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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 due to technological advancements. Due to its high level of accuracy, deep learning can automatically diagnose and classify a wide range of medical conditions in the field of medicine. The coronavirus first appeared in Wuhan, China, in December 2019 and quickly spread worldwide. The COVID-19 pandemic presented significant challenges to the world's healthcare system. PCR and medical imaging can be used to diagnose COVID-19. It hurts the health of people as well as the global economy, education, and social life. The most significant challenge in containing the rapid spread of the disease is identifying positive COVID-19 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 essential 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 utilised pre-trained CNN models, including Xception, Inception, ResNet-50, ResNet-50V2, DenseNet-121, and MobileNetV2, to refine the COVID-19 classification analytics. In this paper, we investigate COVID-19 detection methods that utilise chest X-rays. According to the findings of our research, the pre-trained CNN Model that utilises MobileNetV2 performs better than other CNN techniques in terms of both solution size and speed. Our method may be of use to researchers fine-tuning the CNN model for efficient COVID-19 screening.

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

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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 Organisation (WHO), the coronavirus belongs to a broad group of viruses that encompass 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 COVID-19 strain of the coronavirus, which originated in Wuhan, China, in December 2019, commenced its outbreak. 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 (SARS) coronaviruses. Coronavirus infection symptoms include fluid buildup in the lungs, kidney disease, and respiratory issues, including pneumonia. Coronaviruses are particularly dangerous due to their serial interval and reproduction rate [2].

These viruses can generate epidemics, such as those that caused MERS and SARS in the past 20 years, as they have 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 deaths. 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 coronaviruses, 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 essential to note that in some instances, 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 μm 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 countries most affected by COVID-19, in terms of infection cases and fatalities, are shown.

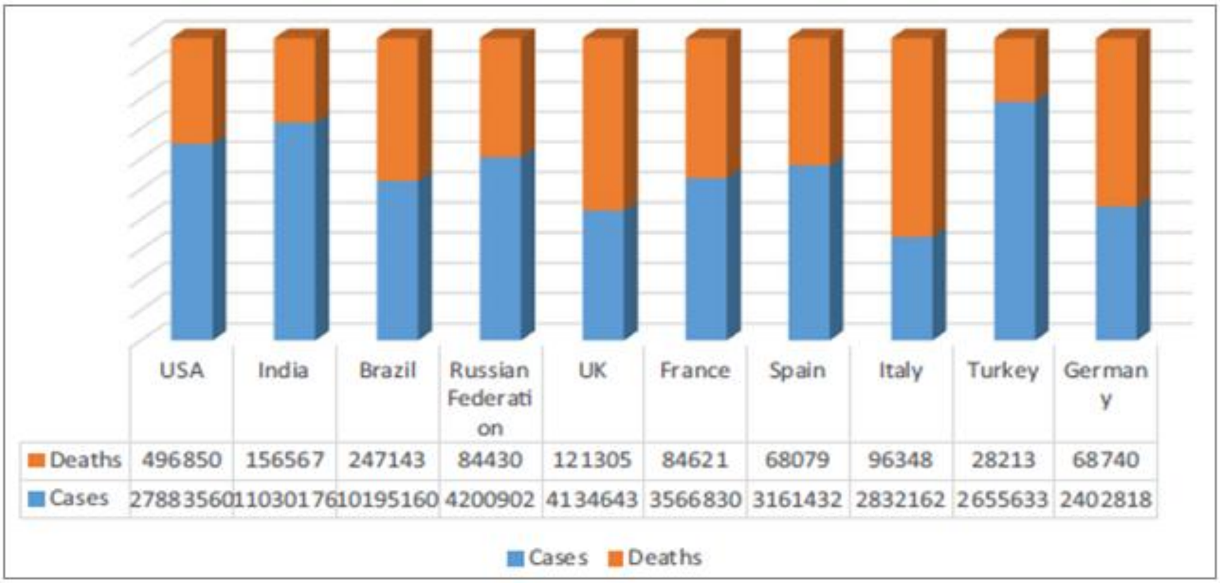

Figure 1. The top ten countries' statistical data about the number of individuals who have been infected and the number of fatalities

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 address the large number of suspected cases in a timely manner. 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]. 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, all methodologies must 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. Many 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 is 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 demonstrated 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 detecting COVID-19 infections through the use of radiological modalities, including X-rays and computed tomography scans, to facilitate clinicians' analysis of the COVID-19 disease and expedite the implementation of preventive and control measures.

CT scans are used in imaging. Ground-Glass Opacities (GGO) are known to be abnormalities that can be seen in COVID-19-infected persons' 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 analyse medical images, such as chest X-rays (CXR) and CT scans, to provide rapid diagnostic information by identifying potential patterns that may lead to the automated detection 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 aid in categorising 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, even though it is thought to be the most difficult plain film to read correctly [18]. For the care of patients in critical condition and to aid in the detection of COVID-19 clustering events, accurate interpretation is essential.

Since CT is a non-invasive imaging technique, it can reveal specific lung symptoms associated with COVID-19 [15, 16]. CT is a valuable tool for the early identification of COVID-19, although it may reveal imaging characteristics that make it challenging to distinguish COVID-19 from

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other kinds of pneumonia. Compared to X-ray imaging, CT imaging takes significantly longer and requires more intricate sanitisation processes between patients. Furthermore, timely viral pneumonia screening may be challenging due to the limited availability 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 diagnose a variety of body ailments automatically [22,23]. The use of deep learning as a feature extractor is employed to enhance 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 pictures. 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), a subfield of machine learning (ML), is used to extract features from images and categorise them. It is motivated by an understanding of how the human brain functions. Being able to learn from unlabeled data, or unsupervised learning, is a key strength of DL. 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 detecting various medical conditions, including 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 favourable ability to distinguish 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 network (CNN)-based deep learning models for COVID-19 detection employ this architecture. These include MobileNet, ShuffleNet, ResNet, AlexNet, GoogleNet, Inception, Xception, VGGNet, 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 this research, the produced systems have demonstrated promising performance; however, further advancements in medical image databases and the development of optimal deep learning algorithms are still required to reduce computing costs and address the issue of sparse data. Accuracy, sensitivity, specificity, precision, F1-score, and other metrics are commonly used to evaluate 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 some instances, 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.

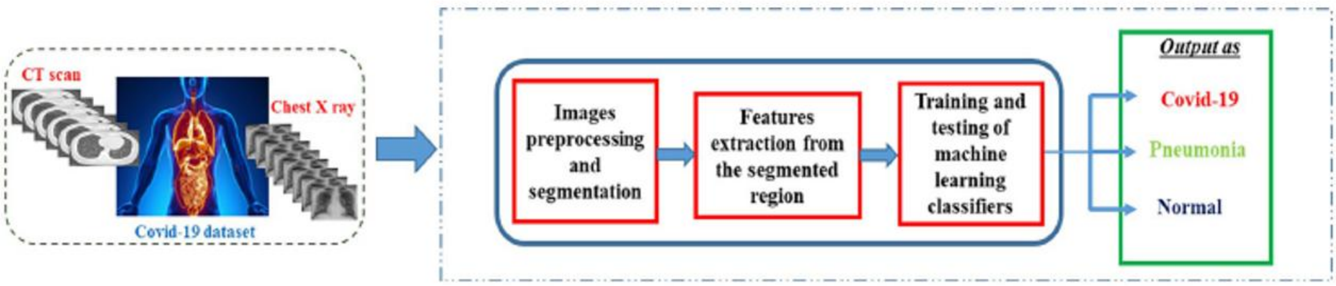

Figure 2. Machine learning-based COVID-19 detection/classification.

