iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** X **Month of publication:** October 2021

DOI: https://doi.org/10.22214/ijraset.2021.38692

A Review on Deep Learning Approaches for COVID-19 Detection in Chest X-Ray Images

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Abstract: COVID-19 also famously known as Coronavirus is one of the deadliest viruses found in the world, which has a high rate in both demise and spread. This has caused a severe pandemic in the world. The virus was first reported in Wuhan, China, registering causes like pneumonia. The first case was encountered on December 31, 2019. As of 20th October 2021, more than 242 million cases have been reported in more than 188 countries, and it has around 5 million deaths. COVID- 19 infected persons have pneumonia-like symptoms, and the infection damages the body's respiratory organs, making breathing difficult. The elemental clinical equipment as of now being employed for the analysis of COVID-19 is RT-PCR, which is costly, touchy, and requires specific clinical workforce. According to recent studies, chest X-ray scans include important information about the start of the infection, and this information may be examined so that diagnosis and treatment can begin sooner. This is where artificial intelligence meets the diagnostic capabilities of intimate clinicians. X-ray imaging is an effectively available apparatus that can be an astounding option in the COVID-19 diagnosis. The architecture usually used are VGG16, ResNet50, DenseNet121, Xception, ResNet18, etc. This deep learning based COVID detection system can be installed in hospitals for early diagnosis, or it can be used as a second opinion.
Keywords: COVID-19, Deep Learning, CNN, CT-Image, Transfer Learning, VGG, ResNet, DenseNet.

I. INTRODUCTION

Coronavirus disease (COVID-19), a disease that is extremely infectious, erupted and was badly spread throughout the world. It was declared as a pandemic by the World Health Organization (WHO) on 11 March 2020 considering the scale of its spread throughout the world. As of August 2021, around 0.22 billion people have been affected with almost 4.5 million deaths in the whole world. Since it has been categorized as a global health crisis, governments of various countries have foisted national lockdown, border and flight restrictions and social distancing.

Now, COVID-19 is a disease that is caused by Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) with a fatality rate of almost 2.2%. People affected by the COVID-19 will mostly experience mild to moderate respiratory illness and some people may even get affected by deadly pneumonia. It has been observed that old people that are already having any chronic respiratory diseases or are diabetic patients are most likely to develop a serious illness. Since the eruption of COVID-19, scientists, machine learning specialists and artificial intelligence specialists have been proposing methods and strategies for foreseeing the infection spread by the disease.

Through various discoveries, one method that has the potential to decide whether a person is infected with COVID-19 or maybe pneumonia is analyzing the X-ray images of the chest. It is manually a very hard or time taking task to process the chest X-ray images of a large number of patients, thus arises the need for an automated solution like a device or a system which can identify the disease with an acceptance level of accuracy. There have been several recent works on various techniques but the transfer learning approach of Deep Learning in detecting COVID-19 chest X-ray images from a comparatively small dataset produced favorable outcomes.

We will be developing a deep learning-based system that will have a good accuracy to automatically identify the disease through X-ray images. We will also be doing a detailed study of different methods and architecture used previously for detecting COVID-19. Datasets of X-ray images of the chest from different sources will be used to create a strong and effective classification model. The diagnostic model that will be developed will have effective results for a variety of X-ray images. The proposed model will help in earlier diagnosis and would help decrease the pervasiveness of disease.

II. LITERATURE REVIEW

TABLE I
Comparison between various techniques used by different authors.

Title of Paper	Author	Techniques	Dataset	Findings
A deep learning-based COVID-19 automatic diagnostic framework using chest X-ray images	J. Rakesh Chandra *et al.*, 2021 [1]	CNN	Consists of 6085 CXR images collected from open-source repository.	The performance of the convolutional neural network after 5-fold cross-validation was giving the average accuracy of 99.61% for binary classification (is or is not COVID-19 disease) using 1132 CXR image samples and average accuracy of 94.79% for multi-class classification of COVID-19, normal (healthy), bacterial pneumonia, and viral pneumonia using 1063 CXR image samples.
Deep learning approaches for COVID-19 detection based on chest X-ray images	I. Aras M. *et al.*, 2021 [2]	Deep Transfer Learning, SVM and CNN.	The input chest X-ray images are initially resized to 224 × 224 pixels for compatibility with the CNN models.	ResNet50 model produced the highest average accuracy score, with an average accuracy score of 92.6%, whilst the VGG16 model produced an average accuracy score of 89.8% as the second-best score.
Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning	M. Shervin *et al.*, 2020 [3]	Deep Transfer Learning, SqueezeNet and DenseNet.	Chest X-ray images from two datasets formed the COVID-Xray- 5k dataset that contains 2084 training and 3100 test images.	For a sensitivity rate of 98%, models achieved a specificity rate of around 90% on average.
COVID-19: Automatic detection from X-ray images by utilizing deep learning methods	N. Bhawna *et al.*, 2021 [4]	VGG16, DenseNet121, Xception, NASNet and EfficientNet.	The dataset includes chest X-ray images collected from various private hospitals from Maharashtra and Indore regions from India. The X-ray images are collected from posteroanterior (PA) frontal chest view from the patients.	The accuracy achieved by the proposed method are 79.01% for VGG16, 89.96% for DenseNet121, 88.03% for Xception, 85.03% for NASNet and 93.48% for EfficientNet.
Machine learning for coronavirus covid-19 detection from chest x-rays	B. Luca *et al.*, 2020 [5]	PACS	The dataset includes 63 images of COVID-19, 6 of Streptococcus, 11 of SARS, 4 of ARDS and 2 of Pneumocystis	The accuracy achieved by the proposed method are 79.01% for VGG16, 89.96% for DenseNet121, 88.03% for Xception, 85.03% for NASNet and 93.48% for EfficientNet.

