International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-12 Issue-9, August 2023

A Comparative Evaluation of Diverse Deep Learning Models for the COVID-19 Prediction

Bhautik Daxini, M.K. Shah, Rutvik K. Shukla, Rohit Thanki, Viral Thakar

Abstract: ***Deep learning methodologies are now feasible in practically every sphere of modern life because to technological advancements. Because of its high level of accuracy, deep learning can automatically diagnose and classify a wide variety of medical conditions in the field of medicine. The coronavirus first appeared in Wuhan, China, in December 2019, and quickly spread throughout the world. The pandemic of COVID-19 presented significant challenges to the world's health care system. PCR and medical imaging can diagnose COVID-19. There has a negative impact on the health of people as well as the global economy, education, and social life. The most significant challenge in stymieing the rapid propagation of the disease is locating positive Corona patients as promptly as possible. Because there are no automated tool kits, additional diagnostic equipment will be required. According to radiological studies, these images include important information about the coronavirus. Accurate treatment of this virus and a solution to the problem of a lack of medical professionals in remote areas may be possible with the help of a specialized Artificial Intelligence (AI) system and radiographic pictures. We used pre-trained CNN models Xception, Inception, ResNet-50, ResNet-50V2, DenseNet121, and MobileNetV2 to correct the COVID-19 classification analytics. In this paper, we investigate COVID-19 detection methods that make use of chest X-rays. According to the findings of our research, the pre-trained CNN Model that makes use of MobileNetV2 performs better than other CNN techniques in terms of both the size of the solution and its speed. Our method might be of use to researchers in the process of fine-tuning the CNN model for efficient COVID screening***

Keywords: ***COVID-19, X-Ray, Image, CNN, Categorization, Deep Learning***

Manuscript received on 11 July 2023 | Revised Manuscript received on 18 July 2023 | Manuscript Accepted on 15 August 2023 | Manuscript published on 30 August 2023.

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I. INTRODUCTION

When referring to coronavirus, the term "novel" is frequently used to denote a new strain within the dangerous virus family [1]. According to the World Health Organization (WHO), the coronavirus belongs to a broad group of viruses encompassing a range of conditions, spanning from mild respiratory infections such as the common cold to more severe and hazardous diseases. These illnesses can affect both people and animals. The outbreak of the COVID-19 strain of the coronavirus commenced in Wuhan, China, in December 2019. Since that period, it has resulted in significant health concerns on a global scale. The COVID-19 coronavirus strain is a component of the Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome coronaviruses (SARS). Coronavirus infection symptoms include liquid buildup in the lungs, renal disease, and respiratory issues including pneumonia. Coronaviruses are particularly dangerous due to their serial interval and reproduction rate [2].

These viruses can generate epidemics like the ones that caused MERS and SARS in the past 20 years since they know no boundaries between species. The SARS-CoV started in China, spread to 24 countries, and resulted in 8000 cases and 800 fatalities. Beginning in Saudi Arabia, the MERS-CoV has been linked to 2500 cases and 8700 fatalities. Healthy CoV carriers make up around 2% of the population, and these viruses cause 5 to 10% of acute respiratory illnesses [3]. SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus-2) is the name of the virus that caused the COVID-19 pandemic [4].

The 2019 discovery of COVID-19 represents a novel species that has not yet been recognised in humans. There are several viruses, including corona viruses, that can naturally infect both people and other animals, such as chiropterans, rodents, and avian species, through the employment of bats as reservoirs and vectors [5]. The CoV received its moniker from its solar corona-like visual characteristics when observed using an electron microscope. According to statistics from the WHO, COVID-19 is a medical condition characterized by its acute nature, which can lead to resolution. However, it is important to note that in certain cases, COVID-19 can also result in fatality, as depicted in Fig. 1. Due to extensive alveolar damage and developing respiratory failure, severe illness may cause mortality when it first manifests [8]. Respiratory droplets larger than 5 to 10 m are capable of transmitting diseases through the air.

Compared to SARS and MERS, COVID-19 has a greater growth factor because it is more likely to spread through unprotected contact and often manifests milder symptoms. with the aid of Fig. 1, the statistics for the top 10 COVID-19 afflicted nations in terms of infection cases and fatalities are shown.

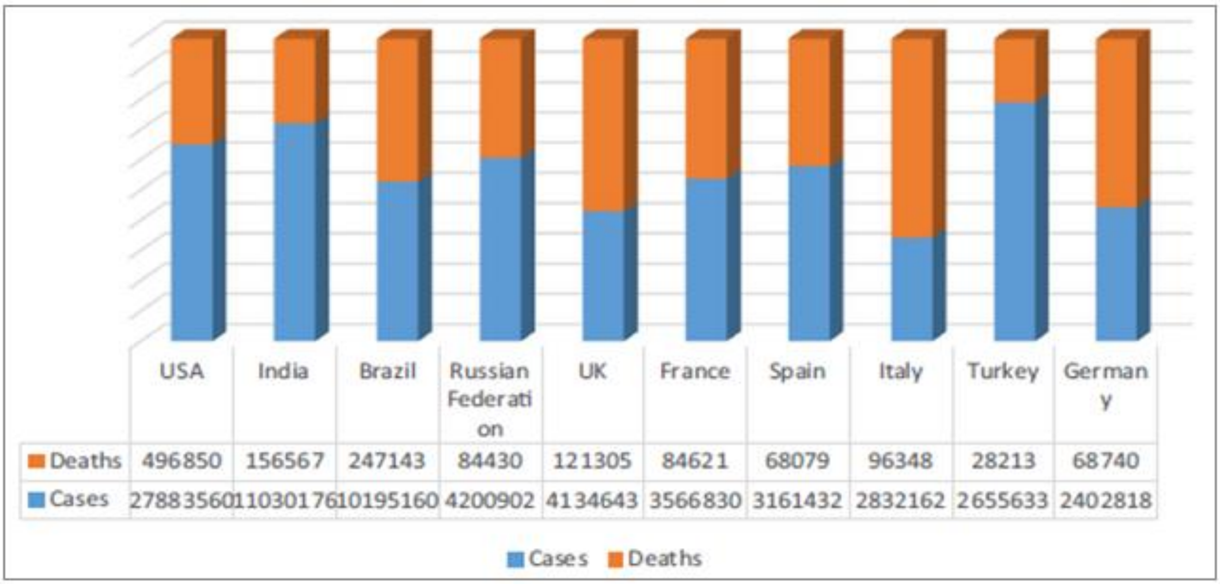

Figure 1. The top ten countries statistical data pertaining to the number of individuals who have been infected and the number of fatalities

In order to stop the COVID-19 pandemic from spreading further, it is crucial to identify those who have the viral infection as soon as possible [6]. The acknowledged standard diagnostic technique is real-time polymerase chain reaction (RT-PCR), which detects viral nucleic acids [7, 8]. However, it is worth noting that this test exhibits sensitivity and specificity levels that are below average. Additionally, numerous regions and countries with a high prevalence of the disease are facing challenges in conducting a sufficient number of RT-PCR tests to promptly address several thousand of suspected cases. The discomfort of RT-PCR, the scarcity of swabs, the requirement for reagents, the time it takes to get results, and the high false-negative rate are additional issues. In light of these worries, other diagnostic strategies merit research [9]. In order to establish a robust framework for the comprehensive identification, tracking, and isolation of individuals who have contracted COVID-19 during the early stages of infection, it is imperative that all methodologies exhibit a high degree of dependability, expediency, and efficacy in detecting the presence of the virus. The use of artificial intelligence tools for training, forecasting, and assessment is now widely recognised as being advantageous. A lot of prediction models are created using neural networks. However, there are still drawbacks with neural networks, such as their poor convergence and learning capacity [10]. Deep learning has been shown to be a helpful technology to speed up diagnostics as it is evident that it has a wide range of uses and can be used to make predictions and clinical judgements in a medical system, as ALzubi et al. [11] showed. These studies also shown that connecting medical images and diagnostic factors is a successful plan that would help doctors diagnose patients using big data. Medical imaging plays a pivotal role in the detection of COVID-19 infections through the utilization of radiological modalities, including X-rays and computed tomography scans, in order to facilitate clinicians the analysis of the COVID-19 disease and expedite the implementation of preventive and control measures fast.

CT scans are used in imaging. Ground-Glass Opacities (GGO) are known to be abnormalities that can be seen in COVID-19 infected person's thorax CT images [12]. Chest CT scans can be used to develop a method for identifying and quantifying COVID-19 instances, according to a large body of research [13]. X-ray pictures can also be used in place of CT scans to identify COVID-19. Because of this, it is feasible to analyze medical pictures like chest X-rays (CXR) and CT scans to provide very quick diagnostic information by looking for potential patterns that might result in the automated identification of the condition. The chest X-ray is a commonly employed imaging technique for the diagnostic evaluation of individuals showing thoracic abnormalities. Its popularity stems from its rapid imaging time, low radiation exposure, low cost, and widespread availability in emergency and hospital settings. Furthermore, it is often interpreted without the involvement of expert radiologists.

X-ray imaging offers a safer alternative to laboratory techniques that investigate the respiratory system, as it does not pose a heightened risk of aerosolizing the pathogen. In addition to demonstrating the extent of the disease at various time points, X-rays can also assist in the categorization of patients based on their respective levels of risk for developing subsequent complications. Chest X-rays, unlike computed tomography (CT) scans, cannot distinguish between pneumonia and other diseases, despite the fact that it is thought to be the most difficult plain film to read correctly [18]. For the care of patients in a dire condition and to aid in the discovery of COVID-19 clustering events, accurate interpretation is essential.

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Since CT is a noninvasive imaging technique, it can show specific lung symptoms that are connected to COVID-19 [15, 16]. CT is a useful tool for the early identification of COVID-19, although it may reveal imaging characteristics that make it difficult to distinguish COVID-19 from other kinds of pneumonia. Compared to X-ray imaging, CT imaging takes a lot longer and necessitates intricate sanitization processes between patients. Further, timely viral pneumonia screening may be challenging due to the lack of readily accessible high-quality CT scanners. For a quick diagnosis of COVID-19, the involvement of medical imaging is crucial [14]. Therefore, using AI in conjunction with chest imaging can be helpful.

Recent studies have shown that deep learning [17, 18], machine learning [19, 20], and computer vision [21] may all be used to automatically diagnose a variety of body ailment [22,23]. The utilization of deep learning as a feature extractor is employed with the objective of enhancing classification accuracy. [24].

The ability of radiologists to accurately interpret radiography images remains a significant issue, primarily attributed to the inherent limitations of human perception in detecting subtle visual cues within the images. Despite the widespread availability and expeditious nature of radiography procedures, particularly in the context of chest radiology imaging systems commonly found in hospitals, the challenge of effectively analyzing these images persists. Radiologists may overlook patterns in chest X-rays that deep learning can spot [25].

