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# A Study of COVID-19 Detection using Deep Learning Methods

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## Abstract

The continuation of COVID-19 over the last two years has highlighted the significant shortcomings of the health care system all over the world. It has forced the healthcare system to bolster its strength in all avenues, including efficient and effective diagnostic tools. Chest X-Ray, CT scan, and Lung Ultrasound are widely used diagnostic tools. The problem of pattern recognition in these imaging techniques is challenging for doctors. Deep learning has proven to be very effective in medical image-based diagnosis in recent times. This paper summarises and reviews popular deep learning models available and the studies carried out using those models for Chest X-Ray, CT scans, and Lung Ultrasound, depending on the research executed. This comparative study discusses the application of different Deep Learning methods for processing the raw data obtained through these imaging techniques. It is expected that the implementation of such Deep Learning methods makes identifying a patient faster and easier, which is especially needed due to the high transmissibility of coronavirus. As per our study, GoogLeNet architecture is still the most efficient model.

***Keywords: Covid19, Deep learning, Googlenet***

## INTRODUCTION

COVID-19, the biggest pandemic outbreak in this century, has caused an unprecedented impact on humankind's psychological, physical, emotional, and social health. The pandemic started in China, in Wuhan, on 31st December 2019 [1]. It was declared a pandemic by the World Health Organization (WHO) after it extended to all the regions of China, and the total number of patients had crossed the total case count of SARS (2003) on 30th January 2020 [2]. It has led to many catastrophic outcomes and the deaths of millions of people all over the world. Currently, there are more than 56 crores of infected cases and 63 lakhs deaths worldwide [3]. The commonly prevalent symptoms caused due to the infection include fever, cough, respiratory problems, loss of smell and taste, decrease in blood oxygen saturation levels, and body aches, to name a few. Early detection of symptoms can help control the problem by taking fast responses, which can help decrease the severity of the symptoms. Hence, there is a need for interdisciplinary approaches to address the potential acute post-care needs of recovering COVID-19 patients [4].

The gold standard for detecting the presence of coronavirus of COVID-19 is the positive result of a swab through reverse-transcription PCR (RT-PCR). However, there can be a delay in that particular result along with other limitations such as long and dispersive incubation time [5].

Medical imaging has played a vital role in the diagnosis of infection, with higher accuracy and in monitoring disease progression. Combining RT-PCR with medical imaging can help better diagnose, especially in triage situations [6, 7]. CT (Computed Tomography) scan has been widely used as the imaging gold standard for pulmonary diseases [8]. It shows high accuracy and reliability [6, 9]. The other method commonly used is chest X-ray (CXR) which is economical and readily available. Lung Ultrasound (LU) is acclaimed as a competent tool for diagnosing pulmonary diseases [10]. Nevertheless, there are significant issues faced in the faster imaging diagnosis to evaluate lung impairment and the patients' clinical evolution, mainly in more severe cases requiring admission into the intensive care unit [11].

Since its emergence, researchers worldwide have been engaged in studies, experimentation, and other research activities related to the diagnosis, treatment, and management of COVID-19. Deep learning has shown a dramatic increase in medical applications, particularly in computer vision problems, in general, and specifically in medical image-based diagnosis. Deep learning methods efficiently represent the ability and characteristics of learning data accurately in a profound manner [12]. Methods like CNN (Convolutional Neural Network) have outperformed other conventional models and image analysis methods [13].

Deep learning methods have proven to be of great significance for detecting COVID-19 through the imaging techniques like chest X-rays, CT images, and Lung Ultrasound, which will be discussed further in the paper.

The following literature survey provides detailed information about the various chest imaging techniques.

## LITERATURE SURVEY

According to the studies, the death rate of COVID-19 cannot be considered the most efficient marker for estimating the severity of the patient's illness as this diagnosis is based on the Real-Time Polymerase Chain Reaction (RT-PCR). In many countries, especially developing and under-developed countries, access to this resource is reduced for multiple reasons, including a lack of materials, equipment, transport logistics, and laboratory staff to meet examinations' demands [14]. The accuracy of this test is not reliable. The sensitivity of RT-PCR for nasopharyngeal swab samples is reported to be as low as 70% at initial presentation. This figure is reduced if there is some error in proper specimen collection [9]. Due to this, many SARS-CoV-2 colonization asymptomatic cases or cases of mild severity remain undetected. The limitations mentioned above show that it is impossible to test every patient exhibiting symptoms or those who are assumed to be recently exposed. [15]. In order to reduce human involvement, there is an acute need for an efficient medical imaging and diagnosis system.

Currently, Chest X-Ray (CXR) and Computed Tomography (CT) scans are two of the most widely used medical imaging and diagnosis methods. Chest radiography (CXR) is a more economical and widely available method of detection. One of the significant limitations of this method is that patients exhibit a wide range of changes, or absence of changes, on direct imaging that may result in diagnostic uncertainty [16]. CXR is found to be less sensitive and has a low specificity [17].

