MONKEYPOX DISEASE DETECTION USING DEEP LEARNING APPROACH

BY
MAHAMUDUL HASAN MEEM
ID: 191-15-12259

MD. ISRAK JAHAN BOISHAK
ID: 191-15-12709

SHEAK AHSAN HABIB BAPPY
ID: 191-15-12083

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

Supervised By

Md. Abbas Ali Khan
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised By

Dr. Md. Zahid Hasan
Associate Professor
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project titled **"Monkeypox Disease Detection Using Deep Learning Approach"**, submitted by Mahamudul Hasan Meem, ID No: 191-15-12259, Md. Israk Jahan Boishak, ID No: 191-15-12709, Sheak Ahsan Habib Bappy, ID No: 191-15-12083 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 *23-01-23*.

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Chairman

Dr. Touhid Bhuiyan
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Daffodil International University

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Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner

Fahad Faisal
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

External Examiner

Dr. Ahmed Wasif Reza
Associate Professor
Department of Computer Science and Engineering
East West University

DECLARATION

We hereby declare that, this thesis has been done by us under the supervision of **Md Abbas Ali Khan, Department of CSE** Daffodil International University. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Md. Abbas Ali Khan
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised By:

Dr. Md. Zahid Hasan
Associate Professor
Department of CSE
Daffodil International University

Submitted by:

MAHAMUDUL HASAN MEEM
ID: 191-15-12259
Department of CSE

Md. Israk Jahan Boishak

MD. ISRAK JAHAN BOISHAK
ID: 191-15-12709
Department of CSE

SHEAK AHSAN HABIB BAPPY
ID: 191-15-12083
Department of CSE

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ABSTRACT

Although humanity is still working to rehabilitate from the harm brought on by the widespread distribution of COVID-19, the Monkeypox disease now poses a fresh threat of spreading worldwide. Due to the recent Monkeypox outbreak's unprecedented advancement in more than 111 countries, public health is now at risk. Monkeypox can be difficult to diagnose clinically in its early stages since it resembles both chickenpox and measles. Under the condition that there are enough training examples available, deep learning techniques have been demonstrated to be useful in the accurate identification of skin lesions. Unfortunately, there are currently no comparable datasets for the Monkeypox disease. So we have found the solution to the problem by utilizing transfer learning approaches. We used thoroughly developed other skin disease datasets. The majority of the images are from news websites, blogs, and other media, and some are available as case studies to the public. We did not use data augmentation to increase our dataset. We only used raw data. Several deep learning models that have already been trained are used in the following stage. For our research, we have worked with VGG16, InceptionV3, ResNet50, InceptionResNetV2, and MobileNetV2. Among them, InceptionV3 model has acquired the best accuracy. It has scored 94.56 %. Although the preliminary findings on this particular dataset are encouraging, a greater dataset with a more mixed population is needed to further improve the universal applicability of such models.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Monkeypox has become one of the most inhumane problems of the twenty-first century. Thousands of people in 111 countries are suffering from this virus. The cause of this particular disease is a zoonotic viral infection. It can spread if a human has close physical contact with a potential Monkeypox-affected human. In 1958, Monkeypox was first identified. After quite a few years, Monkeypox finally reappeared in the Republic of Congo in 2014. Then it steadily gained momentum and start spreading further. Even though Monkeypox had the potential to become a global threat to people's health and welfare, WHO or any other authorities did not take any steps to combat this problem at that time. When Covid-19 finally passed its peak, Monkeypox stunned the world. During the 2022 outbreak, it has been identified that a patient will have fever, muscle aches, back pain, headache, fatigue, and the most noticeable sign: a rash. The rash can affect a patient's various parts of the body, such as the face, mouth, eyes, soles of the feet, palms of the hands, throat, genital and anal areas, etc. These rashes cause a lot of pain and discomfort for the patient. These types of symptoms can remain for a few weeks and go away on their own. But in some cases, this disease can be life threatening. WHO recognized this severe state and announced Monkeypox as a public health emergency of international concern.

Nowadays machine learning (ML) applications have created a significant amount of influence over people's various aspects of life including health care. It is aiding doctors in pre-diagnosis, MRI and X-ray scans, cost reduction, analyzing side effects of a specific drug, and many other tasks. Machine learning has become very easy to implement because of today's technology. Among them, the growth of smartphones is astonishing. The thesis we are working on is image based classification using deep learning. When it comes to detecting various skin diseases, Deep Learning techniques are reliable options. As Monkeypox has recently become a hot research topic, there aren't many reliable deep learning approaches available. But we can use thoroughly developed deep learning models to detect Chickenpox and Measles disease. By transfer learning approaches, we can use those models for Monkeypox, as both of those diseases are almost similar to Monkeypox.

Using five separate improved deep CNN models that we presented and evaluated in this work. These five models are Vgg16, InceptionV3, ResNet50, InceptionResNetv2, and MobileNetV2. After analyzing the result properly, we have discovered that InceptionV3 model has the best accuracy. Even though VGG16 and MobileNetV2 are very close to InceptionV3 mode. The least accuracy for detecting Monkeypox is ResNet50.

The key contributions of our study are summed up as follows:

1. Our dataset was huge without augmentation. We did not have to increase the number of our photos.
2. The accuracy of our CNN models is relatively better than other research works.
3. In order to have precise accuracy we worked on a larger amount of models.

We met the qualifications of "The Washington Accord Graduate." We were able to use our engineering knowledge to analyze this particular problem, Monkeypox. We have achieved the capacity to design and develop solutions. We investigated the problem. We used modern tools such as NumPy, TensorFlow, Keras, and many more. We read and analyzed multiple sources of information from the engineering community and society. We were able to create a strong influence regarding the integrity of the environment. Regarding individual and teamwork, one of us coded the full project, and the remaining two collected data and wrote the report. We communicated using Google Meet.

1.2 Motivation

We are working on the Monkeypox image classification using deep learning so that we can avoid another pandemic. As the disease has already infiltrated multiple countries, our work will help the authority assess the situation and take proper measures. From the general public perspective, this particular disease can be very puzzling. It is our responsibility to simplify the situation. According to reliable sources from multiple health authorities, over 70 thousand Monkeypox cases have been reported globally in 111 countries since January 1, 2022. So we are giving our highest effort to prevent it from spreading further. As it is indisputable fact that there is no cure for this disease, our project will give people hope to fight this crisis. The whole world is exhausted after two years of the covid-19 pandemic. The world is not capable of fighting another pandemic. It will be very difficult from social, economic, and people's health and welfare perspectives. So, we hope to contribute to society by working on this research work.

1.3 Problem Description

Monkeypox is still unfamiliar to the general public. By doing this research work, we are attempting to address the necessity of taking proper steps to comprehend this particular topic. We are working on deep learning techniques to increase the accuracy of VGG16, InceptionV3, ResNet50, InceptionResNetv2, and MobileNetV2. As there is not enough reliable data and study material available, our research work will help to achieve this goal. Since January 2022, the cases of Monkeypox is increasing drastically. This work will help to identify Monkeypox more accurately.

1.4 Investigative Topics

The primary concerns on which this study is focused are as follows:

1. Which model's accuracy is better for detecting Monkeypox?
2. Which model has the lowest accuracy to detect Monkeypox?
3. How is the performance of these models in detecting other skin diseases aside from Monkeypox?

1.5 Research Strategies

In order to do this research work, we used transfer learning approaches. We switched the developed dataset of other skin diseases to the Monkeypox dataset. We collected our data from various respected sources and verified them thoroughly. We used image processing gamma correction and dataset split method. We case studied various countries' statistics on Monkeypox to determine various aspects of our work. All these methods helped us to achieve better results.

1.6 Research Objectives

Our sole objective is to make the process of detecting Monkeypox easier. So that we can save humankind from a horrible disease. It is essential to serve accurate information about

Monkeypox so that people can understand the concept and prepare for themselves. As Monkeypox is almost identical to other skin diseases such as chickenpox, measles, etc to the general public eye. Our work will help to understand and identify the difference. In this research work, we are going to build a CNN model to accomplish that task. As it is a new topic to research, there are not many reliable study materials available. The information on this particular subject is changing consistently so the information we have found in research papers is unreliable. But deep learning techniques solved this problem. By using transfer learning approaches, we can use previously developed models to detect and recognize Monkeypox without any error.

1.7 Research Potential

The potential of our research work is endless as it will help the world to save many human lives. Our work will help several health authorities to identify Monkeypox. As it is a very pressing matter, authorities will give more funds to develop this type of research. Cases of Monkeypox are rising. It will help us to increase the dataset. Thus the accuracy of those models will increase. Our type of research work will help the government to save money and human resources. It will reduce the workload of healthcare workers and doctors. As a result, more patients will be able to receive proper attention.

1.8 Thesis Structure

Our report contains six parts. In chapter one, we discussed introduction, motivation, objective, anticipated output, problem description, investigative topics, research strategies, and research potential. In chapter two, we discussed terminologies, older literature, research void, and summary. In chapter three, we talked about introduction, research method, dataset, data preprocessing, gamma correction, split, deep learning, and summary. In chapter four, we talked about Evaluation Technique, Performance Analysis, Visualization, Model Analysis, and Result Discussion. In chapter five, we discussed impact on society, impact on environment, and the sustainability plan. Finally, in chapter six, we talked Conclusion, Drawbacks, and Future Work.

CHAPTER 2

BACKGROUND

2.1 Terminologies

The main goal of our research is to detect Monkeypox. As there are a number of skin diseases in this world that are very identical to Monkeypox, it is absolutely necessary to identify the difference among those diseases. WHO has identified Monkeypox as a public health emergency of international concern in 2022. A huge number of people's lives are in danger. Especially people who live in underdeveloped countries. As people all around the world are exhausted from fighting Covid-19, it is not possible to fight another potentially deadly disease. So in order to prevent Monkeypox from becoming a pandemic, we worked on five CNN models. In this decade, deep learning has become very popular for its data driven detection models.

The information regarding Monkeypox is changing consistently. So we used a well-known method in deep learning. By conducting transfer learning approaches, we were able to use developed datasets of other known skin diseases such as measles, and chickenpox. Our hope is to contribute to our society at full capacity in order to save human from gave danger.

2.2 Predecessor Literature

Monkeypox is of special concern to nations in west and central Africa as well as the rest of the world due to its widespread effects on public health. The first Monkeypox outbreak outside of Africa occurred in the United States of America in 2003.Epidemiologists found that the source of the illness in this instance was contact with sick prairie dogs kept in captivity. These animals were kept in a cage with imported dormice and Gambian pouched rats. As a result of this outbreak, there have been over 70 confirmed cases of Monkeypox in the US. There have been reports of Monkeypox infections among Nigerian visitors in Israel in September 2018, the UK in September 2018, December 2019, May 2021, and May 2022, Singapore in May 2019, and the USA in July and November 2021.In May 2022, a large number of Monkeypox cases were found in nations where they were not so often found. Research is currently being done to better understand the disease's transmission dynamics, vectors, and epidemiology. [1]

An orthopoxvirus called the Monkeypox virus has the potential to infect people and cause Monkeypox, a viral infection with smallpox-like symptoms such as fever and rash. Monkeypox has replaced smallpox as the most serious orthopoxvirus infection in humans since smallpox was eradicated from the human population in 1980.Most cases are found in remote areas of countries in Central and West Africa, close to tropical rainforests where people would come into touch with infected animals. Monkeypox can be contracted through direct contact with the respiratory droplets of an infected individual, either at home or at a healthcare facility, or through contact with contaminated objects or materials, such as bedding. Monkeypox epidemics frequently start as small clusters of a few cases without developing into widespread community transmission, despite the fact that these are the main methods of person-to-person transmission. This is due to the high contagiousness of Monkeypox. [2]

Over the course of the year, a number of research showed that DL-based models can be a trustworthy way to identify diseases like chicken pox and measles, which have symptoms that are almost identical to Monkeypox. A extremely deep neural network (DNN) and long-short term memory (LSTM) model, for instance, was used by Chae et al. (2018) to identify chickenpox, outperforming the traditional autoregressive integrated moving average (ARIMA) model.[3]

Convolutional neural networks (CNN) were used by Bhadula et al. (2019) to identify skin conditions. The accuracy of the CNN model used by the authors to identify lichen planus and acne was 92% and 96%, respectively. [4]

Sriwong et al. (2019) detected skin disorders with 79.2% accuracy using the CNN technique. Some of the skin conditions that the authors aimed to identify throughout the investigation included actinic keratoses, basal cells, and benign keratosis [5].

