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DEEP LEARNING MODELS FOR EARLY DISCOVERY OF COVID-19 WITH RADIOLOGY MODALITIES

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Abstract- Due to the COVID-19 pandemic, the whole world is experiencing a health catastrophe that is unprecedented in its scope. Since coronavirus spreads rapidly, investigators are worried about finding or assisting in the development of treatments to save lives and reduce the pandemic. The key issues in the present COVID-19 situation are initial identification and diagnosis of COVID-19, as well as precise parting of non-COVID-19 patients in cost-effective methods during the initial period of the illness. Artificial Intelligence (AI), for example, has been modified to solve the issues posed by pandemics. Deep Learning (DL) models' computation power has aided healthcare procedures to be more rapid, accurate, and well-organized. DL networks are revolutionising patient care, and they play a crucial role in clinical practise for health systems. DL approaches in healthcare include computer vision, Natural Language Processing (NLP), and fortification knowledge. DL is a strategy to tackle the COVID-19 outbreak because there are so many bases of medicinal pictures (e.g., X-ray, CT, and MRI). As a result of this statistic, numerous studies have been projected and produced for the first months of 2020. We create a DL method to extract features and identify COVID-19 from Radiology Modalities in this article. In spite of their widespread use in diagnostic centres, diagnostic procedures created on radiological examinations have flaws when it comes to the disease's uniqueness. As a result, DL models are commonly used to evaluate radiological pictures in order to identify the disease in the early stage. AI, notably DL, is being used to solve this challenge. A novel approach of entailing FJCovNet2 which is a DL method built on DenseNet121 to detect COVID-19 using CT-Scan and X-Ray pictures is effectuated. The comparative study of various forms of radiology modalities in deep learning determines the best accurate method to detect the disease earlier using the predefined models namely InceptionV3, ResNet 50, and VGG 16. The maximum accuracy of 98.23% is attained through the proposed model RJCovNet2.

Keywords- Internet of Things (IoT), Deep Learning (DL), Healthcare, COVID-19, CT scan, X-Ray

I. INTRODUCTION

COVID-19, a new coronavirus, caused a global well-being disaster in early 2020. The sickness is instigated by a virus known to create high range respirational disorder, or coronavirus2, which is a communally transmitted illness that can contaminate people through intimate interaction with sick people [1]. As of February 02, 2022, the amount of individuals sick with COVID-19 had surpassed 378 million, with nearly 56 million deaths. While the majority of COVID-19 individuals have modest warning sign [2], a tiny percentage of them have severe or catastrophic symptoms. In a growing number of cases, the infection can cause pneumonia, severe breath loss [3], multiple body parts ailment, and resulting in cost effective method during. Equally hospitals and doctors suffer from increased loads during unembellished transmittable disease outbursts, compromising their capability to categorise and hospitalise suspected patients. According to prior reports, several patients with initial coronaviral contamination tested negative for Computed Tomography (CT), restricting radiotherapists'[4] capability to accurately decree out illness. If inadequate resources are cast to isolate positive patients from other suspected cases. According to study [1], infirmary attained infections were suspected in almost 50% of cases. It's critical to authorize COVID-19 patients' status as soon as possible, since incorrect negative instances can enhance the virus's chance of spreading [5].

Artificial intelligence (AI) is used in the health care structure at several stages, including disease analysis, communal health, medical decision creation, and treatments. During the present pandemic, AI algorithms are very useful in quickly detecting COVID-19 victims. In 2021, the number of studies that used AI to identify COVID-19 skyrocketed. The majority of evaluations concentrate on applying AI technology to diagnose COVID-19 from upper body [6] Computed Tomography (CT) pictures. Fig 1 shows the DL methods for identification of COVID-19 at initial stage.