As per the research, early non-enhanced Computed Tomography [6] scanning of patients has also been beneficial. The CT imaging of the thorax is more sensitive and accurate than RT-PCR and CXR. The infected patients may demonstrate radiologic findings before the onset of severe clinical symptoms [18] and can identify results faster than RT-PCR tests [6]. The CT scan findings show a combination of ground-glass opacities and peripheral consolidations [6, 19]. Unfortunately, it is found that this method poses substantial challenges in terms of infection control, high cost, difficult accessibility for the patients affected, the necessity of physical structure and patient transportation to the tomography equipment, high radiation, and lack of applicability during hospitalization [11] and extra load on hospitals. It also risks cross-infection to healthcare workers and requires extensive, time-consuming sterilization [20]. However, they are highly sensitive in detection but are not completely specific [6, 19]. Moreover, due to the availability of only 30k CT devices worldwide [21], this is an impractical tool for diagnosing all COVID-19 patients.

Recently, the Lung Ultrasound (LU) method has been found to be an effective tool for treating and following patients with COVID-19. Specifically in situations involving high severity of cases when intensive care is required [11]. It is found to be a valuable tool for bedside imaging. It helps periodic monitoring of disease progression in particular cases where the capacities for patient transport and CT imaging of infectious patients are limited [22]. This method is advantageous as it is more economical, with widespread availability and cost-effectiveness, which helps in frequent examinations of patients [23].

Evidence suggests that lung point-of-care ultrasound (PoCUS) may be comparable to CXR and CT in terms of its ability to detect parenchymal and pleural pathology and monitor response to therapies [24]. It is portable, free of radiation risk, and relatively inexpensive compared to other medical imaging techniques. US data can be acquired in "real-time". It offers instantaneous visual guidance for many interventional procedures [25]. It is now used in different settings in intensive care [26]. Nevertheless, Ultrasound (US) is still not widely adopted for many reasons like operator-dependent acquisition [27]. It requires medical image analysis systems based on automation that helps the medical practitioners with data acquisition, understanding, diagnosis, and monitoring of patients.

Deep learning is one of the most representation-learning approaches with multiple levels of representation. Learning methods from simple depictions can explain complicated problems [28]. The following section describes the various models used for medical imaging through Deep Learning.

## APPLICATION OF DEEP LEARNING IN MEDICAL IMAGING

Deep Learning is very effective as it has helped develop models that have end-to-end structures that facilitate feature extraction, selection, and classification without manual processing.

Recently, deep neural networks have been established as successful hands-on models for image classification due to the availability of an enormous ImageNet dataset. However, there is a scarcity of massive datasets like ImageNet for medical image analysis. Some of the popular models have been discussed below.

## METHODS

POCOVID-Net: With the rapid development of COVID-19 into a global pandemic, a deep learning model for diagnosing COVID-19 using ultrasound images was developed using VGG-Net architecture. In this solution, a lung ultrasound (POCUS) dataset consisting of 1103 images (654 COVID-19, 277 bacterial pneumonia, and 172 healthy controls), sampled from 64 videos, was assembled and collected from different online sources, explicitly processed for deep learning models. Further, a deep convolutional neural network (POCOVID-Net) was trained, which was achieved [21].

VGG16: In 2014, Simonyan et al. proposed the VGGnet architecture. It was referred to as Very Deep Convolutional Networks for Large-scale Image Recognition [29]. It consists of 3 × 3 convolutional layers stacked on top of the other, increasing the depth. A maximum pooling treats the reduction in the volume size. This model is still considered one of the best architectures for image classification. VGG19 is an enhanced version of VGG16 architecture. VGG19 has an increased depth of the network compared to its previous version. Horry et al. [30] have optimized the VGG19 model for COVID-19 detection from X-Ray, Ultrasound, and CT scan images.

COVID-Net: COVID-Net is one of the first open-source network designs for COVID-19 detection. It is a neural network that uses a compression network structure to classify and identify Covid-19 pneumonia C.X.R. images. Based on the advantages of CXR imaging for rapid triage of COVID-19 screening and availability, the network makes accurate predictions through the COVID-Net interpretability method allowing the network to analyze the acute symptoms of COVID [31].