By employing modified VGG16, authors in suggested picture data collection and deployment based on a DL model for identifying Monkeypox disease. The dataset was created by compiling images from a variety of open-source and online sources, offering a safer method of using and distributing such data for creating and deploying any ML model. In two different experiments, the modified VGG16 model was utilized. They discovered that for both experiments, our model accurately identified patients with Monkeypox illness. Predictions made by this model and the feature extraction process served to shed more light on particular characteristics of the Monkeypox virus. [6]

In order to automatically identify Monkeypox from skin lesions, they have released the open-source "Monkeypox Skin Lesion Dataset (MSLD)" and conducted a preliminary feasibility study utilizing cutting-edge deep learning architectures (VGG16, ResNet50, InceptionV3) that take advantage of transfer learning. For the 3-fold cross-validation experiment, they assessed the performance of the pre-trained models that they had chosen. [7]

Author unveiled the recently created "Monkeypox2022" dataset, which is accessible to everyone. which propose a modified VGG16 model and assess it. The suggested model has an accuracy of 97 1.8% (AUC = 97.2) and 88 0.8% (AUC = 0.867) for identifying patients with Monkeypox.[8]

Their research intends to construct a CNN model utilizing transfer learning techniques to detect Monkeypox sickness. In their research, they employed pre-trained deep learning architectures to extract crucial traits that, due to their resemblance to other contagious diseases like chickenpox and measles, are first practically challenging to recognize by eye inspection. They next processed their data through a number of layers, using the top, densest layer to identify the Monkeypox virus.[9]

The initial Monkeypox Open picture data collection process is described in their publication. It was built by combining photographs gathered from websites, newspapers, and online portals, and as of now, after data augmentation, it comprises about 1905 images. [10]

2.3 Research Void

Table 1 below shows the research gap in detail, and we used this information to continue the study.

TABLE 2.3.1: RELATED WORKS

Paper	Author	Year	Objective	Data	Methodology	Findings & Limitation
1. This Paper	Md Israk Jahan Boishakh,Sheak Ahsan Habib Bappy,Mahamudul Hassan Meem	Null	Detecting Monkeypox disease	Kaggle, mendeley	Deep Learning architecture are used.	Inception V3 94.56%. Limited dataset.
2. Image data collection and implementation of deep learning-based model in detecting monkeypox disease using modified vgg16	Md Manjurul Ahsan,Muhammad Ramiz Uddin,Mithila Farjana,Ahmed Nazmus Sakib,Khondhaker Al Momin,Shahana Akter Luna	2022	1. Introducing a newly developed "Monkeypox 2022" dataset that is publicly available to use. 2. Propose and evaluate a modified VGG16 model.	Newspapers, and online portals and publicly shared samples	This part describes the procedure for data collection and augmentation, the creation of the modified VGG16 deep learning model, the setup of the experiment, and the application of the quality evaluation matrices..	The generated dataset contains a small number of samples. The data are generally acquired from a number of free sources rather than using a specific hospital or clinical facility.

3. Transfer learning and local interpretable model Agnostic based visual approach in Monkeypox disease Detection and classification: a deep learning insights	Md Manjurul Ahsan,Tareque Abu Abdullah,Fatematuj Jahora,Amin G. Alhashim ,Md Shahin Ali,Md Khairul Islam,Kishor Datta Gupta	2022	Using transfer learning techniques, six different deep learning models—VGG16, Inception-ResNetV2, ResNet50, ResNet101, MobileNetV2 , and VGG19—were modified and put to the test to detect and classify Monkeypox.	From the Kaggle repository.	By using a CNN model utilizing transfer learning techniques, the Monkeypox disease will be detected. To do this, we have employed pre-trained deep learning architectures to extract crucial traits that are initially very challenging to identify by visual inspection due to their similarity with other infectious diseases such as chickenpox and measles. The topmost, densest layer was used to detect the Monkeypox sickness after we ran our data through a number of layers.	Study 1 : Accuracy 90% to 100%. Two Approaches: 1. Wilson Score 2. Binomial proportional interval. Best Model : Inception ResNetV2 Worst Model : ResNet50 Study 2 : 90% to 100%. Two Approaches: 1. Wilson Score 2. Binomial proportional interval. 1.could not evaluate model's performance by comparing it with others' work

						2. lack of data
4. Monkeypox Virus Detection Using Pre-trained Deep Learning-based Approaches	Shams Nafisa Ali,Md. Tazuddin Ahmed,Joydip Paul,Tasnim Jahan,S. M. Sakeef Sani,Nawsabah Noor,Taufiq Hasan	2022	Monkeypox and other diseases are identified using VGG-16, ResNet50, and InceptionV3.	Newspapers, and online portals and publicly shared samples	deep learning architectures are used (VGG16, ResNet50, Inception V3)	Monkeypox and other diseases are categorized using VGG-16, ResNet50, and InceptionV3. The ensemble system and VGG16 both obtained accuracy of 81:48(6:87%) and 79:26(1:05%), respectively. ResNet50 achieves the best overall accuracy of 82:96(4:57%). Less data and inferior results were obtained
5. Poxverifi: an information verification system to	Akaash Kolluri, Kami Vinton, Dhiraj Murthy	2022	Introducing PoxVerifi, an open-source, extendable program that offers a comprehensi	obtained from World Health Organization articles	Machine learning techniques have been used in a variety of ways to	PoxVerifi is designed with an expandable architecture to precisely

Combat Monkeypox misinformation			ve method for evaluating the veracity of claims linked to Monkeypox.	and current fact-checking sources	identify characteristics of material about Monkeypox that is being circulated online.	and easily confirm the accuracy of statements regarding Monkeypox. To achieve the highest level of claim veracity, only WHO content was utilized.
6. Monkeypox Virus Detection Using Pre-trained Deep Learning-based Approaches	Chiranjibi Sitaula & Tej Bahadur Shahi	2022	Compare 13 various pre-trained deep learning (DL) models for the detection of the Monkeypox virus.	publicly available Monkeypox image dataset	13 pre-trained DL models were selected for this study. From heavy-duty DL models like VGG-16, Inception V3, and Xception to lightweight models like MobileNet and EfficientNet these pre-trained models come in a	In contrast to the other contestants, Xception performs the best among the 13 pre-trained DL methods (Precision: 85.01%, Recall: 85.14%, F1-score: 85.02%, and Accuracy: 86.51%). The size of the dataset is significantly smaller.

					variety of weights.	

2.4 Summary

Which approach works faster using our own dataset serves as the central question for our investigation. The CNN-based models will be used in this study to compare performance and identify Monkeypox from 4 categories.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

With 4 multiple categories of images and transfer learning techniques, this work's best accuracy was 94.56%.

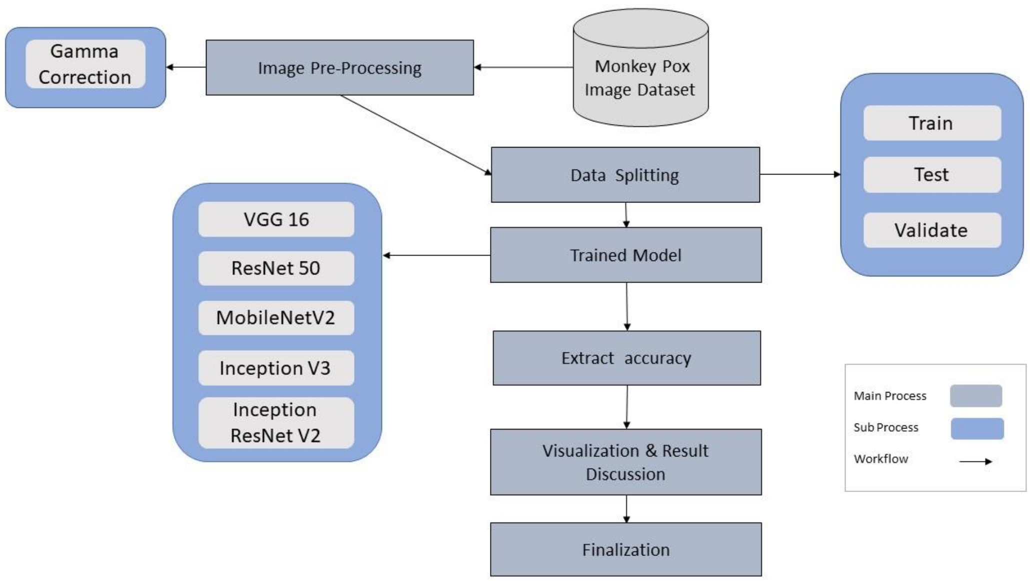

Figure 3.1.1 Methodology Process

3.2 Research Method

Researchers typically employ two types of methodology:

1. Qualitative Method
2. Quantitative Approach

While the emphasis of survey method is on numbers and statistical data, the qualitative study concentrates is on attitudes and the way they are interpreted. Quantitative approaches facilitate the testing of hypotheses and the comparison was made of parameters. Qualitative techniques enable us to delve deeper into ideas and interactions. As a result, our study is quantitative in character.

3.3 Dataset

In order to train, the classic deep learning approach needs a sizable amount of input data. On the contrary hand, the recent development of transfer learning methods shows that a small dataset can be used to train and construct a strong CNN model that can effectively function throughout the predictions. Our data came from the GitHub and Kaggle websites. Data for the binary classification of Monkeypox vs. non-Monkeypox has been included. The non-Monkeypox diseases are measles or chickenpox. These diseases have symptoms similar to Monkeypox. The database was set up to allow for the automated identification of Monkeypox from skin lesion photos. MSLD was developed through the collection and processing of photos from websites, media and is available to public clinical studies. The database we are using has four folders. The database has 3629 photos in total.

Measle **Chickenpox**

Normal **Monkeypox**

Figure 3.3.1 Sample Collected Dataset

3.4 Data Pre-Processing

The first and most important activity before training the model is image pre-processing. To prepare image information for use in a vision-based model, preprocessing is a crucial step. Preprocessing is necessary for both theoretical and work effectiveness. CNN, a popular design in computer vision, demands that all images be the same size arrays in order to have fully connected layers. Because the beginning or original data set is almost always inadequate, understanding it using any model becomes extremely challenging. Consequently, the goal of preprocessing is to enhance image information by removing unwanted subtractions or by upgrading some image properties that are crucial for resulting in significantly higher and streamlining the procedure. Throughout this work, we used mostly row data.

