


Coronavirus Pneumonia Classification Using X-Ray and CT Scan Images With Deep Convolutional Neural Network Models

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ABSTRACT

Pneumonia is a life-threatening infectious disease affecting one or both lungs in humans. There are mainly two types of pneumonia: bacterial and viral. Likewise, patients with coronavirus can develop symptoms that belong to the common flu, pneumonia, and other respiratory diseases. Chest x-rays are the common method used to diagnose coronavirus pneumonia, and it needs a medical expert to evaluate the result of x-ray. Furthermore, DL has garnered great attention among researchers in recent years in a variety of application domains such as medical image processing, computer vision, bioinformatics, and many others. This work represents a comparison of deep convolutional neural networks models for automatically binary classification query chest x-ray and CT images dataset with the goal of taking precision tools to health professionals based on fined recent versions of ResNet50, InceptionV3, and VGGNet. The experiments were conducted using a chest x-ray and CT open dataset of 5,856 images, and confusion matrices are used to evaluate model performances.

KEYWORDS

Coronavirus Pneumonia, Deep CNN, Deep Learning, Healthcare Decision Support Systems, Image Classification, Image Processing, Inception, Knowledge Management, ResNet, VGGNet

1. INTRODUCTION

In most literature, pneumonia is an acute respiratory infection that affects the lungs which can be detected by analyzing chest x-rays. Generally, it is observed that bacterial pneumonia causes more acute symptoms (Hashmi et al. 2020). One of main complications caused by Coronavirus is pneumonia. For (Pereira et al. 2020), the COVID-19 can cause severe pneumonia and is estimated to have a high impact on the healthcare system (Sethy & Behera, 2020). Pneumonia cannot be classified as a single disease, but rather as a group of different infections with different characteristics. According to (Kadam et al. 2019), it is an acute respiratory infection which affects the lungs which can be detected by analyzing chest x-rays. For (Militante & Sibbaluca, 2020), patients diagnosed with pneumonia

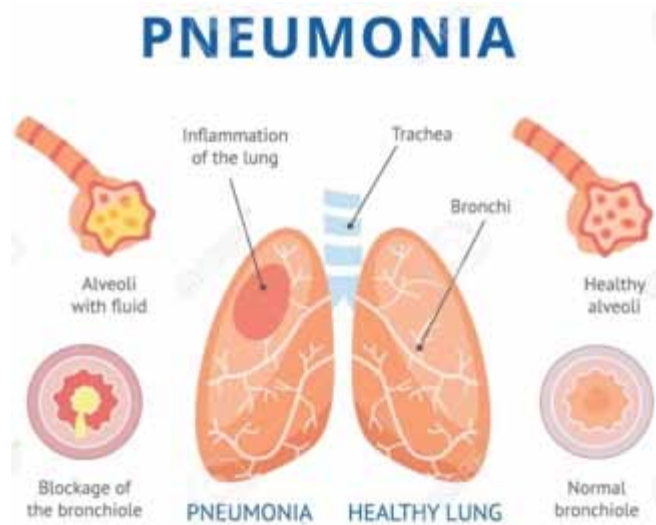
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shows the chest cavity signs of fluids filling the air sacs of lungs as for the radiograph picture appears brighter (see Figure 1.).

Figure 1. Pneumonia Diagram



In today's world, several Coronavirus have passed over the species barrier to cause deadly pneumonia in humans. The global spread of the epidemic had proceeded with such an accelerated speed that hospitals and medical centers witnessed teeming scenarios in a matter of weeks. The origin of Covid-19 is said to be in the starting of December 2019, when several patients from Wuhan, Hubei Province reported severe respiratory infections (Huang et al. 2020). Covid-19 has spread extremely rapidly in recent weeks with a very high number of infections affecting Algeria and most countries in the world. World Health Organization (WHO) and its partners have been working with global experts to learn more about the virus. Their main focus of study are as follows: (1) how it is transmitted, (2) the populations most at risk, and (3) the most effective ways to detect, interrupt, and contain transmission. The outbreak of the disease has made the WHO to declare the international emergency.

Many research work has been underway to investigate the actual fact of the disease. Latter the World Health Organization (WHO) has renamed the disease as Corona Virus Disease (Covid-19). This new virus called Covid-19 was identified in Wuhan, China in December 2019 (Tiana et al. 2020; Zhang et al. 2020). The incubation period for Covid-19 based on WHO reports varies from 2 to 14 days in human to human transmission, with the average incubation period recorded as 5-6 days (Shirani et al. 2020). According to virology experts, similar to other respiratory viruses, severe acute respiratory syndrome coronavirus (SARS-COV-2) may enter the brain via the hematogenous or neuronal route (Haddadi et al. 2020; Haddadi & Asadian, 2020).

Currently many biomedical health problems are using machine and deep learning based techniques. Moreover, application of machine learning methods for automatic diagnosis in the medical field is ascending because of its ability to deal with enormous datasets which is past the extent of human potential, and after that dependably convert examination of that information into clinical. Image analysis and machine learning techniques already have extensive applications in precision health. Besides that, innovations in Deep learning (DL) are tremendous and applications of Deep Learning (DL) techniques are ever expanding and encompassing a wide range of services across many fields

namely feature extraction, recognition, classification, and prediction. Similarly, DL has enabled many practical applications of machine learning and by extension the overall field of AI. Likewise, clinical knowledge extracted from enormous datasets gives better results, less expenses of consideration and improved patient fulfillment. For (Aledhari et al. 2019), DL methodologies are becoming very common in the fields of medical image classification. This can be attributed primarily due to huge success rate of these algorithms. More specifically, deep learning is considered an evolution of machine learning. It uses a programmable neural network that enables machines to make accurate decisions without help from humans (Apostolopoulos & Mpesiana, 2020). According to (Al ayoubi et al. 2020), deep learning has become one of the most common techniques that has achieved better performance in many areas, especially in medical image analysis and classification.

Recently, the Deep Learning (DL) techniques have achieved tremendous success in computer vision area. They can model high-level abstractions in data relative to specific prediction task. This very special potential of Deep Learning (DL) algorithms made it a preferred tool for image analysis. According to (Suganthi et al. 2020), DCNNs models is a class of deep, feed-forward artificial neural networks that has successfully been applied to analyzing visual imagery (Zabalza et al. 2016). DCNNs use relatively minimal pre-processing compared to other image classification algorithms. For (Spanhol et al. 2016), there are three main types of layers used to build CNN architectures; (1) convolutional layer, (2) pooling layer, and (3) fully connected (fc) layer. Moreover, a Deep CNN models such as ResNet50, Inception_V3, DenseNet201, MobileNet_V2 and VGGNet are designed to continually analyze data with a logic structure similar to how a human would draw conclusions. To achieve this, deep learning applications use a layered structure of algorithms called an artificial neural network. DCNN was also applied to identify the nature of pulmonary nodules via CT images, the diagnosis of pediatric pneumonia via chest X-ray images, automated labelling of polyps during colonoscopic videos, cystoscopic image analysis from videos (Wang et al. 2018; Chowdhury et al. 2020; Asif et al. 2020).