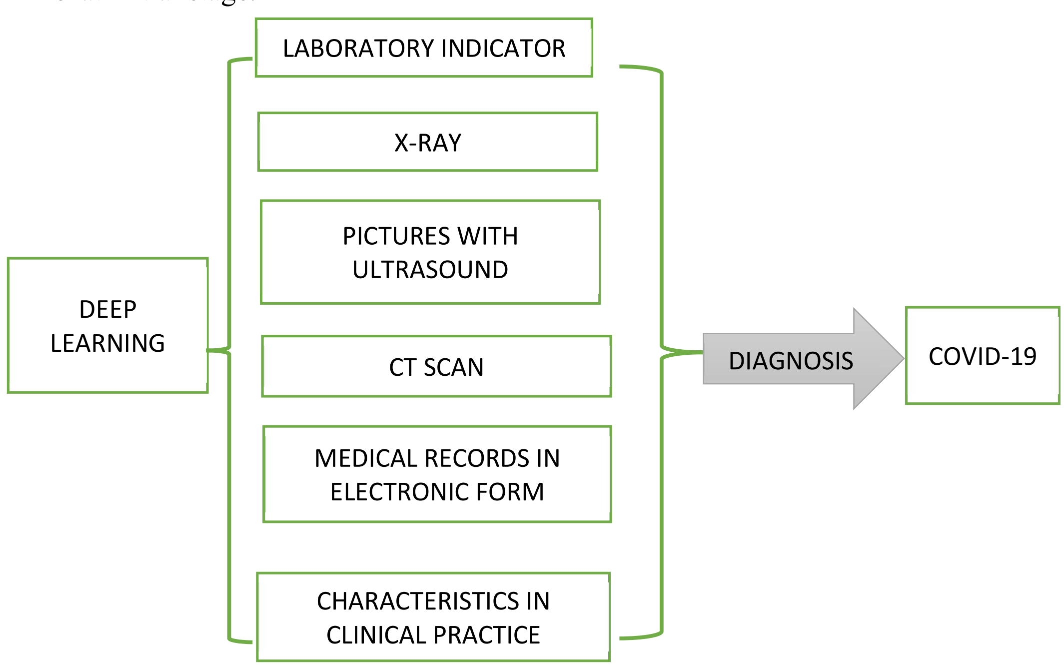

Figure 1: Various DL Modalities for Initial Identification Of COVID-19

This virus most likely came from an animal, not laboratory leakage. COVID-19 cases are examined and treated differently from further coronavirus infections. However, the understanding of the disease is still restricted, and it is growing at the same time as the pandemic. Fever, cough, weariness, an aching throat, and body pain are all the general COVID-19 signs, and many people have informed me of losing their sense of taste or smell. Patients may feel trouble breathing, chillness, weariness, a high temperature fever, muscular or body pain, or even loss of life in uncommon but often more severe patients. Reverse Transcriptase Polymerase Chain Reaction (RT-PCR) [7] is now the significant typical test for detecting COVID-19 cases all over the universe. The examination results, on the other hand, frequently create wrong alarms, with a present success percentage of just 80%. Furthermore, as the test outcomes take longer to obtain, there is a greater hazard caused by the patients as they transmit the sickness to others. Several studies recommended chest radiograph (X-ray) based approaches at the initial phases of the pandemic to bound reliance on restricted test tools and switch the exponential increase of COVID-19 cases, and proved adequate outcomes by attaining higher accurateness than the RT-PCR examination. Though, following the emergence of the pandemic in 2020, utmost scientists have had to work with restricted data and describe their findings using the restricted resources obtainable. The administration has been stunned by the disparity between the quantity of methods for COVID-19 discovery and the decree for COVID-19 assessments from people. AI, notably DL [8], is used to solve this challenge. FJCovNet2, a novel DL model based on DenseNet121, is proposed in this study. The following is how the rest of the article is structured: Section II explicates the prime objectives that the article pivots on, followed by the relevant work in the III section. The fourth section examines the methodology used to create the dataset and outlines the overarching framework that has been proposed. Section VI presents the experimental research as well as evaluations to earlier work along with concluding the article with future enhancements that can augment the viability of research in this domain.

II. KEY OBJECTIVES

Convolutional Neural Networks (CNN) are shown to be particularly effective in mining and learning information, hence these methods are widely used by investigators. Artificial Intelligence (AI) and Deep Learning (DL) can advance COVID-19 analysing and detecting due to significant persistent success in machine learning, particularly statistical knowledge that combines massive information and the growing notice in explainable AI in treatment. The key problem is to use reliable and diminutive cost recognition technologies to identify COVID-19. The goal of this study is to create a completely automatic scheme for early detection of COVID-19 and non-COVID-19 with the radiology modalities. Only a small number of X-ray imageries and CT scans related to COVID-19 queries are now accessible for communal viewing. The following are the work's key goals:

- Through Deep Learning (DL) models radiology images can detect the COVID-19 earlier.
- FJCov Net2, VGG 16, ResNet50 and InceptionV3 are a deep learning approach created on DenseNet121 which uses CT scan and X-Ray pictures to diagnose COVID-19.
- The first step is to create an enhanced dataset using three deep learning-friendly augmentation approaches: spin, arbitrary noise, and parallel flips.

- Next, fine-tuning the preceding layer of 3 widely used predefined models such as VGG-19, Inception and RESNET50 to effectively distinguish the virus from noisy chest pictures and CT-Scan.
- Deep learning's comparative research of several radiological modalities identifies the most accurate way for detecting disease earlier.

III. RELEVANT WORKS

Artificial intelligence (AI) is the science of programming machineries or processors to perform tasks that humans accomplish. AI technology is becoming more advanced with the passage of period, and it is gradually being employed to boost productivity in day-to-day labour due to its ability to perform human-like tasks. AI has the potential to be used to a wide range of scientific subjects. Computer Vision is a discipline of AI that examines and equips machines to do tasks similar to those performed by the human eye. Training statistics is essential for the development of a DL model. X-Ray pictures and CT-Scan are used as training information in this study. CheXNet outperforms the typical radiologist in interpreting novel data. This demonstrates the enormous probable of X-Ray as a training statistics source. As a result, several studies, like COVlD-19, have relied on training statistics in the method of radiology pictures to diagnose illness. Cross et al. [6] developed a DL model that can sense something in lesser than two seconds, which is sooner than RT-PCR test.

The most recent COVID-19 study calls for the use of deep learning techniques. Most investigators have been obliged to employ transference learning due to the uniqueness of COVID-19 and the corresponding lack of big statistics. By adopting three improvement procedures on the chest X-ray [9] pictures are obtained, and using the transference education process of Convolutional Neural Network (CNN) on the improved dataset, help to detect the disease earlier, incorrect positives and wrong negatives in order to reduce death rate. Transference education on chest X-ray pictures are used in a quantity of studies to identify individuals with COVID-19. We focus on those that are directly linked to our idea in this section.

