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MODIFY CONVOLUTIONAL NEURAL NETWORK MODEL FOR THE DIAGNOSIS OF MULTI-CLASSES LUNG DISEASES COVID-19 AND PNEUMONIA BASED ON X-RAY IMAGES

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ABSTRACT
COVID-19 is a new virus able to infect both the upper and lower respiratory lobes of ling. There is a daily increase in cases and deaths in the global epidemic. A number of the test kits now in use are sluggish and in short supply; hence RT-PCR testing is the most appropriate option. To avoid a potentially fatal outcome, early detection of COVID-19 is essential. According to numerous studies, visual markers (abnormalities) on a patient's Chest X-Ray imaging can be a valuable characteristic of a COVID-19 patient, which can be exploited to discover the virus. In this research, Convolutional Neural Networks (CNNs) are being proposed to detect the Covid-19 disease based on X-rays images. The suggested model is based on modified VGG16 architecture for deep feature extraction. The fine-tuning approach with end-to-end training is also 63tilized in the aforementioned deep CNN models. The suggested model has been trained and evaluated on the dataset contains 7,245 X-ray images, comprising 1,420 Covid-19 cases, 4,167 bacterial cases of Pneumonia, and 1,658 normal cases. The model is evaluated using metrics such as accuracy, precision, recall, and f1-score. The proposed model enhanced the accuracy by using less trainable parameters (weights) than the Vgg16 model. Thus, the time needed for training and testing will be less. In addition, it achieved a multiclass micro-average of 97% precision, 97% recall, 97% f1-score, and 97% classification accuracy. The findings obtained show that the proposed strategy outperforms several currently used methods. This model appears to be convenient and forceful for multiclass classification.

KEYWORD: Convolutional neural network, COVID-19, Deep learning, X-Ray images, Pneumonia, Artificial neural network.

1. INTRODUCTION

Coronaviruses are a viral family that can infect both people and pets. Protein spikes surround these viruses, giving them the appearance of a crown, and crown in Latin means "corona" [1]. As a result, these viruses are known as Coronaviruses. It can cause typical colds, flu, fever, and other ailments in humans and more severe infections such as SARS-Cov (Severe Acute Respiratory Syndrome-Coronavirus) and MERS (Middle East Respiratory Syndrome). The complications included acute respiratory distress syndrome, acute cardiac damage, and secondary infections [2].

Pulmonary X-ray and computed tomography (CT) imaging, routine blood tests, nucleic acid tests [3], and other such tests are currently the primary techniques of detecting Pneumonia and COVID-19. In the chest CT, the price is considerable, and the amount of radiation absorbed by the patient's body is substantial. Regular blood tests necessitate a stringent air-free environment where blood samples are not exposed to the elements. In the meantime, it necessitates rapid detection. Samples of blood obtained should be examined within 30 minutes; if not, they must be preserved less than two hours in iced water nucleic acid test has the potential to fail due to the possibility of not collecting pharyngeal swab samples. False-negative occurrences are more likely in patients with a low laryngopharyngeal virus in the early stage. In addition, sampling employees are more likely to become infected since they are more

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exposed to the viral environment. Chest X-ray imaging has several advantages over the other diagnosis methods, including quick detection, crisp imaging, low cost, long-term sample preservation, and convenient review [4]. There are many ways to identify abnormalities in standard chest X-ray images. An enormous amount of resources is expended in this method, like time and personnel and any other aspect, like visual fatigue and mental state. So the identification results will be more ambiguous. COVID-19, Normal, and Pneumonia are seen in Fig.1 [5].