3.5 Gamma Correction

Transforming images Gamma correction is a non-linear modification to the amplitude of each individual pixel. Power law transformation is another name for gamma correction. Gamma correction uses a non-linear procedure to alter the pixels of the actual picture, whereas image normalization used linear operations to multiply, add, and remove from each individual pixel. As a result, the modified image could get too saturated. It is applied to ensure that brightness is correctly shown on the computer as well as other digital display screens. If the gamma quantity becomes too massive or too little, it can also result in poor contrast. However, it remains a crucial operation to discuss. Gamma encoding and decoding are both a part of gamma correction. Gamma encoding makes use of how people perceive color and brightness to optimize the amounts would use when compressing video or photographs. Gamma decoding is the process of correcting saved video and photographs to display tones on your preferred display screen in an accurate manner.

It explains how a black-and-white image turns into a white one and how that impacts every gray in the image. When using this enhancement technique, it is feasible to change the value of each pixel in high grayscale and low grayscale in accordance with the needs of feature extraction from any image whenever the number of pixels is kept within the middle grayscale range. Gamma correction, which adjusts brightness based on pixel brightness. So it regulates the brightness of such photos. It is clear from the foregoing explanation that gamma correction aids in adjusting the relative brightness of all photographs. The average brightness of a visual can be managed with gamma correction. It can be applied to pictures that are deemed to be either overly dark or bleached out. For darker and fading photos, pixel intensity values should be expanded and compressed. The illness spots on the picture in our dataset need to be more distinct to produce the best results. To make the illness spots clearly apparent, the gamma correction instructional design process has to be used. The method's initial color arrangement parameter range is from [0,255] to [0,1,0].

In this gamma correction equation, I stands for the input images, g for the gamma value, and O for the output image.

$$O = l\text{^}(1/g)$$

Where

g=1 means no impact

g>1 means minimizing the specifics.

g<1 means concealing the specifics.

When the value of g >= 2.00, the image becomes faded out at higher gamma ratios and conversely. As a result, an appropriate g, the gamma value is chosen by modifying several quantities and evaluating these on the picture, and the result o is scaled down to the actual range which is 0,255.

In the equation that follows where g= gamma value, r = rescaled image, o = output image.

$$O = ((r/255)\ \hat{}\ g) * 255$$

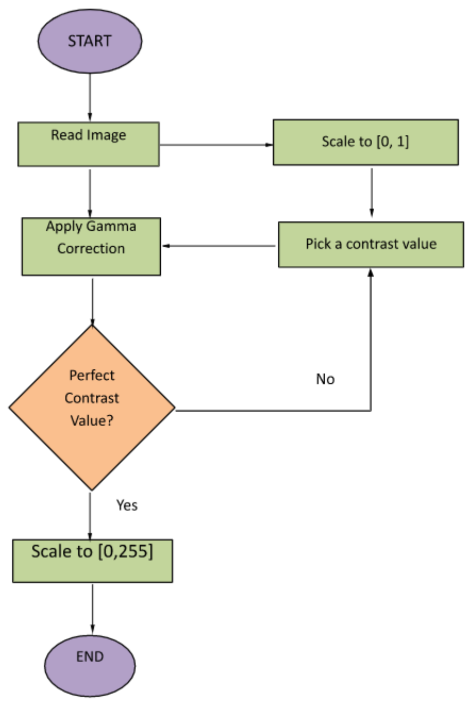

Figure 3.5.1 Sample Pre-Process Data

3.6 Split

Data splitting sometimes referred to as train-test split, is the division of data into smaller subsets for separate model training and evaluation. An algorithm that can recognize pneumonia from chest X-rays was published in a study in 2017 by the Stanford research group led by Andrew Ng. They employed "112,120 frontal-view X-ray scans of 30,805 individual patients," according to the original publication, and "We randomly split the entire dataset into 70% training, 20% validation and 10% training."

3.6.1 Training dataset

The data set that was used to adjust the model. A collection of samples utilized in the process of learning to match the specifications of such a classifier is known as a training data set. The objective is to develop a classification classifier that extrapolates well to new, unknown data. The fitted model is evaluated using "new" instances from the held-out data sources (validation and test datasets) to evaluate the model's accuracy in classifying new data. Supervised learning algorithms are used to classify data using combinations of variables from the training data set. In this research work, we have trained 2537 images.

3.6.2 Validation dataset

The collection of data used to assess a model's fit to a training dataset while adjusting model hyper parameters. As skill from the validation data is absorbed into the model setup, the evaluation gets increasingly skewed. A given model is evaluated using the validation set, although this is done frequently. The Dev set or the Development set are other names for the validation set. This makes sense because the dataset is useful for the model's "development" phase. In validation dataset, it has 724 images. A validation data set must be accessible in addition to the test and training datasets in order to prevent overfitting whenever a classification parameter has to be changed. The training data set is used to train various candidate classifier, the validation data set is used to compare their performances and choose which one to use, and finally, the test data set is used to obtain performance characteristics such as accuracy, sensitivity, specificity, F-measure, and other metrics.

3.6.3 Test dataset

Data set employed to gauge how well a final model fits the training data. It is only applied once the model has undertaken thorough training using the train and validate sets. It is not advisable to utilize the validation set as the test set, despite the fact that this is routinely done. The test dataset is made up of 368 images. It includes information that was carefully gathered and covers every variation that its model might encounter in practice. Therefore, a test set is a collection of cases used solely to evaluate the effectiveness of a fully defined classifier. These predictions from the final model are used to categorize the cases in the test set. To determine the model's accuracy, these predictions are contrasted with the occurrences' actual classifications. Once both the validation and test datasets have been used, the final model chosen by the validation phase is typically evaluated using the test dataset. Only once the initial data set has been divided into training and test datasets can the test dataset be used as an initial model evaluation.

3.7 Deep Learning

Deep learning is a type of machine learning that gives computers the ability to interpret the world in the form of a hierarchy of abstractions and learn from experience. It is not necessary for a human computer operators to expressly define all the data that the computer needs because the computer learns through experience. The concept hierarchy enables the computer to comprehend complex concepts by constructing them from smaller ones; a graph representing these hierarchies would have several levels. Statistics and pattern classification are two crucial components of data science, which also includes deep learning.

3.8 VGG16

A ConvNet is another name for a convolutional neural network, which is a type of artificial neural network. An input layer, an output layer, and many hidden layers make up a convolutional neural network. One of the top computer vision models to date is the CNN (Convolutional Neural Network) variant known as VGG16. This model's developers analyzed the networks and enhanced the complexity using an architecture with incredibly tiny (3x3) convolutional filters, which demonstrated a notable advancement over the state-of-the-art setups. The depth was increased to 16–19 weight layers, yielding around 138 trainable parameters. VGG16 is an object identification and clustering algorithm that has a 92.7% accuracy rate when classifying 1000 photos into 1000 different categories. It is a well-liked technique for classifying images and is simple to employ with transfer learning.

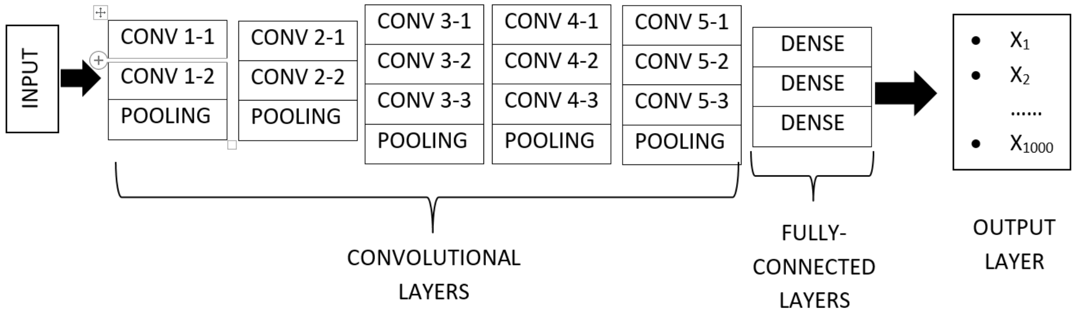

Figure 3.8.1 VGG-16 Architecture

3.9 InceptionV3

The third iteration of Google's Deep Learning Convolutional Implementations is called Inception V3. The initial ImageNet dataset, which was trained to use more than 1 million images for training, yielded 1,000 classes for Inception V3; however, the Tensorflow edition has 1,001 classes since it contains a "background" type that was not present in the initial ImageNet. Factorized Convolutions minimize the amount of elements used in a network, which lowers the system's performance. It also monitors the effectiveness of the network. Training will undoubtedly be completed more quickly if smaller convolutions are used in place of larger ones.

A 3x3 convolution might be changed to a 1x3 convolution succeeded by a 3x1 convolution in an asymmetric convolution. The number of variables would be a little bit higher than the suggested asymmetric convolution if a 3x3 convolution were swapped out for a 2x2 convolution. A tiny CNN that is introduced among layers during training and whose loss is contributed to the loss of the primary network is called an auxiliary classifier. As opposed to Inception v3, where an auxiliary classifier serves as a regularization term, GoogleNet uses auxiliary classifiers for a larger network. Pooling activities are typically used to reduce the size of the grid. Therefore, a more effective method is suggested to address the complexity of the algorithm limitations.

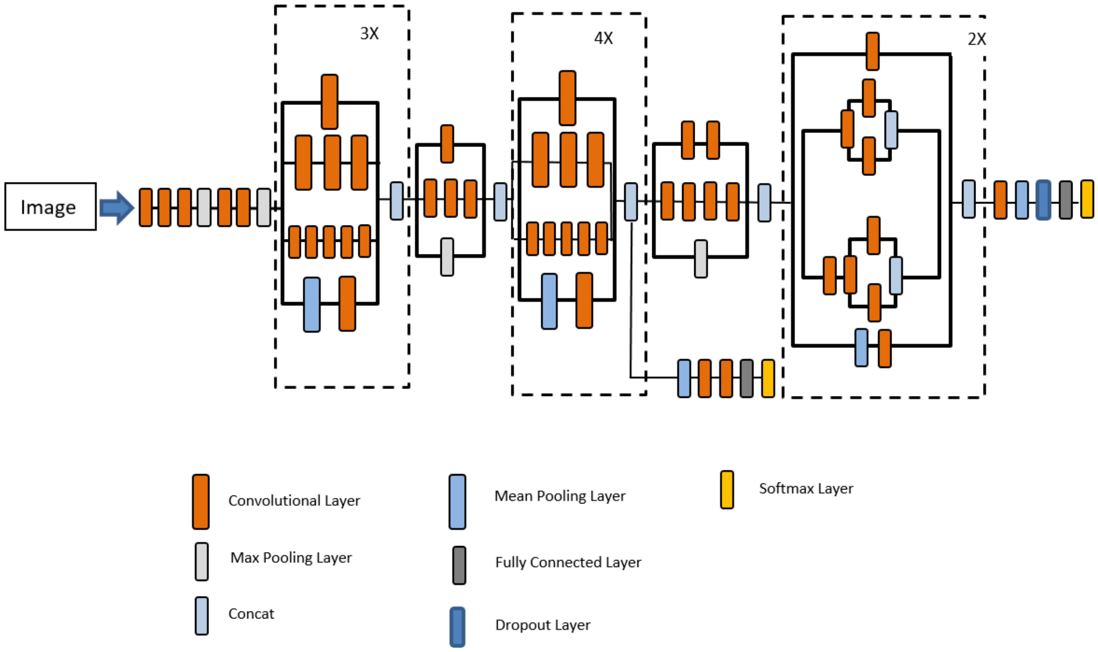

Figure 3.9.1 Inception V3 Architecture

3.10 ResNet50

A ResNet model version called ResNet50 contains 48 Convolution layers, 1 MaxPool layer, and 1 Standard Pool layer. There are 3.8 x 109 floating point operations available. It is a commonly used ResNet model, and we have thoroughly examined the ResNet50 design. There are other versions of ResNet that use the same basic idea but have various numbers of layers. The form that can operate with 50 neural network layers is referred known as Resnet50.