As per our objective, the new techniques of deep learning are able to obtain much quicker classifications in order to aid field experts (clinicians) in real-time classification. Therefore, this paper is focused on applying end-to-end, accurate, and computationally efficient DCNN models for automatic Coronavirus Pneumonia classification. As well, the performance of the proposed binary classification approach is evaluated using the Chest X-Ray & CT images open dataset.

The rest of the paper is organized as follows: Section 2 introduces the related work on feature extraction and classification techniques proposed by various researchers. Section 3 presents the proposed approach used for Coronavirus Pneumonia image classification, and the experimental results and discussion are covered in Section 4. Finally, Section 5 concludes with the scope of the work combined with the challenges.

2. RELATED WORK

A lot of researchers have conducted studies, new frameworks and designs regarding detection of pneumonia in CXR images, and Coronavirus pneumonia detection on CXR or CT scan images using various algorithms, methodologies, techniques, and procedures which will be considered as part of the theoretical framework of this research, enabling afterwards the construction of the conceptual framework of the study.

For instance, (Madaan et al. 2021) have developed a model to detect the COVID-19 infection using chest X-ray images (392 positive COVID+ and negative COVID- X-ray patient images). The authors have implemented three convolutional layer-based models with a kernel size of 3×3 and achieved a COVID-19 detection accuracy of 98.44%. (Ibrahim et al. 2021) have proposed the use of a deep learning approach based on a pre-trained AlexNet model for the classification of COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia, and normal CXR scans obtained from different public databases. For classification CXR images of COVID-19 pneumonia and non-COVID-19

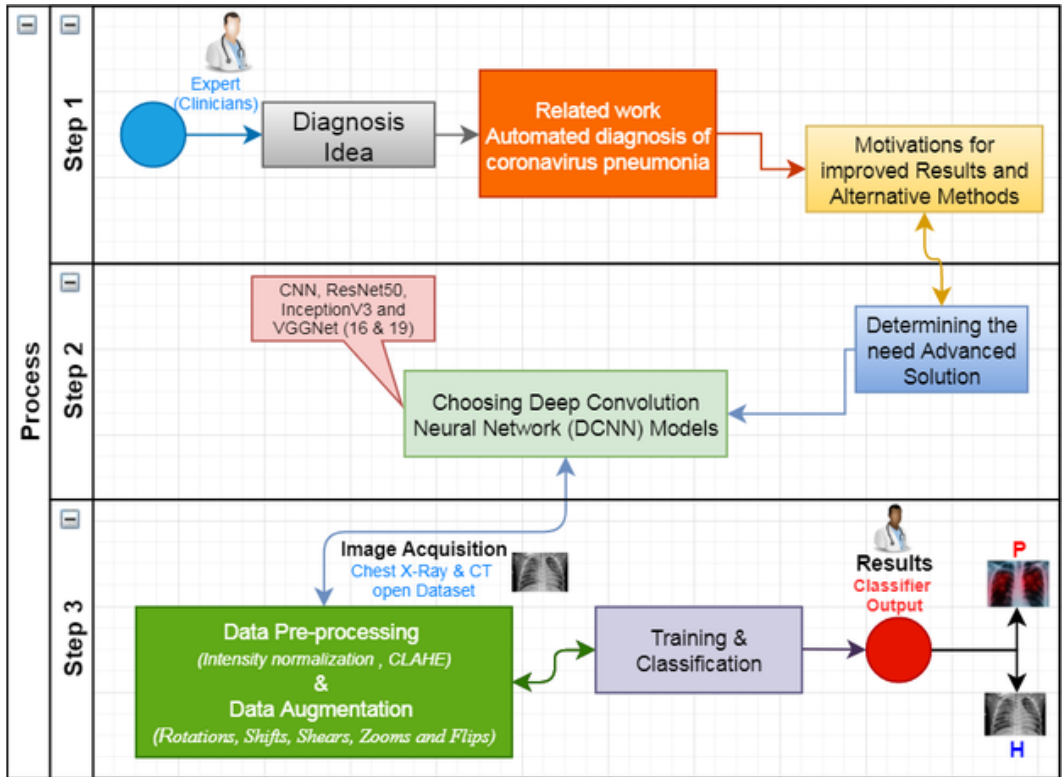
viral pneumonia, the model achieved 99.62% accuracy, 90.63% sensitivity, and 99.89% specificity. In the study done by (Sekeroglu & Ozsahin, 2020), it is to present the use of deep learning for the high-accuracy detection of COVID-19 using chest X-ray images. Publicly available X-ray images (1583 healthy, 4292 pneumonia, and 225 confirmed COVID-19) were used in the experiments, which involved the training of deep learning and machine learning classifiers. (Militante & Sibbaluca, 2020) have developed several models to determine the best possible model in detecting pneumonia with the most accurate results. This study has trained five different models of DCNN, namely AlexNet, LeNet, GoogleNet, ResNet and VGGNet using 1024 by 1024 resolution of 26,684 dataset images. The result achieved a 97 percent accuracy rate for VGGNet and the lowest rate is 74 percent achieved by the ResNet model. A new deep learning framework, that allows classify and quantifying lung abnormalities like pneumonia patients, was reported by (Bhandary et al. 2020) using chest X-ray images and cancer using lung CT images. Hence, they proposed two models: A) a MAN model combined with Support Vector Machine (SVM) used to identify pneumonia images from normal images. For the results, the proposed model showed good results (accuracy 96.8%) compared to other models AlexNet, VGG16, VGG19, ResNet50, and MAN-Softmax. In the comparative study done by (El Asnaoui et al. 2020), it is to present a comparison of recent DCNN architectures for automatic binary classification of pneumonia images based on fined tuned versions of VGG16, VGG19, DenseNet201, Inception-ResNet-V2, InceptionV3, and MobileNetV2. The proposed work has been tested using chest X-ray & CT dataset. In the given study by (Verma & Prakash, 2020), it has been demonstrated that how one can classify the true and false cases of pneumonia easily from a small dataset of X-ray images using CNN approach along with different data augmentation techniques for improving the classification accuracies which will help in improving the validation and characterization of exactness of the CNN model. (Acharya & Satapathy, 2020) have proposed an automatic detection of pneumonia from chest radiography image using the deep Siamese based neural network. Deep Siamese network use the symmetric structure of the two input image to compute or classify the problem. Each of the chest X-ray image is divided into two segment and then feed it to the network to compare the symmetric structure along with the amount of the infection that is spread across these two region. Besides, Aledhari et al. (2019) have proposed a deep learning algorithm based on convolutional neural networks to identify and classify pneumonia cases from these images. Based on the results, the authors obtained better prediction with average accuracy of (68%) and average specificity of (69%). As well, (Kadam et al. 2019) have proposed a deep neural network based on convolutional neural networks and residual network along with techniques of identifying optimum differential rates using cosine annealing and stochastic gradient with restarts to achieve an efficient and highly accurate network which will help detect and predict the presence of pneumonia using chestx-rays. Another study by (Stephen et al. 2019), it is to propose a convolutional neural network model trained from scratch to classify and detect the presence of pneumonia from a collection of chest X-ray image samples. The model could help mitigate the reliability and interpretability challenges often faced when dealing with medical imagery. Moreover, (Rajaraman et al. 2018) have used the simple VGG16 model for the pneumonia detection from the pediatric chest x-ray image. The authors evaluated and visualized the performance of customized CNNs to detect pneumonia and further differentiate between bacterial and viral types in pediatric CXRs. In this research (Abiyev & Ma'aitah, 2018) have demonstrated the feasibility of classifying the chest pathologies in chest X-rays using conventional and deep learning approaches. For comparative purpose, backpropagation neural networks (BPNNs) with supervised learning, competitive neural networks (CpNNs) with unsupervised learning are also constructed for diagnosis chest diseases.