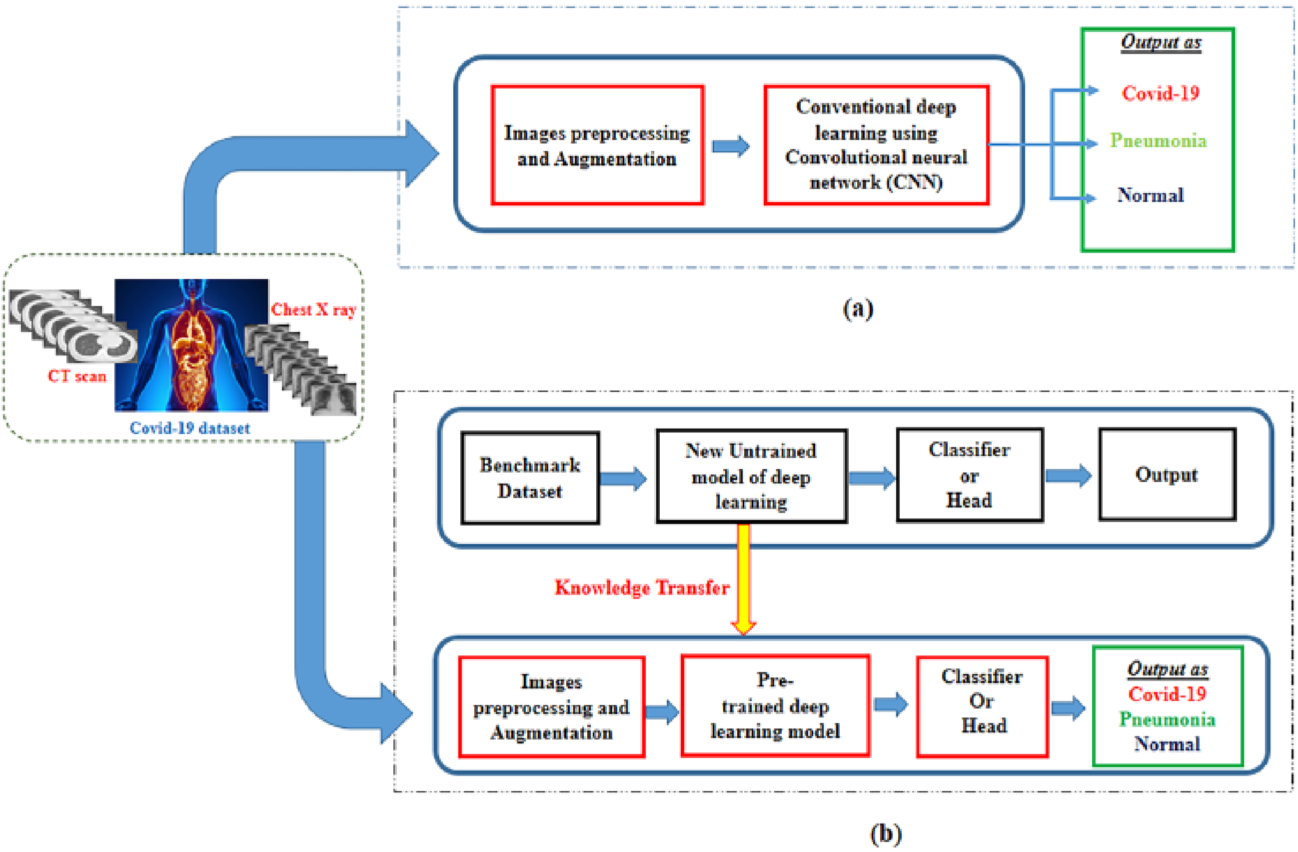

Figure 3. (a) General convolutional neural network-based COVID-19 detection or classification method. (b) Deep transfer learning-based COVID-19 detection or classification method.

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 dataset includes 1,252 CT images of the infected type and 1,230 CT images of the non-infected type.

2.2. Image pre-processing

Two processes are implemented for pre-processing: normalisation and Data Augmentation. The process of normalising the data is an important step typically implemented in CNN designs to maintain stable numerical values. 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, the pixel values of the input photos have been standardised to the range of 0–1 for this investigation. The photos used in the datasets considered were grayscale photographs, and rescaling was accomplished by multiplying the pixel values by 1/255. The data augmentation approach has seen widespread use. It has proven helpful in increasing the quantity of images by applying 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 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 functions in the last layer. The activation functions employed for training are Sigmoid and Softmax. Additionally, six different optimisers were used with each model, and their performance was evaluated for a fixed value of dropout and learning rate. The different optimisers 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

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 replace the final three layers with new ones tailored to the new dataset, allowing us 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

To evaluate the effectiveness of various algorithms used for classifying CXR images into two distinct categories, three key metrics are calculated: 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

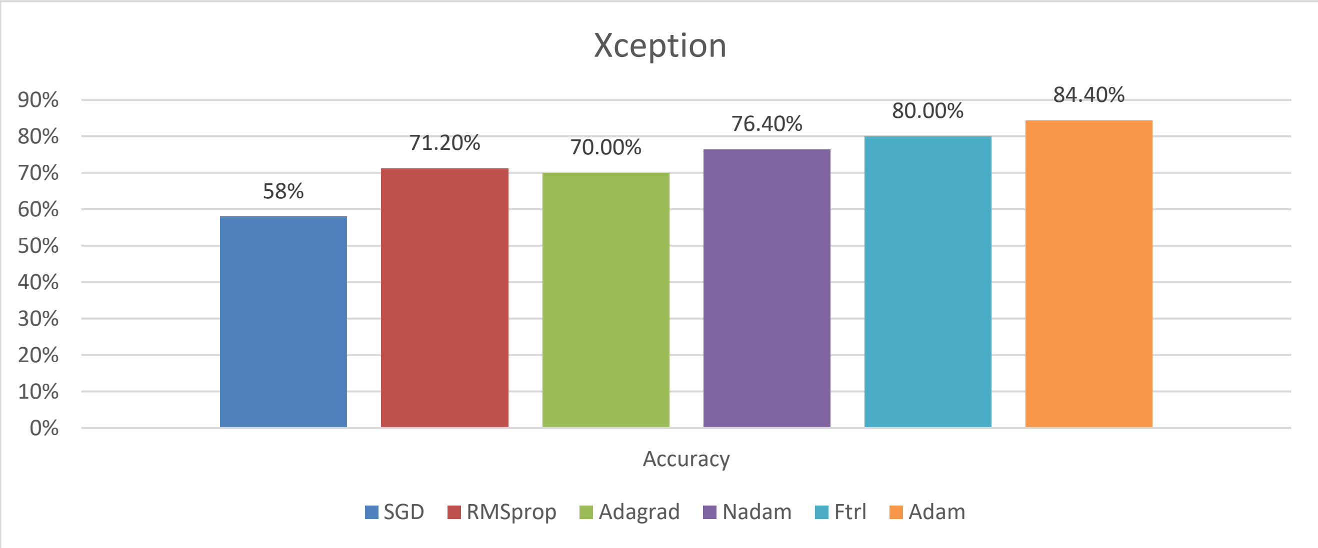

Figure 5. Comparison of the accuracy of the Xception model with different optimizer and Softmax activation function.

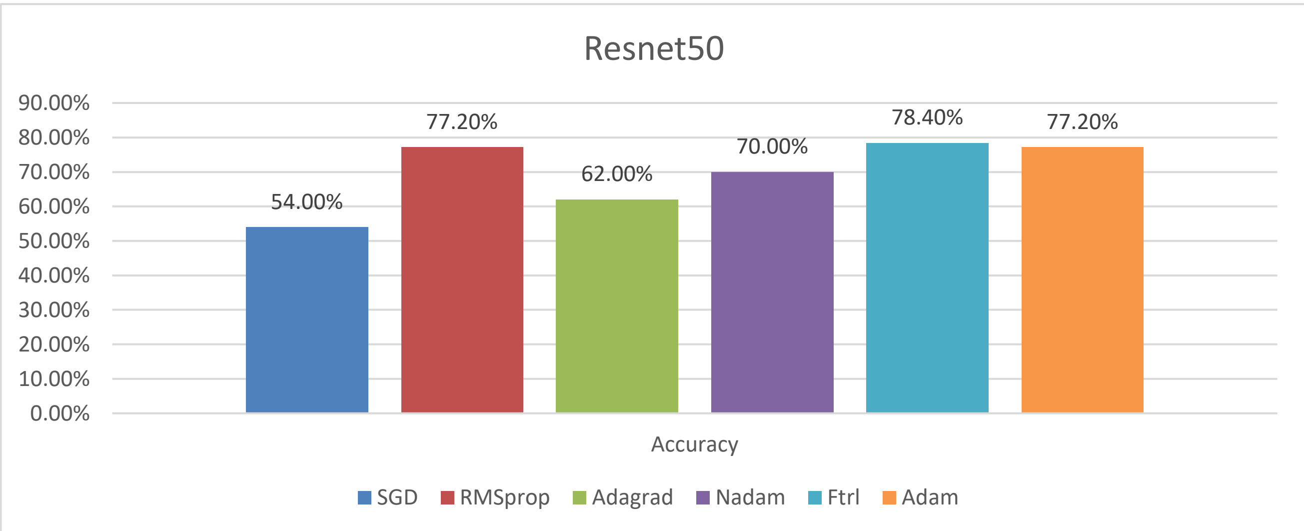

Figure 6. Comparison of the accuracy of the Resnet50 model with different optimizer and Softmax activation function

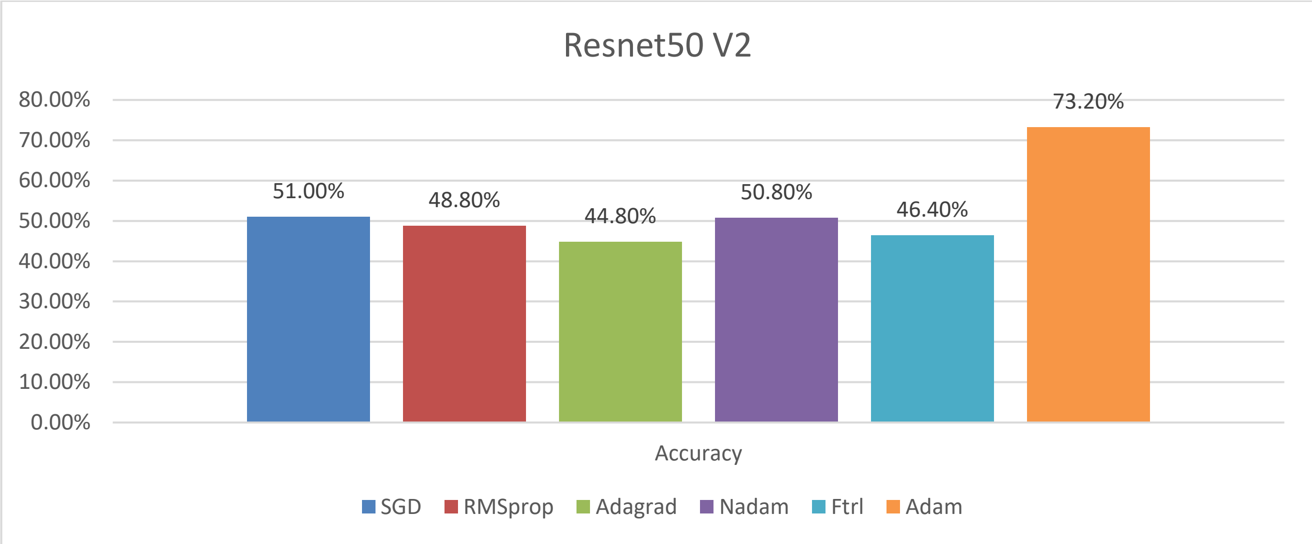

Figure 7. Comparison of the accuracy of the Resnet50 V2 model with different optimizer and Softmax activation function