On the basis of X-ray pictures, Sethy et al. [7] offer a technique built on deep features and Support Vector Machine (SVM) to sense peoples with corona virus contamination. They retrieve deep structures from the CNN model's completely linked layers. After that, they use SVM to classify them using X-ray pictures. COVID-19, normal and pneumonia X-ray pictures are among the 3 kinds of X-ray pictures used in the procedure. With the deep purposes of 13 dissimilar CNN methods, the author [8,9] assesses SVM to identify COVID-19. SVM can achieve the greatest outcomes by utilising ResNet50's deep functions. SVM [10] and ResNet50 had the maximum accuracy of 98.66 percent.

A dataset, which includes testing and training data, is the most critical mechanism of a deep learning approach. With a high sum of datasets, a DL model is more likely to perform effectively. Huge datasets, such as those for COVID-19, a novel disease [11], are difficult to analyze. Even if only uncommon datasets are cast-off, we prerequisite a strategy for producing models with decent presentation. Transfer learning is the name of this strategy for transferring knowledge from one area (source area) to another (target area) with which it has an association [12].

The transference education system is used to create the model and alter the topmost layer in the COVID-19 investigation through CT-Scan samples. The pre-trained classical types [13] are situated trained with information that is comparable to the information cast-off by the handlers of the pre-trained classical method. Pre-defined methods can now extract features, allowing them to be employed at a level with limited training information. Pre-defined Inception classical method is used by the M-Inception classical [14] method. The COVID-19Net classical method employs the DenseNet 121 classical method, whereas the COVNet employs the Resnet50 method.

MobileNet v2, VGG19, Inception-ResNetv2, Inception, and Xception are among the up-to-date CNN designs employed for medicinal image categorization [15] in current period, according to Terpos et al. [10]. Transference education is used by the novelist since it is effective in sensing numerous anomalies in tiny medical imaging data sets. The study of 1,440 patient X-ray data sets, 220 patients with proven COVID-19 illness, and 500 non-COVID-19 individuals. The outcomes demonstrate that VGG19, CNNs, and MobileNet-v2 provide the most accurate categorization [16]. Although VGG19's accurateness beats the other approaches (attainment of 98.75 percent), MobileNet-v2 outperforms MobileNet-v1 in terms of sensitivity and specificity (attainment of 99.10 and 97.09 percent, correspondingly).

Lauer et al. [11] present a new approach that practices underdone radiography images to automatically diagnose COVID-19, in order to appropriately identify COVID-19 and support them to get rid of the death of specialised medical practitioners in distant communities [17]. The DarkNet method, which comprises seventeen CNN layers, is used as the classification method for the real time entity discovery scheme. At a separate layer's stage, the writers apply various filters [18]. The goal of this method is to provide an exact analysis for both two session (COVID) and multi session (COVID with Pneumonia) groupings [19]. The two-fold sorting [20] accurateness is 98.8%, while the multi-classification accurateness is 87.2%.

Some of the other applications such as DL with image compression techniques [21] in industries, Iris [22], Brain [26], Malarial disease detection [27], traffic [28] and E-Commerce [23]. Support Vector Machine (SVM) [24], Natural Language Processing (NLP) [25], other classification algorithms [29] and a predictive model for vehicle system [30] are the methods earlier used for identification and detection using datasets. The business organization mentoring benefits are incorporated in the paper [31].

IV. METHODOLOGY

Train, analyse, and test three already existing pre trained DL models and a novel method to detect radiography photographs in this research. InceptionV3, ResNet50, and VGG16 are examples of DL models that are often used. A novel method of FJCovNet2 is developed to detect the disease earlier. Figure 2 depicts the study's approach in general, describing the DL proposed method, which is based on a modest normal pipeline, namely chest image and scan image pre-processing, and then the classification method created through transference education. A DL method is trained after pre-processing the data.

4.1 Dataset Collection

The dataset consists of 2483 CT scans and 5072 X-Ray which are collected from Kaggle repository and are classified as Viral Pneumonia [32], Bacterial pneumonia [33], COVID-19, normal and train and validation data. We use the normal and COVID-19 dataset for the classification. The content of the dataset prepared for further process is shown in table 1. The pictures of normal cases and X-RAY and CT-SCAN of COVID-19 are represented in figure 3.

4.2 Data Augmentation

DL methods typically necessitate a large amount of training data. Because of the emergence of DL, Image Augmentation methodology has been widely employed in processor image and has got a lot of consideration. The more statistical validation, the better the model performs, and COVID-19 is a unique pandemic for which there is no relevant dataset. Data Augmentation refers to procedures that improve slightly changed copies of current data or recently formed synthetic data from present data to expand the quantity of data available. As an outcome, we must utilise data augmentation, which is a strong strategy for creating a massive dataset overstated. Random Rotation (RR) at a position between 15 and 20 degrees, arbitrary noise [34], and horizontal flip-flops [35] are 3 augmentation tactics we use (in general, moving back the columns of the picture element). In reality, picture noise is a key factor in our model's ability to distinguish between signal and noise.