Based on these related works, many researchers have been applied deep learning architectures for detecting coronavirus pneumonia. Many of them considered Deep Convolution Neural Network (DCNN) models as effective architectures as it provides feature extraction without manual intervention.

3. APPROACH PROPOSED

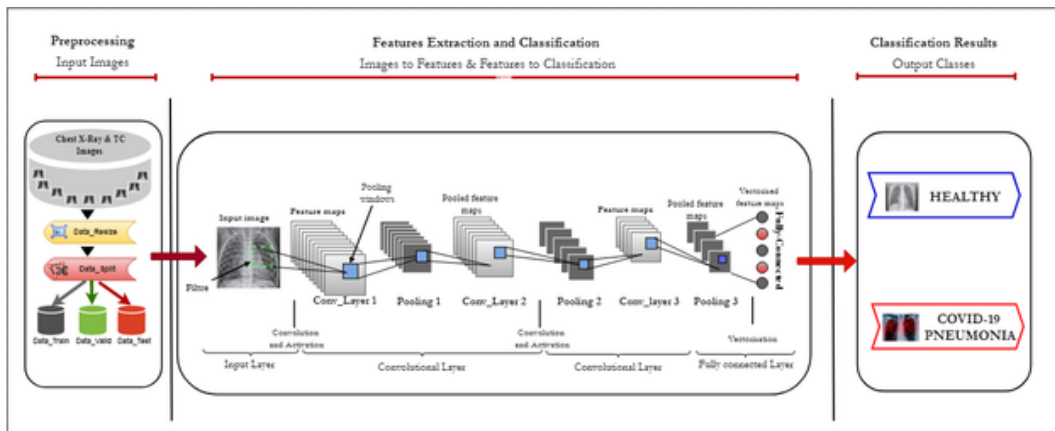
As per our objective and the motivations, this study is associated with some background ideas and research efforts as shown in Figure. 2. Briefly, especially using deep CNN models for diagnosis, analyzing, and classify (Coronavirus Pneumonia) and supporting it with image processing has been remarkable ideas to follow. As general, widely followed automatic binary classification and diagnosis approach performed with Deep Learning models such as CNN, ResNet50, InceptionV3, and VGGNet have been directed to the disease of Coronavirus Pneumonia (see Figure. 2).

Figure 2. Ideas and research efforts on the background of this study



In the context mentioned above, this study followed an easy-to-design image pre-processing and deep learning approach for automatically diagnosing, analyzing, and classify Coronavirus pneumonia, by considering Chest X-Ray & CT Images as input data. In this respect, Figure. 3 represents the stages within the flow of the introduced deep learning approach. After the image pre-processing based enhancement, the classification was made by using Deep Convolutional Neural Networks (DCNN) models (ResNet50, InceptionV3, and VGGNet). In next stages, we evaluate our introduced deep learning approach by using 5,856 X-Ray & CT images, which are performed as part of patients' routine clinical care. Meanwhile, the image processing techniques is important for a good image enhancement, which will be effective for better diagnosis and classification at the end. The whole flow is a deep learning approach applied to target image data, which is essential for diagnosing from medical inputs in the form of visual elements (see Figure. 3).

Figure 3. Main Steps of the proposed hybrid approach



3.1. Datasets (Chest X-Rays & CT)

In our work, pneumonia images used in this study are publicly available image dataset which contains X-Ray and computed tomography (CT) images of patients which are positive or suspected of Coronavirus or other viral and bacterial pneumonia¹ (Cohen et al. 2020). This dataset has been used for analyzing the performance of algorithms (Machine/Deep Learning) used for automated diagnosis of pneumonia. In addition, The dataset is organized into 3 folders (Training, Testing, and Validation) and contains subfolders for each image category (Pneumonia (P) and Healthy (H)). The Pneumonia (P) category is composed of Coronavirus pneumonia images that are labeled either bacterial or viral (Kermamy et al. 2018).

There are 5856 X-Ray & CT images (JPEG) that are performed as part of patients’ routine clinical care. Each training set contains 4192 images (3110 images in pneumonia folder & 1082 images in normal folder), each test set contains 624 images (390 images in pneumonia folder & 234 images in normal folder) and each validation set contains 1040 images (773 images in pneumonia folder & 267 images in normal folder) (Kermamy et al. 2018). Since this dataset was composed of pulmonary images having heterogeneous and large sizes, and to deal with reasonable computational times during the deep CNN models training experiments, all the images were resized to a unique dimension and rescaled into smaller images (e.g.: size 224×224) to fit with standard inputs of tailored architectures (Wu et al. 2020).

Figure 4 shows pneumonia at two different stages. The normal chest X-ray (right panel) depicts clear lungs without any areas of abnormal opacification in the image. Coronavirus pneumonia (left) manifests with a more diffuse “interstitial” pattern in both lungs (see Figure. 4).

Figure 4. Chest X-ray & CT scan samples from the test datasets. The coronavirus CT scan (right) shows multifocal and bilateral ground-glass opacities, the normal chest X-ray (middle) shows clear lungs without any abnormal opacity, whereas the ‘fog’ like discoloration in the coronavirus pneumonia positive chest X-ray image.



3.2. Preprocessing

In theory, image processing techniques are increasingly used as a way of diagnosing diseases, including diseases of the coronavirus pneumonia. Moreover, pre-processing is the method that is applied to the images before the actual processing of the images to enhance the features of the image. The motivation behind image pre-processing is to improve the quality of visual information of each input image. By doing this one can expand the successful size of the dataset. Changes to apply are generally picked arbitrarily from the predefined set. All the images in the dataset are taken of different people, using different clinical settings, and are of different sizes.