Due to its great power of feature extraction [26], deep learning, which has been used to detect TB in chest X-rays, might also be utilized to identify lung abnormalities linked to COVID-19 [27]. This will be useful to physicians as they choose the best course of action for high-risk COVID-19 patients. On pediatric chest radiographs, deep learning was utilized to distinguish between bacterial and viral pneumonia [28]. Additionally, efforts have been undertaken to identify different chest CT scan imaging characteristics [29].

Deep learning (DL), which is a subfield of machine learning (ML), is used to extract features from pictures as well as categorize them. It is motivated by how the human brain functions. Being able to learn from unlabeled data, or unsupervised learning, is DL's main strength. The utilization of unlabeled data, the absence of feature engineering, the ability to achieve accurate and precise predictions, and the capability for image classification are among the notable characteristics of this approach [30], Deep learning (DL) has been extensively utilized in various industries, including but not limited to self-driving vehicles, face recognition, object detection, and image classification.

Convolutional neural networks (CNNs) are DL algorithms that have been widely applied to address issues with document analysis, various picture classifications, posture identification, and action recognition [31]. Convolutional neural networks (CNNs) have demonstrated efficacy in the detection of various medical conditions, such as coronary artery disease, malaria, Alzheimer's disease, several dental disorders, and Parkinson's disease. One area where CNN has shown promising results is in medical imaging [32].

Moreover, CNN exhibits a favorable likelihood of discerning between COVID-19 infections and non-COVID-19 infections by leveraging medical images such as chest X-rays and CT scans, which are readily accessible in public databases .

The majority of convolutional neural networks (CNN)-based deep learning models for COVID-19 detection employ this architecture. These include Mobile Net, Shuffle Net, Res Net, Alex Net, Google Net, Inception or Xception, VGG Net etc. A few publications discussing reviewed investigations of COVID-19 diagnostic systems based on deep learning have recently been published [33,34,35,36,37,38,39]. The researchers have presented their findings on the detection of COVID-19 using a variety of datasets consisting of chest X-ray (CXR) and computed tomography (CT) images. The majority of these datasets were collected from online sources. Based on the findings of these researches, the produced systems have demonstrated promising performance, but further advancements in the databases of medical pictures and the construction of optimal deep learning algorithms are still required to lower computing costs and resolve the issue of sparse data. Accuracy, sensitivity, specificity, precision, F1-score, and other metrics are often employed to assess the effectiveness of deep learning models.

The field of COVID-19 detection based on deep learning has seen a significant amount of study since March 2020. In certain cases, both chest X-ray and CT scan pictures are used to train and evaluate these deep learning models. The general COVID-19 detection methods based on machine learning, deep learning, and deep transfer learning are shown in Figures 2 and 3.

Figure 2. Machine learning-based COVID-19 detection/classification.

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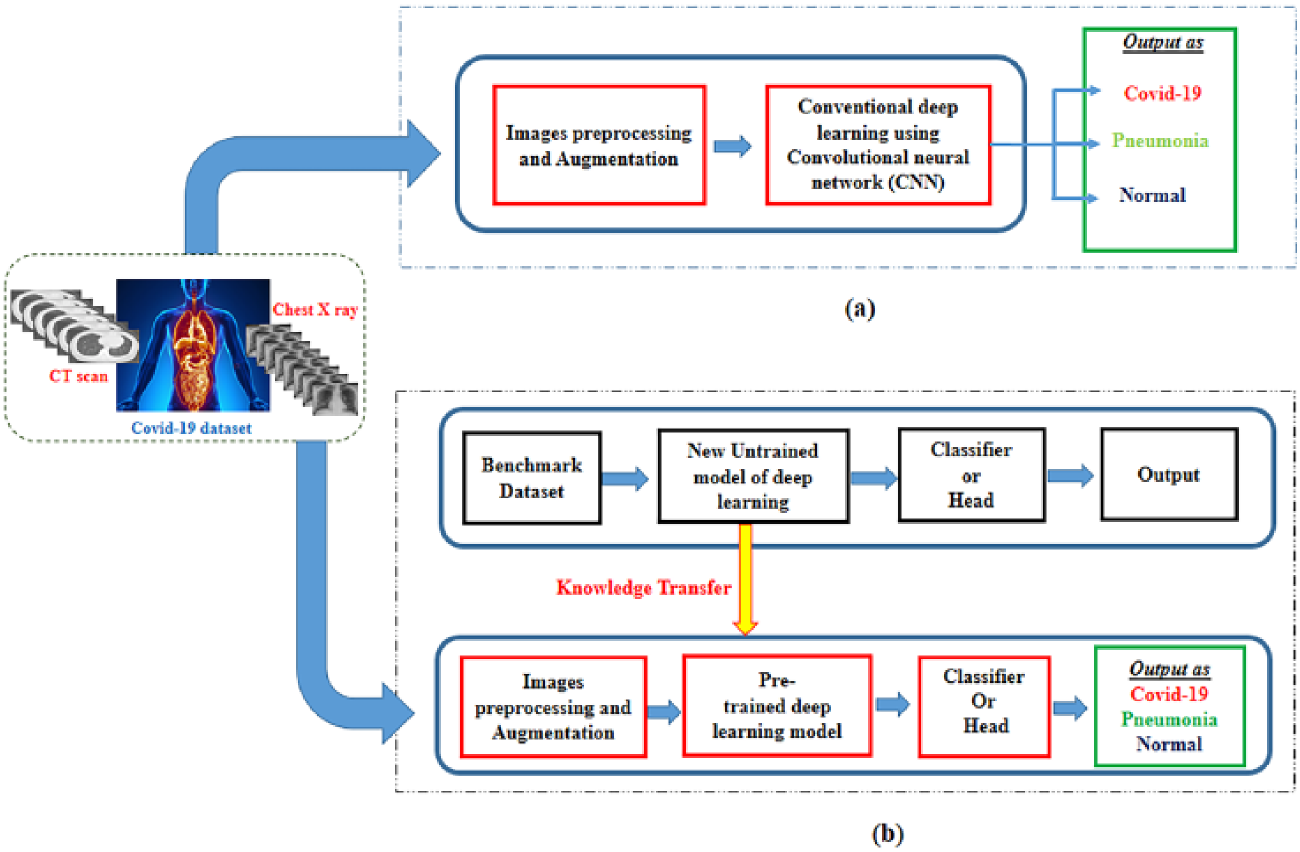

Figure 3. (a) General convolutional neural network-based COVID-19 detection or classification method. (b) Deep transfer learning-based COVID-19 detection or classification method.

II. MATERIALS AND METHODS

This Section describes the dataset, image preprocessing, transfer learning, classification methods, parameter settings, and performance assessment measures.

2.1. Data Set

For the validation of the proposed method, the images that are used are taken from the SARS-CoV-2 CT scan dataset [40]. This data set includes 1252 CT images of the infected type and 1230 CT images of the non-infected type.

2.2. Image pre-processing

Two processes that are implemented for pre-processing are Normalization and Data Augmentation. The process of normalizing the data is an important step that is typically implemented in CNN designs in order to keep the numerical values stable. When normalization is used, a CNN model has a better chance of learning more quickly, and the gradient descent has a better chance of being stable. As a consequence of this, the pixel values of the input photos have been standardized within the range of 0–1 for the purpose of this investigation. The photos that were utilized in the datasets that were taken into consideration were grayscale photographs, and the rescaling was accomplished by multiplying the pixel values by 1/255. The data augmentation approach has seen widespread use and has proved helpful in increasing the quantity of images through the application of a series of modifications while maintaining the integrity of class labels. Augmentation also adds more variation to the images themselves and acts as a regularizer for the dataset.

The following digital methods were utilized in order to enhance the images: rotation_range=40,width_shift_range=0.2,height_shift_range=0.2,shear_range=0.2,zoom_range=0.2,fill_mode='nearest'.

2.3. Algorithms for Classification

COVID-19 and normal are the two classifications into which CXR pictures are divided using six algorithms. Xception, ResNet50, ResNet50V2, InceptionV3, DenseNet121, Inception-v3 [13], MobileNetV2 are pre-trained networks that are used in these techniques. Each of these models is tested with two different activation function in the last layer. The different activation function that were employed for the training are Sigmoid and Softmax. Also 6 different optimisers were also used with each model and their performance evaluated for fixed value of dropout and learning rate. The different optimisers that were used are SGD, RMSProp, Adagrad, Nadam, Adam and Ftrl. Transfer learning is used to fine-tune these networks.

Table 1. Main Characteristics of The Models

Model	Size (MB)	Parameters	Depth
Xception	88	22,910,480	126
ResNet50	98	25,636,712	50
ResNet50V2	98	25,613,800	164
InceptionV3	92	23,851,784	159
DenseNet121	33	8,062,504	121
MobileNetV2	14	3.5M	105

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2.4. Transfer Learning

Transfer learning refers to the method of enhancing the learning capabilities of a pre-trained neural network when applied to a novel task with fewer training pictures by leveraging previously learned information from a related task [10]. Convolutional layers in pre-trained CNNs extract visual characteristics that are used by the final learnable layer and the classification layer to categorise the input picture. We swap out the final three layers for three new ones that are tailored to the new dataset in order to fine-tune the network to categorise CXR pictures into two classes (COVID-19 and normal) using transfer learning.

2.5. Matrices for the evaluation of the algorithms

In order to assess the efficacy of various algorithms employed for the classification of CXR images into two distinct categories, three key metrics are computed: accuracy (Acc), sensitivity (SN), and specificity (SP). In terms of positives and negatives, they are defined as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (3)$$

Figure 4. Matrices for the evaluation of the algorithms.