Automated Detection of Covid-19 from Chest X-ray scans using an optimized CNN architecture	P. Sameena *et al.*, 2021 [6]	ResNet50, ECOC Classifier, Grey Wolf optimizer and WOA-BAT algorithm	The covid-19 images were obtained from the Italian Society of medical and interventional radiology, Joseph Paul Cohen and Morrison Covid-19 dataset and, various publications.	The optimization methodology adopted in reference is somewhat similar to the proposed design, however, the hyper parameter optimization methodology of our proposed design is unique. In contrast to the methodology reported in [9], the proposed design has resulted in improved performance for both datasets.
Comparing CT scan and chest X-ray imaging for COVID-19 diagnosis	P. Sameena *et al.*, 2021 [6]	InceptionV3, ResNet-18 and MobileNetV2	The images are collected from two datasets, HUST-19 for CT scan images, and the CXR images from the COVIDx dataset.	Precision was 97.5% for InceptionV3, 98.5% for ResNet-18 and 95.7% for MobileNetV2.
Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images, Computers in Biology and Medicine	Tawsifur Rahman *et al.*, 2021 [8]	U-Net models	COVQU dataset, which is comprised of 18,479 CXR images across 15,000 patient cases.	The U-Net model gave the accuracy of 98.21% and the one proposed by the authors gave accuracy of 98.63%.
Classification of COVID-19 chest X-Ray and CT images using a type of dynamic CNN modification method	Guangyu Jia *et al.*, 2021 [9]	MobileNet and modified MobileNet	The dataset contains 15184 X-ray images collected from various hospitals.	It was be noted that after using the modified MobileNet, the test accuracy reaches 99.6% which is higher than that of the original MobileNet by 0.8%.
Detection of Covid-19 Patients with Convolutional Neural Network Based Features on Multi-class X-ray Chest Images	Ali Narin, 2020 [10]	CNN, ResNet-50 and SVM	The data set consists of 219” Covid-19”, 1341” Normal” and 1345” Viral Pneumonia” X-ray chest images.	The success of Covid-19 patients detected with the SVM-Quadratic approach is higher than other approaches. At the same time, it is clearly seen that the SVM Quadratic approach gives higher results than other methods in determining healthy individuals, i.e., normal individuals. For Viral Pneumonia, the SVM-Quadratic approach yielded the highest results. The overall performance (ACC) results can also be detected with an accuracy of over 99%.

A Comparative Study of Deep Learning Networks for COVID-19 Recognition in Chest X-ray Images	Sabrina Nefoussi *et al.*, 2020 [11]	VGG, Inception, ResNet-50, Xception and MobileNet	There are 219 COVID-19 positive images, 1341 normal images, and 1345 viral pneumonia images.	Among all the eight models tested, we can assert that Xception model achieved the best results according to all the evaluation criteria.
COVID-19 detection through X-Ray chest images	Diego Hernandez *et al.*, 2020 [12]	ResNet-50 and VGG16	The datasets were retrieved from Italian Society of Medical and Interventional Radiology and ChexPert provided by university of Stanford	The ResNet-50 performed better than VGG16. It gave the accuracy of 0.9063 whereas VGG16 gave accuracy of 0.8229.
Can AI help in screening Viral and COVID-19 pneumonia?	Muhammad E. H. Chowdhury *et al*,.2020 [13]	SqueezeNet, MobileNetV2, ResNet-18, InceptionV3, ResNet101, DenseNet201 and CheXNet	The dataset was collected from Italian Society of Medical and Interventional Radiology, RSNA-Pneumonia-Detection-Challenge and GitHub	With image augmentation, ResNet18 and ChexNet gave the highest accuracy of 99.41%. Whereas without image augmentation DenseNet201 gave highest accuracy of 99.70%.
A Novel Approach of CT Images Feature Analysis and Prediction to Screen for Corona Virus Disease (COVID-19)	Ahmed Abdullah Farid et al., 2020 [14]	SVM, Naïve Bayes, JRIP and Random Forest	The CT images dataset has two classes of images both in training as well as the testing set containing a total of around ~51 images each segregated into the severity of Sars and coronavirus (online access Kaggle benchmark dataset,2020)	Naïve Bayes classifier gave the highest accuracy of 96.07% Post Composite Hybrid Feature Selection Model.