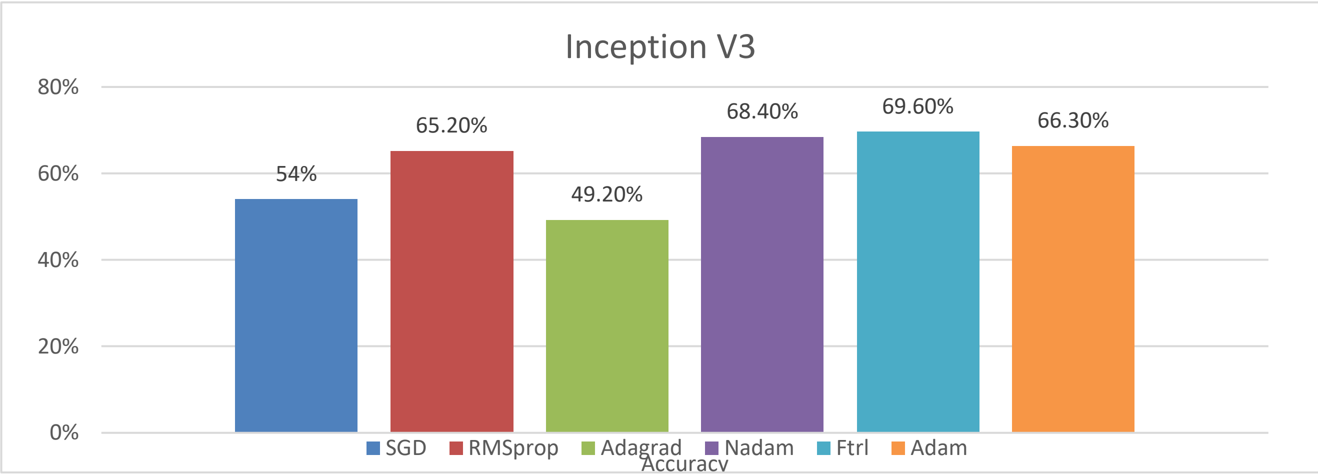

Figure 8. Comparison of the accuracy of the Inception V3 model with different optimizer and Softmax activation function

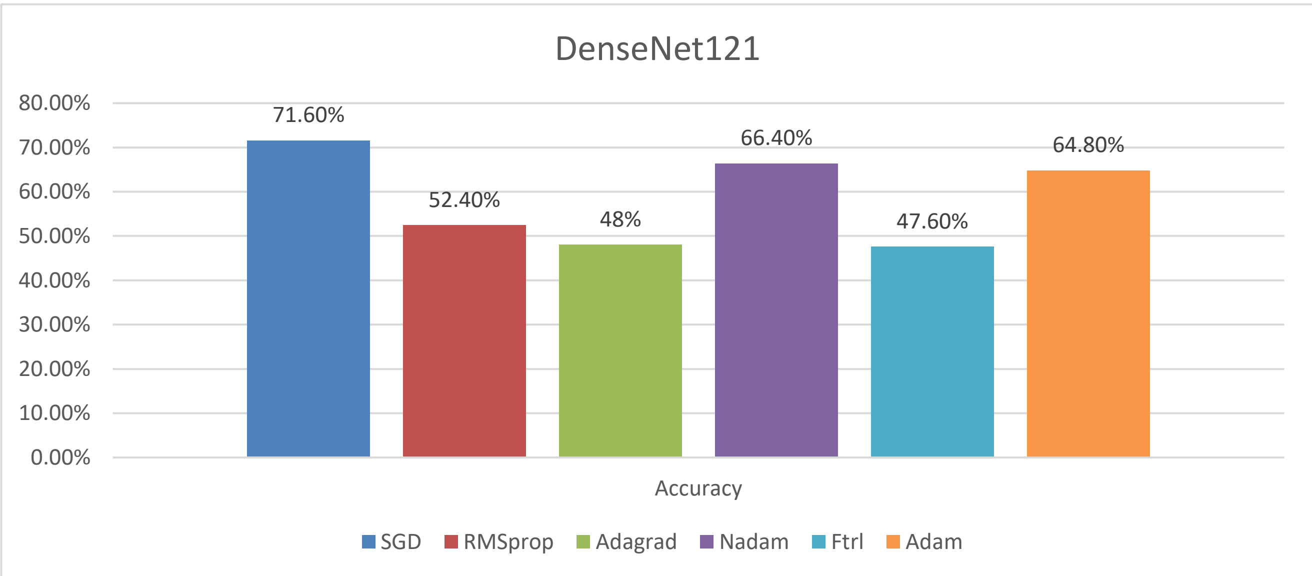

Figure 9. Comparison of the accuracy of the DenseNet121 model with different optimizer and Softmax activation function

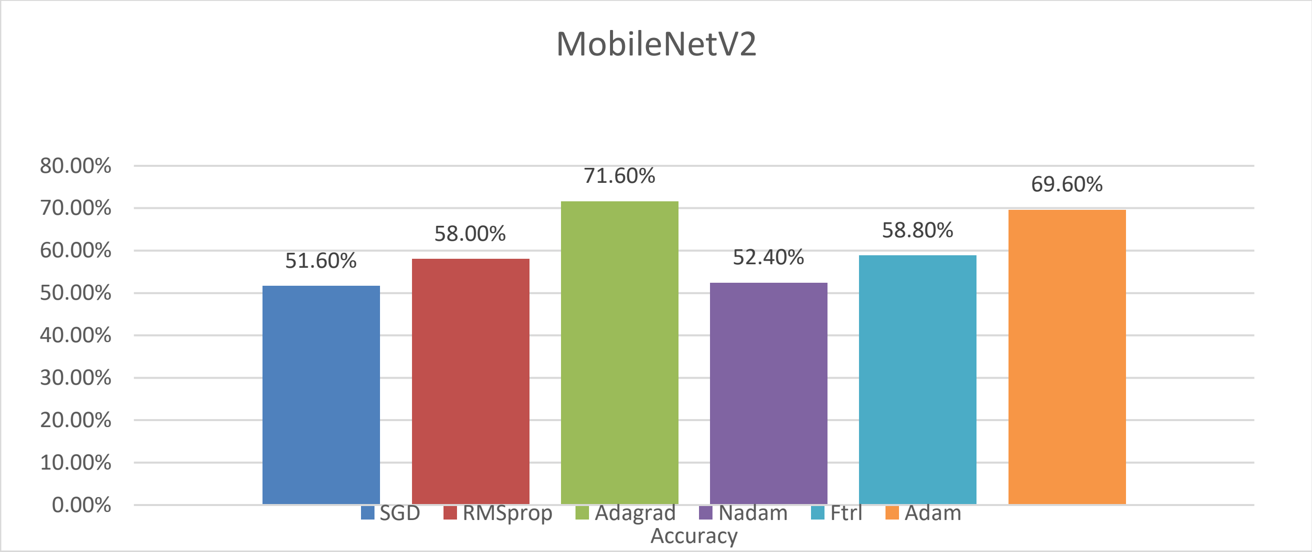

Figure 10. Comparison of the accuracy of the MobileNetV2 model with different optimizer and Softmax activation function

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

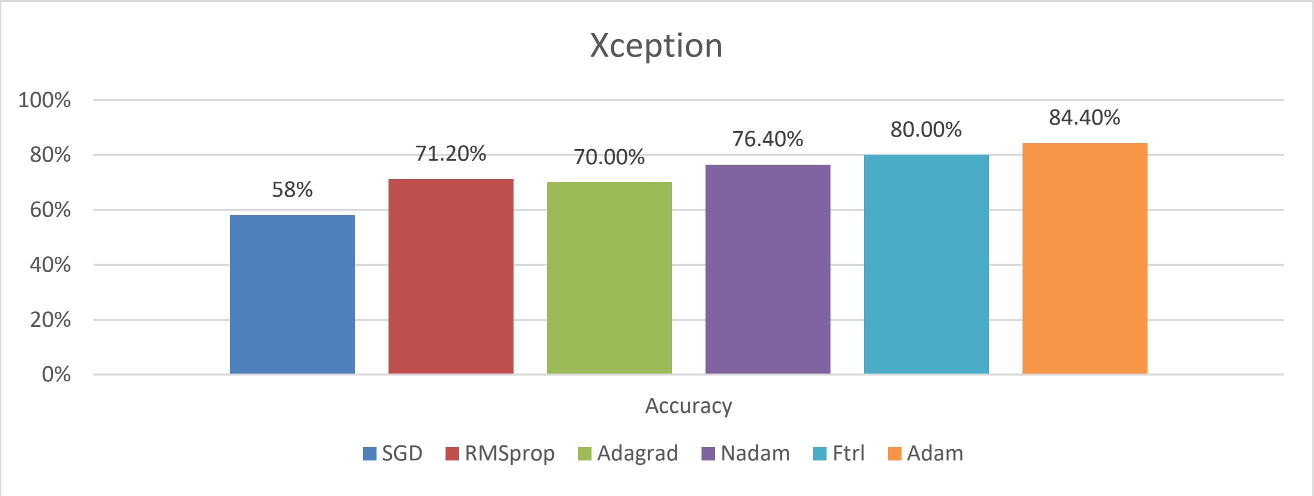

Figure 11. Comparison of the accuracy of the Xception model with different optimizer and the Sigmoid activation function.