A convolution with 64 distinct kernels, each with a phase of value 2, and a kernel input of 7 * 7 gives us 1 layer. Following that, we witness maximum pooling with a step length size of 2. The following convolution consists of three layers: a 1*1,64 kernel, a 3*3,64 kernel, and finally a 1*1,256 kernel. These three levels have been repeated a total of three times, giving us nine layers in this phase. The kernel of 1 * 1,512 is next displayed, followed by the kernels of 1 * 1,128 and 3 * 3,128. For a maximum of four times or 12 layers, we did this process. Then comes a kernel with a value from 1 * 1,256, then two more kernels with values of 3 * 3,256 and 1 * 1,1024; this process is repeated six times, giving us a total of 18 layers. Finally, a 1 * 1,512 kernel was added, followed by two more kernels of 3 * 3,512 and 1 * 1,2048. This process was done three times, giving us a total of nine layers. Then we do an averaged pool, finish it with a completely linked layer made up of 1000 nodes, and add a softmax activation function to produce one layer.

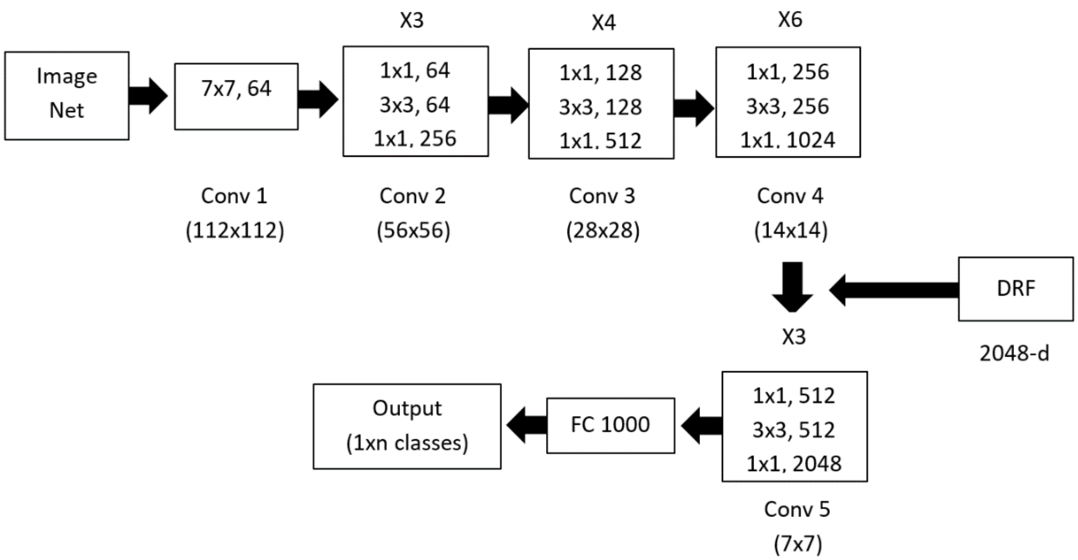

Figure 3.10.1 ResNet 50 Architecture

3.11 MobileNetV2

A convolutional neural network model called MobileNetV2 aims to function well throughout mobile devices. It is built on an inverted persistent structure in which the bottleneck layers are connected by residual connections. In terms of classification, object detection, and semantic segmentation, MobileNetV2 enhances the best quality for mobile visual recognition. It is a huge improvement over MobileNetV1. Lightweight depthwise convolutions are used in the intermediate growth layer as a source of non-linearity to filter features. The architecture of MobileNetV2 includes a 32-filter initial fully connected layers along with 19 intermediate bottleneck layers. There are two different kinds of modules in MobileNetV2. The remaining module has a velocity of one. Another is a module for reducing with a stride of two. For both varieties of modules, there are three levels. The first layer is 11 convolutions with ReLU6 each time. Convolution in depth makes up the second layer. The third layer is an 11 convolution once more, but this time there is no non-linearity. Deep networks are said to possess only the capability of a learning algorithm upon that non-zero quantity portion of the resulting domain if ReLU is performed once again. The expansion factor t is also present. For all major experiments, t=6 as well. The internal result would have 384 channels if the input had 64 channels.

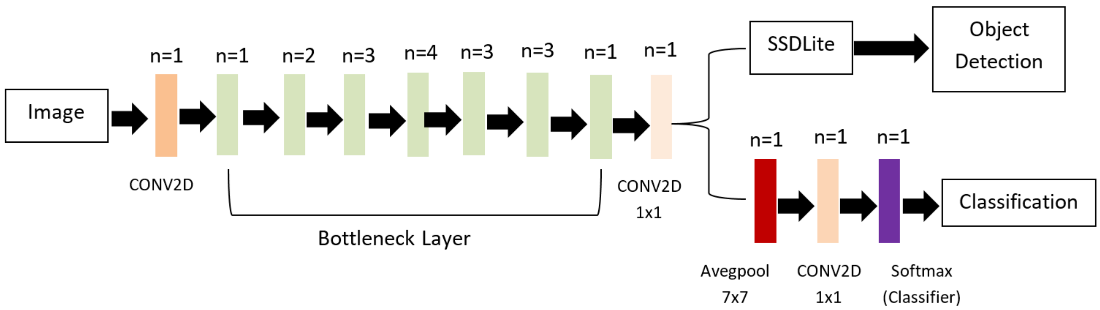

Figure 3.11.1 MobileNet V2 Architecture

3.12 InceptionResNet-V2

A convolutional neural network named Inception-ResNet-v2 was trained using more than a million photos from the ImageNet collection. The 164-layer network can categorize photos into 1000 different object categories, including the keyboard, mouse, pencil, and numerous animals. The network has therefore acquired rich feature representations for a variety of images. The network receives a 299 by 299-pixel picture as input, and it outputs a list of predicted class probabilities. Inception-ResNet-v2 expands on the Inception family of architectures while incorporating residual connections. Inception-ResNet-v2 was trained using more than a million photos from the ImageNet collection. The 164-layer network can categorize photos into 1000 different object categories, including keyboard, mouse, pencil, and numerous animals. A version of the Inception V3 model, the Inception-ResNet-v2 is far deeper than the original Inception V3.

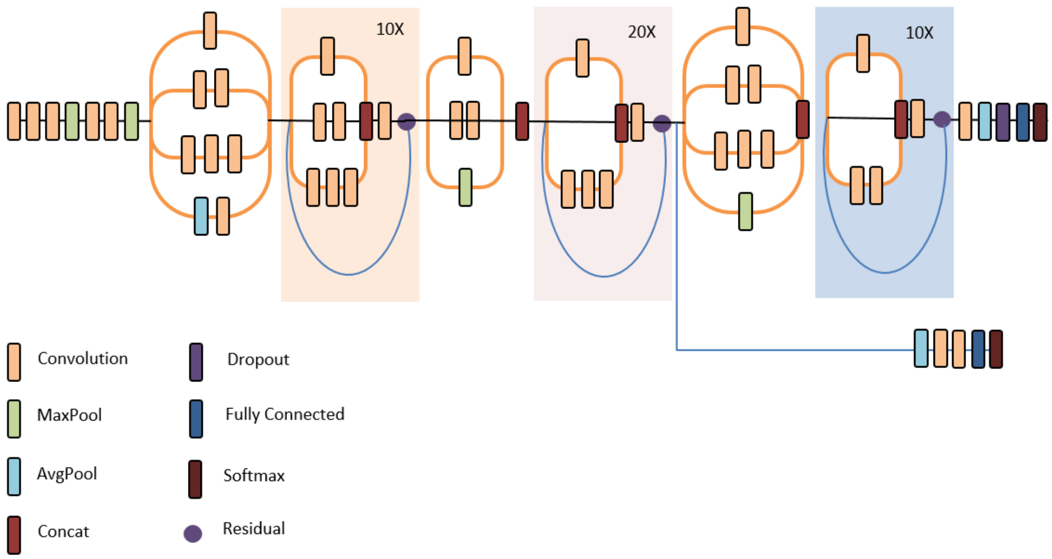

Figure 3.12.1 InceptionResNet V2 Architecture

3.13 Summary

We employ categorical cross-entropy to lament the decline, which acts as an iterative method for numerous classification problems. The optimizer, which helps with executing learning algorithm, and the measures set accuracy are then used, taking into account the fact that this is an issue with categorical variables.

In the chapter after, four-group Monkeypox detection will be used to compare the effectiveness of each Convolutional Neural Network design technique.

CHAPTER 4

EXPERIMENTAL RESULT AND DISCUSSION

4.1 Evaluation Technique

Our research, which largely uses deep learning techniques, aims to identify and classify monkeys from smartphone images. Google's Tensor Flow and the Keras deep learning framework for image processing were used in our research, which was carried out in Python. The models for the experiment were built on the Google Collaboratory's CPU. The scikit-learn, pandas, and NumPy libraries were used to build a deep learning-based model. We used Google Collaboratory to build and simulate our models. The total amount of images is divided into training, test, and validation data, totaling roughly 3629. The study's recommended model performed well.

4.2 Performance Analysis

A confusion matrix must be used while measuring metrics. Deep learning uses a table structure known as a confusion matrix, also known as an error matrix, to show the effectiveness of a controlled learning process. Using a confusion matrix, we identify True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN).

4.2.1 Accuracy

The most obvious performance indicator is accuracy. Its definition can be summed up as the proportion of experimental data that was accurately anticipated to all observations.

$$Accuracy = (TP+TN) / (TP+FP+FN+TN) \quad (1)$$

4.2.2 Precision

The accuracy ratio assesses the degree to which each projected positive study agrees with the measures that have been correctly predicted as positive. How many people have avoided injury according to the measures?

$$Precision = TP / (TP+FP) \quad (2)$$

4.2.3 Recall

Recall the ratio of correct good outcome forecasts to all valid class observations. What percentage of the items did we mark as containing information that is genuinely true?

$$Recall = TP / (TP + FN) \quad (3)$$

4.2.4 F1 Score

The weighted F1 Ranking is exact and simple to remember. When determining the score, false positives and false negatives are also taken into account. F1 is often more useful than accuracy, even though it appears to be more difficult to explain, especially if the categorization is asymmetrical.

$$F1\ Score = 2 * (Recall * Precision) / (Recall * Precision) \quad (4)$$

4.2.5 Sensitivity

The proportion of positive cases that yield a positive outcome when a particular testing is included to a model without changing the samples is known as the real positive rate, also known as sensitivity.

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN}) \quad (5)$$

4.2.6 Specificity

The number of specimens that test negatively when the test is run is known as the true negative rate, often referred to as specificity, in the case of an unaffectedly negative model.