III.PREPROCESSING

Preprocessing the input images is one of the significant requirements in fostering a superior performing detection framework. The raw input images comprised of pointless text data like the name of the individual, age, name of the medical clinic where the scan was taken, and so on. This data might cause an issue in the training process. To avoid this, the images were cropped using Masked Region-based Convolutional Neural Networks. Masked R-CNN is a Convolutional Neural Network (CNN) and cutting edge as far as image segmentation. This variation of a Deep Neural Network distinguishes objects in an image and creates a great segmentation mask for each case. The images considered for the dataset are just of frontal view. Coronavirus X-rays are included in the dataset solely after getting it cross checked by a specialist radiologist to stay away from bogus scans to be included in the training set. The images are put away in RGB arrangement to get the most extreme data as could really be expected. A three-class classification is performed in this project.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue X Oct 2021- Available at www.ijraset.com

IV. METHODS

A. Convolutional Neural Network (CNN)

A convolutional neural network (CNN) is a form of neural network that is especially intended to analyze image input and is used in image recognition and processing. CNNs are image processing, artificial intelligence (AI) systems that utilise deep learning to do both generative and descriptive tasks, frequently including computer vision, such as image and video recognition, as well as recommender systems and natural language processing.

Like different sorts of artificial neural networks, a convolutional neural network has an info layer, a yield layer and different secret layers. A portion of these layers are convolutional, utilizing a numerical model to give results to progressive layers. This mimics a portion of the activities in the human visual cortex. CNNs are a key illustration of deep learning, where a more modern model pushes the development of artificial intelligence by offering frameworks that recreate various kinds of organic human mind action.

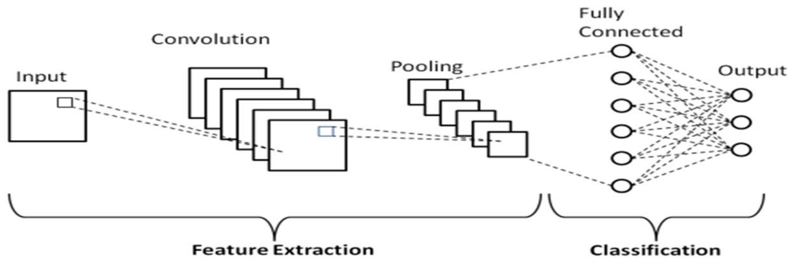

Fig. 1 Process Flow Displaying the CNN Architecture [25]

B. Deep Transfer Learning

Deep Transfer Learning is a deep learning method where a model developed in the first task is used as input to the second task. Given the vast compute and time resources required to develop neural network models on these problems, as well as the huge jumps in skill that they provide on related problems, it is a popular approach in deep learning where pre-trained models are used as the starting point on computer vision and natural language processing tasks.

In computer vision, for instance, neural networks typically attempt to identify edges in the previous layers, shapes in the center layer and some errand explicit elements in the later layers. In transfer learning, the early and center layers are utilized, and we just retrain the last layers. It helps influence the labeled data of the undertaking it was at first prepared on.

C. DenseNet121

DenseNet is a convolutional neural network in which each layer is connected to all other layers deeper in the network; for example, the first layer is connected to the second, third, fourth, and so on, while the second layer is connected to the third, fourth, fifth, and so on. DenseNet-121 has 120 Convolutions and 4 AvgPool. All layers for example those inside a similar dense block and progress layers, spread their weights over numerous data sources which permits deeper layers to utilize features extracted right off the bat. Since change layers outputs numerous excess features, the layers in the second and third dense block dole out minimal weights to the yield of the progress layers. Additionally, despite the fact that the weights of the whole dense block are utilized by the last layers, there still might be all the more significant level features created deeper into the model as there appeared to be a higher focus towards conclusive feature maps in tests.