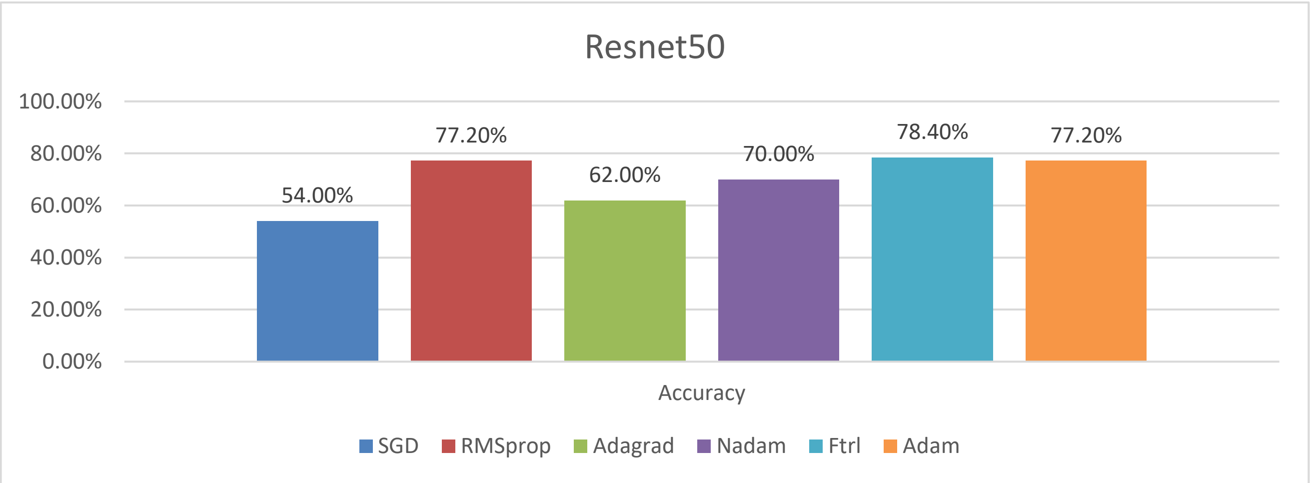

Figure 12. Comparison of the accuracy of the Resnet50 model with different optimizer and the Sigmoid activation function.

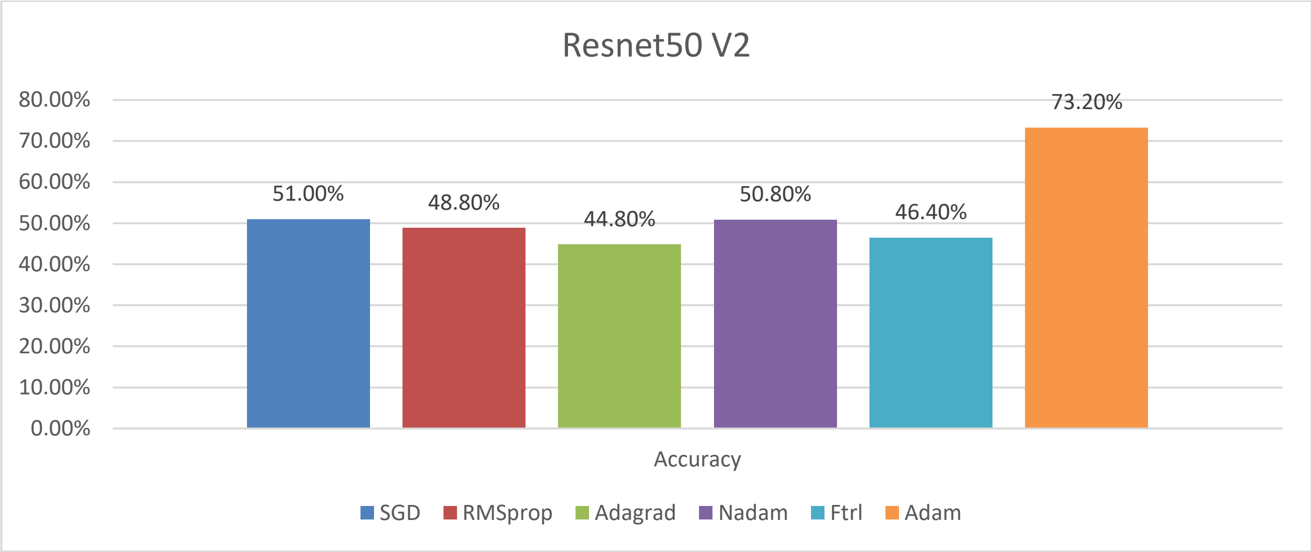

Figure 13. Comparison of the accuracy of the Resnet50 V2 model with different optimizer and the Sigmoid activation function.

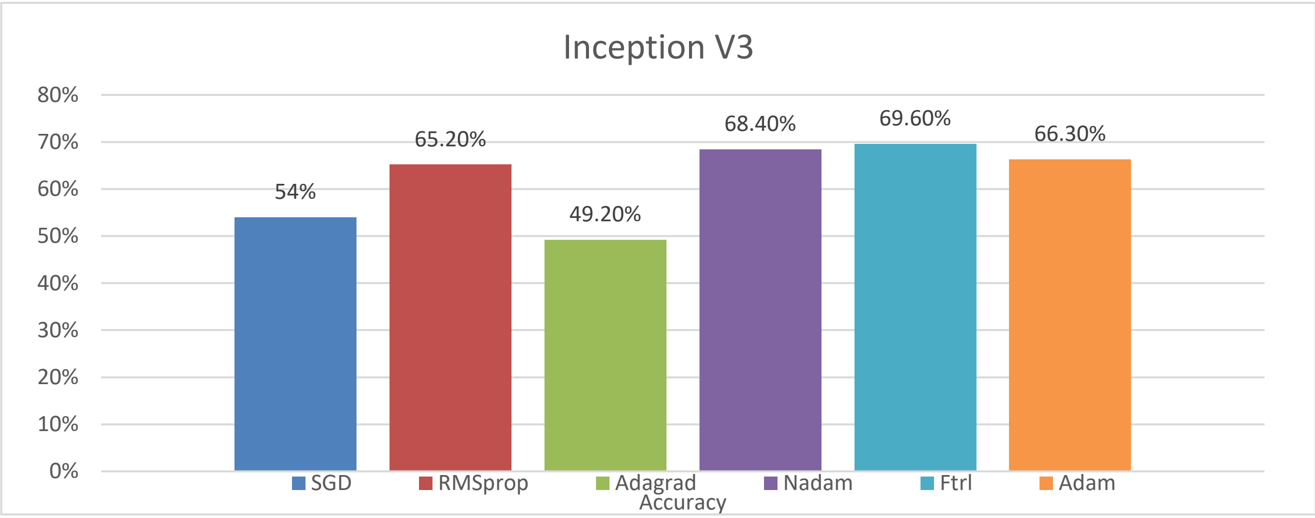

Figure 14. Comparison of the accuracy of the Inception V3 model with different optimizer and the Sigmoid activation function.

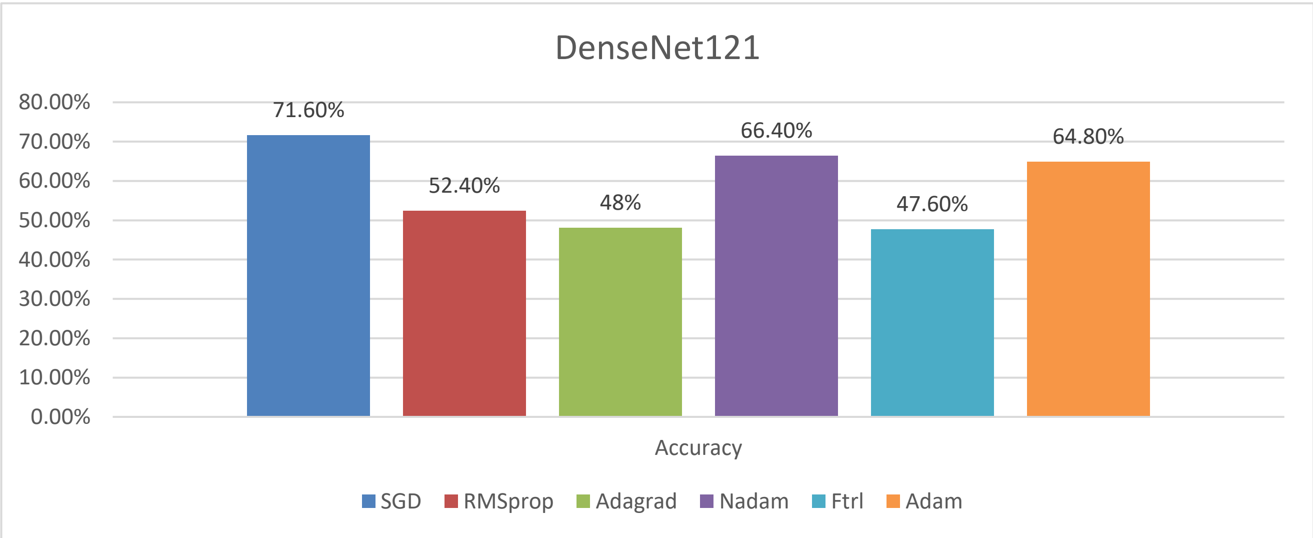

Figure 15. Comparison of the accuracy of the DenseNet121 model with different optimizer and the Sigmoid activation function.