III. RESULTS COMPARISON AND DISCUSSION

Comparison of different models for fixed learning rate = 0.0001 Epoch =5 Drop out = .5 Activation = Softmax

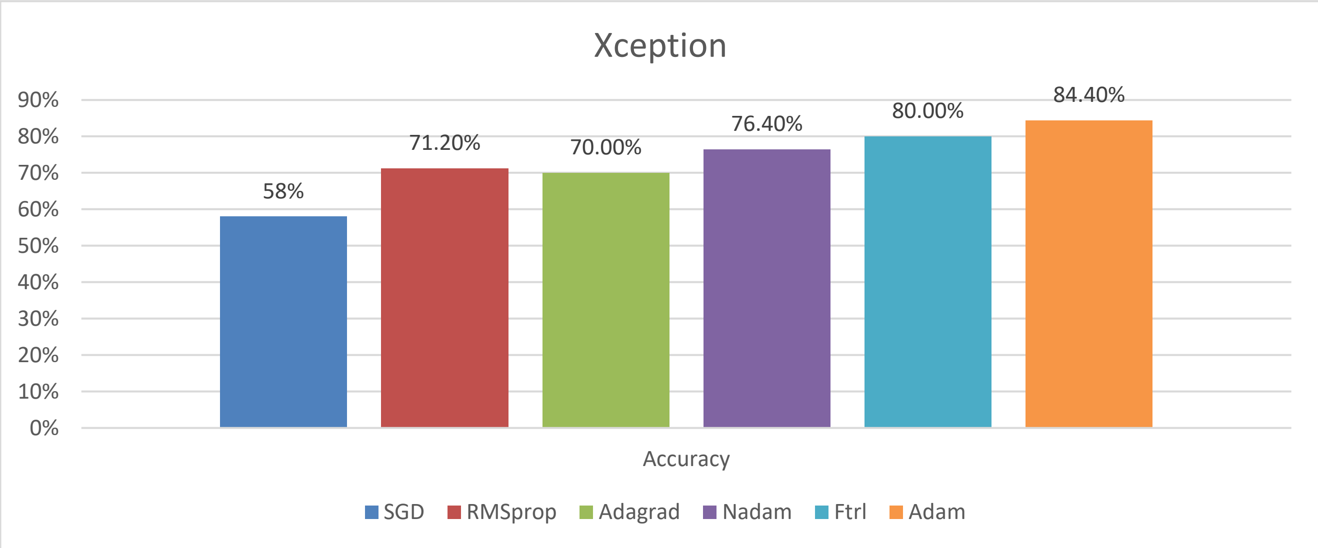

Figure 5. Comparison of accuracy of Xception model with different optimizer and Softmax activation function.

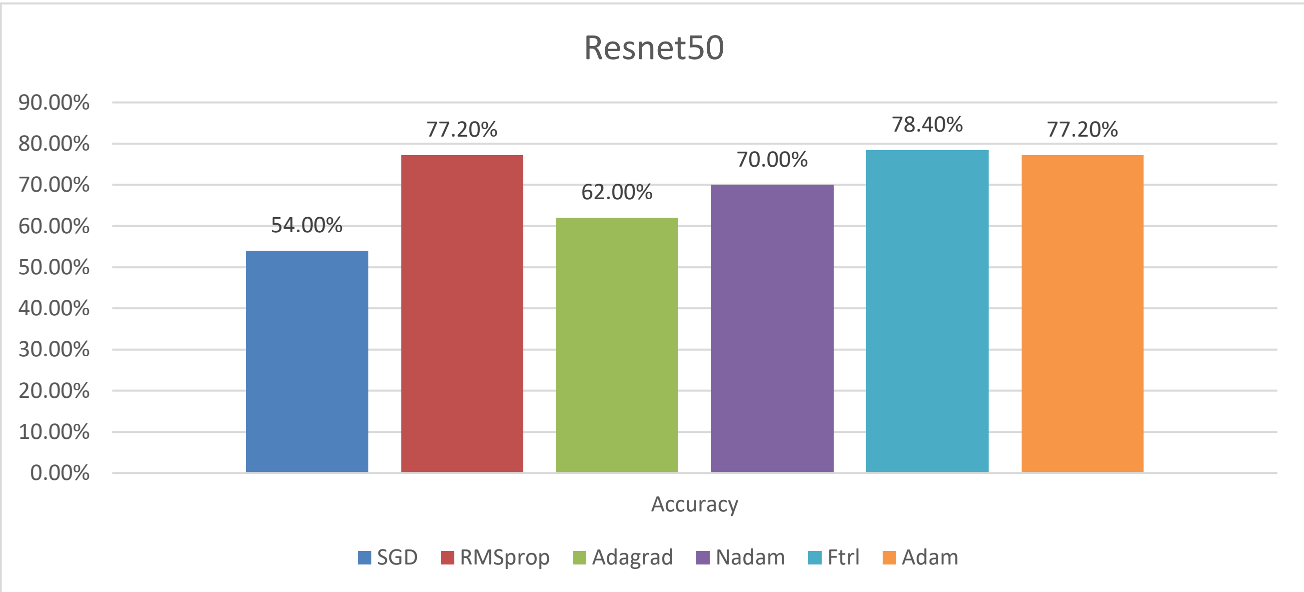

Figure 6. Comparison of accuracy of Resnet50 model with different optimizer and Softmax activation function

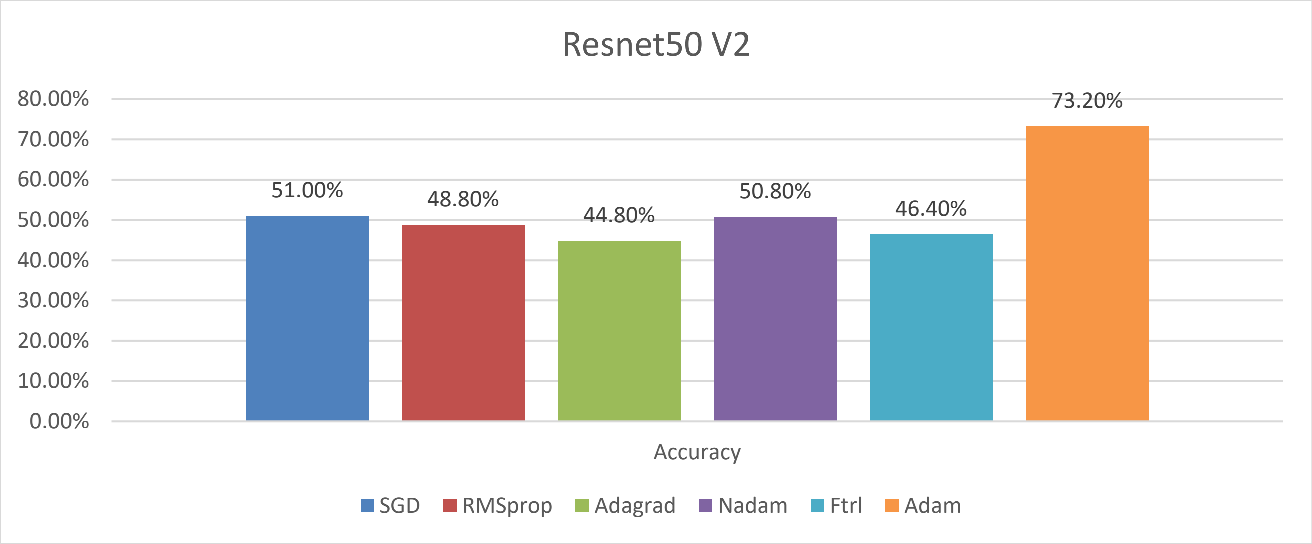

Figure 7. Comparison of accuracy of Resnet50 V2 model with different optimizer and Softmax activation function

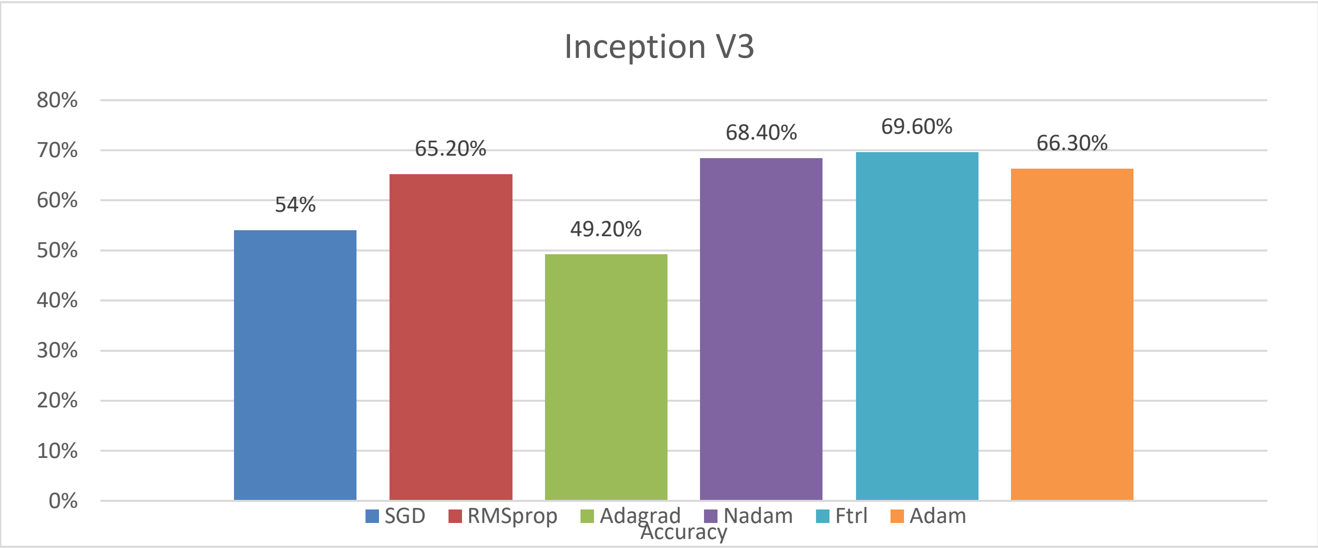

Figure 8. Comparison of accuracy of Inception V3 model with different optimizer and Softmax activation function

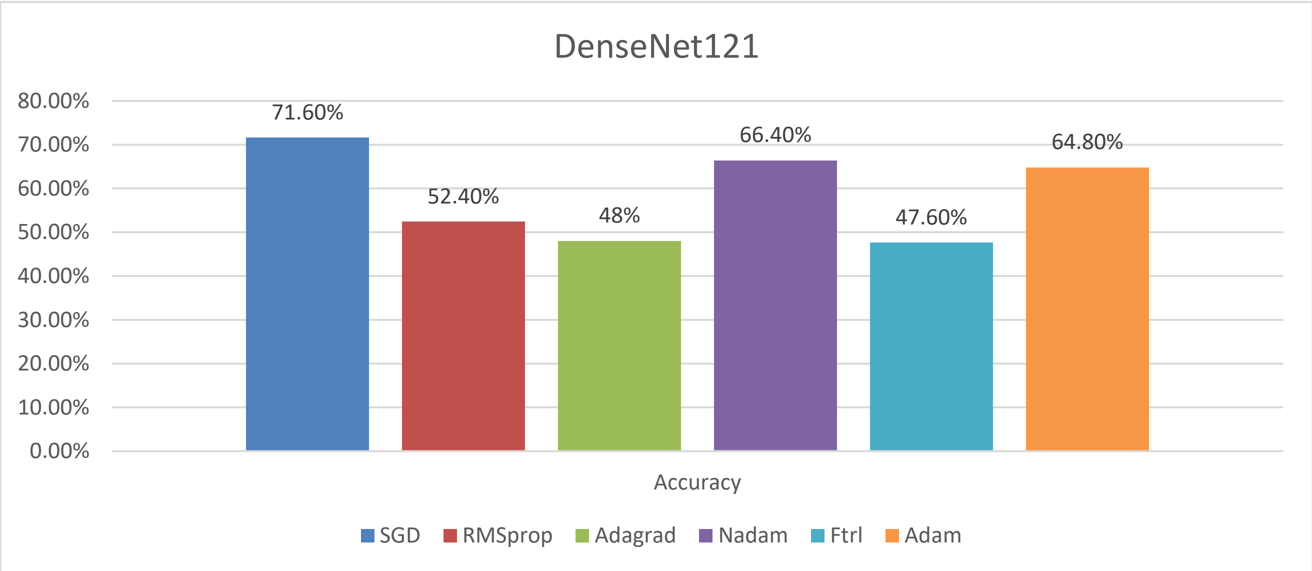

Figure 9. Comparison of accuracy of DenseNet121 model with different optimizer and Softmax activation function