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP}) \quad (6)$$

4.3 Model Analysis

We applied deep learning methods to build the most accurate models for the screening of Monkeypox. Table 4.2.1 presents the effectiveness of the model analysis. It is evident that transfer learning techniques performed better when used with our dataset. They are all between 78% and 94% correct. We must choose the best model out of the many options available now.

TABLE 4.2.1 PERFORMANCE METRICS

Serial	Algorithm	Test Accuracy (%)	Test Loss	Validation Accuracy	Validation Loss	F1 Score	Precision	Recall
1	VGG 16	94.02	0.5508	0.9475	0.4967	0.8241	0.8015	0.8747
2	InceptionV3	94.56	1.5391	0.9627	2.4772	0.8387	0.825	0.8575
3	ResNet50	78.53	0.9146	0.6796	1.1433	0.5959	0.5980	0.60123
4	InceptionResNetV2	92.93	3.2439	0.9572	2.6497	0.7734	0.7661	0.8053
5	MobileNetV2	94.02	4.9883	0.9976	0.0760	0.761	0.8032	0.7955

The five CNN-based architectures that were employed received the following ratings: VGG16, InceptionV3, ResNet50, InceptionResNetV2, and MobileNetV2. Ratings for the F1 score, Precision, Recall, testing accuracy, validation accuracy, and validation loss.

Equations 3, 4, 5, and 6 were used to calculate the accuracy, recall, precision, and F1 score, which are all shown in table 4.2.1. As can be seen, InceptionV3 has the most accuracy (94.56%), making it the best performance. With a 0.54 percent accuracy difference between the top two models, InceptionV3 is superior to MobileNetV2 and Vgg16 at object detection. With accuracy ratings for VGG16, ResNet50, MobileNetV2, and InceptionResNetV2 of correspondingly 94.02%, 78.53%, 94.02%, 92.93 the remaining algorithms are similarly capable of identifying objects that closely resemble the InceptionV3 model. It is crucial to think about which method will correctly identify the four target classes.

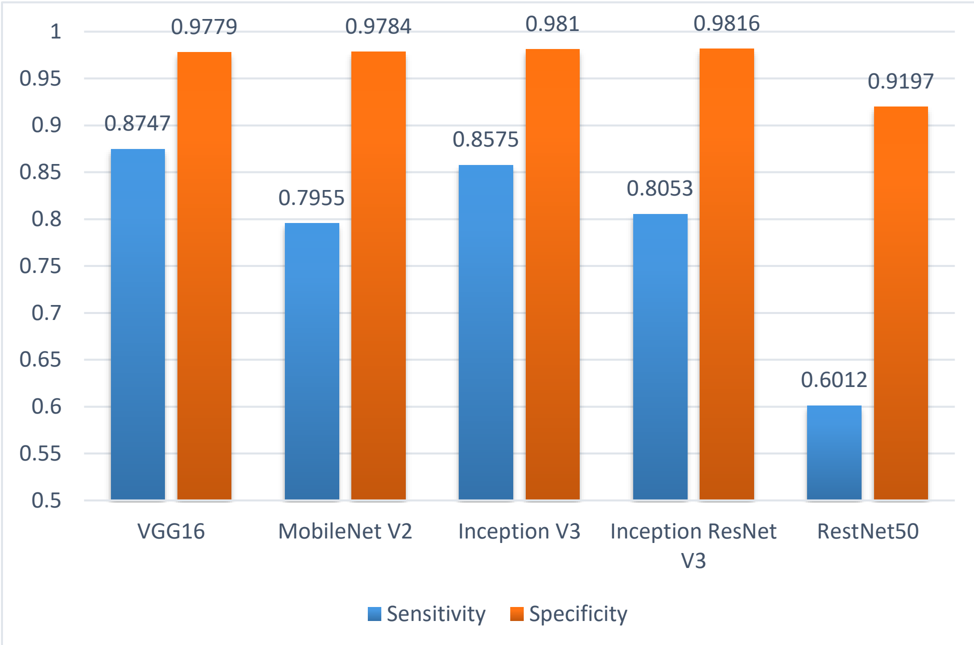

Figure 4.2.1 Sensitivity and Specificity of Models

We tested our model using the data from our test set after it had been trained. We already know that InceptionV3 outperforms the other five models based on previous conversations. The sensitivity and specificity were calculated using Equations 5 and 6, and the results are shown in Figure 4.2.1, where it is obvious that InceptionV3 obtained the highest rating.

4.4 Visualization

Upon completion of the terms of classification accuracy, the task obtains a consecutive accuracy rate. Depending on the accuracy and confusion matrix generated by this work, it can be said that the suggested model is suitable for the task of identifying road damage. This is how this job has been performed.