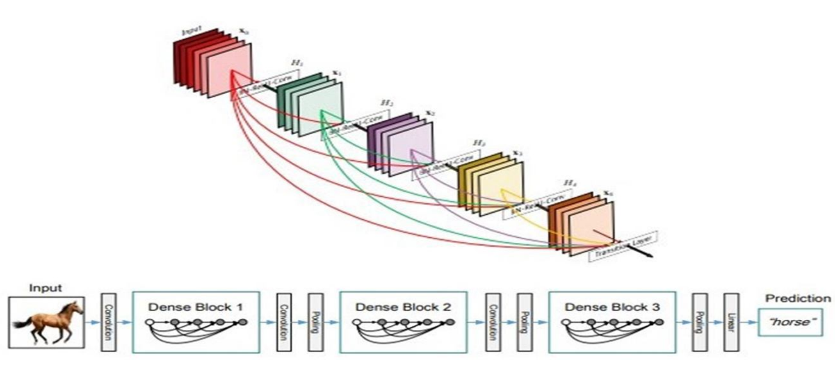

Fig. 2 Dense Net Layers [26]

D. VGG16

The VGG16 architecture is a convolutional neural network (CNN) that won the 2014 ILSVR(Imagenet) competition. It is regarded as one of the best vision model architectures ever created. The most distinctive feature of VGG16 is that, rather than having a huge number of hyper-parameters, they concentrated on having 3x3 filter convolution layers with a stride 1 and The padding and maxpool layer of the 2x2 filter stride 2 were always the same. The convolution and max pool layers are placed in the same way throughout the design. It features two FC (fully connected layers) in the end, followed by a softmax for output. The 16 in VGG16 suggests to the fact that it contains 16 layers with different weights. This network is rather big, with around 138 million (estimated) parameters.

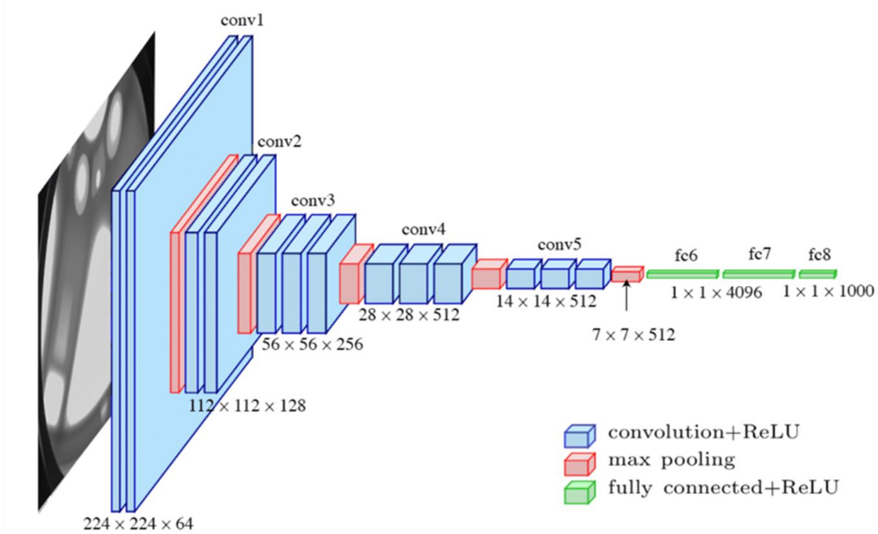

Fig. 3 Architecture of VGG16 [27]

E. Xception

Xception is a 71-layer deep convolutional neural network. You can load a pre-trained version of the model trained on more than a million images from the ImageNet database. The network can categorize pictures into 1000 different object categories, including keyboards, mice, pencils, and a variety of animals. As a result, the network has picked up a wide range of useful features representations for a variety of pictures. The model has an image input size of 299-by-299.

Xception offers an architecture that is made of Depth Wise Separable Convolution blocks + Max Pooling, all connected with alternate ways as in ResNet executions. The Depth wise Convolution is not followed by a Pointwise Convolution in XCeption; instead, the order is flipped.

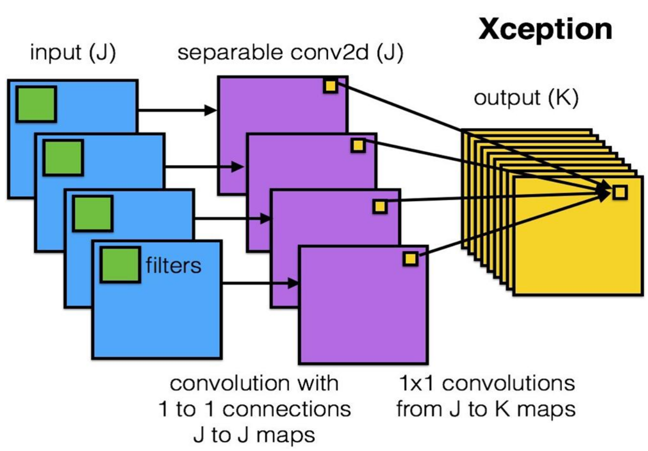

Fig. 4 Xception Process Flow [28]

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue X Oct 2021- Available at www.ijraset.com

F. NASNet

This is the age of machine learning, especially after 2012, when significant advances in the performance and accuracy of deep neural networks occurred. These technologies are undoubtedly culturally accepted, but they are restricted, meaning there's a long way to go in democratizing Machine Learning.