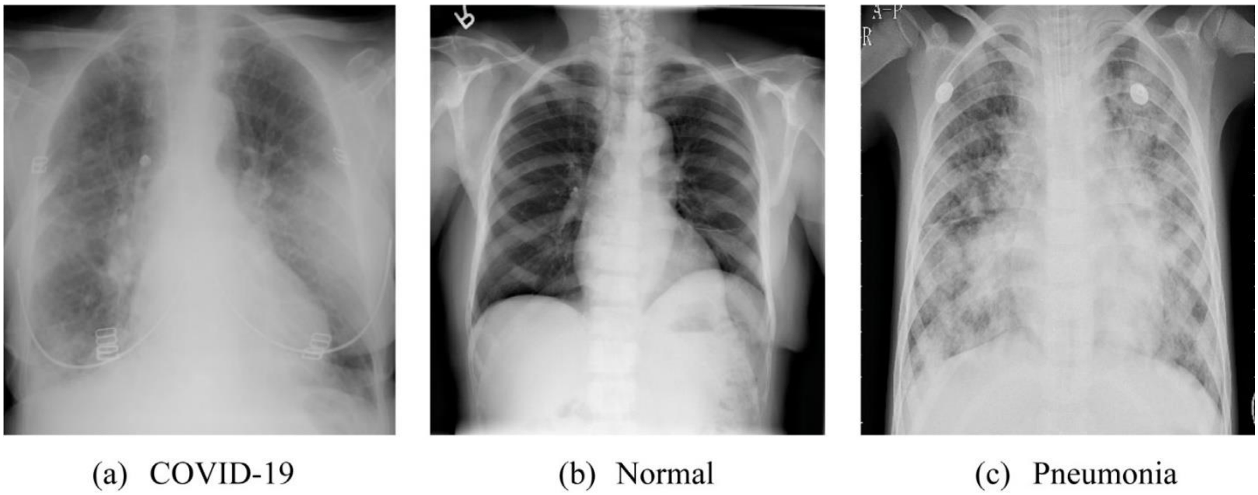

Fig. (1): Sample of chest X-ray images [5].

With the help of Machine Learning and AI, Computer-aided Diagnostic (CAD) technologies can make classification and interpretation easier for clinicians. Medical image analysis relies heavily on Deep Learning (DL) because of its capacity to extract features from images. Multimodal medical photos are processed automatically by DL models. Diabetic retinopathy, cancer identification and classification, polyp detection during colonoscopy, and classification of skin lesions are just a few examples of how DL might be used in practise [6][7]. DL is rapidly becoming a critical technique in classifying and detecting images and videos. DL relies on algorithms for reasoning process simulation and data mining. Data is mapped to labels at the deepest layers of the DL to uncover patterns in complex data. DL architectures are also employed in medical image processing and computer vision, such as medical X-ray recognition. To achieve better outcomes and deploy relevant real-time medical image disease detection systems, DL enhances a system like this in the health care industry [8]. To improve the accuracy of the CNNs for detection of COVID-19, Normal, and Pneumonia. We upgraded one of the most popular deep learning architectures, vgg16. X-ray images are gathered from a variety of sources. X-ray images of low quality and various sizes often make up the bulk of the raw input images. The images must be resized before being fed into the classifier.

The paper's contributions can be summarised like this:

- COVID-19 patients can be accurately identified quickly using a deep CNN model based on modified VGG-16.
- Reduce the number of trainable parameters compared to the original model of VGG-16.
- The created diagnostic model provided more accurate results for a broader range of images.

The remaining sections of this paper are organised as follows. A summary of current developments in AI systems that use deep CNN for detecting COVID-19 is presented in Section 2 of this report. The collected dataset and suggested architecture are described in depth in Section 3. The study's findings are discussed in detail in Section 4. In addition, we learn about the model's performance in this section. The last section of the study concludes.

2. RELATED WORK

Although vaccination has been developed, the best way to curb the spread of the disease is to isolate those who are infected. However, it is difficult to identify healthy patients from negative ones quickly. This scenario offered several methods for identifying Chest X-ray and CT abnormalities.

Apostolopoulos et al. [9] evaluated five well-known pre-trained methods (VGG19, Inception, MobileNet v2, Inception ResNet v2, and Xception) using two datasets. Firstly, collect 1427 X-ray images (Covid-19 disease 224 images, 700 images with bacterial Pneumonia, and 504 images of normal). The second dataset contains a collection of 1,442 X-ray images (224 images with Covid-19 disease, viral and bacterial Pneumonia, 714 images, and 504 normal conditions). The classification accuracy was obtained for two classes, 98.75%, and three classes, 93.48%, using VGG16 architecture. Better classification accuracy has been obtained for two classes, 96.78%, and three classes, 94.72%, using MobileNet v2 architecture. Loey et al. [8] presented three in-depth transfer scenarios for pneumonia disease detection (normal, COVID-19, and bacterial and virus pneumonia) and utilized three deep transfer models: Alexnet and Googlenet Restnet18. Generative Adversarial Network (GAN) is an effective method for generating X-ray images used to overcome the small dataset in the training model. In the first scenario, the four dataset classes are based on Googlenet as the primary machine transfer model. The second scenario involved three classes, which have chosen Alexnet as the base model for Deep Transfer. While the third scenario consists of two classes (normal and COVID-19), Googlenet has chosen the base architecture. The accuracy has been obtained for four, three, and two scenarios were 80.6%, 85.2%, and 99.9%, respectively.