Table 1: Prepared dataset with normal cases and COVID-19 cases

Dataset	Normal healthy cases	COVID-19 cases
Train	880	160
Validation	901	160
Non-Augmented	450	9
Total	2231	329

4.3 Data Pre-Processing

The X-ray pictures can be resized during the data pre-processing step. This is because dissimilar picture inputs are required by dissimilar processes. The photos must be normalised to the model's specifications. The original sizes of the input photographs were diverse; therefore, they were all progressed and the dimensions were changed to 224*224 pixels [36] to make them unvarying. The pictures are rescaled initially in this procedure. The rotation series was then customary to 30 degrees. Later, the sheer scale set to 20% and the width and height shift ranges to 20%. Subsequently, the zoom series was set to 30% and ensured that the vertical and horizontal flips were true. Then, the integration of each pretrained model's and novel method pre-process the input.

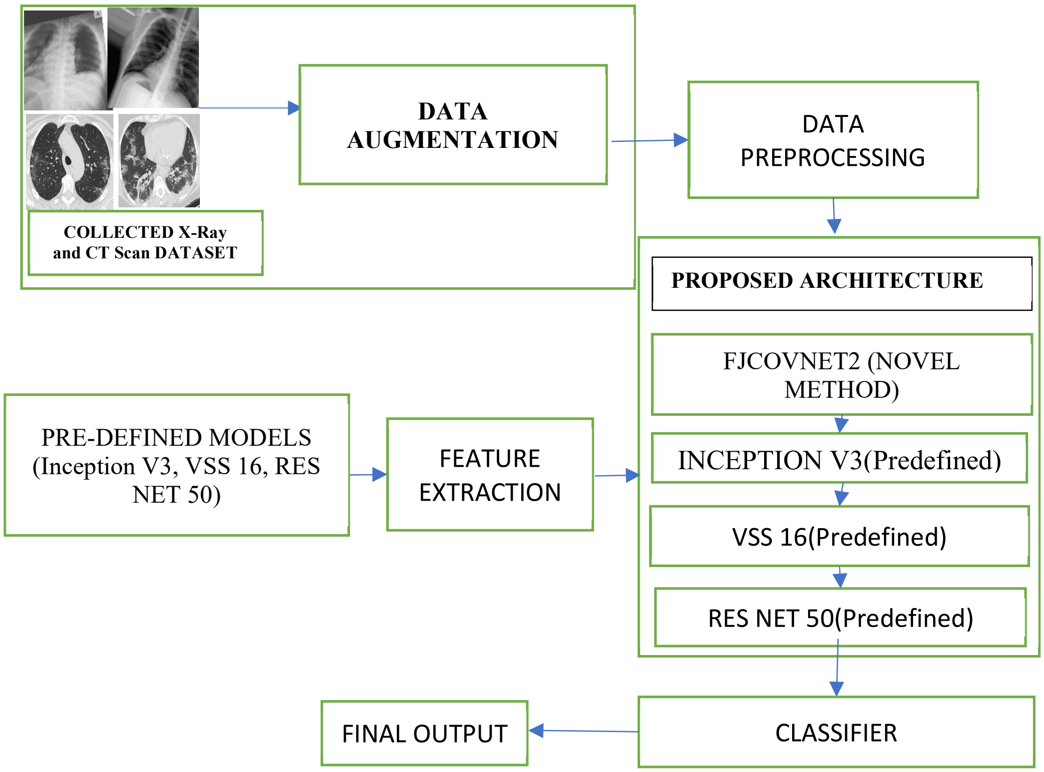

Figure 2: Overview of Radiology Modalities of sample dataset for affected and non-affected patients using DL models

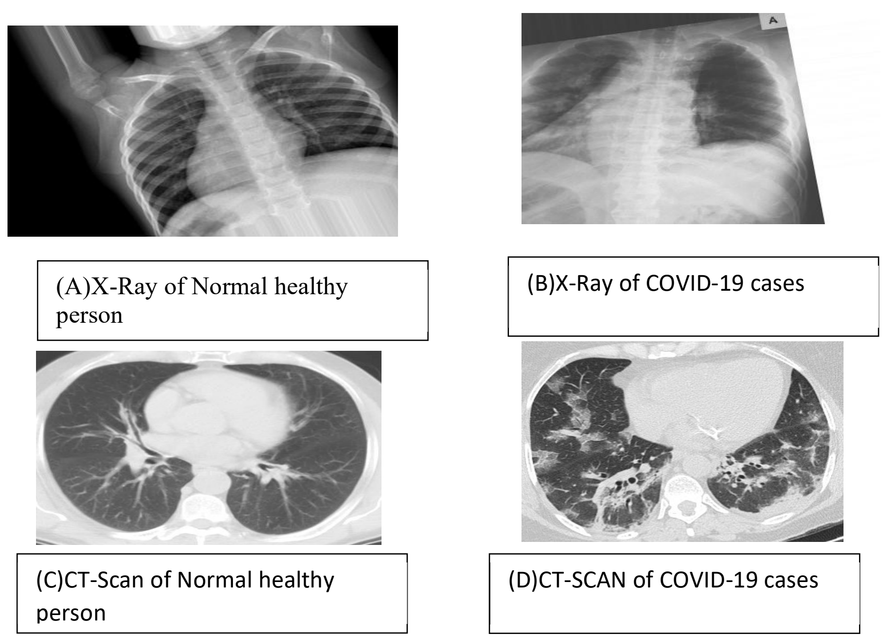

Figure 3 Samples of X-Ray and CT-Scan of normal and COVID-19 patients

V Proposed System

The transference education method is castoff in most DL methods, and it necessitates modification of the pre-trained models. Initially, adding novel data with modules that were formerly unidentified. Achieve a new mission as soon as you finish making changes to the system. When it comes to using pre-trained representations for numerous responsibilities, there are two main trends [37]. The initial way is pre-defined methods are used as feature extractor. Since their weights are non-appropriate for performing novel responsibilities, the mined features are inserted into a novel method which are created from the beginning of the process.