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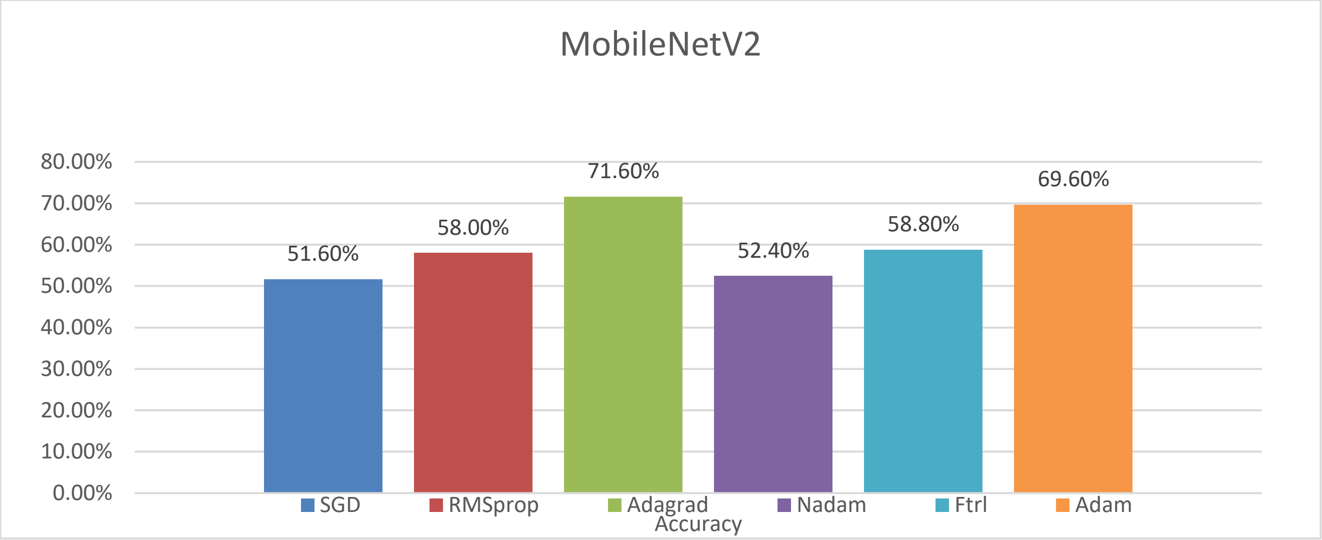

Figure 16. Comparison of the accuracy of the MobileNetV2 model with different optimizer and the Sigmoid activation function.

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

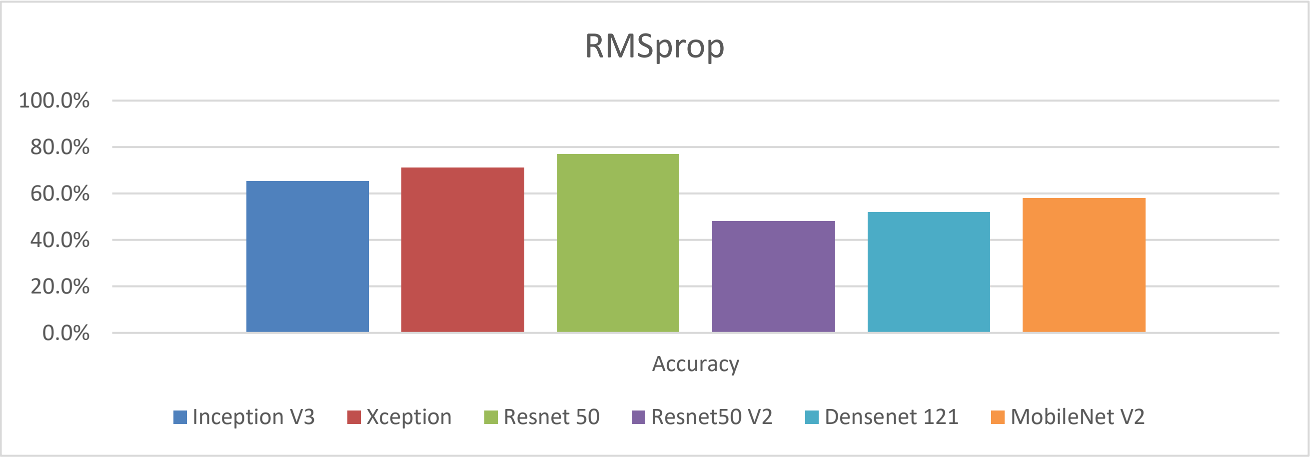

Figure 17. Comparison of accuracy for the RMSprop optimiser with various models using the Softmax activation function.

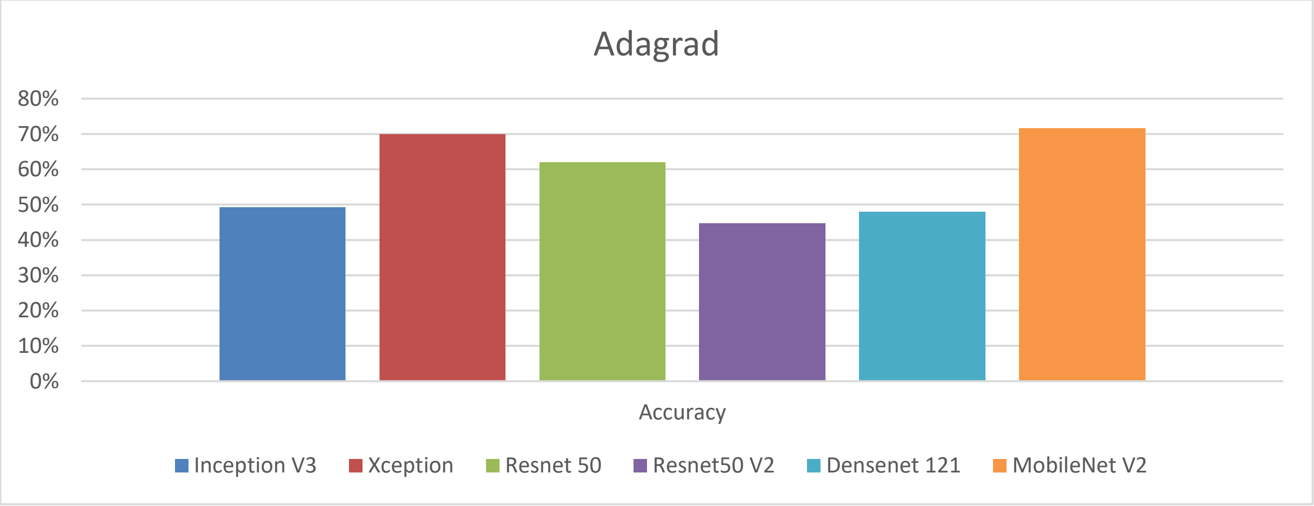

Figure 18. Comparison of accuracy for the Adagrad optimiser with various models using the Softmax activation function.

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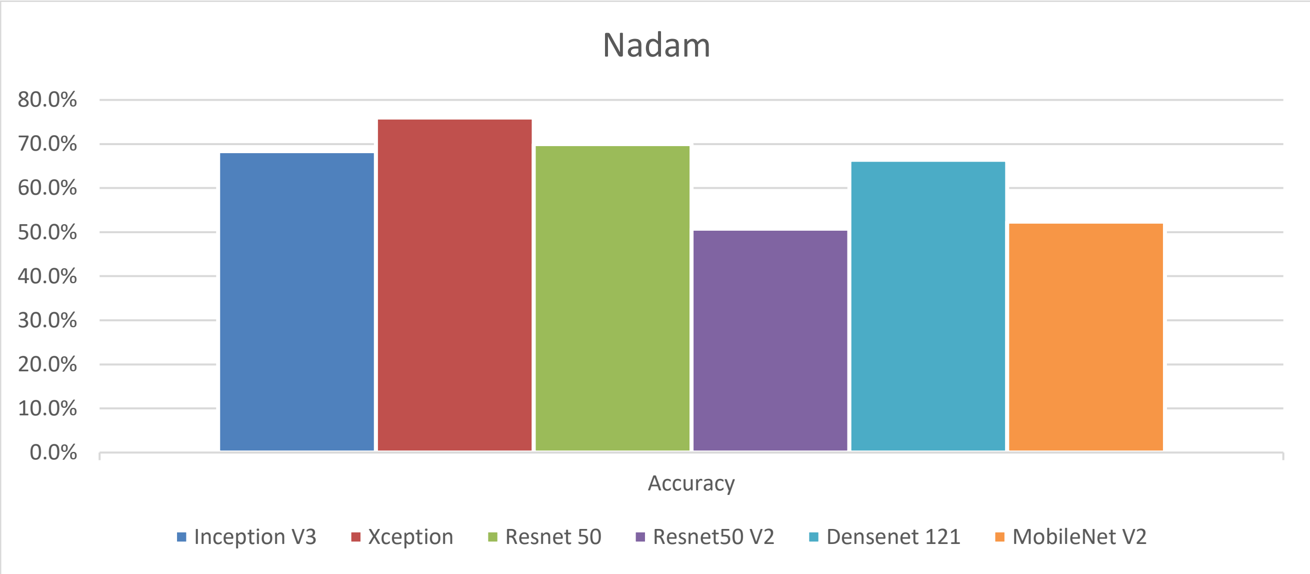

Figure 19. Comparison of accuracy for the Nadam optimiser on various models with the Softmax activation function.