Asnaoui et al. [10] compared a dataset of three classes of chest x-ray and CT images, which included normal, bacterial Pneumonia, and Covid19 using recent deep learning models (VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, Resnet50, and MobileNet_V2) for detection and classification of coronavirus pneumonia. Results found that Densnet201 and inception_Resnet_V2 provide better accuracy than other architecture used in work (Inception-ResNetV2 with 92.18% accuracy and 88.09% accuracy for Densnet201). A Deep CNN model (CoroNet) was proposed in the study [11] to diagnose COVID-19 disease based on X-ray images automatically. The suggested model is built on the Xception, pre-trained on the ImageNet dataset. CoroNet was trained and tested on two publicly prepared datasets sources. The experimental findings show that for 4-class cases, the suggested model attained an overall accuracy of 89.6% (COVID vs. Pneumonia bacterial vs. Pneumonia viral vs. normal). The proposed model had a classification accuracy of 95% for 3-class classification (COVID vs. Pneumonia vs. normal).

Toraman et al. [12] proposed a robust CNN CapsNet to identify COVID-19 disease using X-ray images with capsule networks. The suggested method is meant to deliver fast and accurate diagnoses of COVID-19 cases with binary classification (COVID-19 and normal) and multiclass classification (COVID-19, normal, and Pneumonia). The suggested technique achieved 97.24% for binary classification and 84.22% accuracy in multiclass classification. The authors of [13] proposed the Residual Neural Network (RNN) model, termed CVDNet, which is based on two parallel tiers with varying kernel sizes to capture both global and local aspects of the inputs, according to its creators. The trained dataset includes 1341 normal, 219 COVID-19, and 1345 viral pneumonia chest x-ray images that are all publicly available. For COVID-19 detection, CVDNet attained an average accuracy of 97.20%, and for multiclass (COVID-19 vs. viral Pneumonia vs. normal), it achieved an average accuracy of 96.69%.

In [14], a deep CNN dubbed DeTraC has been proposed to classify COVID-19 chest X-ray images. Using a class decomposition approach, DeTraC can deal with any irregularities in the image dataset. Experiment findings indicated that DeTraC could detect COVID-19 instances from a large image dataset collected from various hospitals worldwide. DeTraC demonstrated a 93.1% accuracy in detecting COVID-19 X-ray pictures from normal and Severe Acute Respiratory Syndrome (SARS) cases. Several new approaches have been proposed and investigated by [15] et al. to improve deep transfer learning to diagnose pneumonia cases using X-ray images. The results showed that the presented model generates better input image data by preprocessing operation includes removing unrelated regions (diaphragm regions) normalizing image contrast using a histogram equalization algorithm. In addition, using a bilateral low-pass filter to remove noise, the original image and two filtered images are used to generate pseudo color images to feed into transfer learning CNN models to classify pneumonia disease. The transfer learning approach is the VGG16 model, which shows a higher accuracy of 94.5%.

Based on the X-ray image, Chakraborty et al. [16] proposed a deep CNN to detect COVID-19, Normal, and Pneumonia cases. In addition, the effect of transfer learning of CNNs models is being explored for diagnosing COVID-19 infection using chest X-rays. VGG19 beats other pre-trained CNN models; the model attained a 95% accuracy for three-class categorization. In [17], and enhanced Snapshot Ensemble approach for COVID-19 chest X-ray classification based on deep learning. This method also uses the ResNet-50 model, a pre-trained model, as a basis for the transfer learning process—a freely available dataset to the public consisting of 2905 images. The model was able to classify 95% of the cases correctly.

3. MATERIAL AND METHODS

3.1 Datasets

Despite Covid-19's recent appearance, labeled data on the species is not readily available. Therefore, we must rely on various online images of normal, Pneumonia, and COVID-19 from Kaggle. Several datasets have been combined into one. For training the model, the 7,245 X-ray images from the Kaggle were collected, with resolutions ranging from 240px240p up to 3480px4248p. Three chest X-ray images (Normal, COVID-19, and Pneumonia) are included in the original dataset from the Kaggle repository and utilised for multiclass classifications [18]. The second dataset of positive, negative COVID-19, and pneumonia photos increased the number of cases [19]. The data was divided into 4,947 training photos, 1,149 validation images, and 1,149 testing images. Table 1 shows the division of images into three sets of training, test, and validation images.

Table (1): Distribution of dataset into three sets.

Type	Training	Test	Validation	Total
Normal	1,108	275	275	1,658
COVID-19	920	250	250	1,420
Pneumonia	2,919	624	624	4,167
Total	4,947	1,149	1,149	7,245

3.2 CNNs architecture

CNNs became common because of their improved image recognition efficiency. The network's layers of convolutions and filters automatically detect an image's important spatial and temporal features. A CNN's layers work as feature extractors. Lower layers learn fundamental features (edges and borders), middle layers extract colour and shape information, and deeper layers learn to recognise the objects in the image. These networks also include a fully-connected layer that works as a classifier [20]. The layers have shared the intra-network weights for better performance and efficiency, reducing computation efforts [21]. The intermediate representations are used in CNN's learning process, the same as the hierarchical learning in biological brains. The success of CNN in most image processing applications is due to this unique ability. The shape of input image is (number of images) * (height) * (width) * (depth). Convolutional layer transforms image into a feature map containing shape information as: (number of images) * (feature height) * (feature weights) * (feature channels) [21]. The CNN models are employed to train and evaluate each input image of the dataset that crosses layers with kernel-based filters, pools, fully connected layers, and then softmax used to classify an image between the stochastic values of 0 and 1.