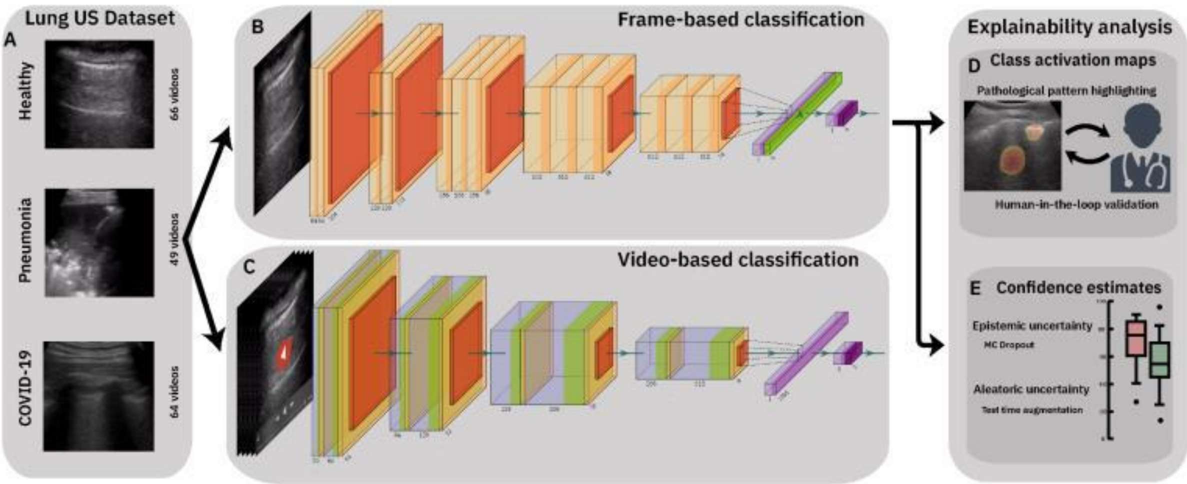


Fig 1 Graphical Overview of POCOVID-Net

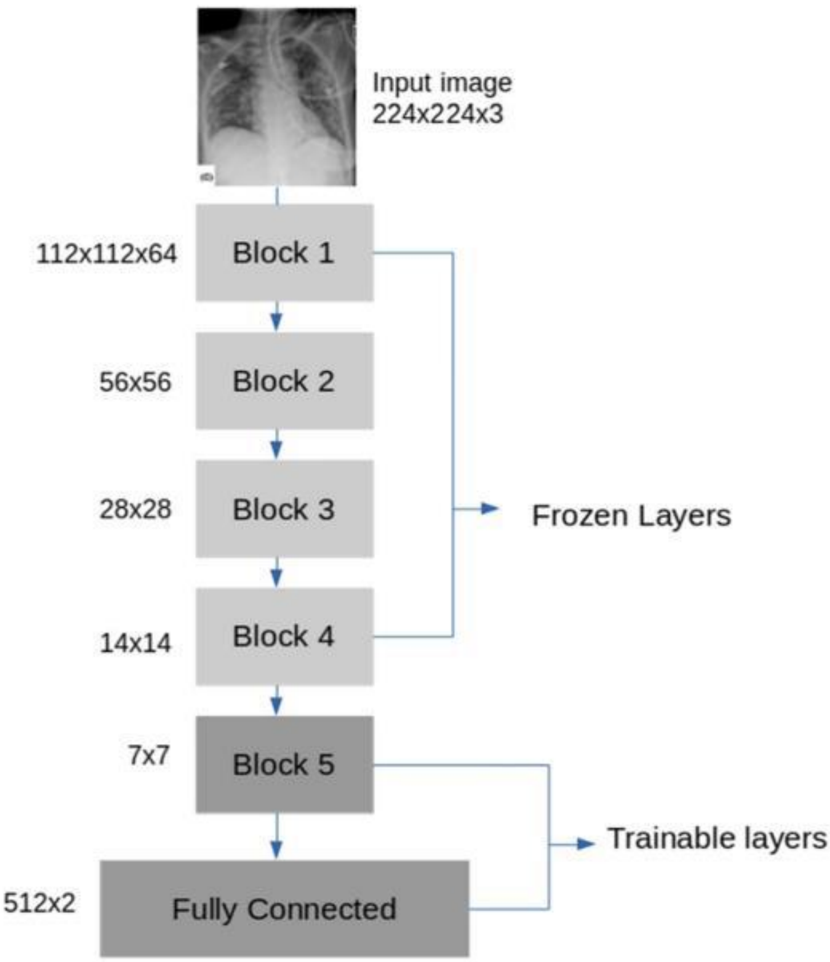


Fig 2 Architecture of VGG16

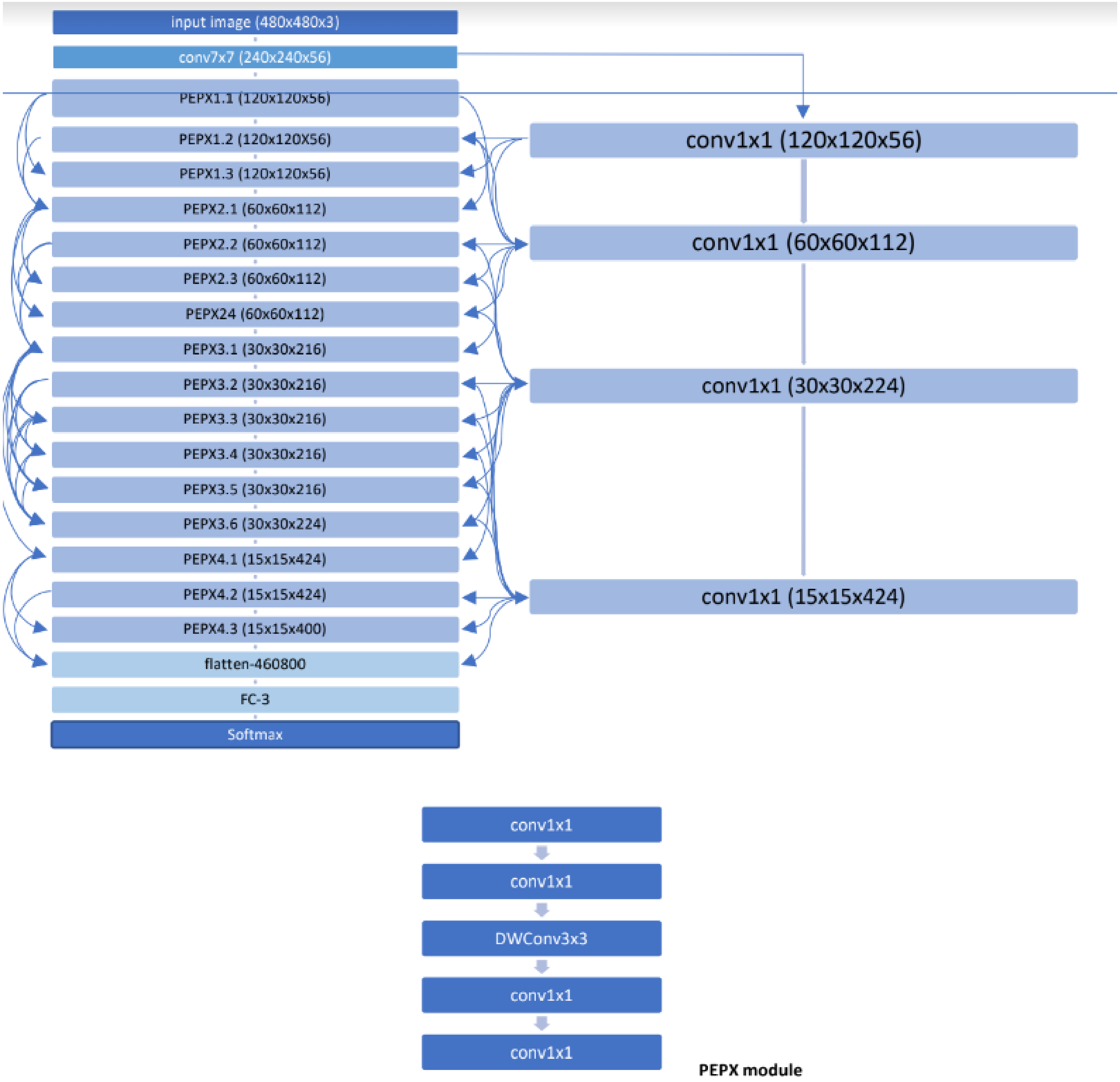


Fig 3 Architecture of COVID-Net

AlexNet: AlexNet is a 8 layers based CNN model. It can be used to load a pre-trained version of a network trained on large Image datasets up to a million from the ImageNet database. Multiple studies were carried out on the AlexNet model to increase model efficiency [32, 33]. For example, a study aimed to build a comprehensive dataset of X-rays, and CT scan images from multiple sources was carried out and provided a simple but effective COVID-19 detection technique using deep learning and transfer learning algorithms. In this vein, a simple convolution neural network (CNN) and modified pre-trained AlexNet model have been applied to the prepared X-rays and CT scan images dataset. The experiments show that the utilized models can provide up to 98% accuracy via a pre-trained network and 94.1% accuracy using the modified CNN.