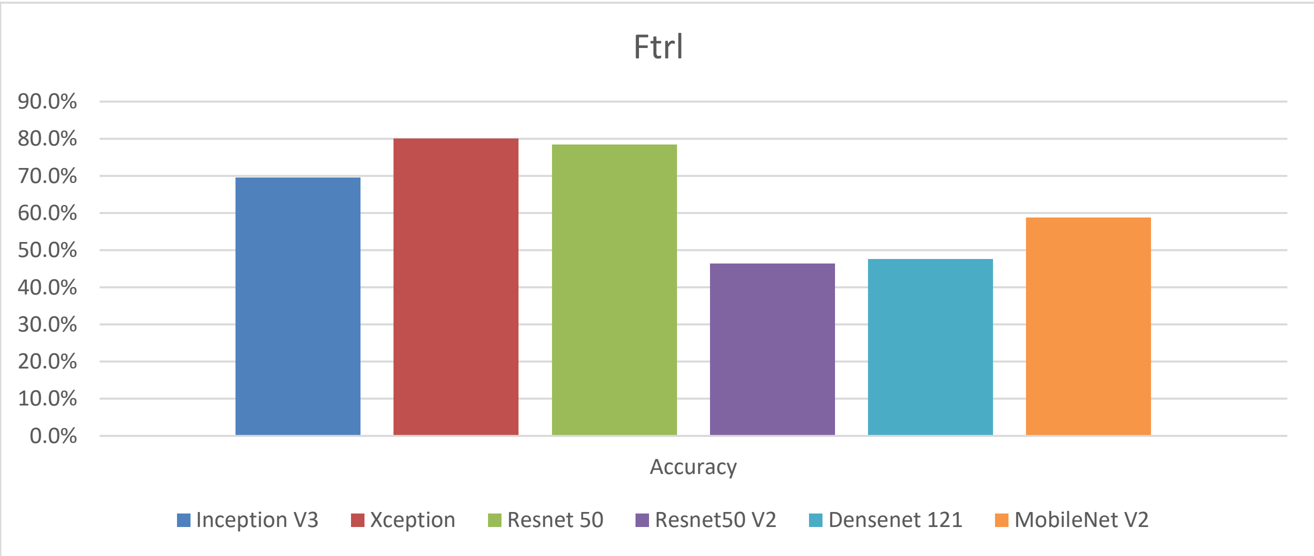

Figure 20. Comparison of accuracy for the FTRL optimiser with various models using the Softmax activation function.

Figure 21. Comparison of accuracy for the Adam optimiser with various models using the Softmax activation function.

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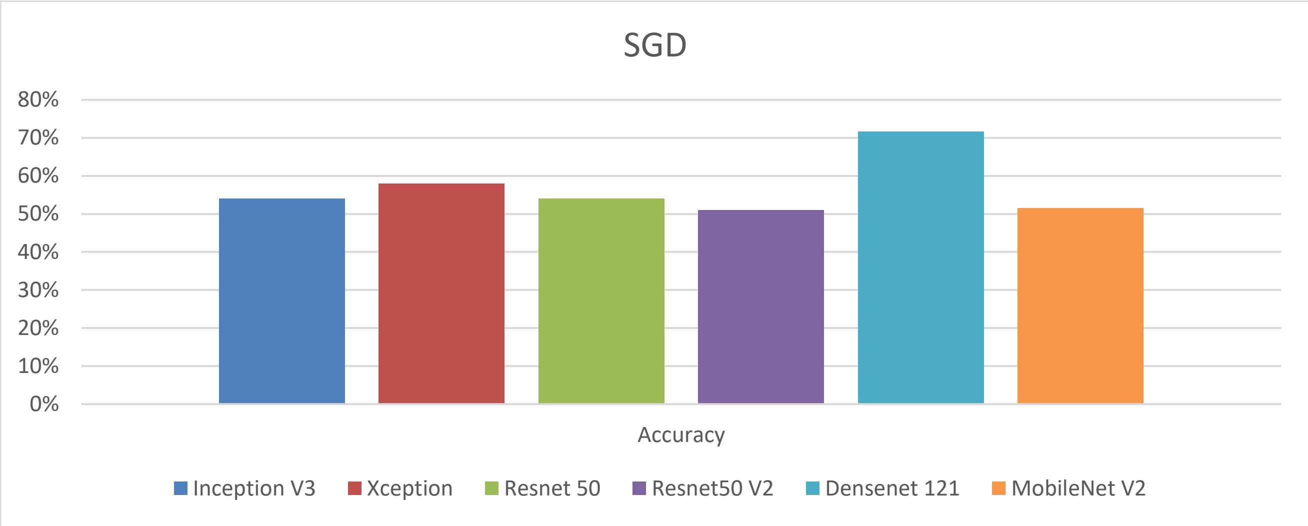

Figure 22. Comparison of accuracy for the SGD optimiser with various models using the Softmax activation function.

Comparison of various optimisers for different models for fixed learning rate = 0.0001, Epoch =5, Dropout = .5, Activation = Sigmoid.

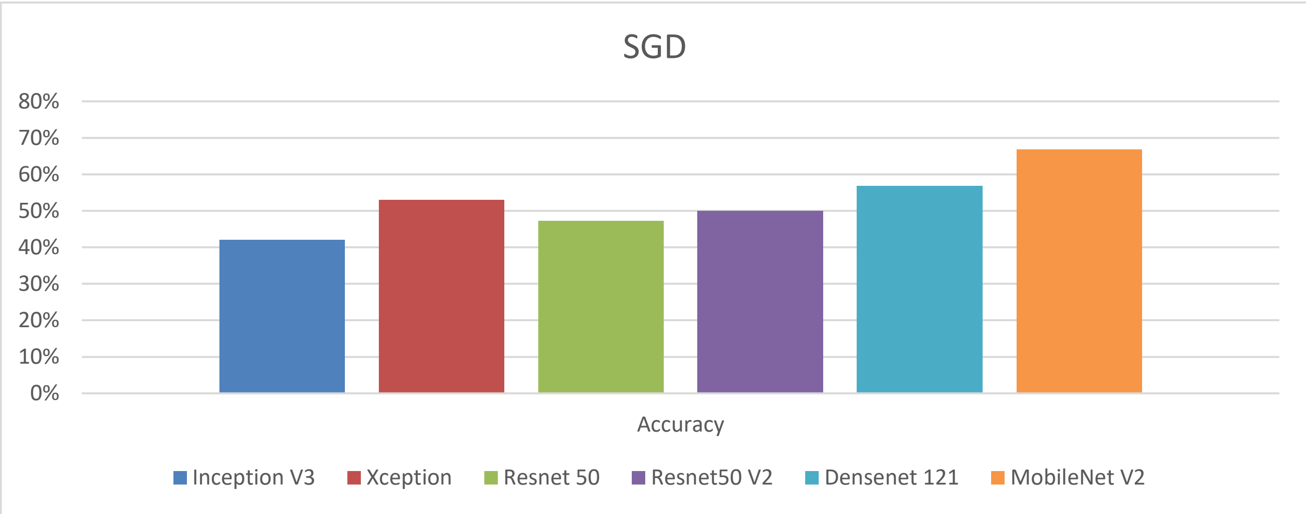

Figure 23. Comparison of accuracy for SGD optimizer for various model with Sigmoid activation function.

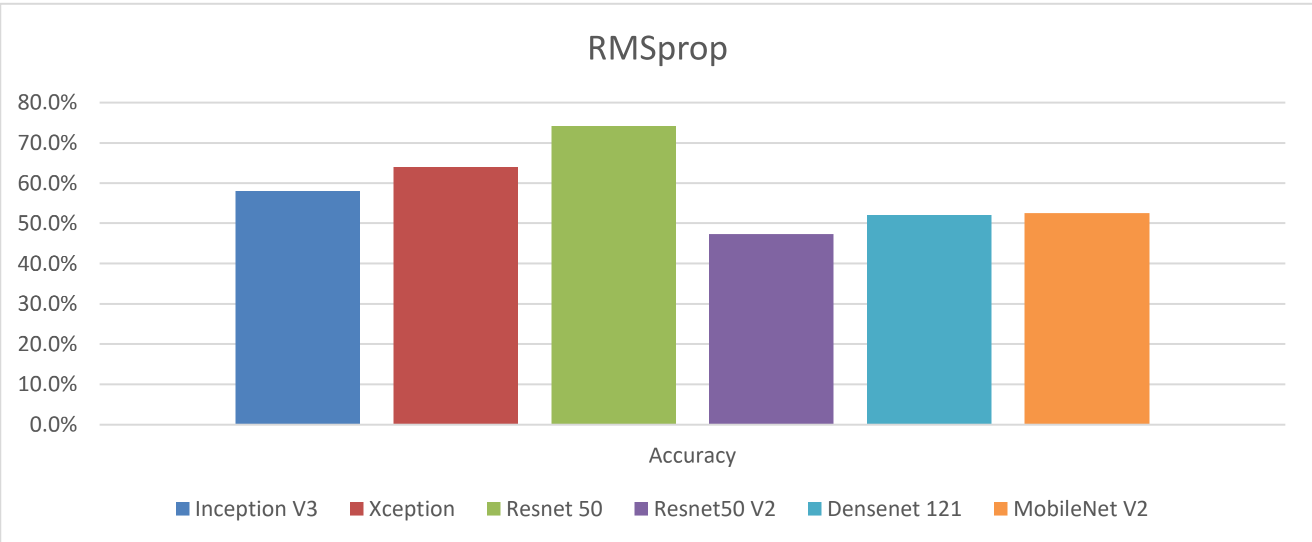

Figure 24. Comparison of accuracy for the RMSprop optimiser with various models using the Sigmoid activation function.