In this study, we propose an improved medical image enhancement method that combines the intensity normalization and Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithms (Kandel et al. 2020) to gain image quality of the raw X-ray & CT image in the pre-processing stage. According to (Lidong et al. 2015), applying this method only may lead to overexpose or underexpose the X-ray image.

As per our models, we propose to import the OpenCV-Python package in order to spread out the pixel intensity values. In addition to OpenCV-Python, we will also import NumPy and Matplotlib to demonstrate the histogram equalization. In this, the image is divided into small blocks called “tiles” (tile Size is 8x8 by default in OpenCV). Then each of these blocks are histogram equalized as usual. In summary, we illustrate through Figure 5 the result of using these techniques (see Figure. 5).

Figure 5. Original, Normalized and CLAHE image.



3.3. Data Augmentation

In the literature, data augmentation is a technique that could help fight overfitting. Basically, during the training phase, the generator will randomly perform some transformations on the original image such as rotating, shearing, shifting, flipping. In this study, we applied augmentation on images in real-time to reduce overfitting. During each epoch, a random augmentation of images that preserve collinearity and distance ratios was performed. According to (Verma & Prakash, 2020), this technique helps to improve and add some effective knowledge about the data for enhancing the classification accuracy of the images and better results. Besides that, the model trained with data augmentation is more robust and can generalize better. For image augmentation, we use strategies for our DCNN models that include geometric transforms such as rescaling, rotations, shifts, shears, zooms, and flips. Each option has its ability to represent images in different ways to provide important features during the training phase and thus enhances the model’s performance better. Table 1. shown below the settings utilized in image augmentation.

Table 1. Augmentation techniques used in the proposed approach.

Technique	Setting	Description
Retation	45	Degree range of the random rotations
Zoom range	0.2	Allows the image to be “zoomed out” or “zoomed in”
Vertical Shift	0.2	The parameter value of horizontal and vertical shifts (20%) is a fraction of the given dimension
Horizontal Shift	0.2	The parameter value of horizontal and vertical shifts (20%) is a fraction of the given dimension
Range-Shear	0.2	Controls the angle in counterclockwise direction as radians in which our image will allowed to be sheared
Flip-Horizontal	True	Controls when a given input is allowed to be flipped horizontally during the training process
Flip-Vertical	True	Controls when a given input is allowed to be flipped vertically during the training process
Re-scale	1/255.0	Scale images from integers 0-255 to floats 0-1

As a result, the images after using the ImageDataGenerator functionality from the TensorFlow Keras framework (Shorten & Khoshgoftaar, 2019) (see Figure. 6).

Figure 6. Example Image after performing the augmentation technique.

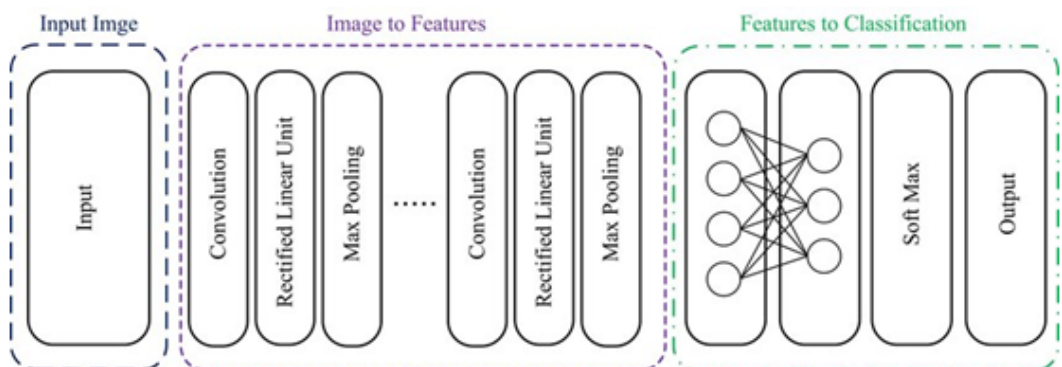


3.4. Deep Convolutional Neural Networks (DCNNs)

Deep Learning (DL) is a part of an artificial neural network technique and a subclass of machine learning. Moreover, DL is part of a broader family of machine learning methods based on learning data representations. In DL, multiple layers used for a higher level of feature from the input dataset. DL methodologies are becoming very common in the fields of medical image classification (Aledhari et al. 2019). Many of the notable and most successful works in medical image classification involved implementing deep learning algorithms such as Convolutional Neural Networks (CNNs). In this field, Convolutional Neural Networks (CNNs or ConvNets), a branch of deep learning, have an impressive record for applications in image analysis and interpretation, including medical imaging (Pratt et al. 2016). For (Militante & Sibbaluca, 2020), it is very effective in a multi-layered structure when obtaining and assessing necessary features of graphical images. Furthermore, DCNN is a class of deep, feed-forward artificial neural networks that has successfully been applied to analyzing visual imagery. DCNNs use relatively minimal pre-processing compared to other image classification algorithms (Suganthi et al. 2020). According to earlier works, DCNN is a type of deep neural networks that learns features from the input data and uses two dimensional convolutional layers for the processing of two dimensional image data (Jyotiyana & Kesswani, 2020). In general, the deep convolutional neural network is composed of many layers in which many two-dimensional planes of feature mapping form (Wang et al. 2019). According to (Abdolmanafi et al. 2018), the popular network in this DCNN, which has a broad application in medical image analysis is Inception-v3 (Szegedy et al. 2015), VGG16 model (Litjens et al. 2017) and ResNet50 (Abdolmanafi et al. 2018) model is other network of this group. The architecture of CNN models, in any CNN model there are three types of main layer as convolutional layer which, pooling layer and dense layer.

Most of the layers in CNN convert an input image to features. Only the last few layers are used for classification (Gadekallu et al. 2020). Finally, Figure 7 graphically presents the general architecture of a CNN, with its main elements.

Figure 7. General architecture of CNN



In this light, we briefly discuss the parameters, architecture of deep CNNs and sub-networks of the three CNNs models (Inception-v3 (Ji et al. 2019), ResNet50 (He et al. 2016) and VGG16 & 19 (Simonyan & Zisserman, 2015)) for diseases Coronavirus pneumonia detection and classification in order to obtain high accuracy and reduce parameters. As well, the outstanding performance of CNN models inspires us to apply them on medical images.

3.4.1. Inception(v3) Network Architecture

The Inception network was an important milestone in the development of CNN classifiers. Unlike traditional deep neural network, the Inception(V3) network is known for its parallel stacked convolutional layers. Moreover, it is a convolutional neural network architecture from the Inception family that makes several improvements including using Label Smoothing, Factorized 7 x 7 convolutions, and the use of an auxiliary classifier to propagate label information lower down the network (Ji et al. 2019). The network architecture is composed of 11 Inception modules of five kinds in total. Each module is designed by experts with convolutional layer, activation layer, pooling layer and batch normalization layer. In the Inception-v3 model, these modules are concatenated to achieve maximal feature extraction.