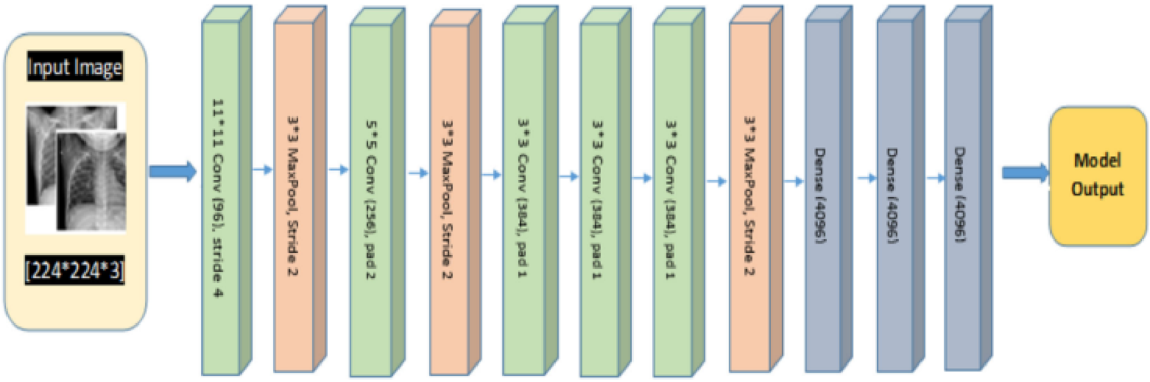


Fig 4 Architecture of Alexnet

ResNet/ResNet50: The residual neural network (ResNet) model is a better version of CNN. ResNet has proven its efficiency in previous applications like in ImageNet. ResNet50 is an advanced version of ResNet and is a 50-layer network. This model evolves the convolutional layer, 4 convolutional blocks, max pool, and average pool to address the accuracy degradation. This model has helped simplify the training task of deep networks. [33]. It was amongst the first models to use batch normalization features. Recently, ResNet101 and ResNet152 consisting of 101 and 152 layers, respectively, are also being used [34].

One of the studies that used five pre-trained convolutional neural network-based on ResNet has been proposed for detecting coronavirus pneumonia-infected patients using chest X-ray radiographs. Three different binary classifications with four classes (COVID-19, normal (healthy), viral pneumonia, and bacterial pneumonia) were implemented using five-fold cross-validation [34].