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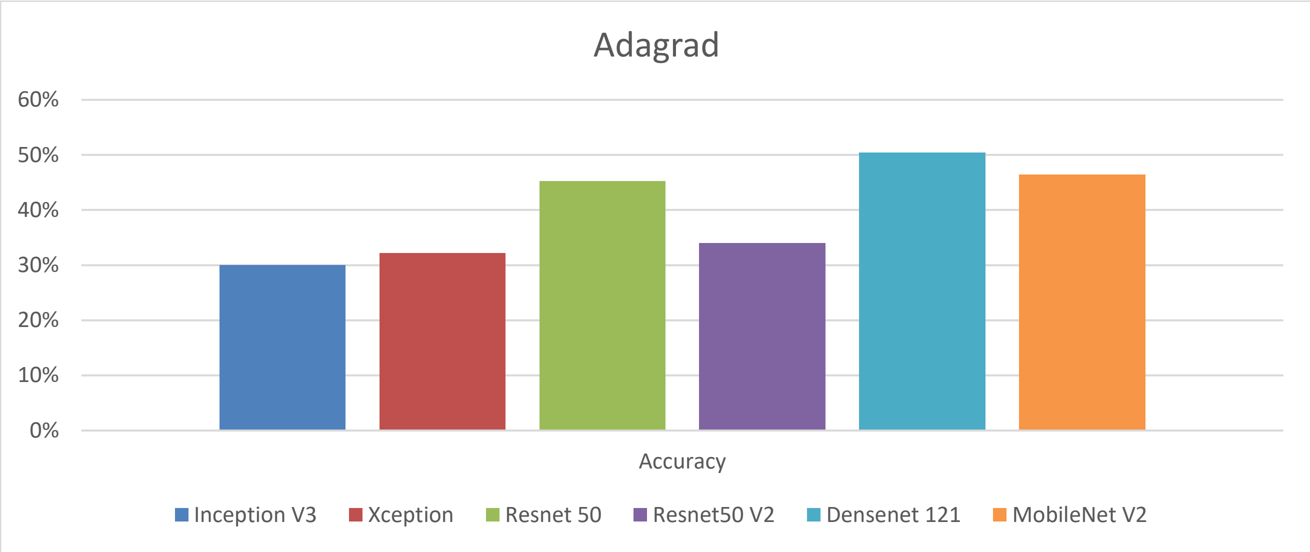

Figure 25. Comparison of accuracy for the Adagrad optimiser with various models using the Sigmoid activation function.

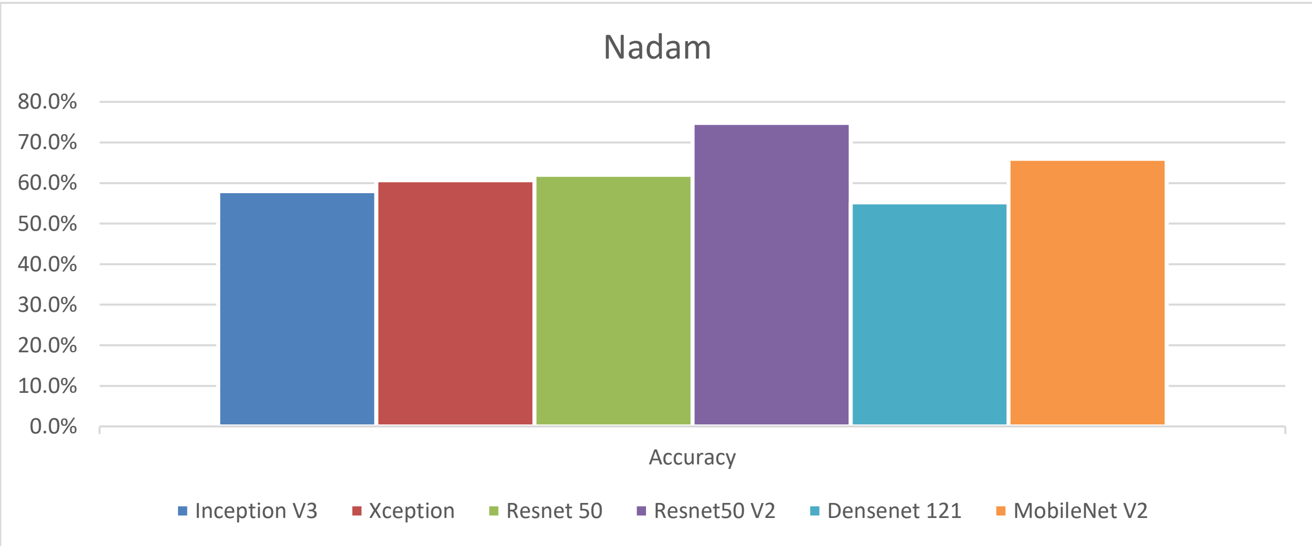

Figure 24. Comparison of accuracy for the Nadam optimiser on various models with the Sigmoid activation function.

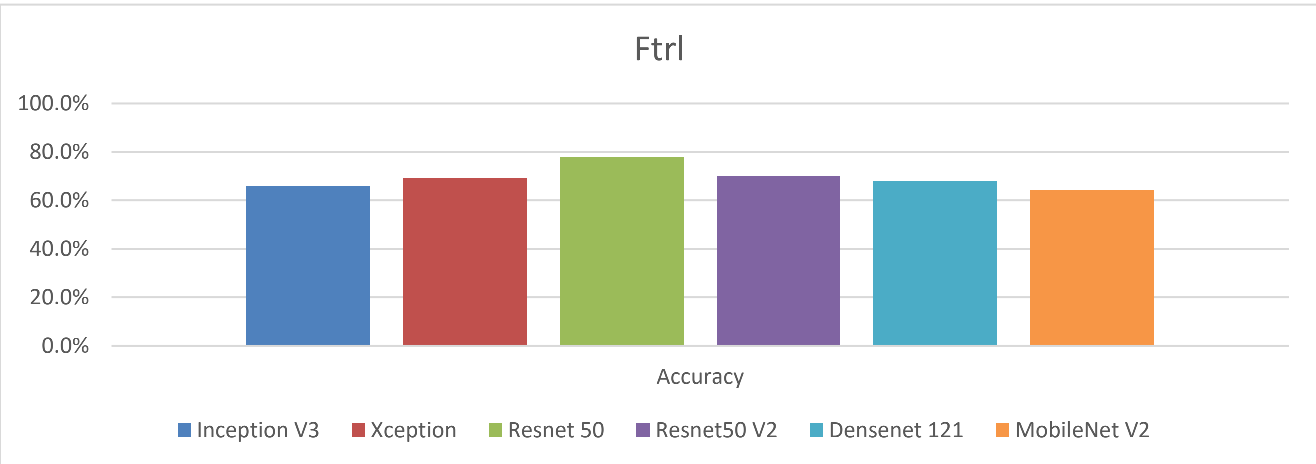

Figure 24. Comparison of accuracy for the FTRL optimiser with various models using the Sigmoid activation function.

