my study will contribute to the development of a society where individuals can precisely identify insects and then prevent them from entering their fields. As a result, it will create a better environment for Bangladesh's agricultural fields.

#### **5.3 Ethical Aspects**

As our main economic sector, agriculture is something we have a moral obligation to protect. We thus take a meagre precaution to safeguard our agricultural crops. In addition, this model has several ethical considerations:

1. To keep hazardous insects away from agricultural crops
2. To assist the farmer in determining if the bug is dangerous or not.
3. to safeguard farmland crops.

#### **5.4 Sustainability Plan**

My goal is to support those involved in agriculture so they may enhance agricultural production and advance our nation. An agricultural bug is a type of insect that can severely harm agricultural crops. In Bangladeshi agriculture, this is the most detrimental issue. I made the model for this reason, and I need to edit it correctly so that people can recognize these insects and avoid them. We ought to have been aware of this insect and should have discovered a way to stop it. I must correctly maintain this model in order to do it. To get the right identification result, we must build a suitable model.

## CHAPTER 6

### Summary, Conclusion, Recommendation and Implication for Future

#### 6.1 Summary of the Study

With a 19.6% GDP contribution and 63% of the people employed, agriculture continues to be the most significant sector of the Bangladeshi economy. In Bangladesh, because agriculture is such a significant industry, there are many areas of study. In this project, I work with Bangladeshi agricultural insects identification. For agricultural insects, I've constructed a few deep convolutional neural networks (DCNNs). Then I compared the outcomes and put up a model that yields the best outcome. And that is the ResNet50 architecture. I used a dataset of 7890 photos that included 14 different classes of Bangladeshi agricultural insects for this experiment.

#### 6.2 Conclusions

For Bangladeshi agricultural insects, I compared the effectiveness of many well-known deep convolutional neural networks (DCNNs) in this study. And I get 96.4% accuracy for ResNet50, 96.04% accuracy for VGG16, 92.41% accuracy for InceptionV3 and the accuracy for sequential CNN is 68.17%. According to the trial findings, ResNet50 is the most effective at identifying agricultural insects in Bangladesh. Other DCNN models, such as NasNetMobile, NiN, FractalNet, and others, will be used in the future to enhance the performance of Bangladeshi agricultural insect recognition.

#### 6.3 Recommendations

Deep convolutional neural networks are very prevalent. For now, I recently used CNN and three other well-known architectures. I obtain accuracy ranging from 68.17% to 96.4%. The agricultural insect recognition is archived through training and testing models.

- A more effective algorithm can also enhance the outcome.
- Epoch size and data can be increased to improve the outcome.

#### **6.4 Implication for Further Study**

This time I worked with 14 classes of agricultural insects only. And I implemented InceptionV3, VGG16, ResNet50 architecture and compared those results. Future works will involve various architectures, like FractalNet, NiN, NasNetMobile, and others. And at that time, I'll work with more classes and data. I'll also try to create a model that can more accurately identify agricultural insects. This model can recognize agricultural insects from the image of a single insect. In the future I'll look at a model that can identify a group of insects and then make some recommendations for how to stop them.

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## Appendices

### Appendix A:

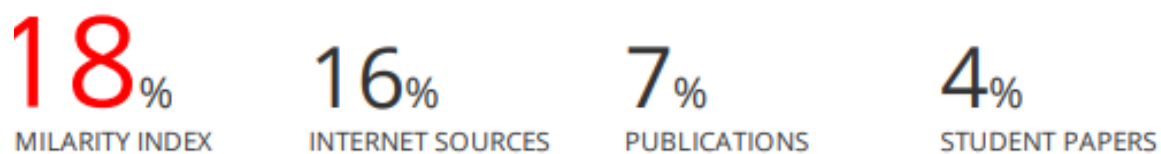
Research Analysis After completing this project, my knowledge of this subject has increased. I have discovered that utilizing a Deep Neural Network (DNN) with a created dataset, it is possible to recognize Bangladeshi agricultural insects accurately after analyzing the experimental results of this work and looking into comparable works. If I have another opportunity to work with Bangladeshi agricultural insects, then for better outcomes, I'll use a few other well-known Deep Neural Networks (DNN).

### Appendix B:

Related Concerns Data gathering and dataset preparation are two crucial challenges. There were a few challenges I encountered while carrying out this endeavour. Data collection comes first, followed by image dimension correction for resizing functionality. Additionally, some of the architectures that were implemented took a very lengthy time to execute. That slows down my system. Making a suitable model that can recognize the wide range of insect patterns is a common challenge.

# Recognizing Bangladeshi Agricultural Insect using Machine Learning

## ORIGINALITY REPORT



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