As a result, the NAS architecture is a key step toward democratizing ML and solving basic efficiency and automation concerns with these technologies. NASNet stands for Neural Search Architecture (NAS) Network. It is equipped with plenty of computing power and engineering genius which was designed to find the best CNN architecture as a Reinforcement Learning problem.

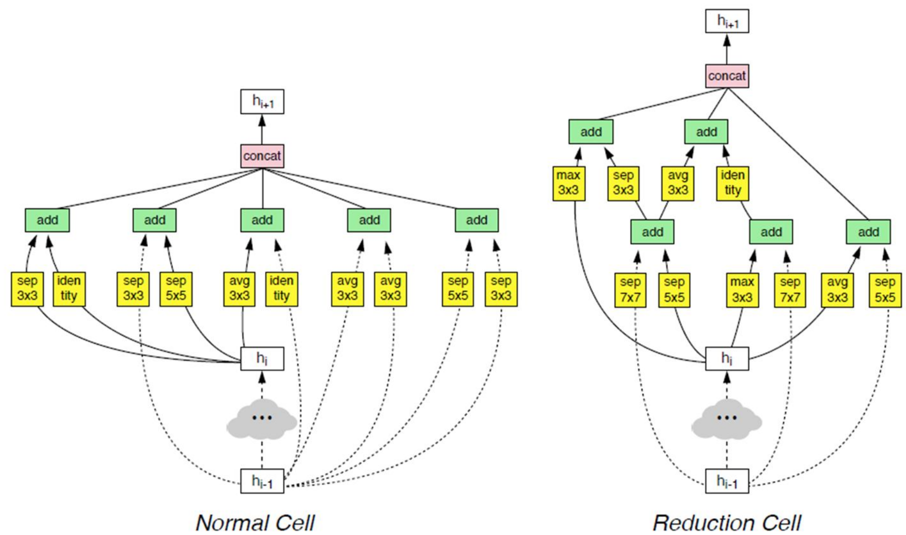

Fig. 5 NASNet Chart for layers [29]

G. EfficientNet

EfficientNet is a convolutional neural network architecture and scaling technique that consistently scales all elements of depth/width/resolution utilizing a compound coefficient. Not at all like regular practice that self-assertive scales these variables, the EfficientNet scaling technique consistently scales network width, profundity, and goal with a bunch of fixed scaling coefficients. For instance, assuming we need to utilize 2N times more computational assets, then, at that point, we can just expand the network depth by αN, width by βN, and picture size by γN, where α, β, γ are consistent coefficients dictated by a little lattice search on the first little model. EfficientNet utilizes a compound coefficient ϕ to consistently scale network width, depth, and resolution in a principled way.

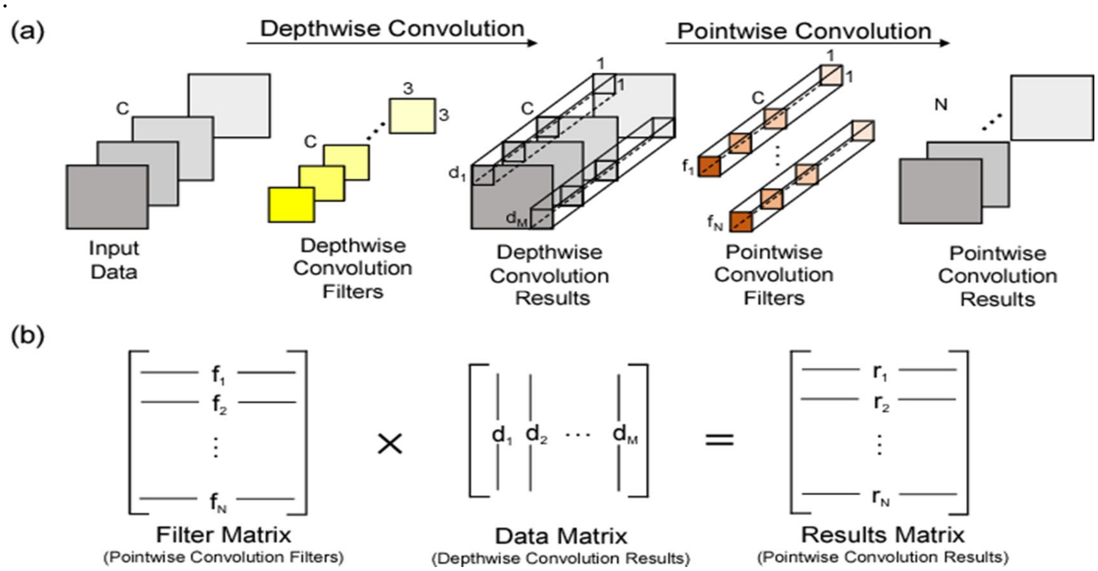

Fig. 6. EfficientNet Architecture [30]