In summary, we present across the Table 2 lists the parameters of the original network structure of Inception(V3) network. The neural network layers in the Table 2 are connected in series from top to bottom.

Table 2. Network structure of Inception(V3) network

Type	Patch size/stride or remarks	Input size
Conv	3*3/2	299*299*3
Conv	3*3/1	149*149*32
Conv Padded	3*3/1	147*147*32
Pool	3*3/2	147*147/64
Conv	3*3/1	73*73*64
Conv	3*3/2	71*71*80
Conv	3*3/1	35*35*192
3*Inception	First Inception block structure	35*35*288
3*Inception	Second Inception block structure	17*17*768
2*Inception	Third Inception block structure	8*8*1280
Pool	8*8	8*8*2048
Linear	Logits	1*1*2048
Softmax	Classifier	1*1*1000

The purpose of Inception(V3) architecture was to reduce computational resource usage in highly accurate image classification using deep learning.

3.4.2. VGG Network (VGG16 & VGG19) Architecture

The visual geometry group network (VGGNet) is a deep neural network with a multilayered operation. The VGGNet is based on the CNN model (Mateen et al, 2019). This deep learning method is one of the first attempts at adding depth to improve classification accuracy. The major characteristic of this architecture is instead of having a large number of hyperparameters, they concentrated on simple 3x3 size kernels in convolutional layers and 2x2 size in max pooling layers (El Asnaoui & Chawki, 2020). During testing, in VGGNet, the test image is directly go through the VGGNet and obtain a class score map. This class score map is spatially averaged to be a fixed-size vector. For (Setiawan & Damayanti, 2020), VGGNet created the VGG16 (Simonyan & Zisserman, 2015) network architecture with 16 layers and VGG19 (Simonyan & Zisserman, 2015) with 19 layers. According to (Hieu &

Hien, 2020), VGG16 is a CNN architecture that was used to win the ImageNet ILSVR competition 2014. It is as yet considered as one of the outstanding vision model architecture. Moreover, VGG-19 is useful due to its simplicity as 3×3 convolutional layers are mounted on the top to increase with depth level (Saikia et al. 2019; Mateen et al. 2019). For (Zhang et al. 2016), VGG-19 model has roughly 143 million parameters, where the parameters are learned from the ImageNet dataset containing 1.2 million general object images of 1,000 different object categories for training.

The use of uniform and smaller filter sizes on VGG can produce more complex features and lower computing when compared to AlexNet. In summary, we present across the Table 3 (See Table. 3) the difference between VGG16 and VGG19.

Table 3. Comparison of VGG16 and VGG19 Layers

Layer	VGG16	VGG19
Size of Layer	41	47
Image Input Size	244*244 pixel	224*244 pixel
Convolutional Layer	13	16
Filter Size	64 & 128	64,128,256, & 512
ReLU	5	18
Max Pooling	5	5
FCL	3	3
Drop Out	0.5	0.5
Softmax	1	1

3.4.3. ResNet50 Network Architecture

In the research work of (Mishra et al. 2020; Rahimzadeh & Attar, 2020), the key idea in ResNet architectures is that stacking up of convolutional and pooling layers one on top of another, can cause the network performance to degrade, due to the problem of vanishing gradient. To deal with this, identity shortcut connections can be used which can basically skip one or more layers. According to (Zhao et al. 2019), the Resnet50 consists of five steps each with a convolution and Identity block and each convolution block has 3 convolution layers and each identity block also has 3 convolution layers. Resnet50 has 50 residual networks and accepts Input images of 224 by 224 pixels by 3 bytes (RGB) = about 0.05Mbytes and Weights of 22.7Mbytes (Wu et al. 2018). For (He et al. 2016), Residual Networks (ResNets) are deep convolutional networks where the basic idea is to skip blocks of convolutional layers by using shortcut connections. The basic blocks named “bottleneck” blocks follow two simple design rules:

1. for the same output feature map size, the layers have the same number of filters;
2. if the feature map size is halved, the number of filters is doubled.

4. EXPERIMENTAL AND RESULTS

In the literature, most of the research works that apply deep CNN models for Coronavirus pneumonia classification use hundreds of thousands of images to train the model. In this section, we presents the results of the performance on the Chest X-Rays & CT dataset.

4.1. Evaluation Criteria

The performance of a coronavirus pneumonia classification approach is evaluated by various performance metrics. The accuracy metric, which determines the correctness of the identified instances in both classes of binary classification (Pneumonia (P) and Healthy (H)), must be supplemented by other metrics such as precision, recall, *F1* score, and AUC. These popular parameters are defined as follows:

$$Sensitivity(Recall) = TP / TP + FN \quad (1)$$

The recall metric will tell us how well a model is in finding all of the true positives and is a ratio of true positives over all entities in the testing set.

$$Specificity = TN / TN + FP \quad (2)$$

In general, sensitivity and specificity evaluates the effectiveness of the algorithm on a single class, positive and negative respectively.

$$Accuracy = TP + TN / TP + TN + FP + FN \quad (3)$$

$$Precision = TP / TP + FP \quad (4)$$

The precision metric will show the ratio of true positives over the total number of detected entities. In other words, this metric will help us understand how well a model is in returning only the true positives and not unrelated entities.

$$F - score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (5)$$

Commonly, accuracy is the most used metric to evaluate the classification performance. This metric calculates the percentage of samples that are correctly classified. As well, precision is how “precise” the model is out of those predicted positive and how many of them are actually positive. A high value of the metric (F-score) indicates that the model performs better on the positive class. Thus, F1 Score (also known as F-measure) might be a better measure when a balance between Precision and Recall is needed with an uneven class distribution (large number of Actual Negatives). This metric can be used to show the overall performance of a tool.

Likewise, a confusion matrix is commonly used to visualize the performance of a classification algorithm. Measurement of TP, FP, TN, and FN uses a confusion matrix of a classification with two classes. where TP, TN, FP, and FN stand for true positives, true negatives, false positives, and false negatives, respectively (see Figure .8).

In this study, an assessment of state-of-the-art pre-trained models for the task of classification of Coronavirus pneumonia disease using images was done. The objective of this research was to compare all the models evaluating the Accuracy, Precision, Sensitivity, Specificity and F-Score.