3.2.1 Convolution Layer

The convolution layer is the central part of a revolutionary neural network that uses convolution. The convolutional layer's primary function is to discover features expected in the dataset within the local areas of the input image through a range of kernel filters. The convolution equation is shown below:

$$F(i,j) = (I * K)_{(i,j)} = \sum_{m}\sum_{n} I(i+m, j+n)K(m,n) \quad (1)$$

In every convolutional layer, the output is given to an activation function that introduces non-linearity. The Rectified Linear Unit (ReLU) is the most widely used activation function for deep learning. ReLU returns 0 if the input is less than 0 and raw otherwise.

$$f(x) = \max(0, x) \quad (2)$$

3.2.2 Subsampling (Pooling) Layer

CNNs use a downsampling (pooling) layer after each convolution layer to minimise the number of parameters in the network. A pooling layer then downsamples each feature map generated by the convolutional layer.

3.2.3 Fully Connection Layer

The output from the feature extractor is converted into 1D feature vectors for classifiers. This process is known as flattening. The convolution operation output is flattened to generate a single long feature vector for the dense layer to be utilized in the final classification process [22]. Every neuron in the previous layer is connected to the next one in a completely connected layer. Each value helps to predict how good the value of a given class matches. The last utterly connected output layer will then be routed to the activation feature that generates the class scores. Softmax distributes probability in decimal form to each class. The sum of their decimal probabilities must be 1.0, as seen in the equation below:

$$Z^k = \frac{e^{x^k}}{\sum_{i=1}^{n} e^{x^n}} \quad (3)$$

All of the above layers are used to create a complete CNN architecture, as seen in figure 2. Over and above these, CNN can have optional layers such as the batch standardization layer to accelerate training and the dropout layer for treating overfitting issues.

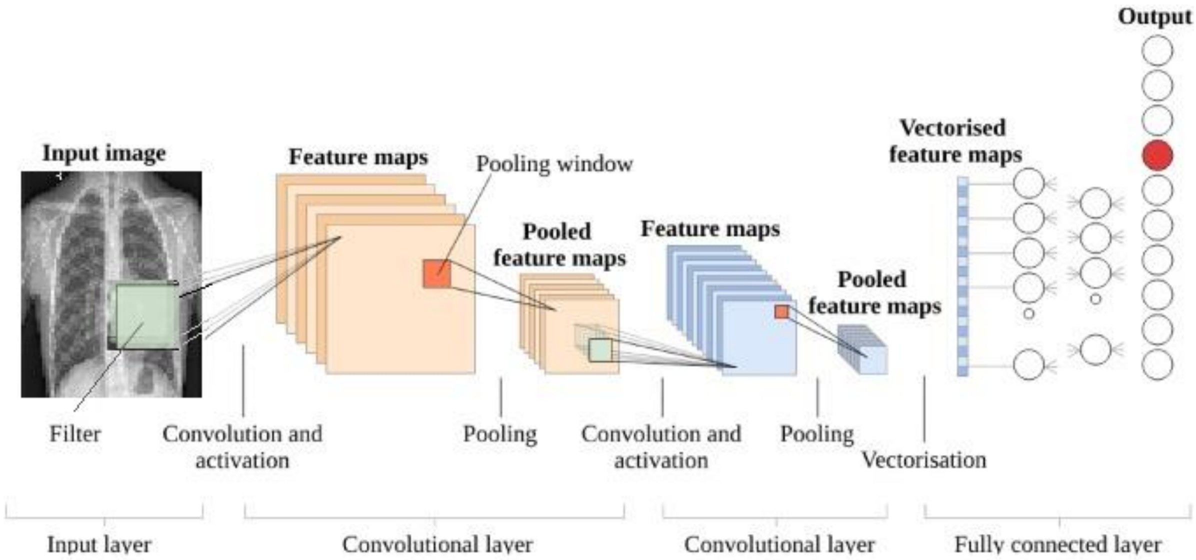

Fig. (2): Building blocks of CNN architecture [22].

3.3 CNN model architecture

In deep learning, the initial training of CNN for a given goal (e.g., classification) is done using large-scale datasets. An image's essential qualities (features) may be extracted using CNN training data; therefore, having access to such data during initial training is critical to success. The capacity of the CNN to detect and extract the most noteworthy visual characteristics determines whether this model can be used for learning [23]. The following is a brief introduction to the pre-trained networks:

3.3.1 Inception net V3

Inception Net V3 is a categorization network based on CNNs. " An inception module, consisting of a concatenated layer with one, three, and five convolutions, is used 48 layers. So, it allows fast and more efficiency and reduces the number of parameters. GoogleLeNet architecture is another name for it [4].