H. InceptionV3

Inception V3 is the third edition of Google's Inception CNN. The design of this model has been made in a manner where it intends to allow deeper networks and also keeping the no. of parameters to minimum. Inception V3 is a CNN architecture from the inception family that makes a few enhancements including utilizing label smoothing, factorized 7 × 7 convolutions, and the utilization of an assistant classifier to spread label data lower down the network (alongside the utilization of batch normalization for layers in the side head). It is a very common and widely used image recognition model that gives more than 78.6% accuracy. This model is made up of symmetric and asymmetric building blocks This network scales in manners that endeavor to utilize the additional computation as adequately as conceivable through effectively factorized convolutions and forceful regularization.

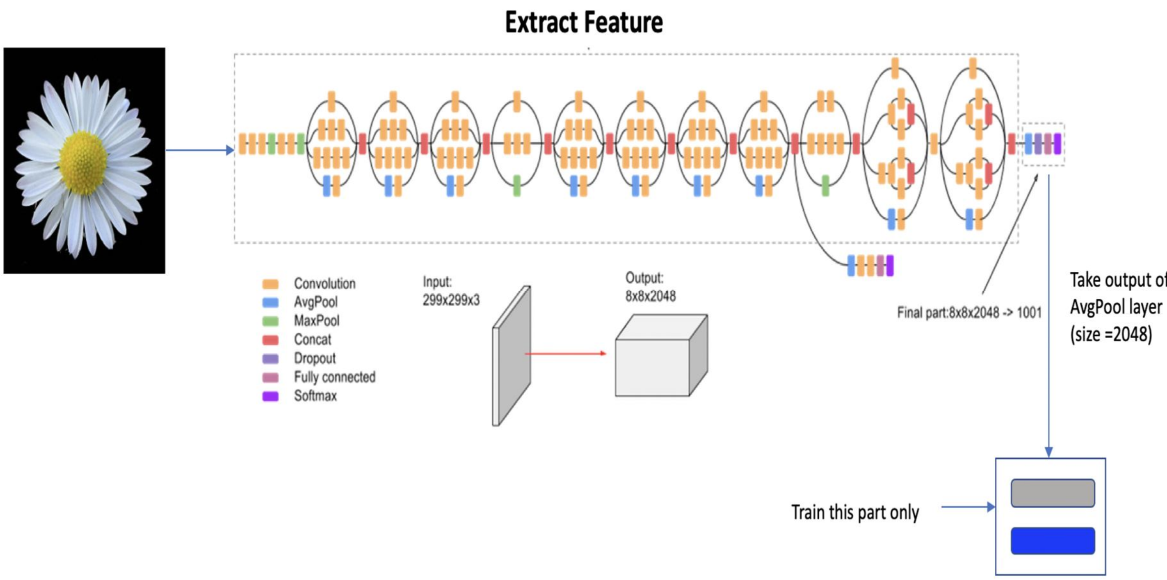

Fig. 7. InceptionV3 Process Visuals [31]

I. ResNet18

ResNet-18 is an 18-layer deep convolutional neural network. You can stack a pre-trained form of the network trained on in excess of 1,000,000 images from the ImageNet data set. The pretrained network can group images into 1000 article classes, like keyboard, mouse, pencil, and numerous animals. Subsequently, the network has learned rich feature portrayals for a wide scope of images. The network has an image input size of 224-by-224.

For its core ResNet uses Batch Normalization which adjusts the layer that is inputted to increase the performance of the network. It also makes use of Identity Connection which helps in protecting the network from the vanishing gradient problem.