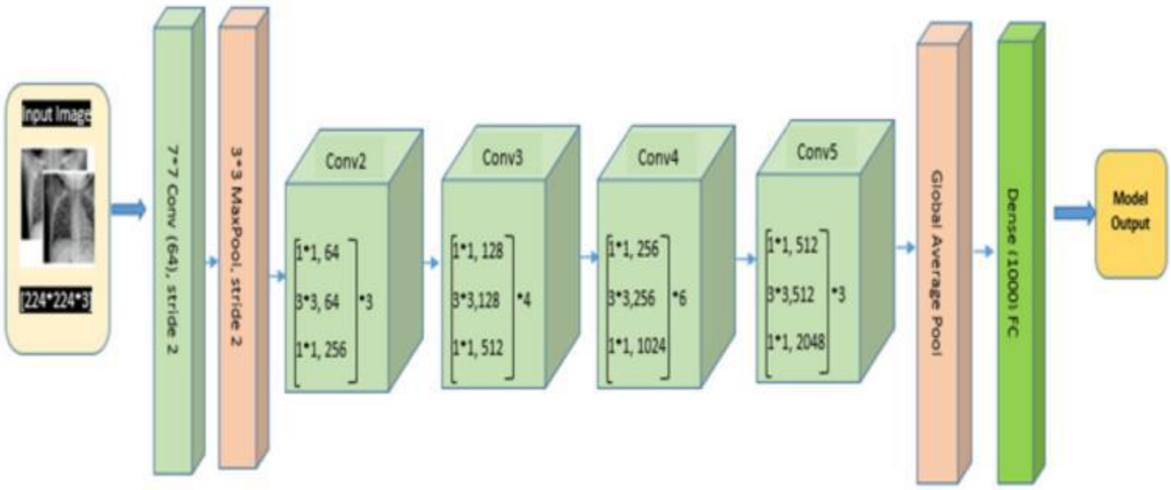


Fig 5 Architecture of ResNet50

Mobile-Net/MobileNetV2: This is a smaller neural network model effective in mobile and embedded vision applications. The model was initially developed for detecting the objects for mobile-based and embedded computer vision applications [35]. An enhanced version MobileNetV2 model is built on the architecture of MobileNet. It uses an inverted residual structure with shortcut connections between bottleneck layers. This has improved accuracy and performance compared to others [36].

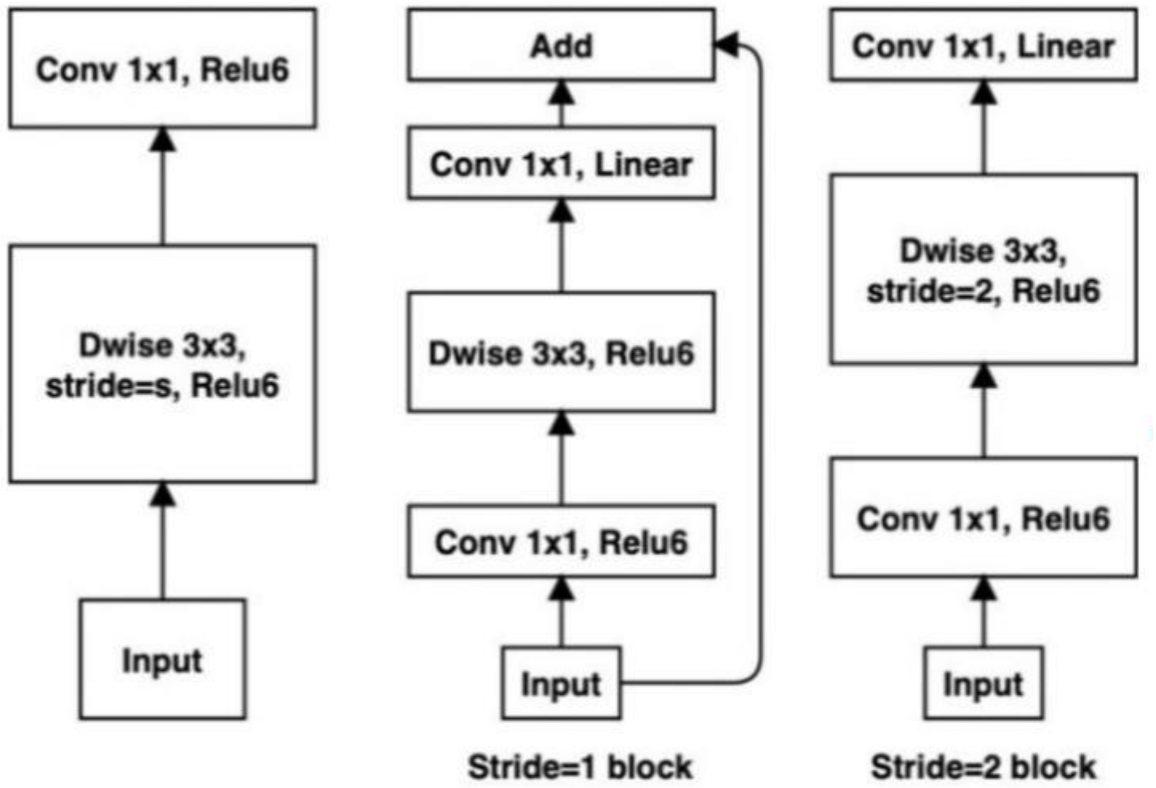


Fig 6 MobileNetV2 Architecture

Mini-COVIDNet: As per the study by Awasthi et al., the available deep learning models for COVID-19 detection were heavy and not easily deployable in the mobile platforms in point-of-care testing. In order to overcome these problems, they developed a lightweight mobile-friendly, efficient deep learning model using LU images, known as Mini-COVIDNet. The model achieved the highest accuracy of 83.2% and required a training time of 24 min. This model has 4.39 times fewer parameters in the network than its following best-performing network and was found to require memory of 51.29 MB, which was lower than other models. Hence, It was found to be versatile and efficient [37].