3.3.2 ResNet50

The ResNet model is an enhanced version of CNN. When the network develops more profound and sophisticated, it prevents distortion. Additionally, bottleneck blocks are included in the ResNet model to speed up training. Using the ImageNet dataset, ResNet50 is a 50-layer network that has been trained. ImageNet has a database of more than 14 million photos and more than 20 thousand categories [7].

3.3.3 AlexNet

AlexNet can categorise more than 1000 distinct data types with 650k neurons and 60 million parameters. This network has five convolutional layers (CL): three pooling layers, two fully connected layers (FLC), and a Softmax layer. A 227x227x3 picture is required for AlexNet, and the first CL transforms the input image into 96 kernels of 11x11x3 with a 4-pixel stride, which is the input to the second layer's second layer [24].

3.4 Development of the proposed model

This paper proposed a new deep CNN model for lung disease classification using Chest X-ray images to three classes (COVID-19, normal, and bacterial Pneumonia). The dataset was used to train the model content pulmonary images that were heterogeneous and of various sizes. To reduce computation time as low as possible during training and testing of the proposed CNN model, we downsampled all of the original X-ray images to a unique dimension. We rescaled them into smaller images (128x128 pixels) to meet the standard inputs of the proposed CNN model. Feature extraction in the proposed CNN model consists of five blocks and takes its input from the outputs of the preceding intermediate. Its output is passed to other subsequent layers in the CNN model. There are two conv layers in each block, and batch normalisation improves model training's accuracy. The max-pooling is used between convolution operation in blocks and the dropout rate between blocks#1,2,3,4, and 5 with values 0.1, 0.2, 0.3, 0,4, and 0.5. It is a regularisation method for CNN models where random neurons are omitted from training. Max-pooling between convolution produces 2-D planes known as feature maps, and we obtained 64×64×32, 32×32×64, 16×16×128, 8×8×256, 4×4×512 for output of block #1, 2, 3, 4, and 5, respectively, as shown in figure 3.