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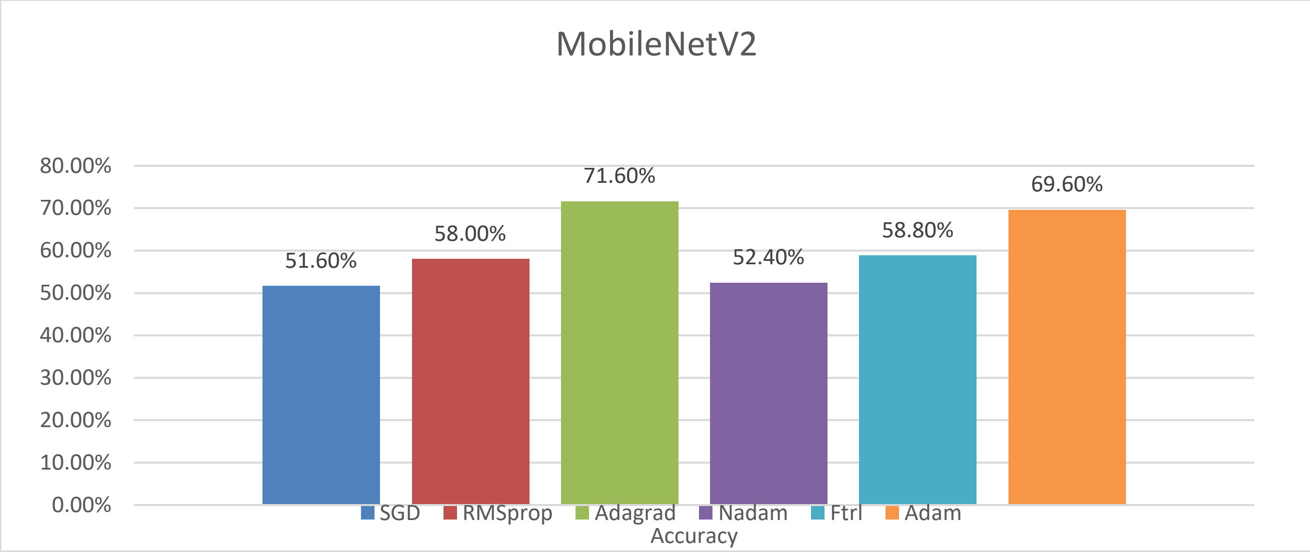

Figure 10. Comparison of accuracy of MobileNetV2 model with different optimizer and Softmax activation function

Comparison of different models for fixed learning rate = 0.0001 Epoch =5 Drop out = .5 Activation = Sigmoid

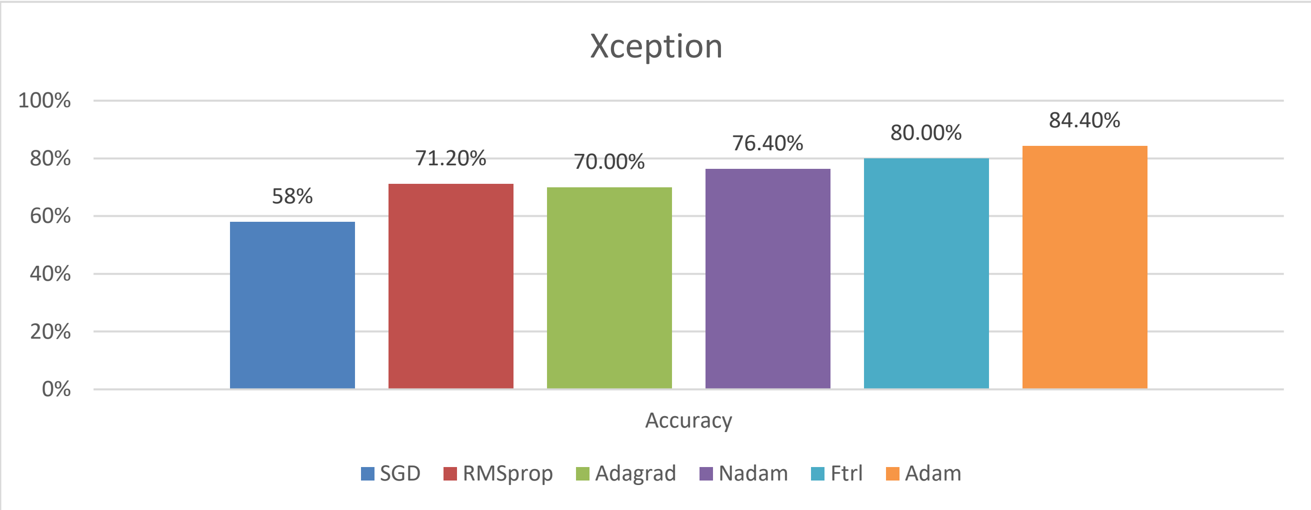

Figure 11. Comparison of accuracy of Xception model with different optimizer and Sigmoid activation function.

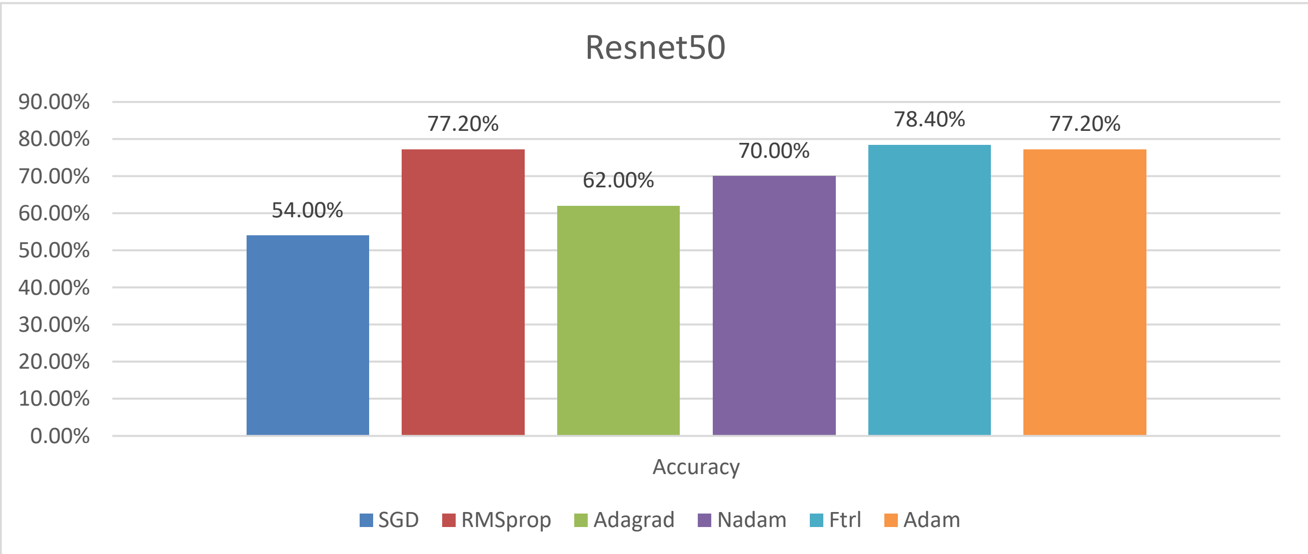

Figure 12. Comparison of accuracy of Resnet50 model with different optimizer and Sigmoid activation function.

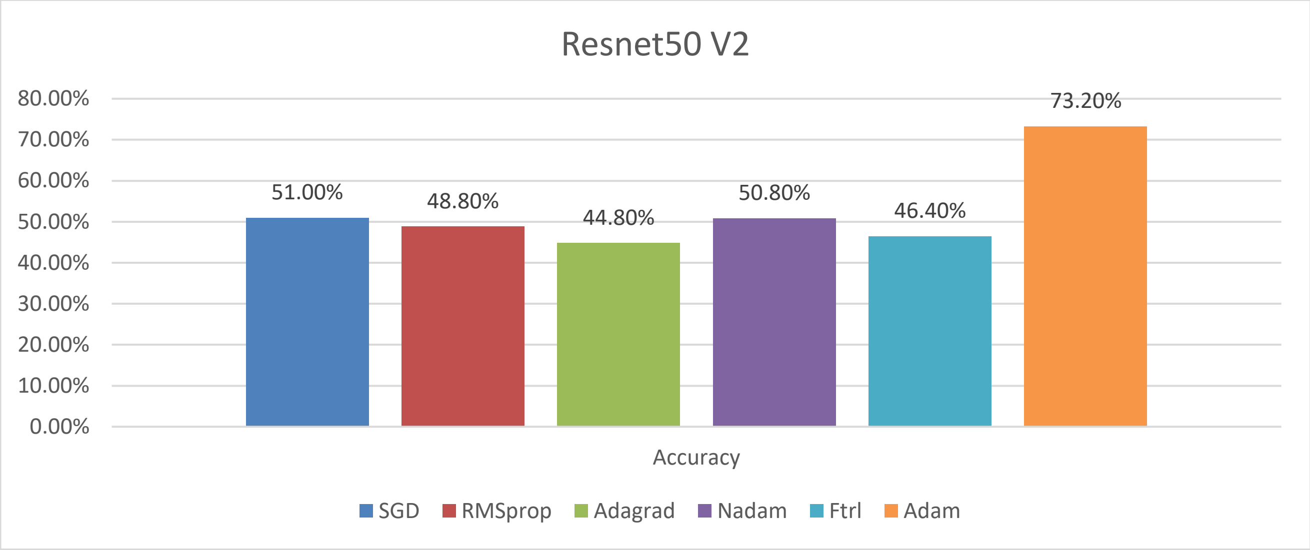

Figure 13. Comparison of accuracy of Resnet50 V2 model with different optimizer and Sigmoid activation function.