COVID-CAPS: Capsule Networks (CapsNets) [38] models can capture spatial information using routing by agreement, through which Capsules try to reach a mutual agreement on the existence of the objects. The significant advantage of this agreement is that it leverages the information coming from instances and object parts and can recognize their relations. Moreover, there is no requirement for a large dataset [39]. This is an ultracompact model used previously on CXR images to detect COVID-19 infections. It has shown high specificity and sensitivity values for identifying COVID-19 infected cases [37]. Three Capsule layers are embedded in the model, which performs the routing by agreement process. The last Capsule layer contains the instantiation parameters of the two classes that segregate between positive and negative COVID-19. The length of these two Capsules represents the probability of each class being present [39].

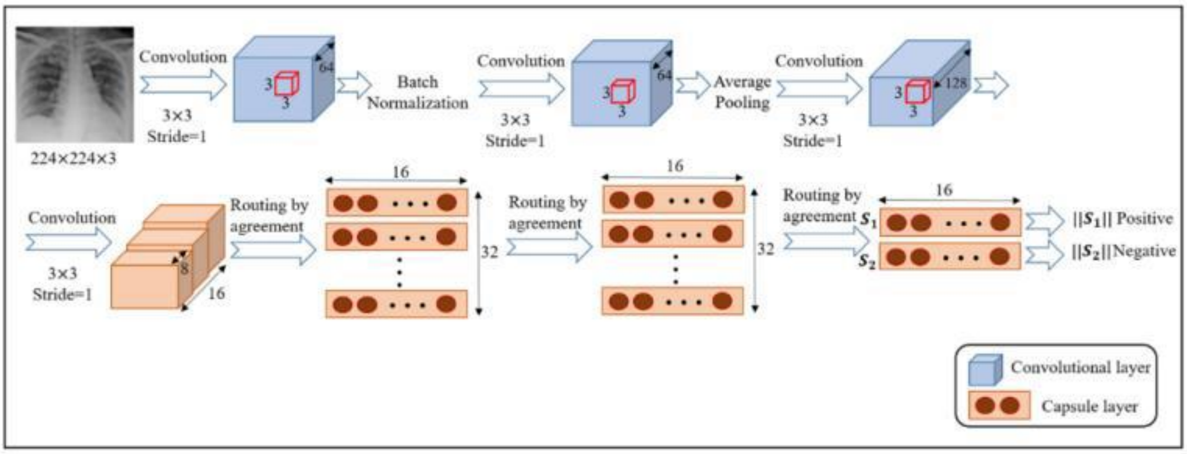


Fig 7Architecture of Covid-CAPS

Inception: The Inception deep network architecture was developed by Ioffe S and Szegedy [40] as Inception-v1. It was enhanced to Inception- v2 by introducing batch normalization [39]. Inception-v3 was created by introducing the factorization idea. This model has better efficiency as it uses factorized convolutions and aggressive regularization. It was created by Szegedy et al. at Google in 2013–2014 [41]. This helps preserve spatial information and maintain accuracy with significantly less computation [42]. This model aids the network in learning separately rather than in an ordinary way. It serves as a "multi-level feature extractor" [43]. It consists of numerous convolution and maximum pooling steps. The last stage contains a fully connected neural network [44], the output and channel size of these filters are then fed back to the followed layer [42]. It requires lesser computational efforts in terms of memory and is more economical.

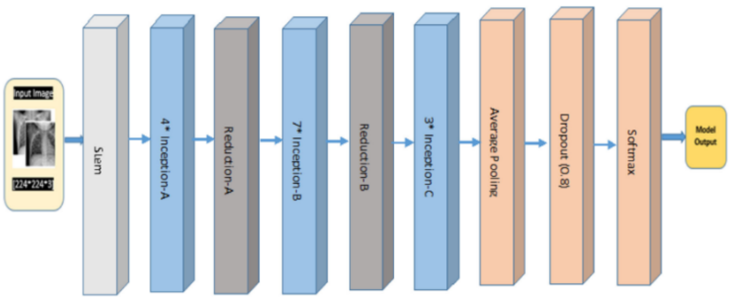


Fig 8 Architecture of Inception

Xception: This is a model based on the Inception model. It was created in 2017 by Chollet [45]. This model uses an extreme form of an Inception module. Learning channel-wise features are entirely separated from the spatial learning features. It also supports depth-wise separable convolutions [46]. It makes better model parameters, so it has better runtime and latency.