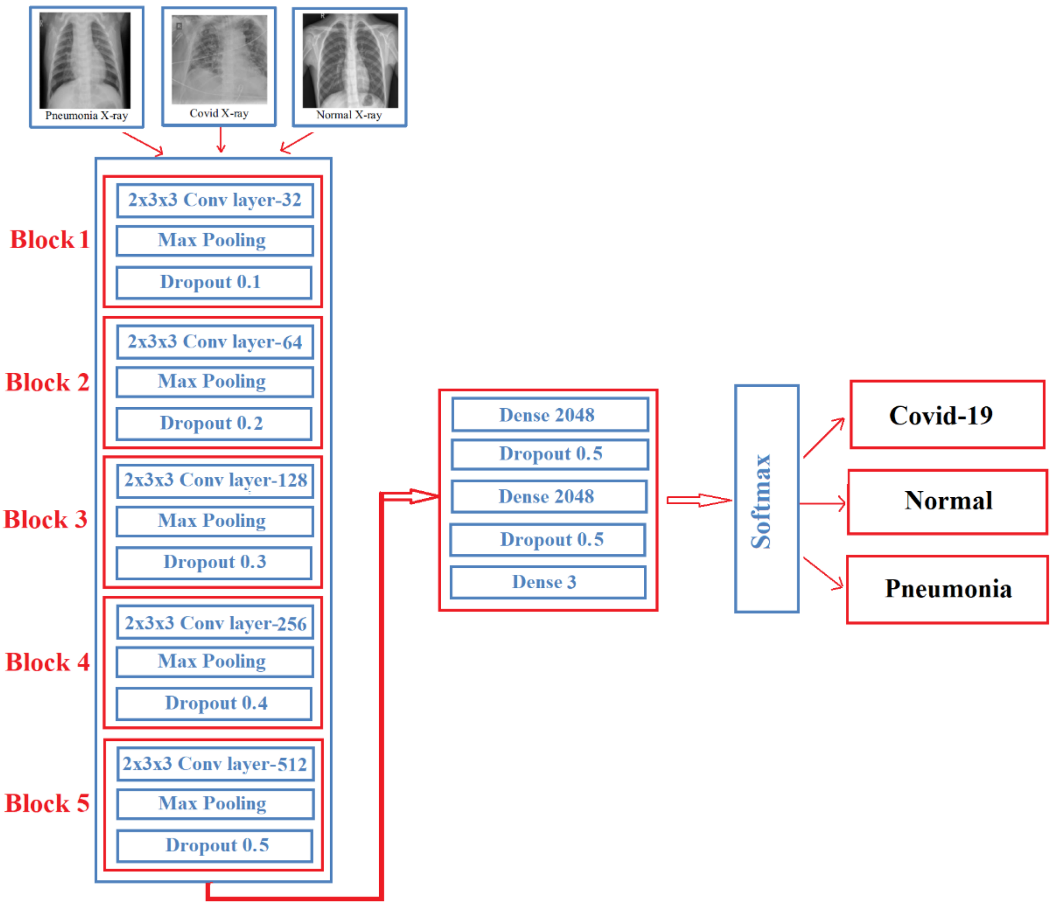

Fig. (3): Proposed CNN model

An Artificial Neural Network (ANN) serves as the classifier. Often referred to as dense layer, it sits at the end of the CNN model. The computations and parameters are fixed through training using individual features as inputs. The result of the feature extractor is turned into a 1-D vector and utilised as an input to a classifier. Also, in the dense layer, eliminate the neurons 50% by adding dropout in this model's classifier. Softmax routines perform the multiclass classifications. Table 2 provides an overview summary of the suggested CNN architecture.

Table (2): Summary details of our proposed model.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 128, 128, 32)	896
batch_normalization_1 (Batch)	(None, 128, 128, 32)	128
conv2d_2 (Conv2D)	(None, 128, 128, 32)	9248
batch_normalization_2 (Batch)	(None, 128, 128, 32)	128
max_pooling2d_1 (MaxPooling2)	(None, 64, 64, 32)	0
dropout_1 (Dropout)	(None, 64, 64, 32)	0
conv2d_3 (Conv2D)	(None, 64, 64, 64)	18496
batch_normalization_3 (Batch)	(None, 64, 64, 64)	256
conv2d_4 (Conv2D)	(None, 64, 64, 64)	36928
batch_normalization_4 (Batch)	(None, 64, 64, 64)	256
max_pooling2d_2 (MaxPooling2)	(None, 32, 32, 64)	0
dropout_2 (Dropout)	(None, 32, 32, 64)	0
conv2d_5 (Conv2D)	(None, 32, 32, 128)	73856
batch_normalization_5 (Batch)	(None, 32, 32, 128)	512
conv2d_6 (Conv2D)	(None, 32, 32, 128)	147584
batch_normalization_6 (Batch)	(None, 32, 32, 128)	512
max_pooling2d_3 (MaxPooling2)	(None, 16, 16, 128)	0
dropout_3 (Dropout)	(None, 16, 16, 128)	0
conv2d_7 (Conv2D)	(None, 16, 16, 256)	295168
batch_normalization_7 (Batch)	(None, 16, 16, 256)	1024
conv2d_8 (Conv2D)	(None, 16, 16, 256)	590080
batch_normalization_8 (Batch)	(None, 16, 16, 256)	1024
max_pooling2d_4 (MaxPooling2)	(None, 8, 8, 256)	0
dropout_4 (Dropout)	(None, 8, 8, 256)	0
conv2d_9 (Conv2D)	(None, 8, 8, 512)	1180160
batch_normalization_9 (Batch)	(None, 8, 8, 512)	2048
conv2d_10 (Conv2D)	(None, 8, 8, 512)	2359808
batch_normalization_10 (Batch)	(None, 8, 8, 512)	2048
max_pooling2d_5 (MaxPooling2)	(None, 4, 4, 512)	0
dropout_5 (Dropout)	(None, 4, 4, 512)	0
flatten_1 (Flatten)	(None, 8192)	0
dense_1 (Dense)	(None, 2048)	16779264
dropout_6 (Dropout)	(None, 2048)	0
dense_2 (Dense)	(None, 2048)	4196352
dropout_7 (Dropout)	(None, 2048)	0
dense_3 (Dense)	(None, 3)	6147
Total params: 25,701,923 Trainable params: 25,697,955 Non-trainable params: 3,968		

4. RESULTS AND DISCUSSIONS

4.1 Results

In this section, the proposed model has been trained to categorise X-ray images into multiclass: normal, COVID-19, and viral Pneumonia. The dataset was partitioned into three independent sets (i.e., 70% for training, 15% for testing, and 15% for validation). The suggested model was trained for 100 epochs with a batch size (8) and used Tensorflow. After each epoch, the validation loss and validity accuracy of architectures were evaluated. During the initial stages of training, a significant drop in validation loss values was noted. After that, the curves were almost in steady-state conditions since they had reached saturation, as shown in figure 4. Accuracy in training and validation attained a maximum of 99.56% and 97.21%, respectively, while validation lost 0.0913 and training was down 0.0147.