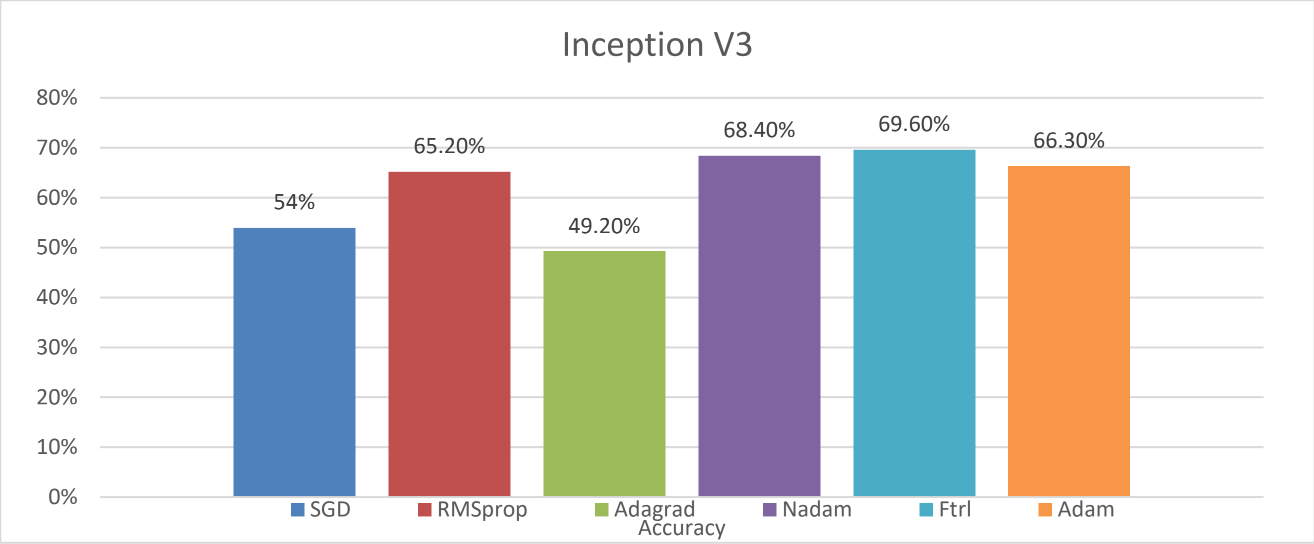

Figure 14. Comparison of accuracy of Inception V3 model with different optimizer and Sigmoid activation function.

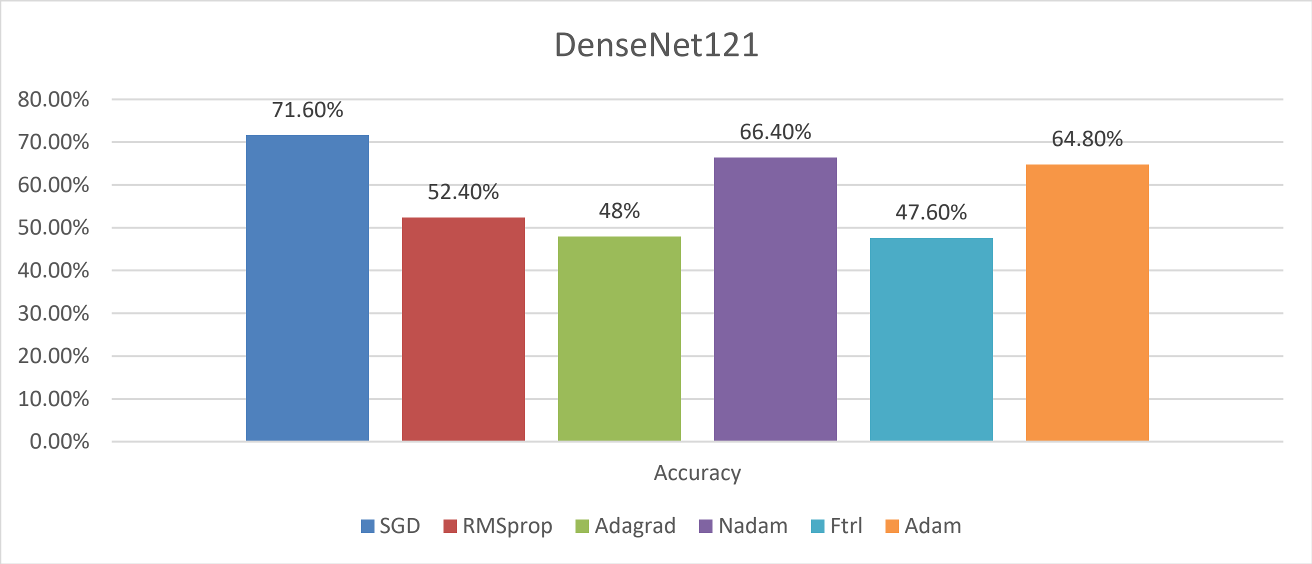

Figure 15. Comparison of accuracy of DenseNet121 model with different optimizer and Sigmoid activation function.

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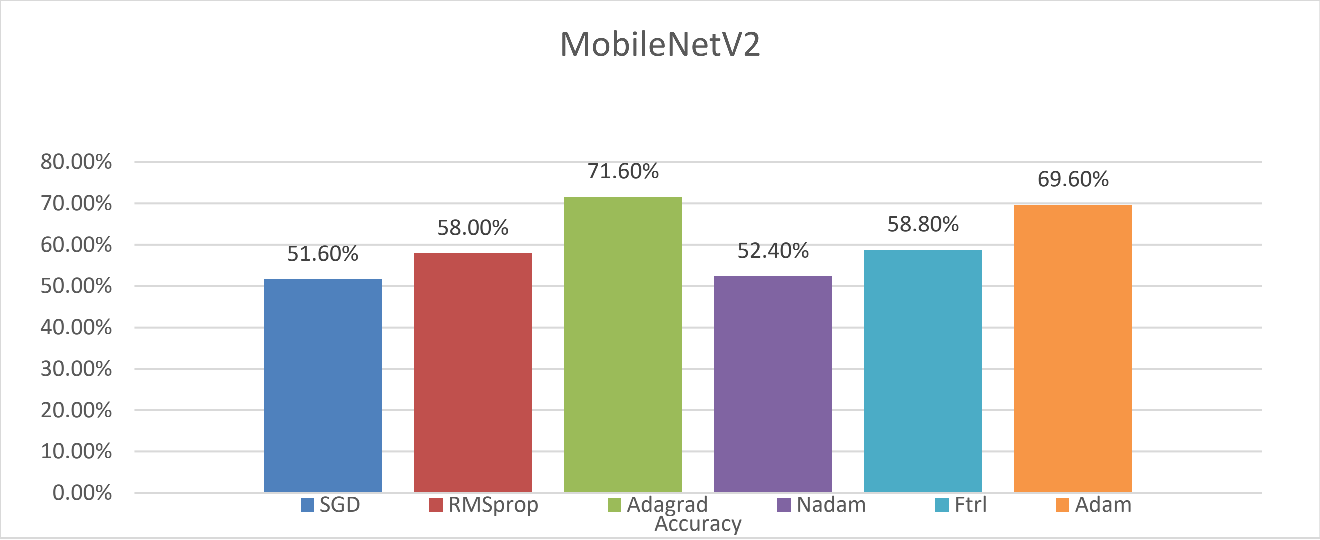

Figure 16. Comparison of accuracy of MobileNetV2 model with different optimizer and Sigmoid activation function.

Comparison of various optimiser for different models for fixed learning rate = 0.0001 Epoch =5 Drop out = .5 Activation = Softmax

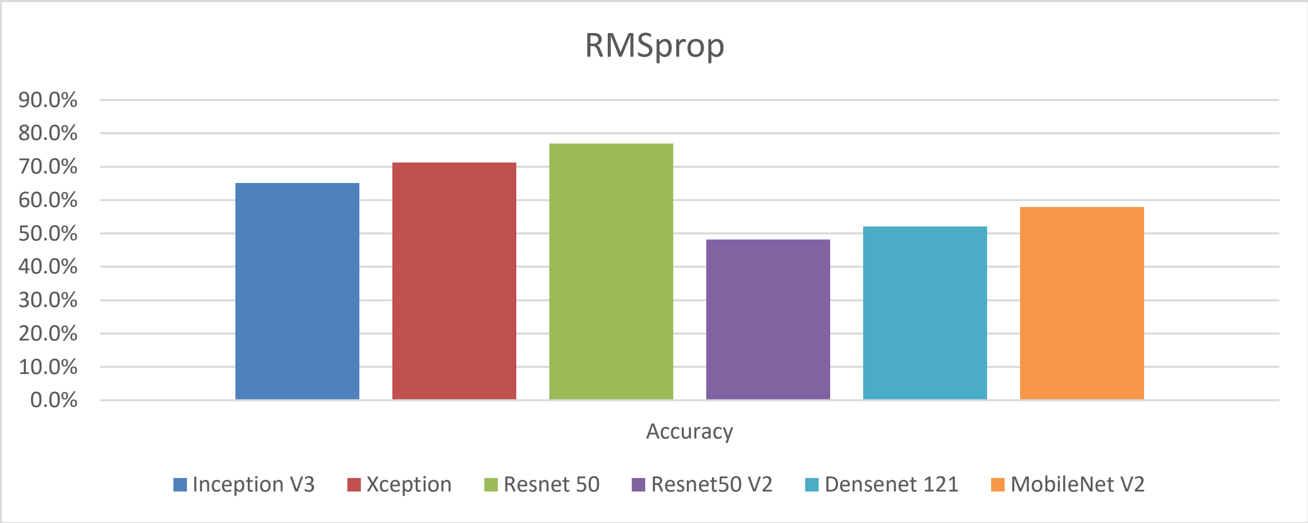

Figure 17. Comparison of accuracy for RMSprop optimizer for various model with Softmax activation function.