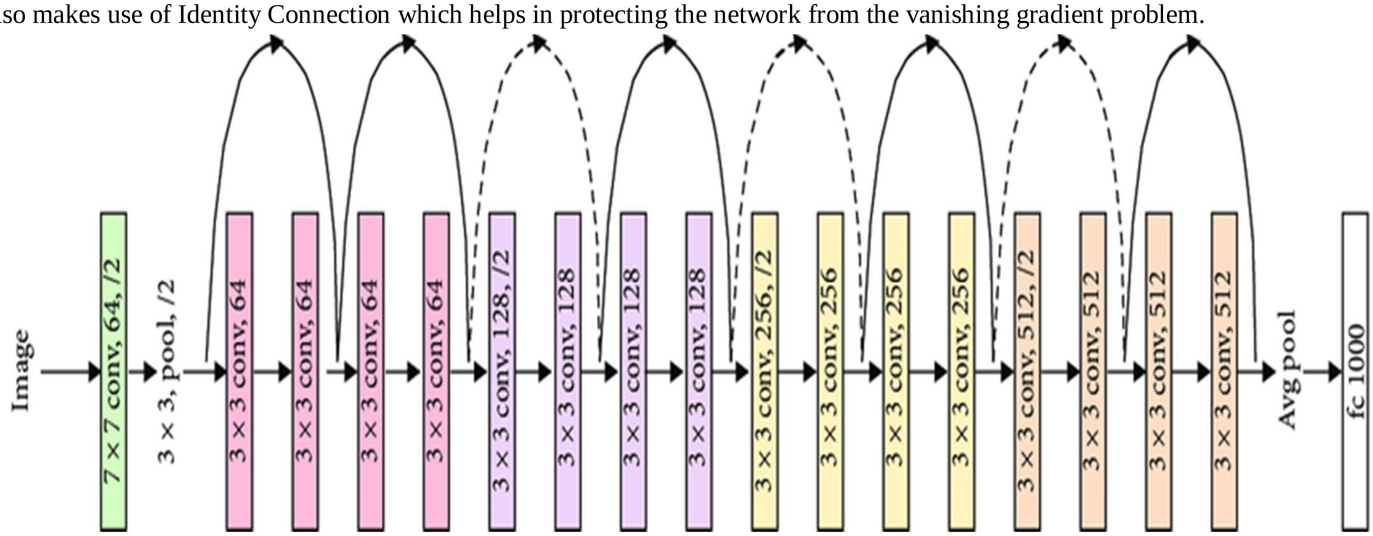

Fig. 8. ResNet18 Convo Layers [32]

J. MobileNetV2

MobileNets are basically small, low-latency and low-powered models that are designed to meet the need for resources for various use cases. MobileNetV2 was released by Google as a part of TensorFlow-Slim Image Classification Library. It follows convolutional neural network architecture that is made to perform well on mobile devices and improve the state-of-the-art performance of mobile devices during the time when multiple tasks and benchmarks are running. MobileNetV2 is very effective for extracting features during object detection and segmentation. MobileNetV2 is faster than MobileNetV1.

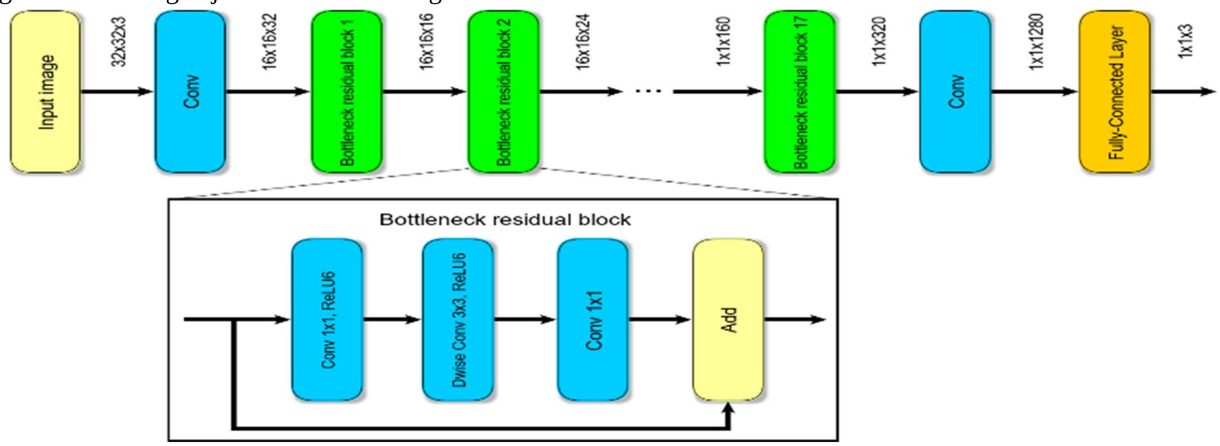

Fig. 9. MobileNetV2 Process Flow [33]

V. CONCLUSION

In this paper we have discussed and used different methodologies and deep learning architectures for early automatic detection of COVID-19 and pneumonia in the suspected patients by analyzing their chest X-ray images. By combining the above discussed deep learning models with chest X-ray images, we get an accurate or simply a more efficient method to classify and detect COVID-19, and to keep track of the evolutions that occur in this disease. The paper discusses four main steps, that is, Preprocessing, Segmentation, Feature Extraction and finally Classification. The project successfully identified whether people are suffering from COVID-19 or pneumonia and also identified the negative cases. This proposed model of ours helps in detecting COVID-19 faster than the current method of RT-PCR and thus preventing it from spreading further in a person.