4.4.1 VGG16:

Fig.4.4.1.1 VGG16 Training vs Validation accuracy

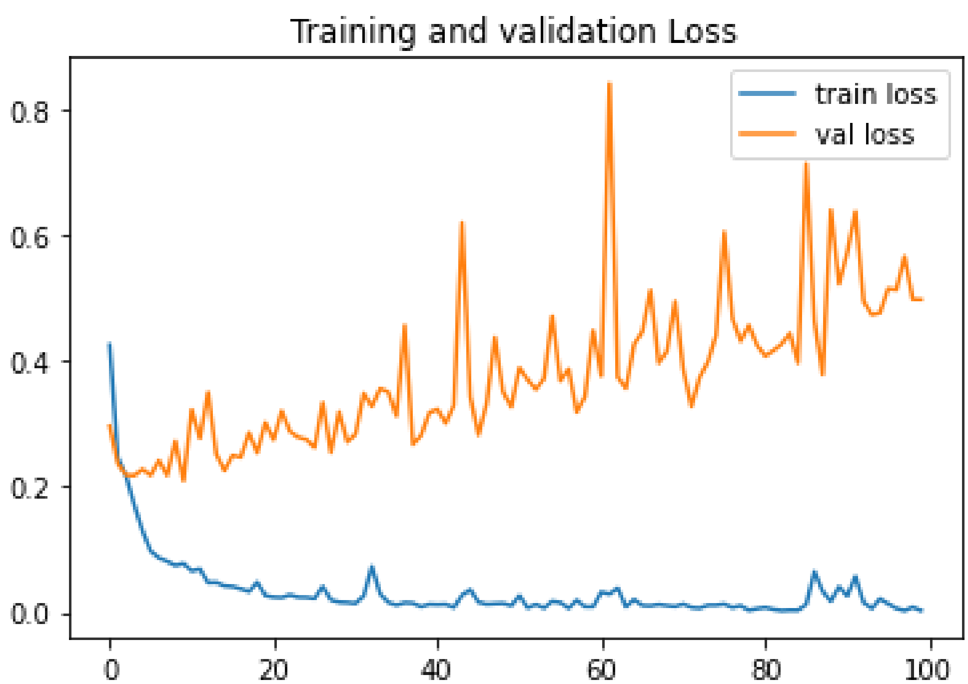

Fig.4.4.1.2 VGG16 Training vs Validation Loss

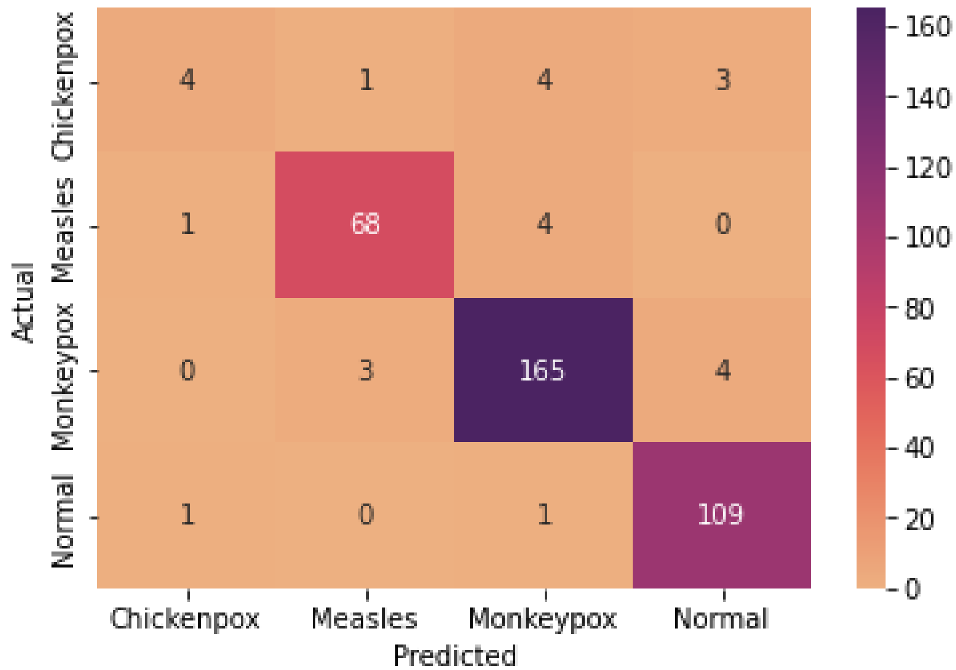

Fig.4.4.1.3 VGG16 Confusion Matrix

4.4.2 ResNet50:

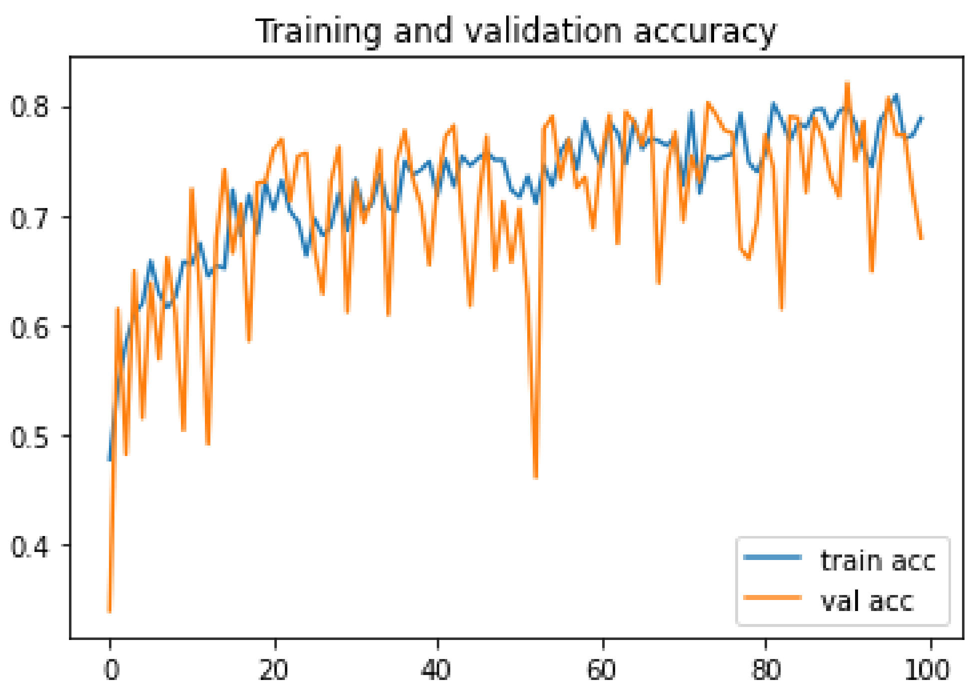

Fig.4.4.2.1 ResNet50 Training vs Validation Accuracy

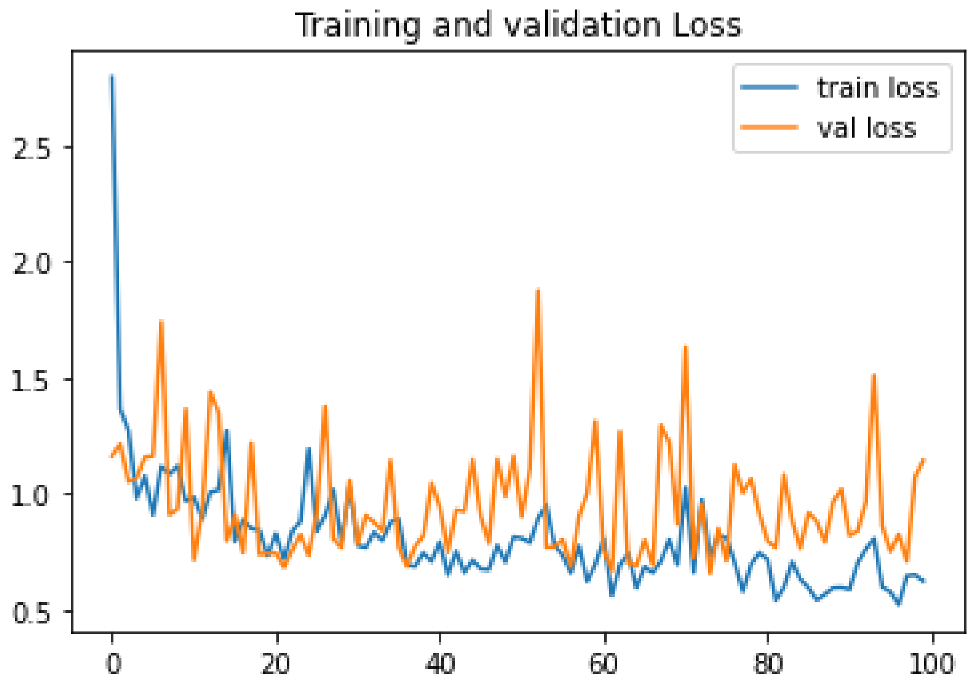

Fig.4.4.2.2 ResNet50 Training vs Validation Loss

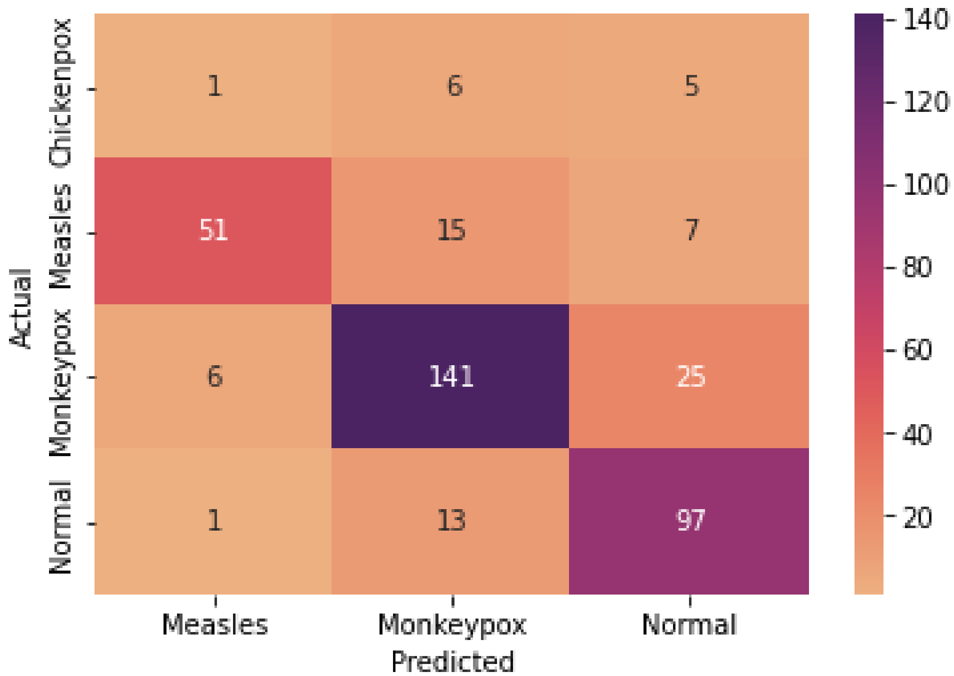

Fig.4.4.2.3 ResNet50 Confusion Matrics

4.4.3 MobileNetV2:

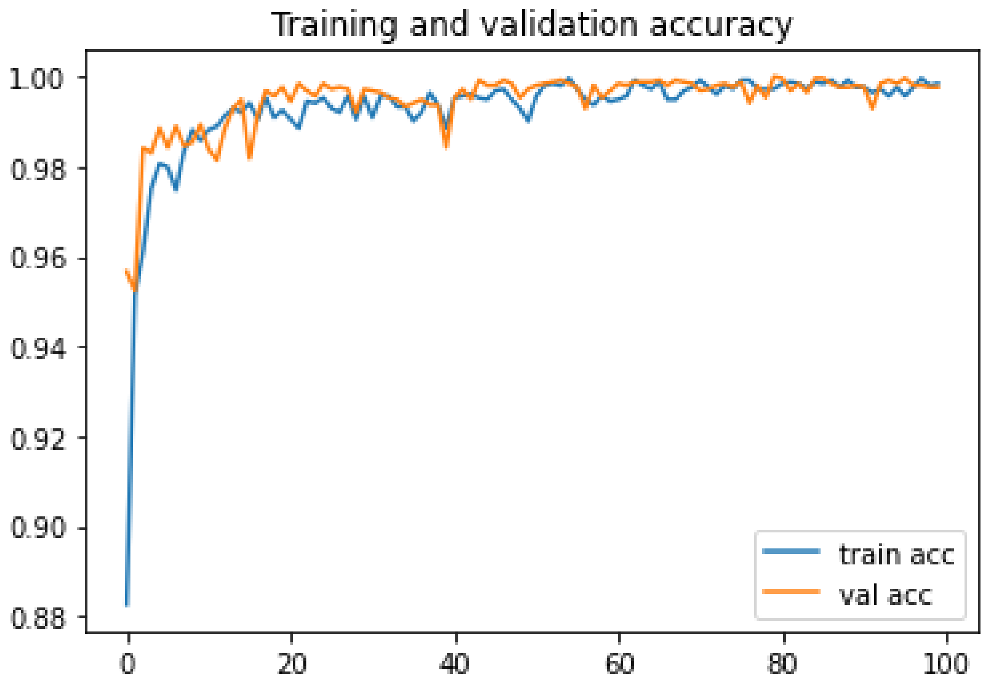

Fig.4.4.3.1 MobileNetV2 Training vs Validation accuracy

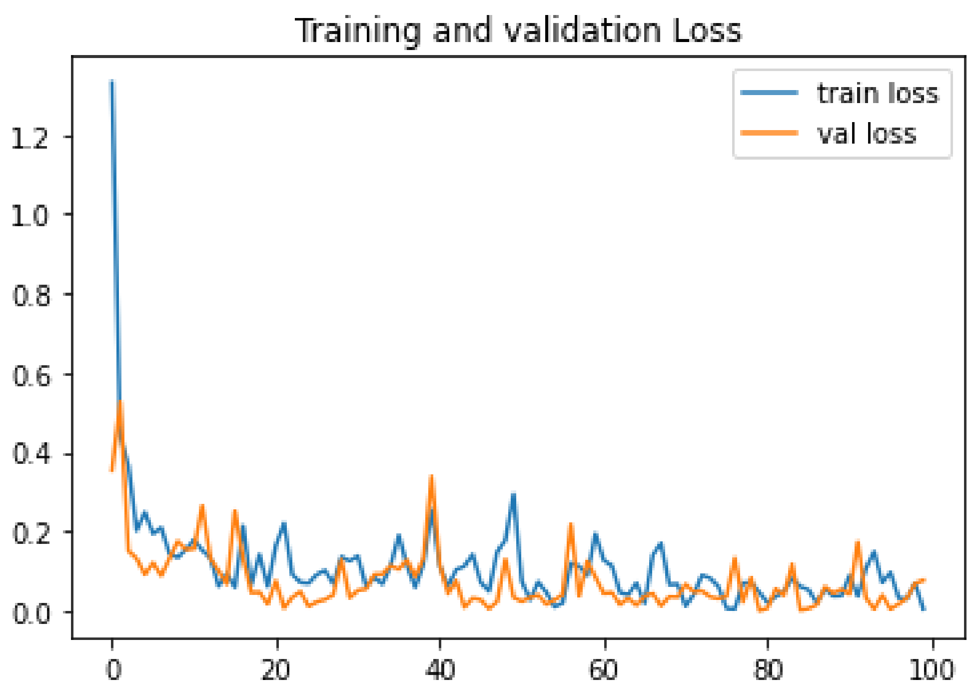

Fig.4.4.3.2 MobileNetV2 Training vs Validation Loss

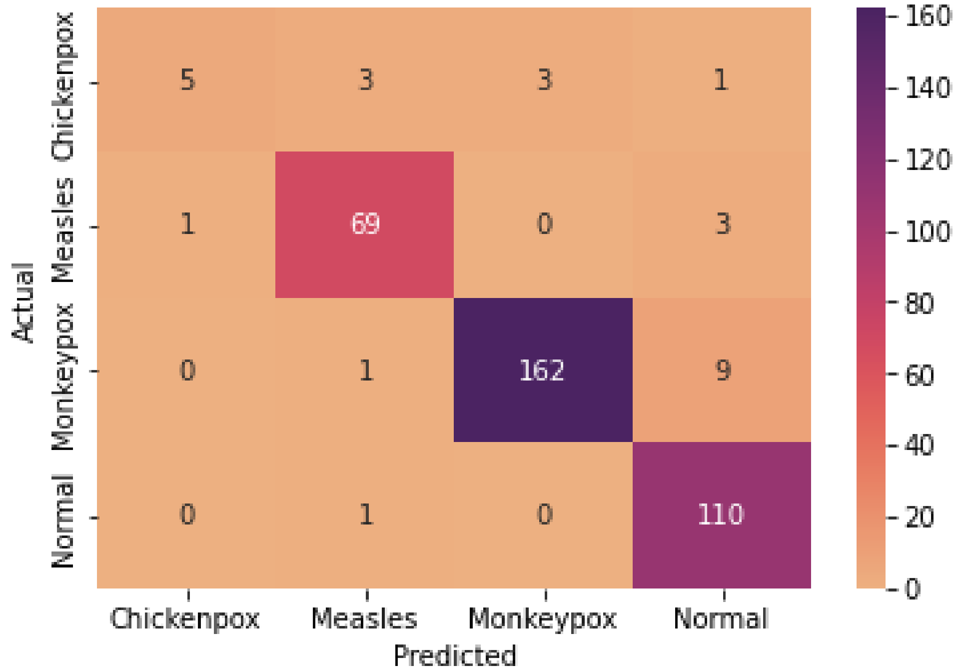

Fig.4.4.3.3 MobileNetV2 Confusion Matric

4.4.4 InceptionV3:

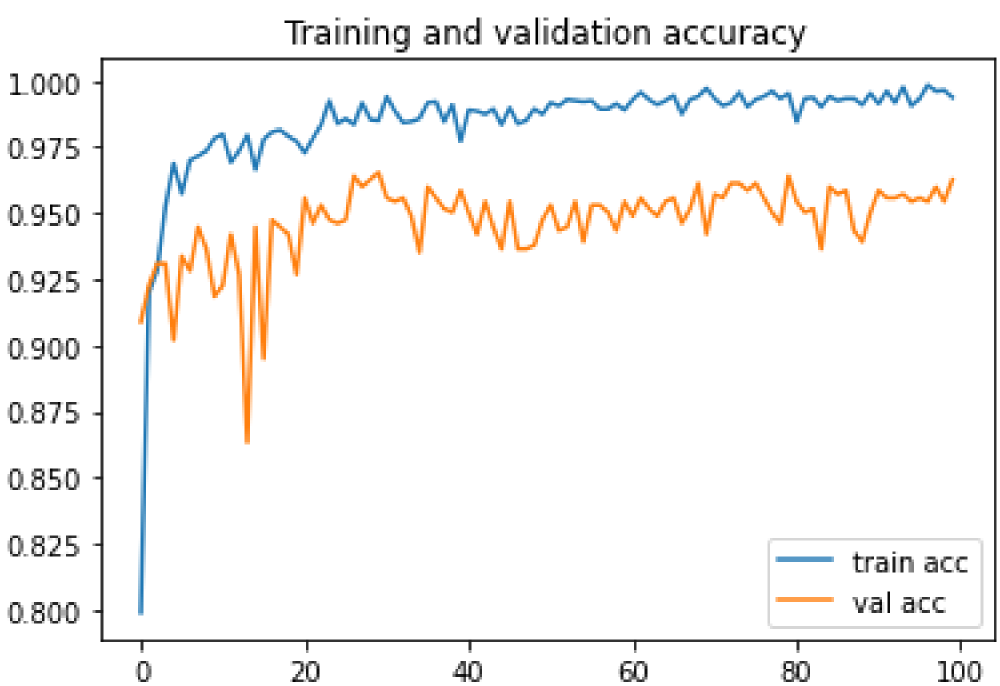

Fig.4.4.4.1 InceptionV3 Training vs Validation Accuracy

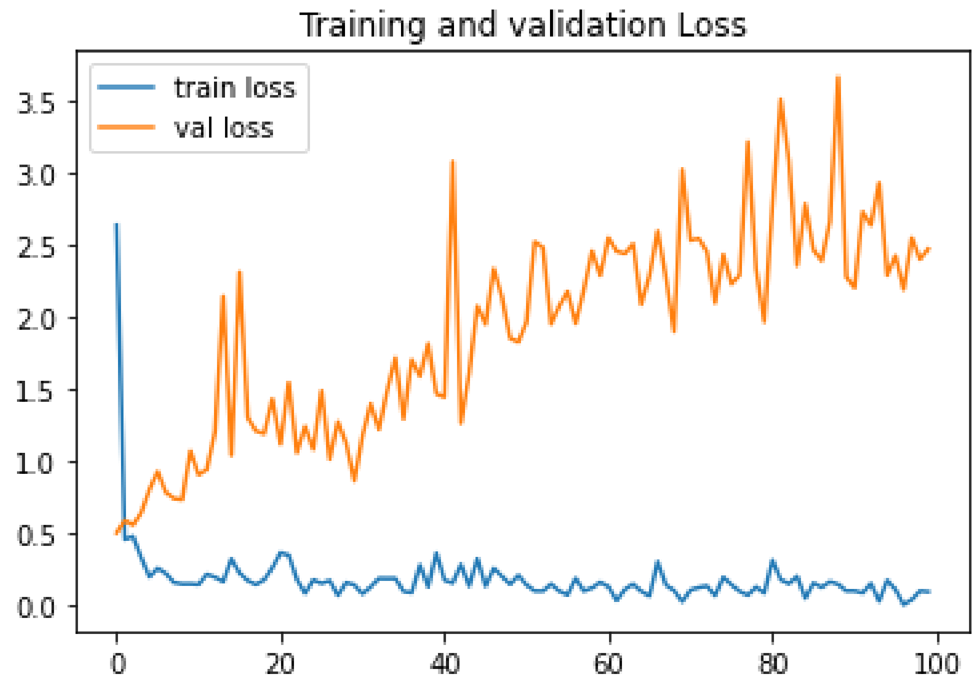

Fig.4.4.4.2 InceptionV3 Training vs Validation Loss

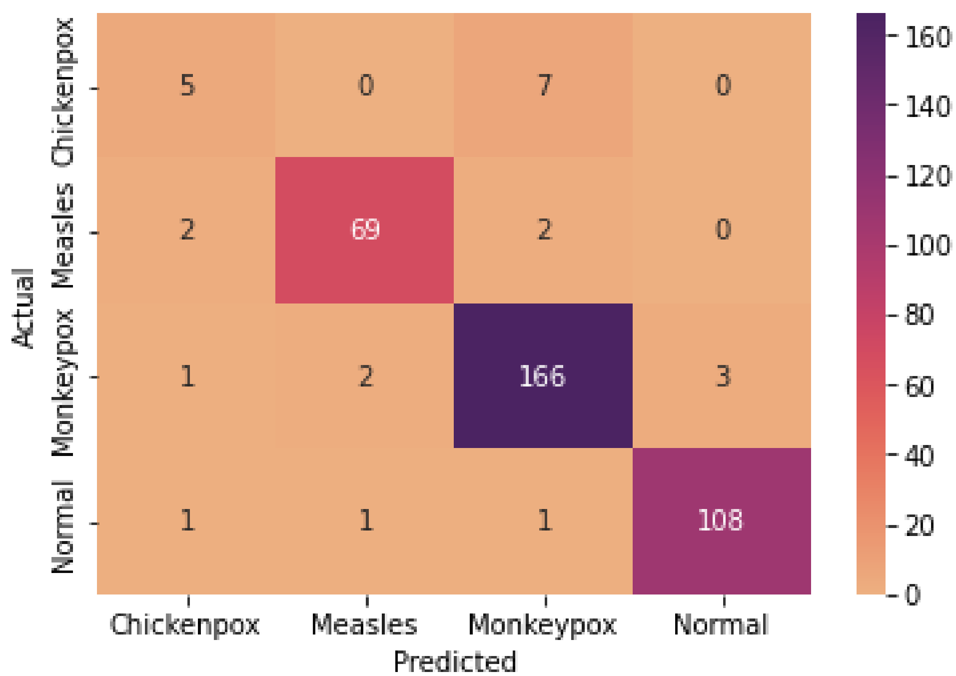

Fig.4.4.4.3 InceptionV3 Confusion Matric

4.4.5 InceptionResNetV3:

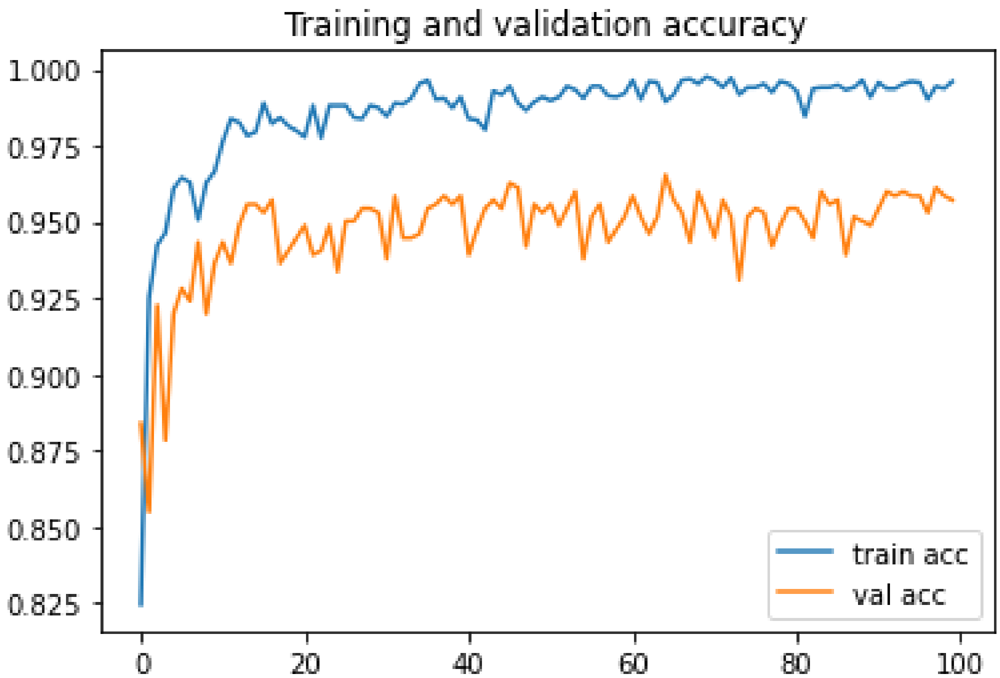

Fig.4.4.5.1 InceptionResNetV3 Training vs Validation Accuracy

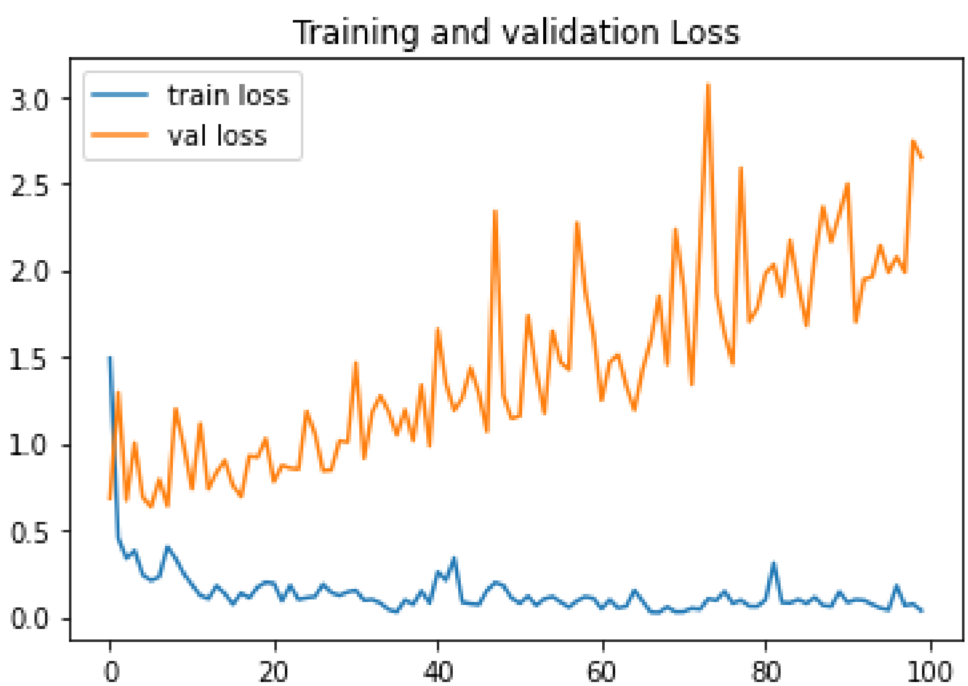

Fig.4.4.5.2 InceptionResNetV3 Training vs Validation Loss

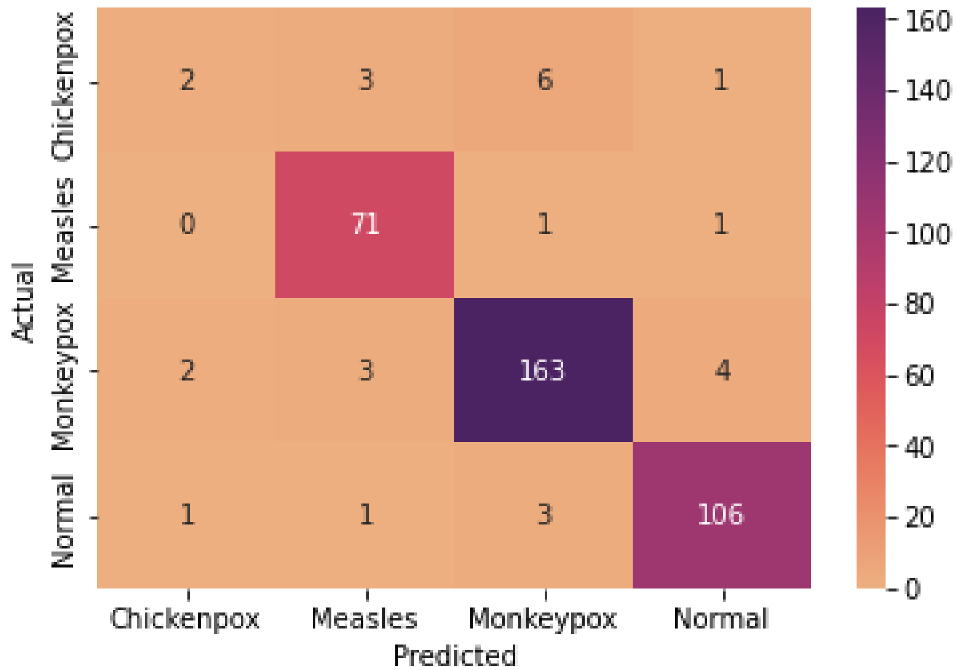

Fig.4.4.5.3 InceptionResNetV3 Confusion Matric

4.5 Result Discussion

For categorization and detection of Monkeypox, we can recommend the inceptionV3 model above all others because it outperforms them. For the inceptionV3 model, we achieved the greatest accuracy of 94.56%. The inceptionV3 model likewise has the top scores for sensitivity and specificity.

CHAPTER 5

Impact on Society, Environment, and Sustainability

5.1 Impact on Society

The main goal of this research is to decrease the number of Monkeypox cases by detecting the virus accurately as soon as possible. Within this decade, people have suffered so much. The last pandemic disease, covid-19 has disrupted millions of lives. It is fair to be concerned that Monkeypox, another virus, would spread swiftly over many nations. People are not ready to fight another deadly illness again. So, it is vital to stop this disease before it reaches its full potential. Monkeypox can shatter the social order. A deeper comprehension of the social, ecological, and scientific linkages between endemic and non-endemic regions is necessary to stop the spread of Monkeypox. Our research work can help people from Monkeypox. As Monkeypox is still an unknown disease, our research work will give people the necessary information to understand this disease. It will give ordinary people hope to move forward with their lives without the fear. Monkeypox is a disease that spreads while being in close contact with a potential patient of Monkeypox. It will create chaos within society. This research work aims to deliver accurate knowledge so that people can comprehend the situation and make better decisions for the sake of their lives. Our work will improve the health and welfare of the people and create a good influence on their lives. Therefore, it should be obvious that this research has a significant impact on society.

5.2 Impact on Environment