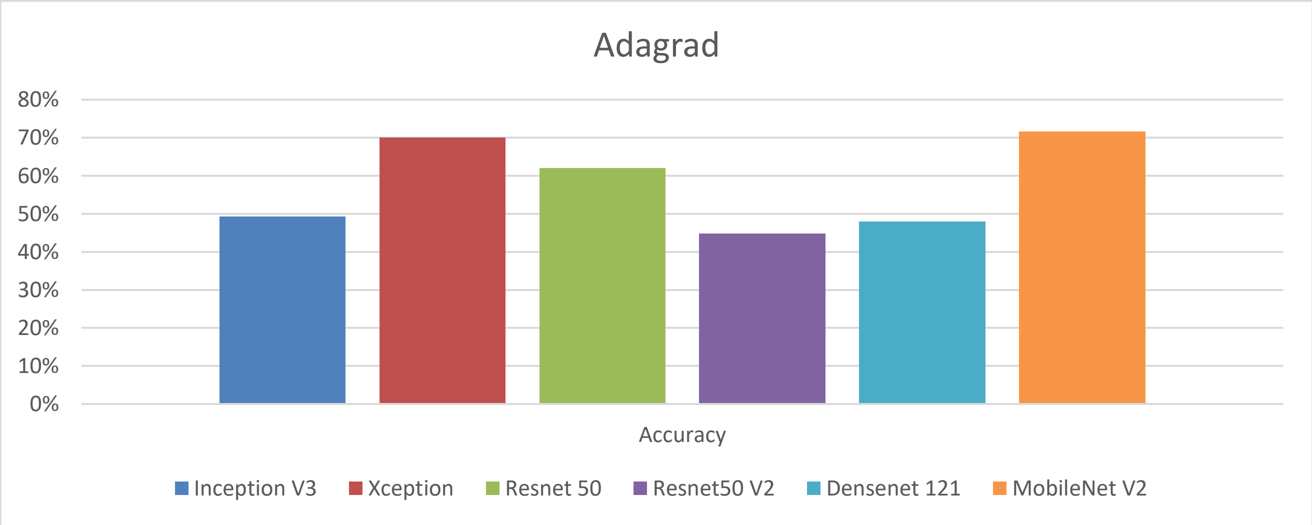

Figure 18. Comparison of accuracy for Adagrad optimizer for various model with Softmax activation function.

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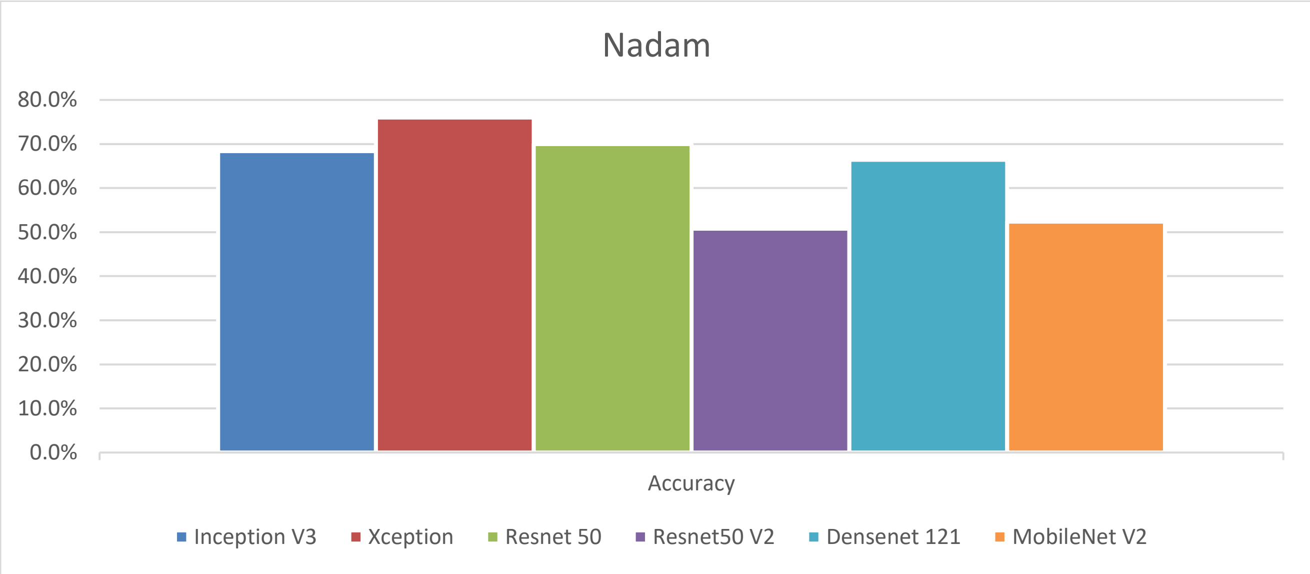

Figure 19. Comparison of accuracy for Nadam optimizer for various model with Softmax activation function.

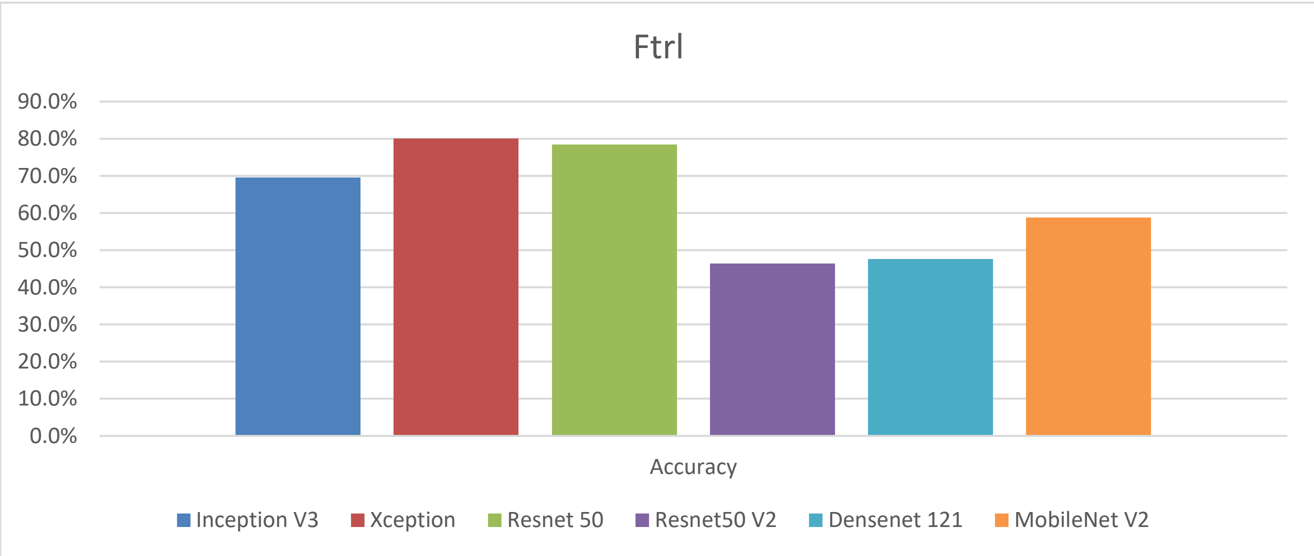

Figure 20. Comparison of accuracy for Ftrl optimizer for various model with Softmax activation function.

Figure 21. Comparison of accuracy for Adam optimizer for various model with Softmax activation function.

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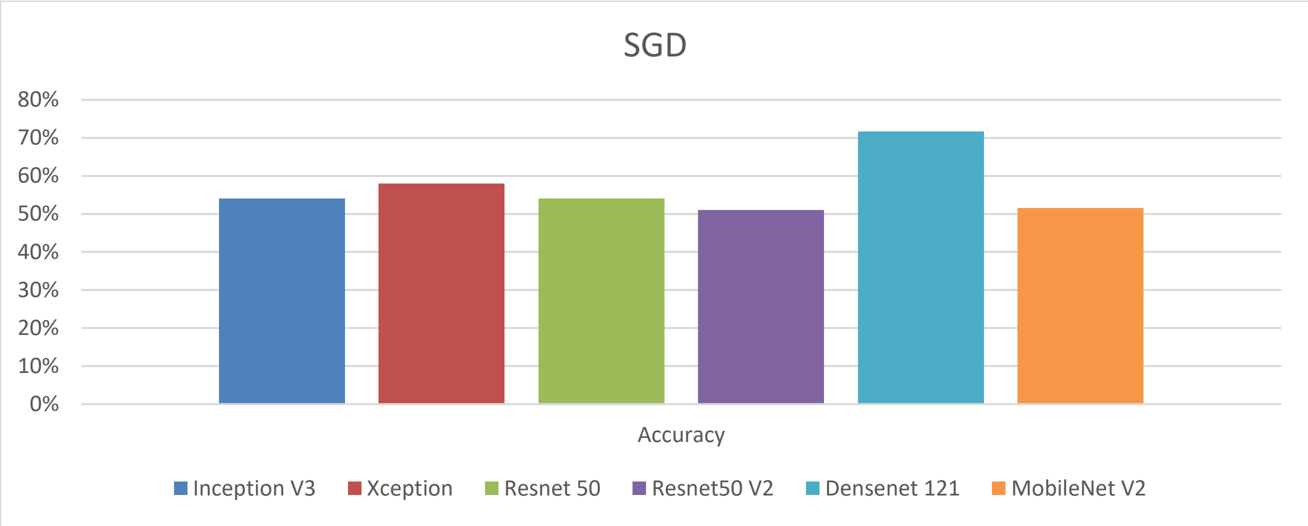

Figure 22. Comparison of accuracy for SGD optimizer for various model with Softmax activation function.

Comparison of various optimiser for different models for fixed learning rate = 0.0001 Epoch =5 Drop out = .5 Activation = Sigmoid.

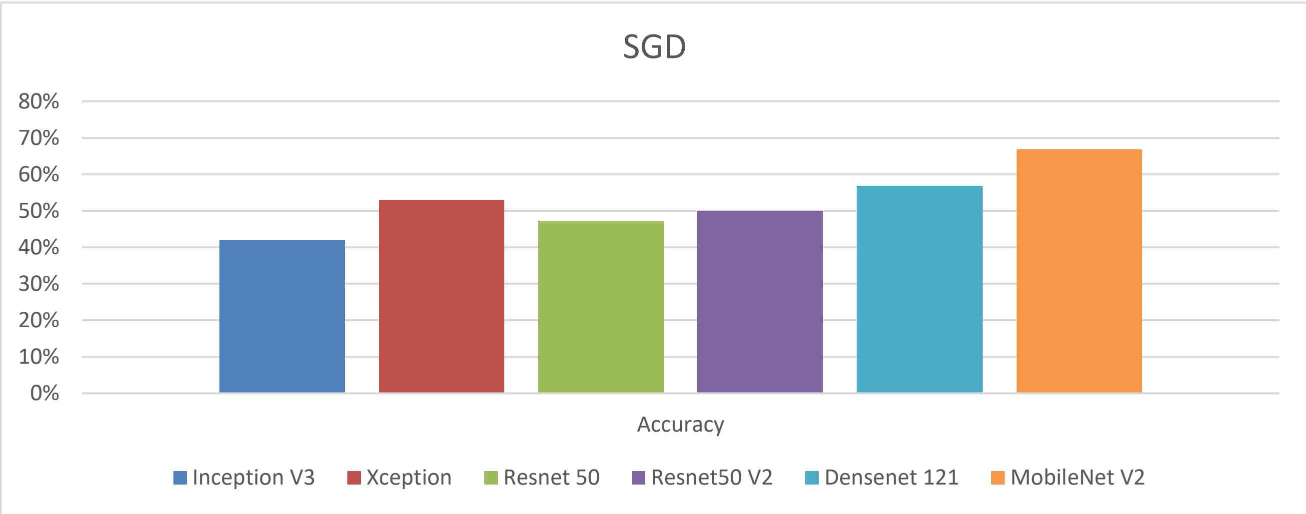

Figure 23. Comparison of accuracy for SGD optimizer for various model with Sigmoid activation function.