5.1 Early detection of COVID-19 using VGG 16

The suggested processes for VGG16 are shown in Figure 4, with the frozen and trainable levels highlighted. The CNN layers that are one on topmost of the additional levels, and the depth is increasing greater and higher, are the physical characteristics of VGG sequence series. Extreme sharing is used to reduce the volume proportions. The VGG16 [38] processes are made up of the following components such as 2 CNN 64-filter, 2 CNN 128- filter layers and 3 CNN 256-filter are tailed by a Max merging layer.2 stacks, each with three CNN layers with 512-filters and a maximum merging layer between them. A last layer of Max merging with 4096 frequencies, there are two fully connected levels.

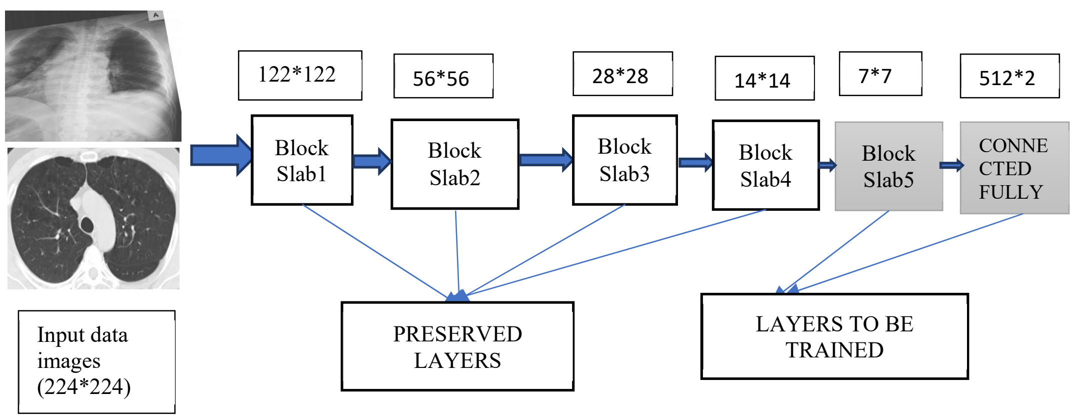

Figure 4 VGG16 ARCHITECTURE

5.2 Early detection of COVID-19 using ResNet50

Figure 5 depicts the architecture of ResNet50 [39] design, emphasising the preserved and layers to be trained. ResNet-50 is a Convolution with fifty layers, making it more complex than VGG16. The dimensions of the method are in point of fact significantly smaller because a global average pool is employed as a replacement for a fully linked layer, bringing ResNet50's method size down to 102 mb. Residual block slab learning is a unique feature of ResNet 50. Each level should be tailed straight into the following level as well as the ones 2–3 stages not here. Its structure is made up of the following elements: A filter-64 CNN with a kernel-7 size. A maximum merging level with a tread dimension of two follows this. Formerly a CNN with slab-64 and a kernel dimension of 1 ×1, then a subsequent CNN with slab-64 and a kernel dimension of 3 × 3. Next, there's a filter-256 CNN with a kernel dimension of 1 × 1. Three layers are reproduced three times in over-all, yielding a total of nine layers. Following that are three CNN, the foremost of which has filters-128 and a kernel size of 1 * 1. Following that, we take a CNN with filters-256 and a 1 * 1 kernel dimensions, as well as 2 additional convolutional layers CNN with filters-256, 1024 and a 3 * 3, 1 * 1 of kernel dimensions respectively. This is repeated six times in total, giving us eighteen layers. Formerly there's a CNN with filters-512 and a 1*1 kernel dimensions, followed by 2 more with filters- 2048, 512, and a 1 * 1, 3 * 3 kernel dimensions respectively. This is done three times, totalling nine layers. Lastly, used normal merging and quality with a completely linked layer and a Soft Max method to achieve a single layer as a last period.