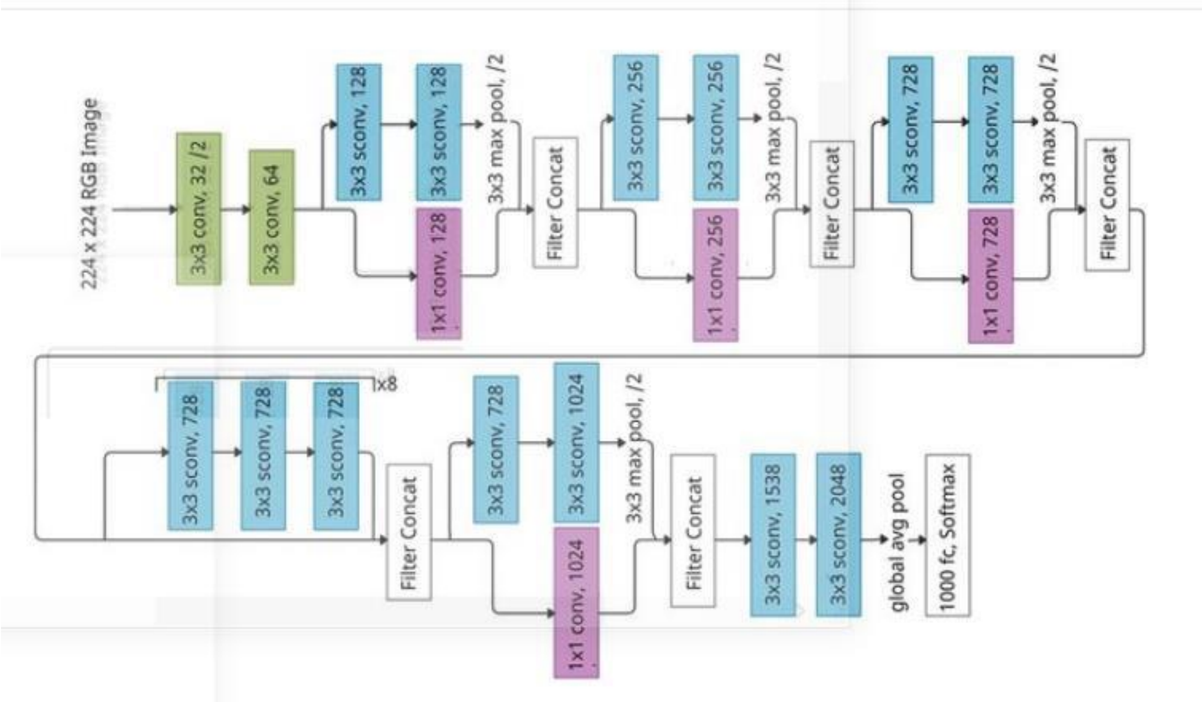


Fig 9 Architecture of Xception

Densenet121 - DenseNet121 is an efficient model for usage. It uses convolutional layers, max pool, global average pool, dense block, and transition layer. It solves training time issues because the next layer uses each layer output as input. It uses loss function gradient values which help to reduce the computation time and cost [33].

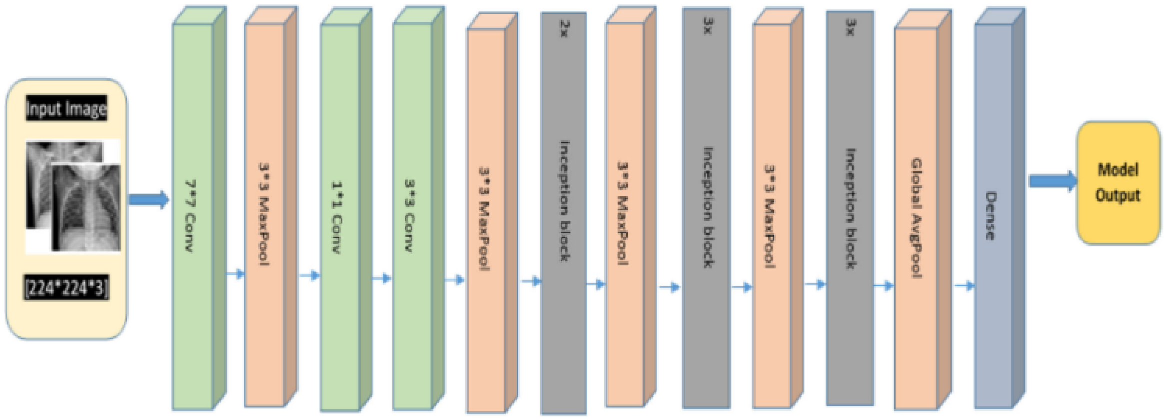


Fig 10 Architecture of GoogLeNet

GoogLeNet: This model uses global average pooling and max pooling [33]. It is a 22-layer network that shows high performance on image classification. At the base of the network, two pairs of convolution layer and max-pooling layer are used for feature extraction and feature reduction. In the middle, the inception block is used, which utilizes parallel convolution that increases the width and depth of networks. As a result, this model shows promising results in terms of accuracy [35].