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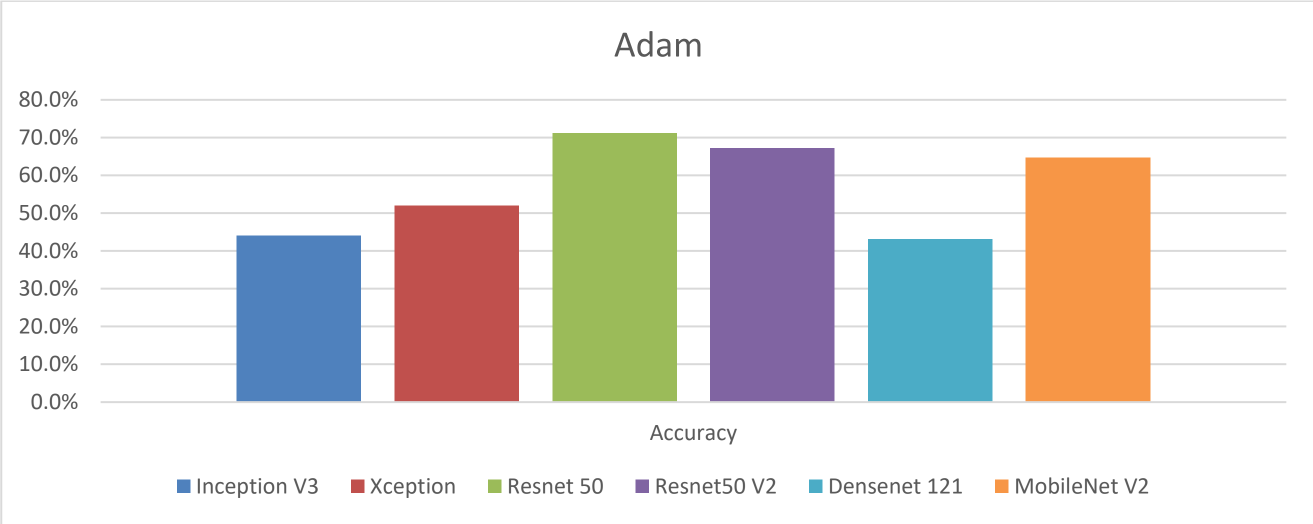
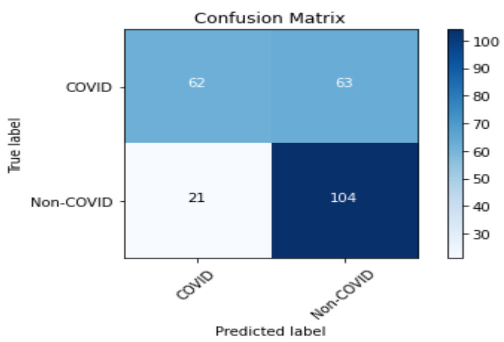
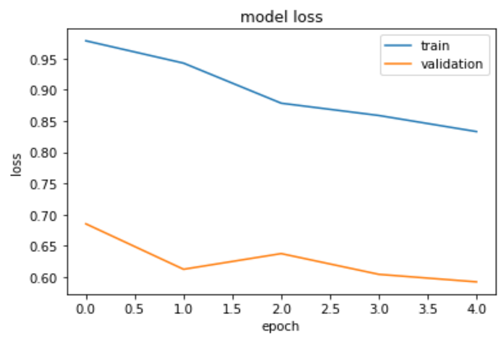
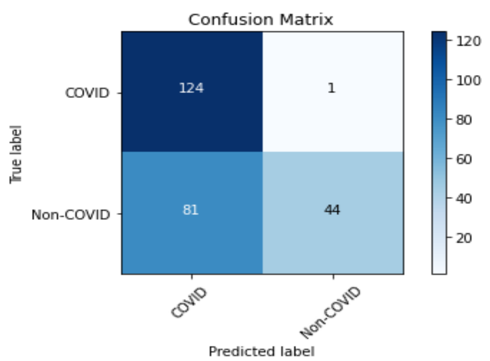
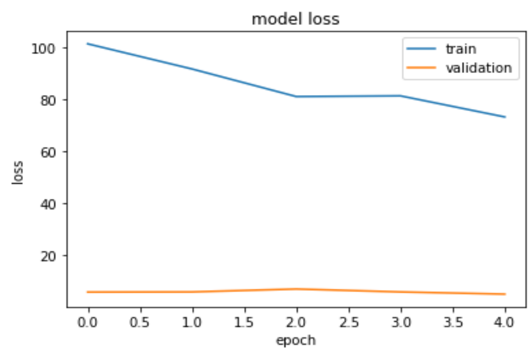
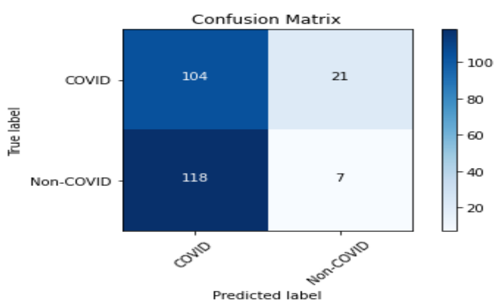
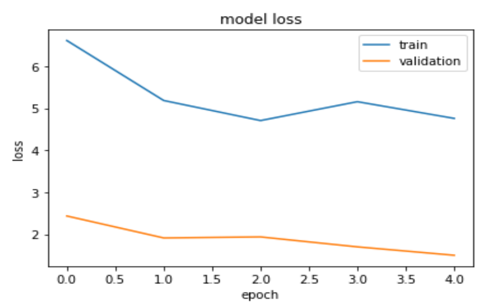


Figure 25. Comparison of accuracy for the Adam optimiser with various models using the Sigmoid activation function.

The confusion matrices for the six models using the ADAM optimiser are given below.

Model	Confusion Matrix	Loss Curve
Mobilenet V2		
Resnet V2		
Densenet		

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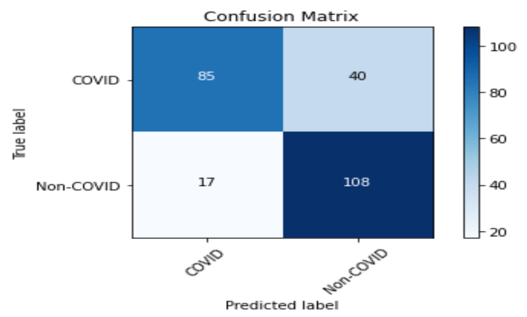
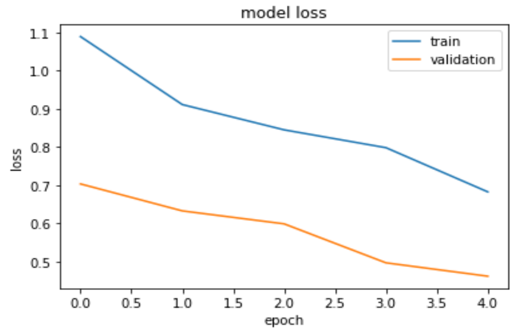
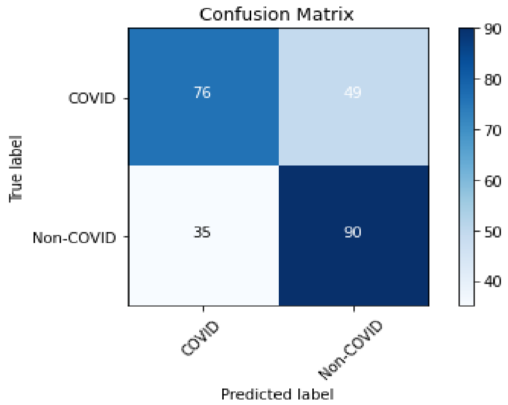
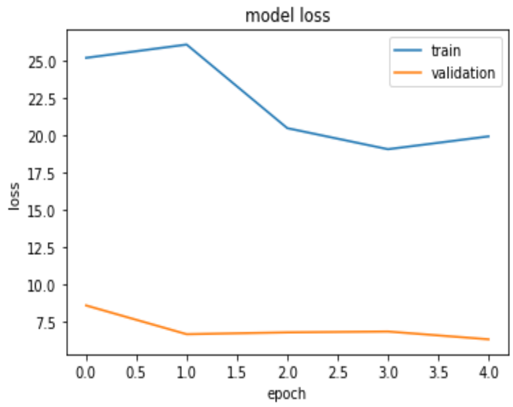
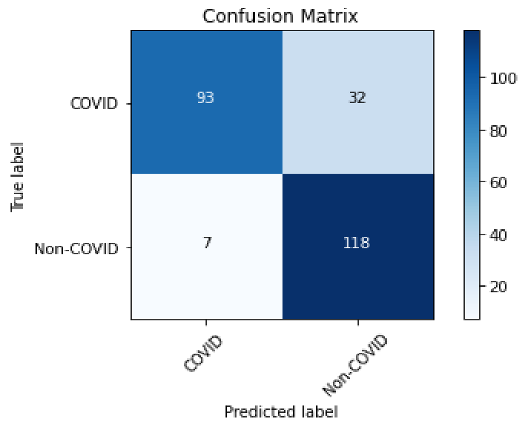
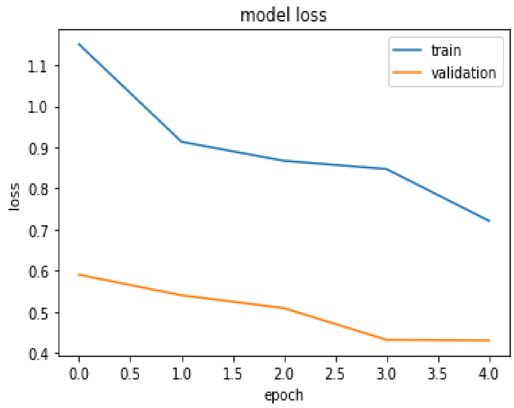
Resent 50		
Inception V3		
Xception		

IV. CONCLUSION AND FUTURE WORK

This paper presents a comparative study of six deep learning models applied to 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 binary classification can be accelerated by employing transfer learning. MobileNetV2 shows comparatively better performance compared to others, considering its size, and hence provides faster results. In our future work, we will address the challenge of generalising the proposed model to a broader range of practical scenarios, thereby facilitating the diagnosis of more disease types from CXR and CT images.

DECLARATION

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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 or consent to participate, as it presents 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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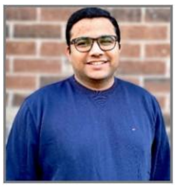

Viral Thakar is a highly skilled Machine Learning Research Engineer with expertise in computer vision, natural language processing, and IoT. He has a strong background in both research and applied engineering, with a focus on unsupervised domain adaptation, self-supervised learning, structured and unstructured data, 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 areas also include 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.