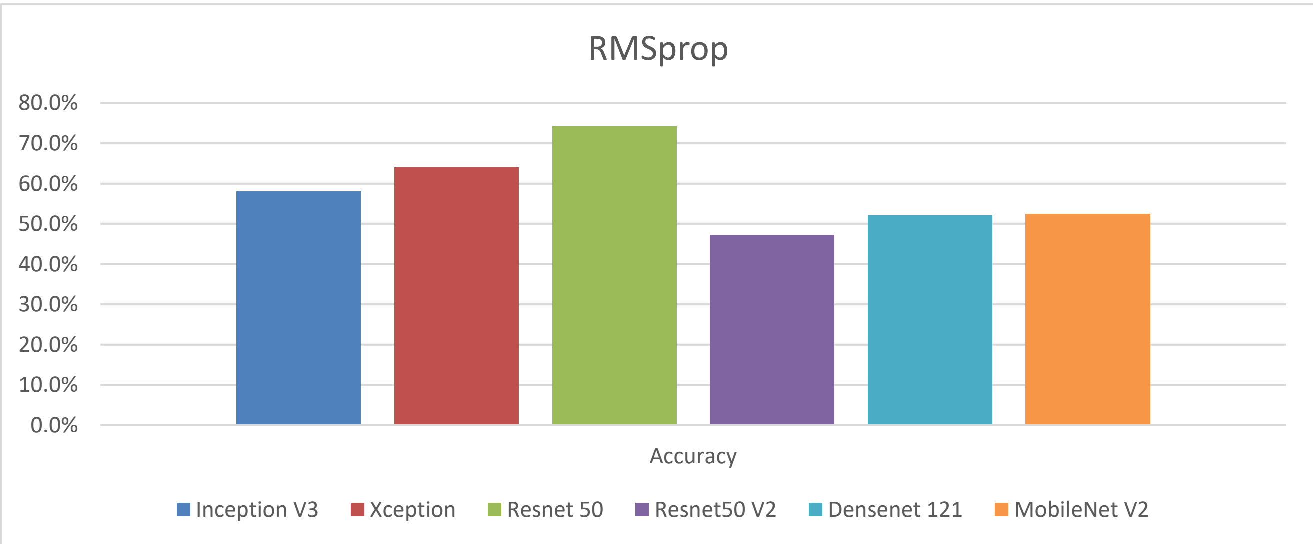

Figure 24. Comparison of accuracy for RMSprop optimizer for various model with Sigmoid activation function.

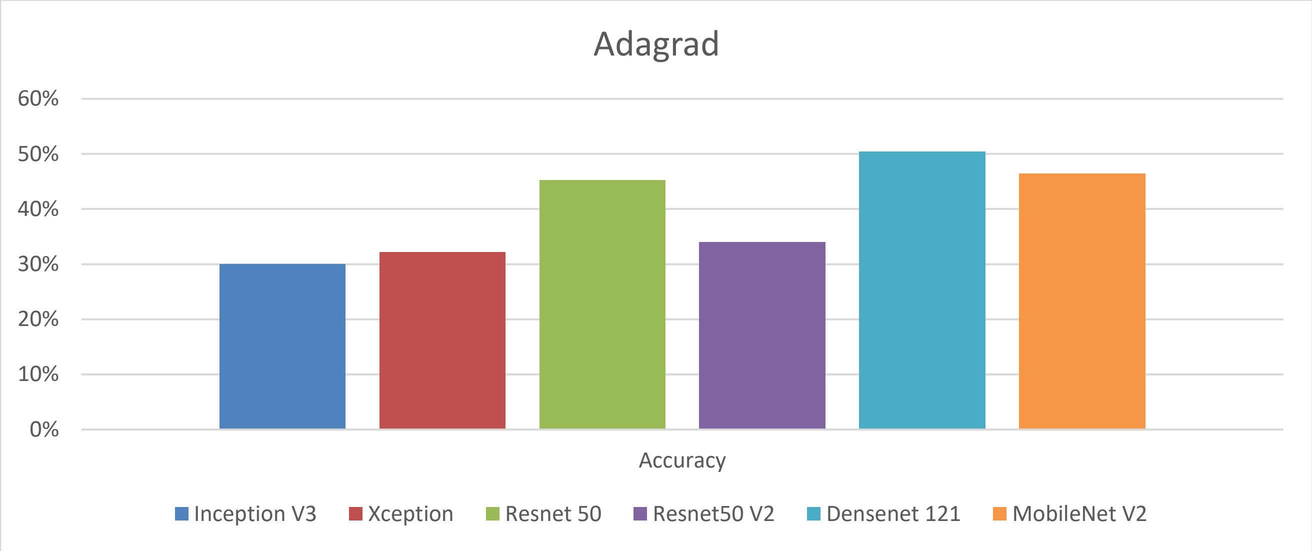

Figure 25. Comparison of accuracy for Adagrad optimizer for various model with Sigmoid activation function.

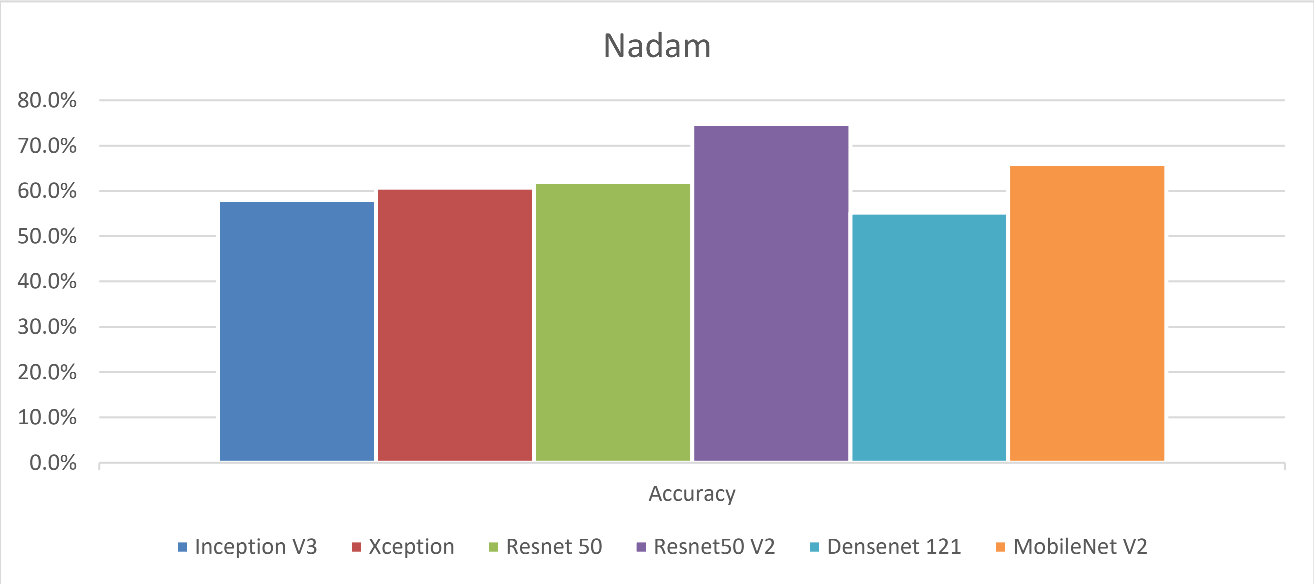

Figure 24. Comparison of accuracy for Nadam optimizer for various model with Sigmoid activation function.

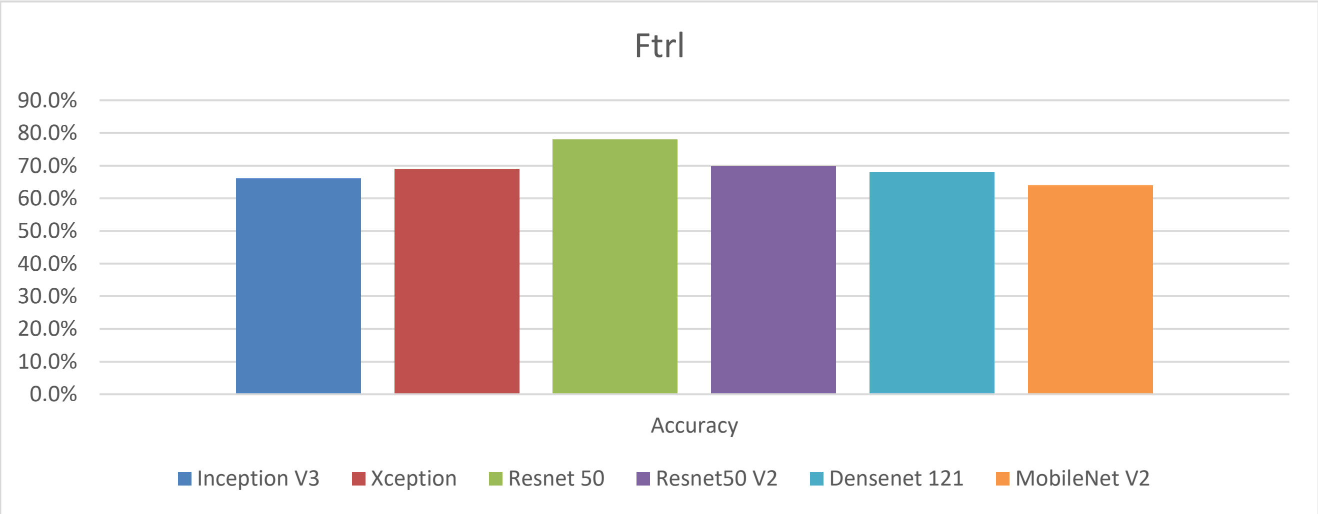

Figure 24. Comparison of accuracy for Ftrl optimizer for various model with Sigmoid activation function.