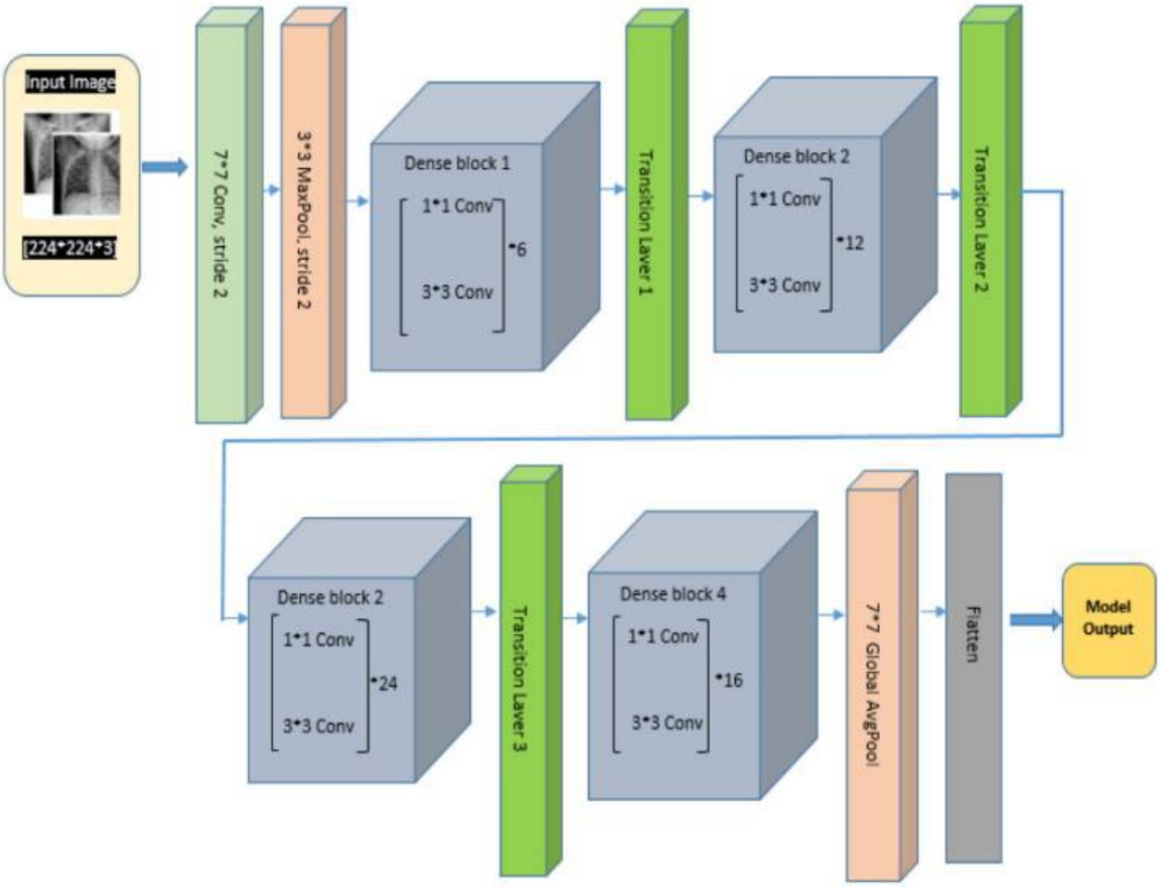


Fig11 Architecture of DenseNet121

## CONCLUSION

Based on the above studies, it is visible that Deep Learning Models have come a long way in medical image analysis. An effective imaging technique will help in the early detection and classification of patients so that appropriate medical assistance can be provided in time. LU has one of the better modalities when it comes to medical imaging. It is a portable, cost-effective, relatively fast, and powerful tool for diagnosis and efficient treatment by providing real-time visualization. More recently, point-of-care ultrasound (POCUS) is the method that is being preferred for diagnosis[47], Application of Deep learning, through frame-based and video-based models can prove to be one of the most effective methods for dealing not only with COVID-19 but also other diseases like bacterial and viral pneumonia, bronchiolitis and others. According to our analysis, GoogLeNet is more efficient than others.

Table 1 Comparison of various models

| MODEL | SENSITIVITY | SPECIFICITY | PRECISION | F1-SCORE | ACCURACY |
|---|---|---|---|---|---|
| POCOVID-NET | 0.88 | 0.76 | 0.85 | 0.87 | 0.829 |
| MOBILE-NET-V2 | 0.96 | 0.61 | 0.81 | 0.88 | 0.793 |
| ResNet50 | 0.84 | 0.57 | 0.76 | 0.8 | 0.704 |
| Mini-COVIDNET | 0.92 | 0.68 | 0.82 | 0.86 | 0.811 |
| VGG | 0.88 | 0.94 | 0.9 | 0.89 | 0.878 |
| NASNET-Mobile | 0.63 | 0.79 | 0.67 | 0.63 | 0.625 |

| | | | | | |
|---|---|---|---|---|---|
| Xception | 0.882 | 0.843 | 0.8 | 0.868 | 0.863 |
| AlexNet | 0.982 | 0.958 | 0.914 | 0.946 | 0.965 |
| GoogleNet | 0.986 | 0.964 | 0.926 | 0.955 | 0.971 |
| DenseNet121 | 0.973 | 0.966 | 0.932 | 0.951 | 0.968 |
| Inception v3 | 0.915 | 0.899 | 0.759 | 0.83 | 0.903 |
| COVID-CAPS | 0.9 | 0.958 | 0.97 | 0.89 | 0.957 |

## LIMITATIONS AND FUTURE WORK

One of the significant limitations noticed in this study is that Lung Ultrasound, even after being proclaimed one of the best methods for medical diagnosis of COVID-19, is not used in most countries. Due to this, the availability of raw data is still limited. Hence, this field has limited research, especially regarding applying Deep Learning Models. Secondly, it is not mentioned in most papers whether the problem of repetitive training has been taken into account. The high accuracy could be due to redundancy in data. Thirdly, most of the models are CNN-based. The models based on CNN are prone to lose spatial information between image instances and require large datasets. Hence, more research is required in the area of Deep learning, specifically for non-CNN-based models, that can provide better results with a small dataset.

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