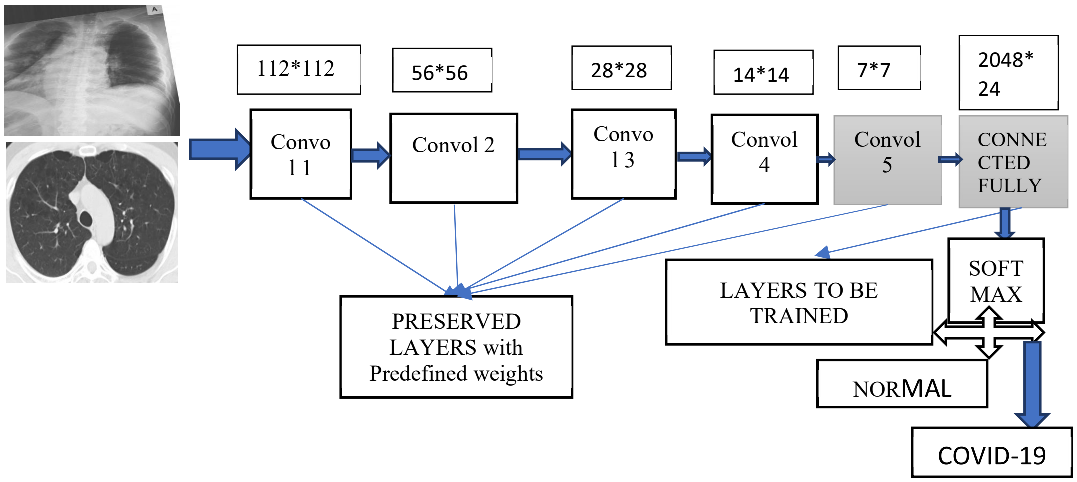

Figure 5 RESNET 50 ARCHITECTURES

5.3 Early detection of COVID-19 using Inception V3

` The proposed process for Inception V3 is shown in Figure 6, with the preserved and layers to be trained are highlighted. The early component's goal is to operate as a "multi level feature separator" by scheming 1×1, 3×3, and 5×5 CNN [39] in the similar network component. The filter productivity and system size are formerly sent posterior to the following level. In relation to computation efforts, Inception processes are not as challenging as VGG16 and ResNet 50. Regardless, it curved out to be a high-performing machine.

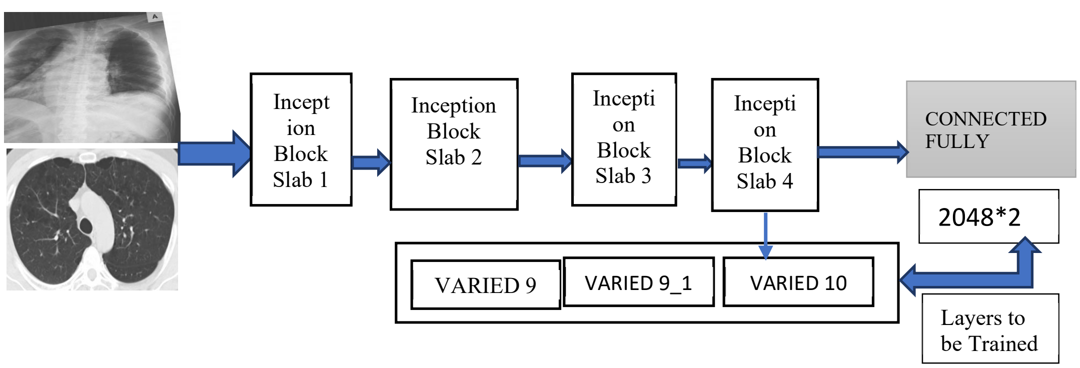

Figure 6 Inception V3 architecture

5.4 Early detection of COVID-19 using FJCovNet 2: A Novel Method

FJCovNet2 is a suggested method constructed on the Dense Net 121 [40] predefined method. FJCovNet2, which does not include the topmost layer of the Dense Net 121 predefined method, was built via transference education. This allows the predefined method to function as a feature separator while still being able to categorise. To allow the classification method in this work, the topmost layer of the Dense Net 121 is added, which functions as the classification methods. Consignment Normalization, Universal Average Merging, Compressed, and Dropout are the layers that make up this system. Figure 7 depicts the entire architecture of FJCovNet2. The Consignment Normalization layer since it has a lot of advantages when it comes to improving the methods evaluation metrics. Batch normalisation rearranges the dimensions of the optimization issues through improving its stability and smoothness. This will result in more efficient and operative optimization whereas dropout levels are also castoff. Dropout levels, like consignment normalisation, can increase efficiency. Through the training phase, the dropout layer functions by discarding components and the system connection at arbitrary times. This considerably lowers overfitting, hence improving the system performance and accuracy.

VI. PERFORMANCE EVALUATIONS

The proposed FJCovNet2 is pitted against three well-known CNN methods: Inception V3, VGG16, and ResNet 50. FJCovNet2 was compared to the other methods using the identical dataset and inputs as shown in Table 1. The Training Accuracy, Training Losses, Validation Accuracy, Validation Losses, and Training Epochs of the methods are the comparison features of the system. FJCovNet2 training accurateness ranges at a higher rate in less period than VGG16 and Resnet50, and roughly at the identical period as Inception V3, as shown in Fig. 8. FJCovNet2 also continues its accurateness steadiness, which is better than Resnet50 and comparable to Inception V3 and VGG16. In figure 9, FJCovNet2 training losses ranges a low rate in a portion of the time it takes Inception V3, VGG16, and ResNet50, and it sustains its steadiness better than Resnet50 and similarly to Inception V3 and VGG16.