Figure 8. Confusion matrix for binary classification

		Predicted	
		Positive	Negative
Actually	Positive	True Positive (TP)	False Negative (FN) Type II error
	Negative	False Positive (FP) Type I error	True Negative (TN)

4.2. System Requirements

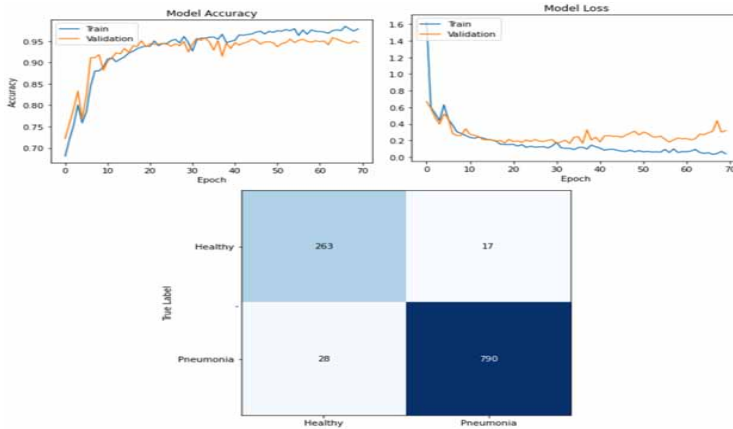
The experimental environment of this paper is Windows 10 system, Python 3.6.2, Tensorflow 1.11.0, and Keras 2.2.4. In the hardware device section, the CPU is Intel Core i5 4300U @ 1.90 GHz 2.50 GHz specifications, GPU 1060 6 Gb D5 amp, Solid State Drive, Double Data Rate4 16 Gb, and MSI Z270 GAMING PRO CARBON Motherboard. The emulator is written in Python and uses the neural network library Keras and GPU.

4.3. Results and Discussions

In this work, the most widely used Chest X-Ray & CT images dataset has been chosen to verify the proposed approach using Python programming language with Tensorflow framework. For this, we investigated the automatic binary classification of the cases of coronavirus pneumonia disease using deeper and dense networks (Baseline CNN, Fine-tuning the top layers of Inception_V3, Resnet50, VGG16 and VGG19). This method can perform classification based on the various status of the Chest X-Ray & CT images (See section 3.1). Multiple layered models have been designed for performing convolution and feature extraction. The Rectified Linear Unit (ReLU) activation function is used to define the output of internal layers. Moreover, the training curve is calculated from the training dataset that provides an idea of how well the model is learning. Similarly, the validation curve or test curve is calculated from a hold-out validation dataset that provides an idea of how well the model is generalizing. In theory, losses are the errors that occurred in the process of prediction while training the model. The optimum training process always reduces errors and increases accuracy. As per our approach, the lower the loss better is the model and the higher the accuracy more satisfactory is the classification results. During the training process, the approach determines the graphs for the model's loss and accuracy for 70 epochs.

§ **Baseline CNN:** The graphical representation of training loss vs validation loss and training accuracy vs validation accuracy of baseline CNN model is displayed from Figure. 9.

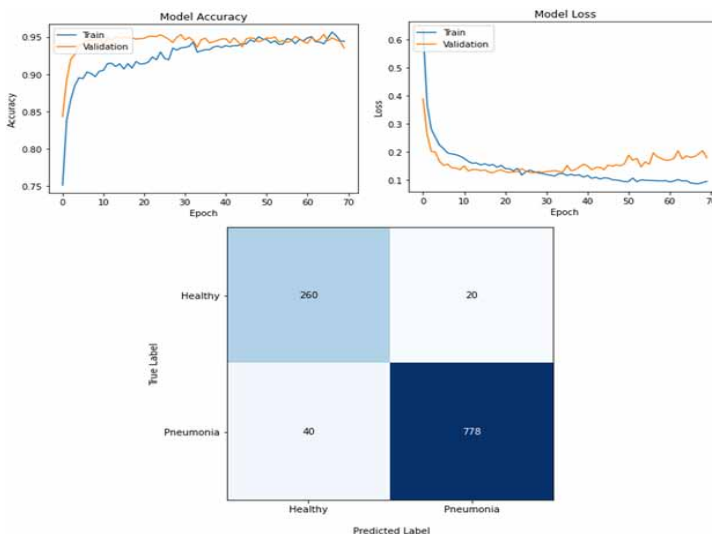
Figure 9. Result of Baseline CNN Model (Accuracy, loss curve and confusion matrix ‘Actual and predicted labels are displayed on the y-axis and x-axis, respectively’)



According to the figure above, it is observed that the accuracy curve of train data is rapidly increasing from epoch 0 to epoch 7 then it starts to be stable until epoch 70 where the total well classified images is 1053 with an accuracy curve of test data with 95.11% for epoch 70. As well, we find that the best results are obtained in the two classes (Healthy) and (Pneumonia) with an F1-score 0.92 and 0.97 respectively. From the confusion matrix, it is observed that the first images class (Healthy), the CNN model was able to identify 263 images correctly in the Healthy class, but 17 were labelled as Pneumonia. Likewise, for the second images class (Pneumonia), the model was able to identify 790 images correctly, but 28 images were labelled as Healthy.

§ **VGG16**: The graphical representation shown in Figure 10 gives the percentage values of performance measures obtained for VGG16 Model in binary classification scenario.

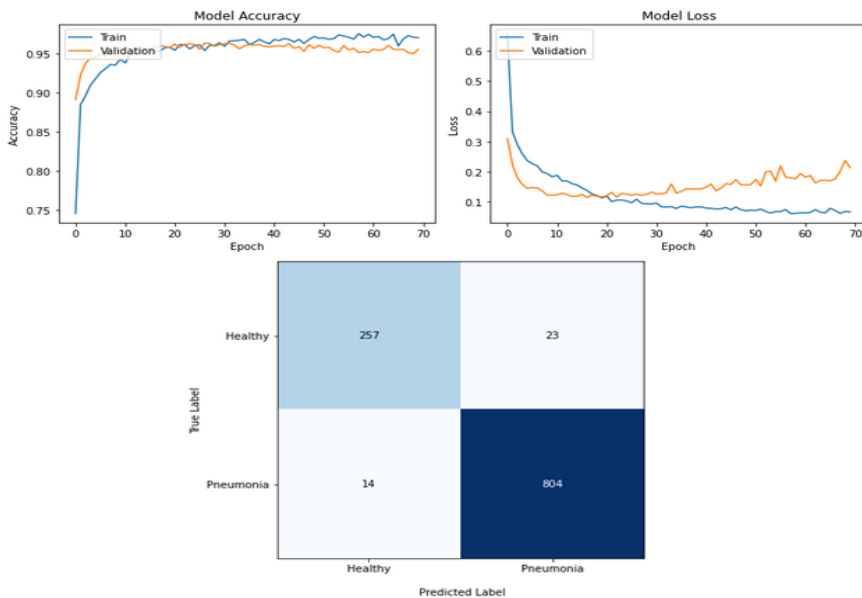
Figure 10. Result of VGG16 Model (Accuracy, loss curve and confusion matrix ‘Actual and predicted labels are displayed on the y-axis and x-axis, respectively’)



The results given by VGG16 (See Figure. 10) show that Pneumonia class was detected with good sensitivity (95.01%) that is caused by the low sum of false negatives with reasonable precision 97.01%. As it is observed, the accuracy value is 95.04%. From these graphs, we notice that the training and validation precision increases with the number of epochs. Likewise, the training and validation error decreases with the number of epochs. From the confusion matrix, we can observe for images class (Pneumonia) the model was able to predict 778 images correctly in the pneumonia class, but 40 were labelled as Healthy. For the images class (Healthy), the model was able to identify 260 images correctly, but 20 images were labelled as Pneumonia.