Monkeypox also referred to as zoonotic infection or those that passes between humans and animals, will grow more prevalent as a result of factors like the intensification of habitat loss for animals and human expansion into formerly unoccupied areas. The borders between the areas where people and wild animals reside have been eroded by factors including deforestation, population growth, and animal breeding, bringing them closer to each other. Our research work will put a spotlight on these problems. We will be able to provide the necessary information to create awareness among people. As climate change has become one of the pressing matters in this world, our type of work will make an impact. We will be able to create a realization within people that there is a need for an obligation on the part of people to respect, defend, and protect nature against anthropogenic harm. Our research will give a warning to people that it is now time to take proper action.

5.3 Sustainability Plan

The mission of our research is to help people to detect Monkeypox without any error. Ministry of Health and other medical organizations can use our research work to reduce the workload. It will help medical workers and doctors to serve more patients quickly. As our research work is in demand all over the world, it will also have an effect on the national economy.

CHAPTER 6

Conclusion, Limitation, Future Work

6.1 Conclusion

While the globe is still battling Coronavirus disease 2019, the recent spread of the Monkeypox virus among many nations offers a threat of a global pandemic. The gradual and steady spread of the Monkeypox disease among people needs to be taken seriously at this early stage. People are terrified of it because they believe that it will spread like COVID-19. As an outcome, it is essential to find them earlier. Otherwise, they spread widely across society. By offering facilities for quick, low-cost, and early diagnosis, deep learning-based disease prediction has already shown great potential. In our study, we applied transfer learning techniques to modify and test five separate deep learning models which are Vgg16, InceptionV3, ResNet50, InceptionResNetv2, and MobileNetV2. Among them, InceptionV3 has performed very well. Its accuracy is 94.56 %; F1 Score is 0.8387; precision=0.825; Recall value is 0.8575. This algorithm will help healthcare organizations to identify Monkeypox disease easily. The procedures used in this research will be taken into consideration while creating deep learning models containing mixed data and assessing the effectiveness of the algorithm on the highly skewed dataset. Our study suggests that Monkeypox potential patients will be able to have a pre-phase evaluation and will possess the knowledge health authorities require to respond appropriately when the disease is still in its initial stages.

6.2 Research Drawbacks

Even though we are able to have the best accuracy by using these trained models, we could have had much better results if we could acquire more data. Crucial information regarding Monkeypox is constantly changing, so by the time we publish our work, it could be labeled as out of date. As a result, it will not be able to contribute to future work.

6.3 Future Work

Our research has limitless potential since it will enable the world to save a great number of lives. Several health authorities will benefit from our efforts in identifying Monkeypox. Authorities will provide more funding to develop this kind of research because it is a really serious issue. Monkeypox rates are increasing. We'll be able to grow our dataset as a result. Consequently, such models will get more accurate. The government will benefit from our research by saving money and labor. The workload of doctors and healthcare professionals will be lessened. More patients are going to get the care they need as a result.

REFERENCE

[1]K. K. Mohbey, G. Meena, S. Kumar, and K. Lokesh, "A CNN-LSTM-based hybrid deep learning approach to detect sentiment polarities on Monkeypox tweets," arXiv:2208.12019 [cs], Aug. 2022, Accessed: Jan. 01, 2023. [Online]. Available: https://arxiv.org/abs/2208.12019