As we all know that the virus has globally impacted the people and the economies of different countries, thus this model will help in distinguishing COVID-19 affected people with the non-affected ones at a faster rate. It was observed through our study and outcomes from the different models that deep learning architectures or models provide us with good accuracy and faster results. Through our findings, we observed that while using smaller datasets the findings or the results cannot be generalized for real applications. So, in order to get required efficiency, we need to use larger datasets. But one of the possible drawbacks of using the proposed model is that if the image quality is poor and also, we are merging multiple datasets then it could result in poor classification performances.

In conclusion, Artificial intelligence and deep learning techniques gives us exceptional performance in classifying the patients as COVID-19 positive or pneumonia positive provided that the network is effectively trained from a large dataset. This method will be highly effective in these days' situation where the burden of the disease is high, and availability of resources are low.

VI. ACKNOWLEDGEMENT

We wish to acknowledge our university and our mentor for providing an inspirational and encouraging support throughout the process.

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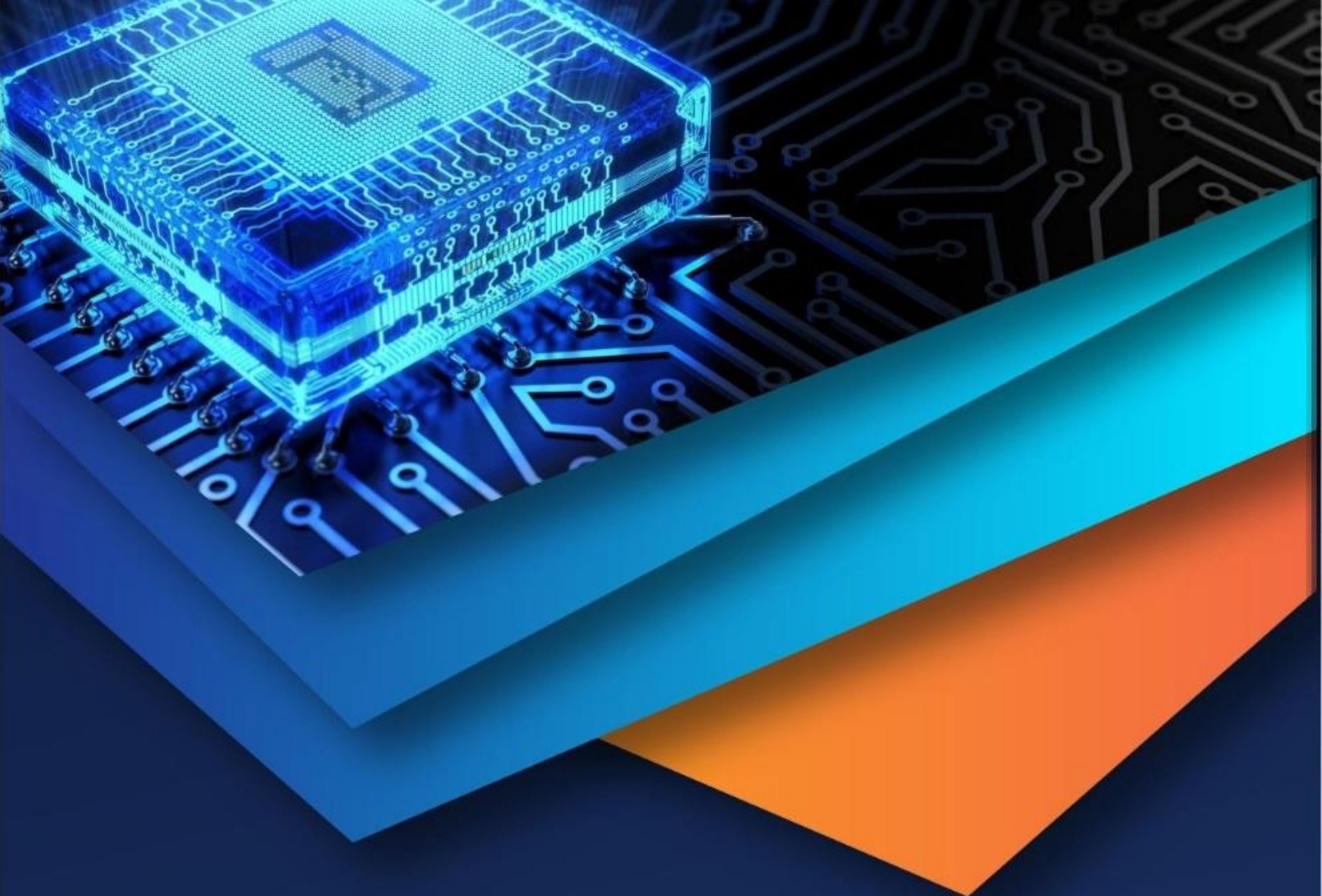

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