§ **VGG19:** As it is showed in the figure below (see Figure. 11), it is observable that the VGG19 model provided an average accuracy of 97.36% that increases with the number of epochs in the curve of training data (validation data), this reflects that with each epoch the model learns more information. Likewise, we notice that the total misclassified images is 37 images, an error rate of 3.37% and the total well classified images is 1057 an accuracy rate of 96.90%. From the confusion matrix, we can observe for images class (Pneumonia) the model was able to predict 804 images correctly in the pneumonia class, but 14 were labelled as Healthy. For the images class (Healthy), the model was able to identify 257 images correctly, but 23 images were labelled as Pneumonia.

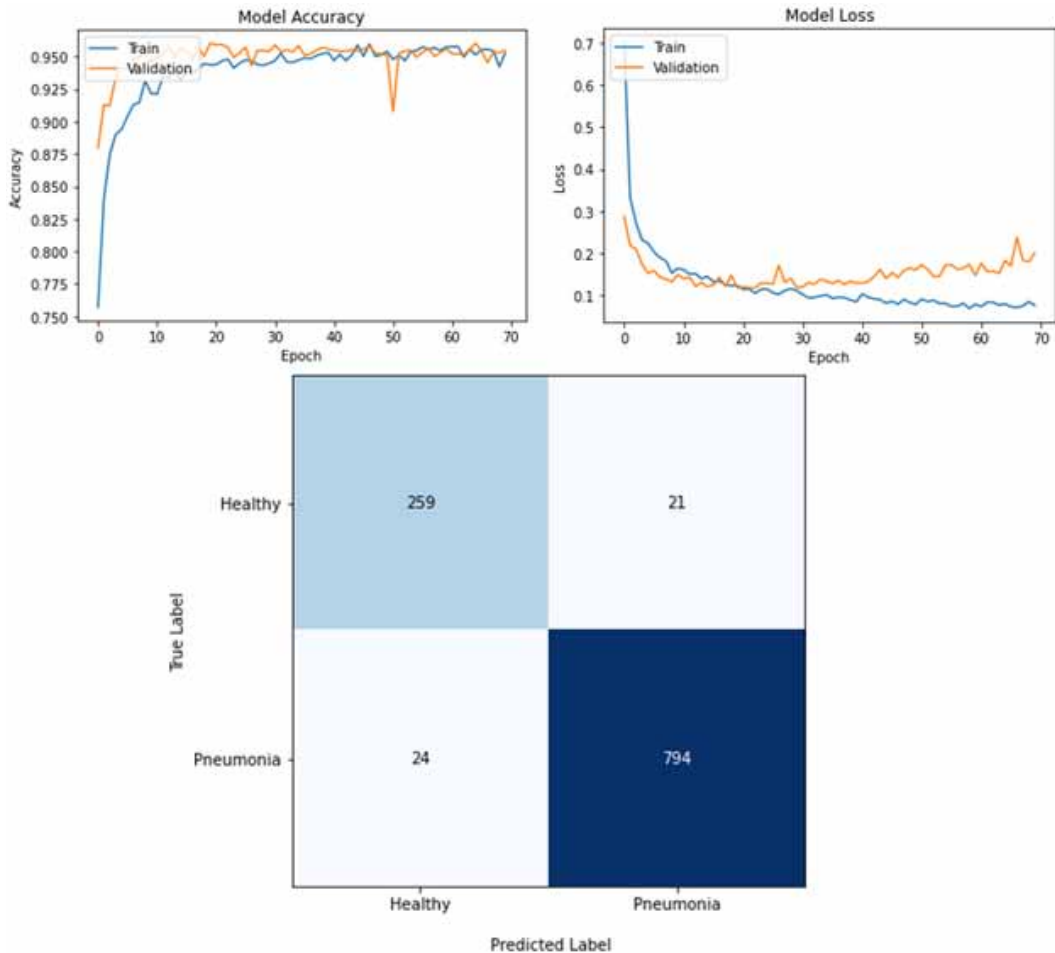
Figure 11. Result of VGG19 Model (Accuracy, loss curve and confusion matrix 'Actual and predicted labels are displayed on the y-axis and x-axis, respectively')



§ **ResNet50:** Concerning the Resnet50 model results (See Figure. 12), we may notice that Pneumonia class was detected with good precision, sensitivity, and specificity (97.73%, 96.65% and 97.01% respectively). This can be explained by the sum of false positives and false negatives were low (precision and sensitivity). It also provides an accuracy rate of 96.90% and a loss of 14.25%. The confusion matrix indicates that, for images class (Pneumonia), 794 images were predicted correctly as Coronavirus Pneumonia and 24 were labelled as Healthy . Same for the second

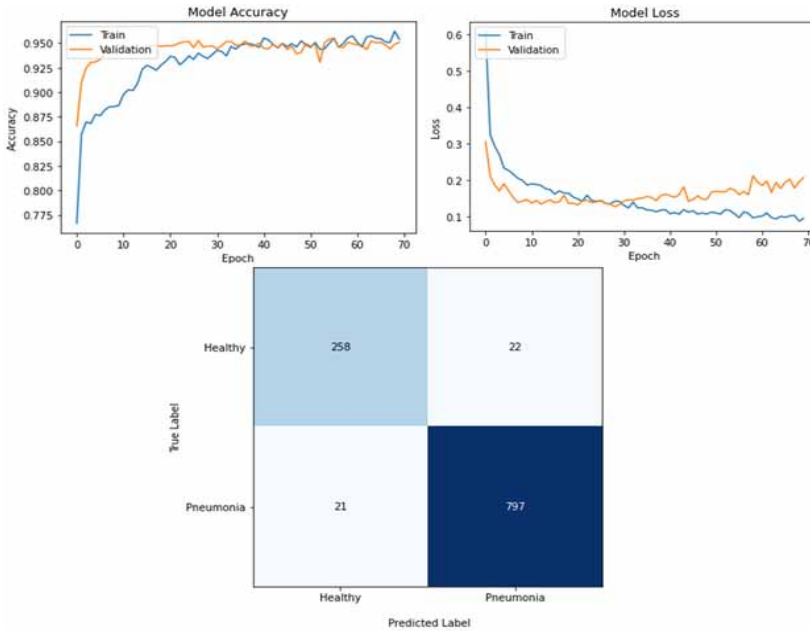
images class (Healthy), the ResNet50 model was able to identify 259 images correctly, but 21 images were labelled as Pneumonia.