[2]M. Manjurul Ahsan, M. Ramiz Uddin, M. Farjana, A. Nazmus Sakib, K. Al Momin, and S. Akter Luna, "Image Data collection and implementation of deep learning-based model in detecting Monkeypox disease using modified VGG16," NASA ADS, Jun. 01, 2022. https://ui.adsabs.harvard.edu/abs/2022arXiv220601862M/abstract (accessed Jan. 01, 2023).

[3]S. N. Ali et al., "Monkeypox Skin Lesion Detection Using Deep Learning Models: A Feasibility Study," arXiv:2207.03342 [cs, eess], Jul. 2022, [Online]. Available: https://arxiv.org/abs/2207.03342

[4]M. M. Ahsan, M. R. Uddin, and S. A. Luna, "Monkeypox Image Data collection," arXiv:2206.01774 [cs, eess], Jun. 2022, Accessed: Jan. 01, 2023. [Online]. Available: https://arxiv.org/abs/2206.01774

[5]M. Manjurul Ahsan et al., "Transfer learning and Local interpretable model agnostic based visual approach in Monkeypox Disease Detection and Classification: A Deep Learning insights," NASA ADS, Nov. 01, 2022. https://ui.adsabs.harvard.edu/abs/2022arXiv221105633M/abstract (accessed Jan. 01, 2023).

[6]A. A. Abdelhamid et al., "Classification of Monkeypox Images Based on Transfer Learning and the Al-Biruni Earth Radius Optimization Algorithm," Mathematics, vol. 10, no. 19, p. 3614, Jan. 2022, doi: 10.3390/math10193614.

[7]M. M. Eid et al., "Meta-Heuristic Optimization of LSTM-Based Deep Network for Boosting the Prediction of Monkeypox Cases," Mathematics, vol. 10, no. 20, p. 3845, Jan. 2022, doi: 10.3390/math10203845.

[8]M. Qureshi et al., "Modeling and Forecasting Monkeypox Cases Using Stochastic Models," Journal of Clinical Medicine, vol. 11, no. 21, p. 6555, Jan. 2022, doi: 10.3390/jcm11216555.

[9]A. Kolluri, K. Vinton, and D. Murthy, "PoxVerifi: An Information Verification System to Combat Monkeypox Misinformation," arXiv:2209.09300 [cs], Sep. 2022, Accessed: Jan. 01, 2023. [Online]. Available: https://arxiv.org/abs/2209.09300

[10]F. Yasmin, M. M. Hassan, S. Zaman, S. T. Aung, A. Karim, and S. Azam, "A Forecasting Prognosis of the Monkeypox Outbreak Based on a Comprehensive Statistical and Regression Analysis," Computation, vol. 10, no. 10, p. 177, Oct. 2022, doi: 10.3390/computation10100177.

[11]C. Sitaula and T. B. Shahi, "Monkeypox Virus Detection Using Pre-trained Deep Learning-based Approaches," Journal of Medical Systems, vol. 46, no. 11, Oct. 2022, doi: 10.1007/s10916-022-01868-2.

[12]V. H. Sahin, I. Oztel, and G. Yolcu Oztel, “Human Monkeypox Classification from Skin Lesion Images with Deep Pre-trained Network using Mobile Application,” Journal of Medical Systems, vol. 46, no. 11, Oct. 2022, doi: 10.1007/s10916-022-01863-7.

[13]R. Mungmunpuntipantip and V. Wiwanitkit, “Monkeypox Virus Detection and Deep Learning-based Approaches: Correspondence,” Journal of Medical Systems, vol. 46, no. 12, Nov. 2022, doi: 10.1007/s10916-022-01889-x.

[14]M. Patel, M. Surti, and M. Adnan, “Artificial intelligence (AI) in Monkeypox infection prevention,” Journal of Biomolecular Structure and Dynamics, pp. 1–5, Oct. 2022, doi: 10.1080/07391102.2022.2134214.

[15]M. E. Haque, M. R. Ahmed, R. S. Nila, and S. Islam, “Classification of Human Monkeypox Disease Using Deep Learning Models and Attention Mechanisms,” arXiv:2211.15459 [cs, eess], Nov. 2022, Accessed: Jan. 01, 2023. [Online]. Available: https://arxiv.org/abs/2211.15459

[16]T. B. Alakus and M. Baykara, “Comparison of Monkeypox and Wart DNA Sequences with Deep Learning Model,” Applied Sciences, vol. 12, no. 20, p. 10216, Oct. 2022, doi: 10.3390/app122010216.

[17]M. C. Irmak, T. Aydin, and M. Yağanoğlu, “Monkeypox Skin Lesion Detection with MobileNetV2 and VGGNet Models,” IEEE Xplore, Oct. 01, 2022. https://ieeexplore.ieee.org/abstract/document/9960194 (accessed Jan. 01, 2023).

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