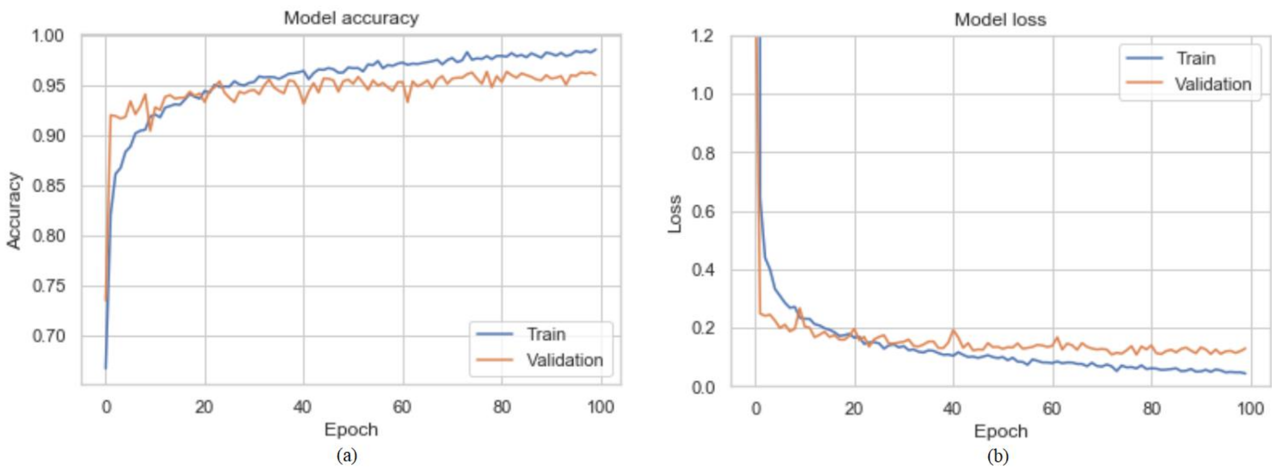

Fig. (4): The learning curve of training and validation of 100 epochs (a) Accuracy. (b) Loss.

Accuracy (Acc), Recall (Rec), Precision (Pre), and F1-Score (F1) were used to test the method's performance in medical imaging. The confusion matrix was used to calculate the metrics. They are described as the following:

$$Acc = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (4)$$

$$Rec = \frac{TP}{(TP+FN)} \quad (5)$$

$$Pre = \frac{TP}{(TP+FP)} \quad (6)$$

$$F1 = \frac{2\,(precision \times Recall\,)}{(precision + Recall\,)} \quad (7)$$

In the case of COVID-19, TP is the true positive, and TN is the true negative, whereas FP and FN are the inaccurate model predictions for COVID-19 and other cases. The results of both categories are displayed in a confusion matrix. All of the performance metrics are generated using the confusion matrix. According to the confusion matrix in Figure 5, our multiclass classification model failed to distinguish 4 out of 250 COVID-19, two as normal and two as Pneumonia. In addition, it failed to classify 15 out of 275 normal cases, one as COVID-19 and 14 as Pneumonia. The last model distinguished 607 images correctly as Pneumonia but failed to classify 17 of them.

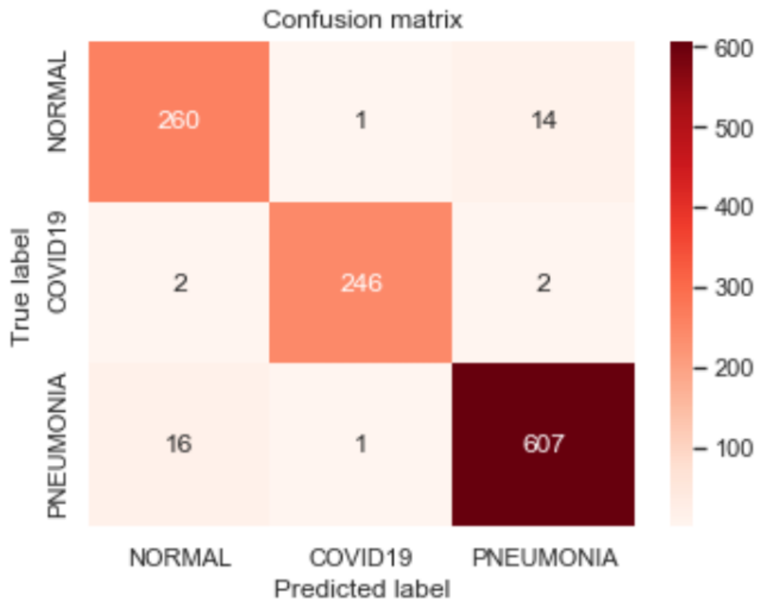

Fig. (5): Confusion matrix of our proposed model for multiclass classification.

The recall, precision, F1-score, and accuracy for each classifier (COVID-19, normal, and Pneumonia) are presented in Table 3.

Table (3): Evaluation of overall model performance.