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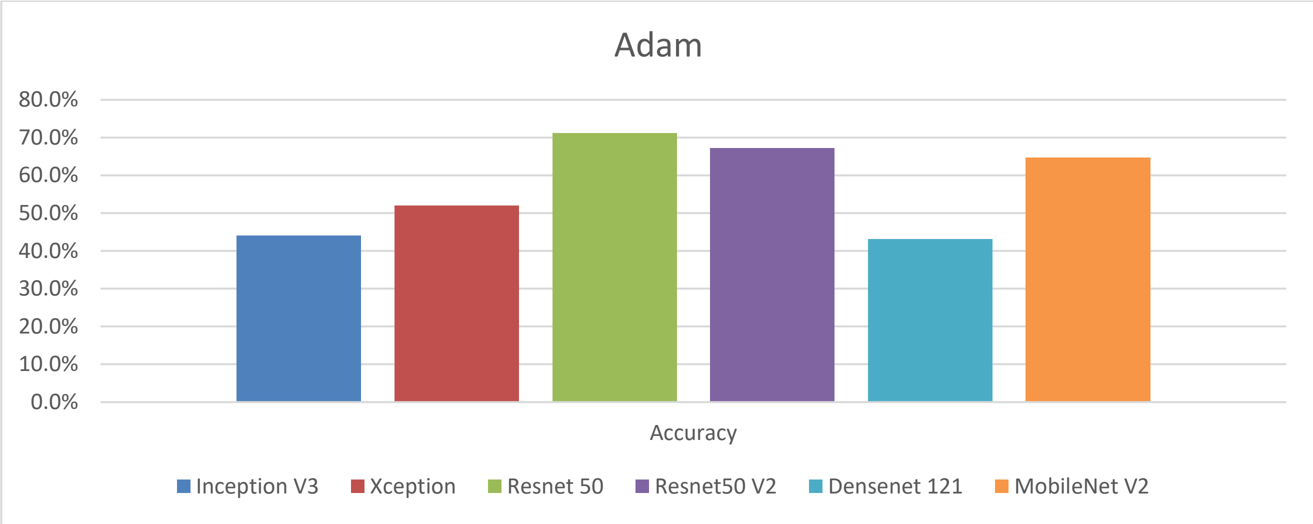
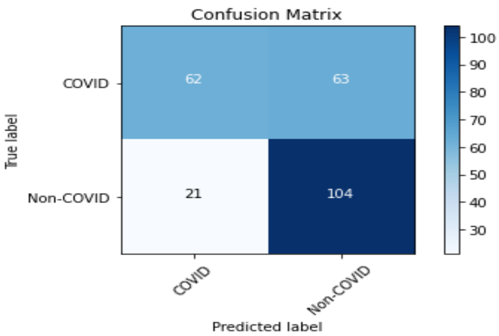
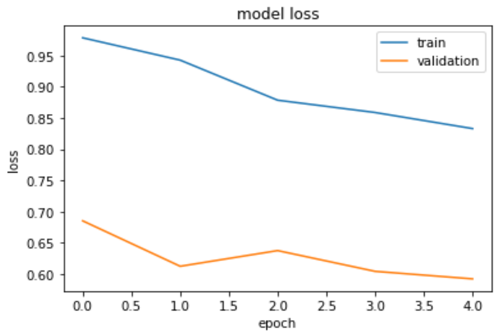
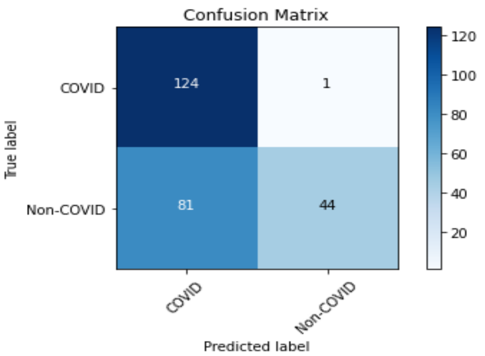
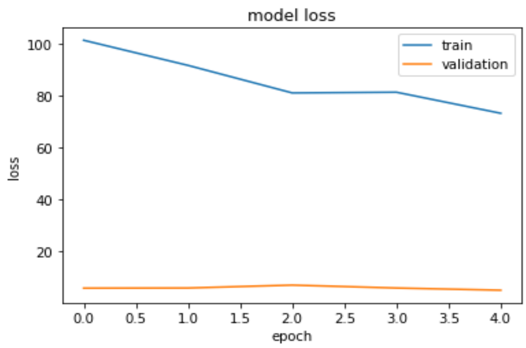
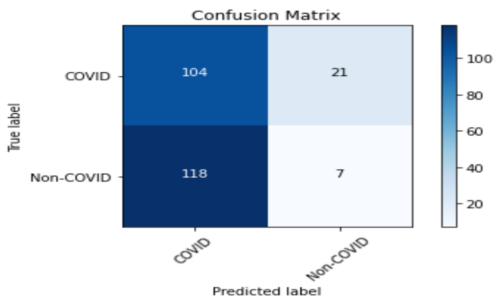
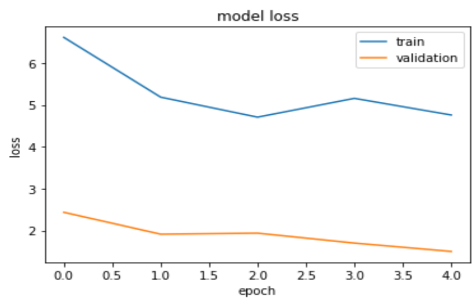


Figure 25. Comparison of accuracy for Adam optimizer for various model with Sigmoid activation function.

Confusion matrix for the 6 models for ADAM optimiser are given below.

Model	Confusion Matrix	Loss Curve
Mobilenet V2		
Resnet V2		
Densenet		

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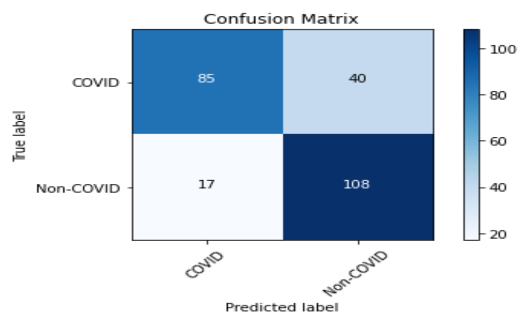
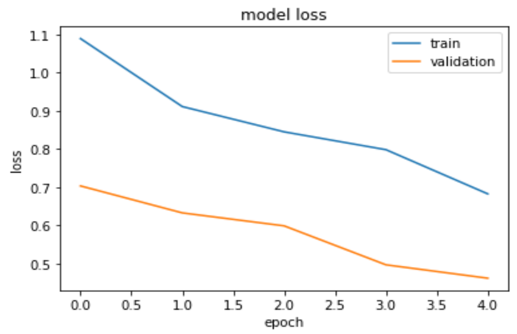
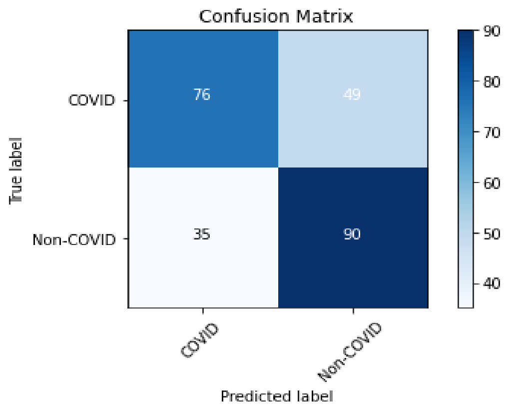
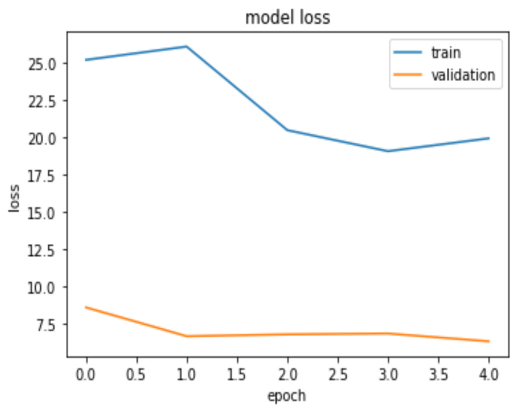
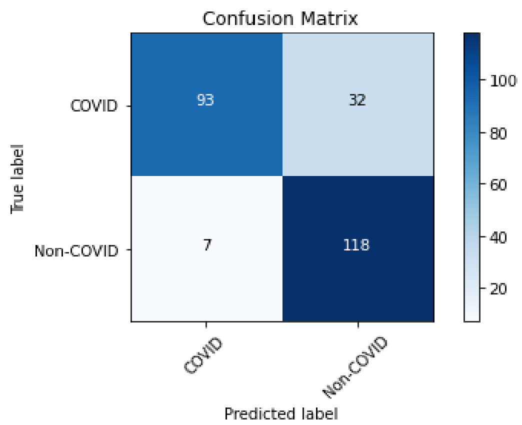
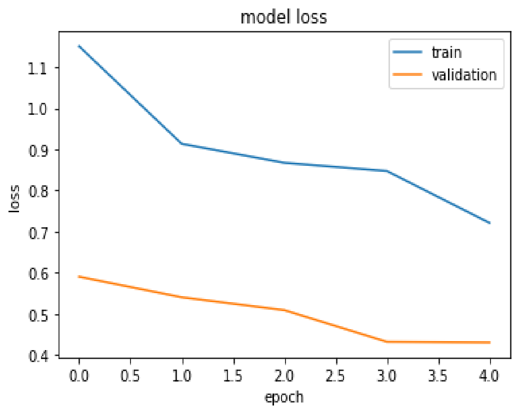
Resent 50		
Inception V3		
Xception		

IV. CONCLUSION AND FUTURE WORK

This paper describes a comparative study of six deep learning models for COVID-19 images from a publicly available dataset. These models were used to automatically classify the COVID-19 images into two classes. Analyzing the performance of various DL model for binary classification for various parameters, it is observed that the softmax activation function and the adam optimiser provides the better performance in general. The training for the binary classification can be made faster by employing transfer learning. The MobileNetV2 shows a comparative better performance comparted to others considering the size and hence provide a faster result. In our future work, we will tackle the problem of generalizing the proposed model to a wider range of practical scenarios to facilitate the diagnosis of more types of diseases from CXR and CT images.

DECLARATION

Funding/ Grants/ Financial Support	No, I did not receive it.
Conflicts of Interest/ Competing Interests	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	All authors have equal participation in this article.

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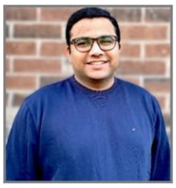

Viral Thakar is a highly skilled Machine Learning Research Engineer with expertise in computer vision, natural language processing, and IoT. He has a strong background in both research and applied engineering, with a focus on unsupervised domain adaptation, self-supervised learning, structured and unstructured as well as euclidean and non-euclidean data and one-shot learning. Viral has successfully contributed to the development of multidisciplinary AI-based solutions and has been recognized for his work in the field. With expertise in machine learning on edge devices and image and video signal processing, His interest area also includes, generative models, graph neural networks and convolutional neural networks. He did his M.Tech in Communication System Engineering (2013) from Charotar University of Science and Technology. He completed his B.E. Electronics and Communication (2011) from Atmiya Institute of Technology & Science.