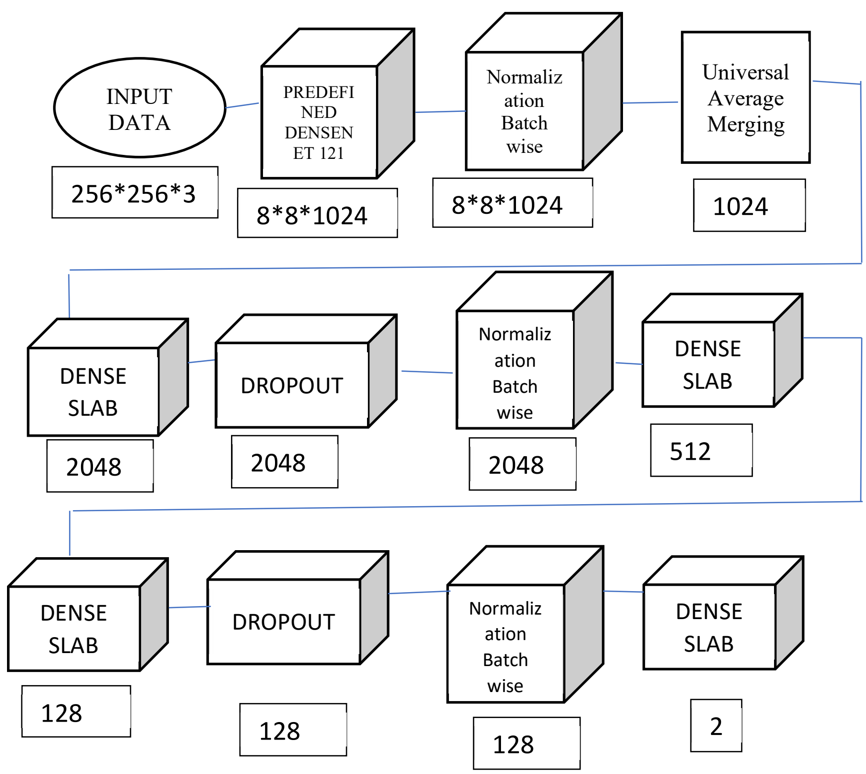

Figure 7 FJCOVNET2 Proposed Architecture

Figure 10 displays that FJCovNet2 achieves the maximum accurateness in the shortest amount of period and can keep the precision value stable until the last period, outperforming

Inception V3, VGG16, and Resnet50. FJCovNet2 outperforms Inception V3, VGG16, and ResNet50 in terms of achieving the lowest rate of validation loss in the shortest amount of period and maintaining loss rate steadiness until the preceding epoch as shown in Fig. 11. FJCovNet2 requires about the same amount of training period as Resnet50, as shown in Fig. 12. Resnet50 has the shortest time to train (610 seconds), although FJCovNet2 takes only three seconds.