Figure 12. Result of ResNet50 Model (Accuracy, loss curve and confusion matrix 'Actual and predicted labels are displayed on the y-axis and x-axis, respectively')



§ **Inception_V3:** For the Coronavirus Pneumonia class, the Inception_V3 model was able to identify 797 images correctly as Pneumonia and 21 images as Healthy. On other hand, for the Healthy class, 258 were correctly classified as Healthy and 22 images as Pneumonia. The accuracy and loss curves in the training and validation phases are shown in Figure. 13. The highest accuracy is observed 96.08% and loss is 16.25 at epoch 70. It is also noticeable that both training loss and validation values increased significantly at the primary epoch because of the number of coronavirus pneumonia data in that specific class. After training our model for 70 epochs, a good fit can be observed for the loss curve of train data in either the quick increasing interval.

Figure 13. Result of Inception_V3 Model (Accuracy, loss curve and confusion matrix 'Actual and predicted labels are displayed on the y-axis and x-axis, respectively')



As per our objective, we investigated in this paper the binary classification (Healthy and coronavirus pneumonia) based on X-Ray & CT images using deep convolutional neural networks architectures, in order to identify the best performing architecture based on the various performance metrics defined in evaluation criteria (See Section 4.1). Precision, sensitivity, and specificity are the key metrics for checking the accuracy of a model. Moreover, we evaluate the F1-score, which checks the accuracy of the test data in the form of harmonic average specifically for imbalance X-Ray & CT images dataset. Table 4 illustrates a comparison between our different deep learning models used in our experiment in terms of popular parameters.

Table 4. Illustrates a report of evaluation metrics

	Precision	Recall (Sensitivity)	F1-score	Specificity	Accuracy	Loss	ROC-AUC Score
CNN	95.10%	94.12%	94.50%	94.01%	95.11%	18.65%	95.11%
VGG19	97.10%	96.30%	96.50%	96.22%	97.36%	15.23%	97.36%
VGG16	94.54%	95.01%	95.00%	94.78%	95.04%	14.14%	95.04%
InceptionV3	94.55%	94.50%	94.52%	94.15%	96.08%	16.25%	96.08%
ResNet50	97.73%	96.65%	96.43%	97.01%	96.90%	14.25%	96.90%

Furthermore, based on the Table. 4, it can be seen that the table depicts in detail classification performances across multi-experiment classification, based on different fine-tuned versions of recent deep learning architectures. From the results, it's notable that the accuracy when we use baseline

CNN and VGG16 is low compared with other DL architectures, since these last models help to obtain respectively 95.11% and 95.04% of accuracy. In contrast, the highest accuracies are reported by VGG19, Resnet50, and Inception_V3. Therefore, these models attain better classification accuracy since they achieve respectively 97.36%, 96.90% and 96.08%.

Besides that, we conducted a comparative study of our proposed approach with other existing Coronavirus pneumonia diagnostic models on grounds of approach used, number of X-ray & CT images used in experimentation, performance metrics used for evaluation and percentage accuracy achieved (see Table. 5).

Table 5. Comparison of proposed Coronavirus pneumonia classification approach with existing classification methodologies

Approach	Dataset	Performance Metrics	Classifiers	Accuracy
Deep CNNs	X-Ray images (Pneumonia & Covid-19)	Accuracy, sensitivity, F1-score and Precision	Xception and ResNet50V2	96.50% (Multiclass Classification)
Deep CNNs	X-Ray images (Covid-19)	Accuracy, sensitivity and specificity	VGG19 and the MobileNet v2	96.78% (Binary classification)
Deep Learning	X-Ray images (Covid-19)	Accuracy, FPR, F1 score, MCC and Kappa	ResNet50 + SVM	95.38% (Multiclass Classification)
Deep Learning	X-ray and CT images (Coronavirus pneumonia)	Accuracy, sensitivity, F1-score, specificity and Precision	VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, Resnet50 and MobileNet_V2	92.00% (Binary classification)
Convolutional Neural Network (CNN)	chest X-ray image (Pneumonia)	Accuracy and precision	CNN	93.73% (Binary classification)
Deep CNNs	X-ray and CT images (Coronavirus pneumonia)	Accuracy, sensitivity, F1-score, specificity and Precision	CNN, VGG16, VGG19, Inception_V3, and ResNet50	97.36% (Binary classification)

Moreover, the higher performance achieved for classification of Coronavirus pneumonia with healthy X-ray & CT images has shown that the computer-aided detection approach can be used as an alternative or a confirmatory approach against others method which has shown to be less sensitive, time-consuming, and laborious. However, due to the diversity in Coronavirus case symptoms, the robustness of our automatic classification and diagnosis approach proposed needs further testing and validation using other diverse and larger image datasets.

5. CONCLUSION

The medical field is the most sensitive of all the domains ever known, for the simple reason that it deals with humans. More recently, the coronavirus pneumonia disease outbreak has a tremendous impact on global health and the daily life of people still living in more than two hundred countries. This paper presents an automated approach used to classify the chest X-Ray into coronavirus pneumonia and the healthy class using five DL architectures. In the right context, the experiments were conducted

using chest X-Ray & CT open dataset which contains 5856 images (4273 coronavirus pneumonia and 1583 healthy), and performances were evaluated using various performance metrics. Likewise, the obtained results show that the VGG19, ResNet50, and Inception_V3 gave high performance (accuracy is more than 96%) against other architectures cited in this study (accuracy is around 95%). This automated approach can perform binary classification without manual feature extraction with an accuracy of 97.36%. Due to the high performance achieved by this model, we believe that these results help medical experts to make decisions pertinent. Moreover, this approach may be employed as a supplementary tool in screening COVID-19 patients in emergency medical support services with the rt-PCR machine.

A limitation of the study is the use of a limited number of our current datasets images. We intend to make our model more robust and accurate by using more such images from our local hospitals. The results generated from the experiments in several numbers epochs. It is concluded that more amount epochs are needed to improve the accuracy level. since the model exercises a lot of convolutional layers, the model needs very high computational power otherwise it'll eat up a lot of time in computations. Therefore, one of our future works is to develop deeper collaborative relations with hospitals and clinics to acquire more data.

For future works, we aim to develop a full system for pneumonia via deep learning detection, segmentation, and classification with covid-19 research labs. In addition, the results may be improved using more datasets that can be added to improve the model performance, more experiments on hyperparameters settings in order to improve the approach, and more sophisticated feature extraction techniques based on deep learning that was developed for the biomedical image. Finally, we plan to improve the result visualization using class mind mapping in order to give a better understanding of the result.

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ENDNOTE

- ¹ <https://github.com/ieee8023/covid-chestxray-dataset> & <https://www.kaggle.com/allen-institute-for-ai/CORD-19-research-challenge/discussion/139292>

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