Case classify	Evaluation metrics			
	Recall%	Precision%	F1-score%	Accuracy of proposed model %
COVID-19	98	99	99	96.86%
Normal	95	94	94	
Pneumonia	97	97	97	

4.2 DISCUSSION

The key to controlling and avoiding the spread of COVID-19 is an early and prompt diagnosis, as well as speedier quarantining. As a result, the development of quick-to-diagnose techniques appears to be critical for early disease identification, treatment, and pandemic isolation. Artificial intelligence-based innovative models have risen to popularity among traditional methodologies due to their advantages of accuracy, speed, and ease of application. Using Chest X-ray images to classify COVID-19 Pneumonia has several advantages, including a lower radiation dose than computer tomography, practical and accessible, and cost-neutral. X-ray images are also less expensive than CT scans and have convenient access. Models derived from deep learning can help prevent the spread of disease by providing early and effective treatment. Many high-quality studies have produced artificial intelligence models with good accuracy values for COVID-19 pneumonia detection utilising X-ray images. To recognise and classify COVID-19 infections from X-ray images, we created a new DL model based on VGG-16. The number of filters used to extract features has risen in the VGG-16. In the last three blocks, three levels were lowered to two.

Another thing to remember is that a large and diverse image collection is required for training and identification to achieve reliable results with a CNN model. As a result, we reduced the number of parameters in the VGG-16 model from over 138 million to 25 million. In comparison to prior studies, our proposed model yields superior outcomes. As seen, Table 4 summarises studies on automated COVID-19 diagnosis from chest X-ray pictures and compares them to our suggested. All comparisons are performed only for the multiclass data.

Table (4): Comparison of the proposed model with existing models.

Study	Number of datasets	Techniques	Performance (Accuracy %)	Parameters (in a million)
Apostolopoulos et al. [9]	Dataset1: 224 COVID-19, 700 Pneumonia, and 504 Normal. Dataset2: 224 COVID-19, 717 Pneumonia, and 504 Normal.	MobileNet v2 and VGG-19	Acc= 94.72% Acc = 93.48%	20.55
Loey et al. [8]	69 COVID-19, 79 Normal, 79 Pneumonia bacterial, and 79 Pneumonia virus.	Transfer learning (Alexnet, Googlenet, and Resnet18)	Acc = 85.19% Acc = 81.48% Acc = 81.48%	61 in Alexnet
Asnaoui et al. [10]	CT and X-ray dataset of 6,087 images (2,780 pneumonia bacterial, 1,724 of Covid19, and 1,583 normal).	Transfer learning (best model Inception_Resnet_V2)	Acc = 92.18%	-
Khan et al. [11]	310 Normal, 284 COVID-19, 327 Viral Pneumonia, and 330 Bacterial Pneumonia.	Xception model	Acc = 95%	33
Toraman et al. [12]	1050 COVID-19, 1050 Pneumonia, and 1050 Normal.	CapsNet	Acc = 84.22%	-
Ouchicha et al. [13]	219 COVID-19, 1341 normal and 1345 pneumonia.	CVDNet (residual neural network)	Acc = 96.69%	5.3
Abbas et al. [14]	105 COVID-19, 80 normal and 11 SARS.	DeTraC	Acc = 93.1%	-
Heidari et al. [15]	8474 X-ray images 415 COVID-19, 5179 pneumonia and 2,880 normal	VGG16	Acc = 94.5%	138
Chakraborty et al. [16]	245 COVID-19, 8,066 Normal, and 5,551 Pneumonia.	Corona-Nidaan	Acc = 95%	4.02
Babu et al. [17]	219 COVID-19, 1345 Pneumonia, and 1341 Normal.	ResNet-50 model	Acc = 95.18%	23.85
Our proposed model	X-ray images COVID-19 = 1,420, Normal = 1,658, and Pneumonia = 4,167	Modified VGG-16	96.86%	25.6

5. CONCLUSION

In this paper, a deep CNN model was proposed for COVID-19 detection by classifying the X-ray pictures of suspicious patients. There is vital information in the radiologic images, such as X-rays and CT scans. So, many Coronavirus detection systems might be benefitted dramatically from the models' performance. The pandemic has triggered a worldwide economic downturn. The virus's global impact is still unknown. Analysing chest X-ray pictures, the models distinguish healthy people, Coronavirus infected people, and non-COVID19 illnesses. The proposed model has the highest accuracy among other models, utilising up to 97% of the two datasets. Our findings suggest that improved performance will assist radiologists in making clinical judgments. In summary, the suggested CNN model for screening COVID-19 based on X-Rays is beneficial to the healthcare system since it reduces diagnosis time, radiation dose, and costs. This approach helps speed up diagnosis/treatment and reduces the danger of COVID-19 virus spread.

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