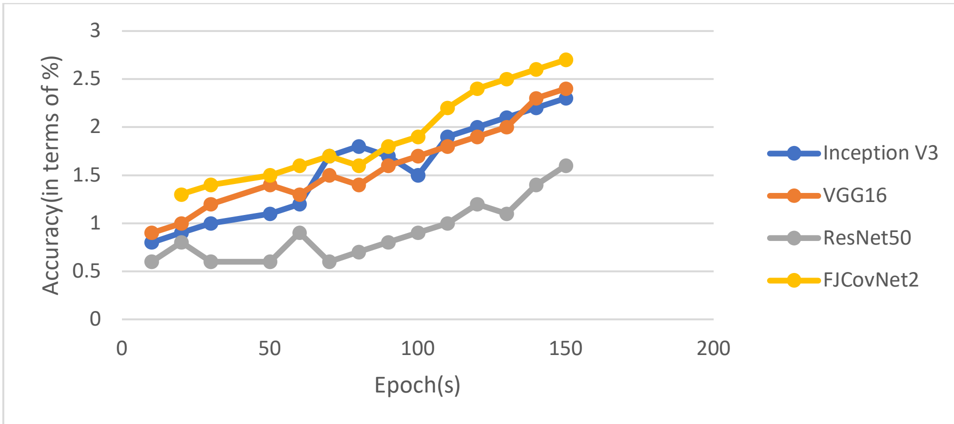

Figure 8 Evaluation of Training Accuracy

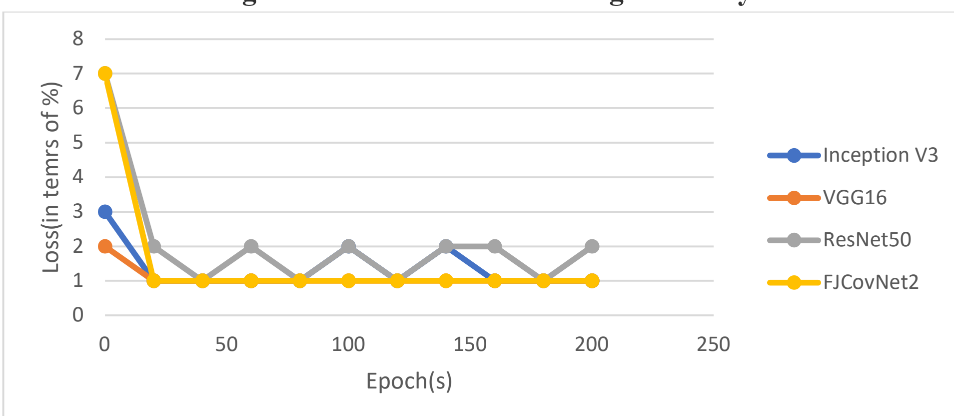

Figure 9 Evaluation of Training Loss

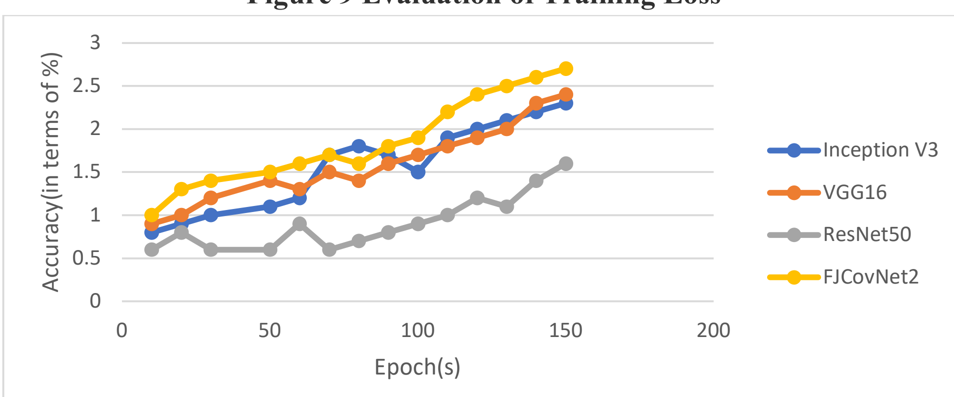

Figure 10 Evaluation of Validation Accuracy

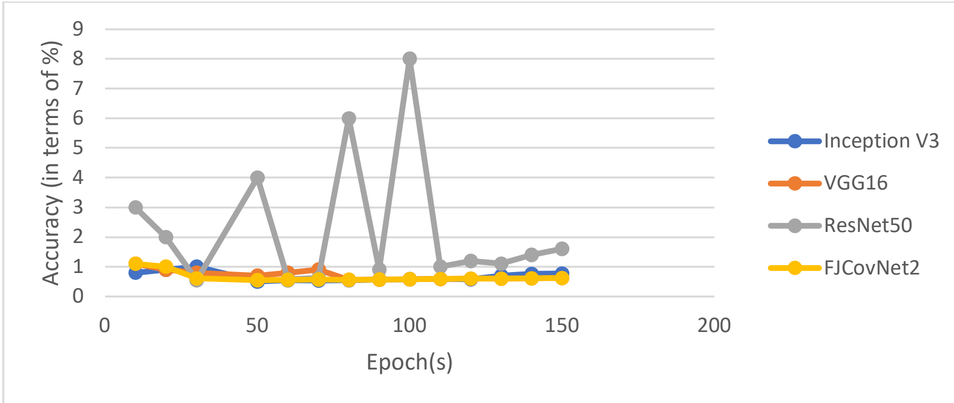

Figure 11 Evaluation of Validation Loss

As can be observed in Table 2 and the pictures, FJCovNet2 outperforms Inception V3, VGG16, and ResNet50 in terms of validation accurateness as displayed in Fig. 10 and training time as Fig. 12. FJCovNet2 not only outperforms the competition in terms of accuracy, but it also outperforms the competition in terms of training period. We used four distinct DL models, and the results were assessed using several performance criteria. According to the results, the FJCovNet2 models are the utmost appropriate models for early detection of COVID-19.

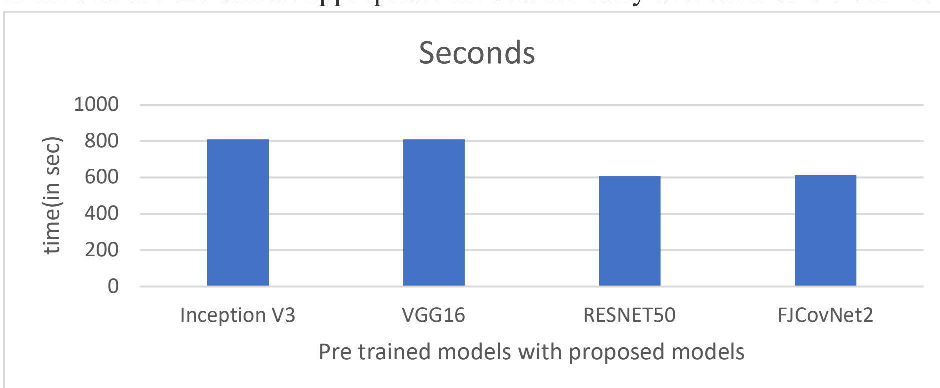

Figure 12 Evaluation of Training Time

Table 2 Comparative values of proposed model with the existing models

Method	Training Time (TT) in terms of sec	Accuracy Validation	Accuracy Loss
Inception V3	810	84.25%	0.7678
VSS16	809	95.26%	0.1633
ResNet50	610	91.45%	0.3822
FJCovNet2	613	98.23%	0.1546

VII. CONCLUSION

DL research is continually aiming to improve certainty depictions and develop models' illustrations on a massive gauge from unlabelled statistics. The promising findings of the DL model for sensing COVID-19 in radiological picture discovery suggest that DL will play a bigger role in tackling this pandemic in the future. When comparing FJCovNet2 to Inception V3, VGG16, and ResNet50 with the same dataset castoff for testing and training, it can be noted that FJCovNet2 attained the maximum validation with the least amount of training period. This demonstrates how FJCovNet2, when used in computer systems in real time, can aid in the COVID19 identification process. FJCovNet2 is a computer request that may be implemented in healthcare services. Users, such as radiologists or medical workers, can submit CT-scan images and X-Ray pictures of assumed cases using Application Program Interface (API). The photos are then fed into FJCovNet2, which produces a forecast of whether the patient is positive or negative. In the future, we are considering combining the five proposed DL models in this article and training all the layers as a novel strategy to deliver a superior outcome.

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