



CovMnet–Deep Learning Model for classifying Coronavirus (COVID-19)

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Received: 9 May 2022 / Accepted: 25 July 2022 / Published online: 4 August 2022

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Abstract

Diagnosing COVID-19, current pandemic disease using Chest X-ray images is widely used to evaluate the lung disorders. As the spread of the disease is enormous many medical camps are being conducted to screen the patients and Chest X-ray is a simple imaging modality to detect presence of lung disorders. Manual lung disorder detection using Chest X-ray by radiologist is a tedious process and may lead to inter and intra-rate errors. Various deep convolution neural network techniques were tested for detecting COVID-19 abnormalities in lungs using Chest X-ray images. This paper proposes deep learning model to classify COVID-19 and normal chest X-ray images. Experiments are carried out for deep feature extraction, fine-tuning of convolutional neural networks (CNN) hyper parameters, and end-to-end training of four variants of the CNN model. The proposed CovMnet provide better classification accuracy of 97.4% for COVID-19 /normal than those reported in the previous studies. The proposed CovMnet model has potential to aid radiologist to monitor COVID-19 disease and proves to be an efficient non-invasive COVID-19 diagnostic tool for lung disorders.

Keywords COVID-19 · Chest X-ray · Deep learning · Convolutional neural network

1 Introduction

COVID-19 is a deadly communicable disease which was first reported in Wuhan, China in December 2019 [1–3]. COVID-19 has created a big outbreak as till now

no solution has been found. The biological structure has included a positive centered single-stranded RNA and due to mutating properties, it is very hard to treat this virus. COVID-19 is the cause for thousands of deaths worldwide and has affected various countries like the USA, Spain, India, China, Italy, UK, Australia etc. Several forms of COVID-19 are present in humans, cat, dogs, pigs, poultry

This article is part of the COVID-19 Health Technology: Design, Regulation, Management, Assessment

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and rodents. COVID-19 symptoms include a headache, fever, sore throat, cough and runny nose. The virus can cause death in humans with weak immune systems. The infectious disease of COVID-19 spreads from person to person, and is spreading rapidly across the world. It can spread from individual to other individual often by physical touch, breath contact, contact with the hand or contact with the mucus. This virus belongs to a family where acute respiratory symptoms can occur. The structure of the virus includes spikes on the crown in the outer surface. Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS) also belong to the same category [4]. As of 13 November 2020; 5,28,84,83 people were infected worldwide and 12,95,613 resulted in death [3]. COVID-19 severely affected the USA (1,06,37,418 cases), Italy (10,66,401 cases), Brazil (57,81,582 cases), India (86,83,916 cases), Russia (18,58,568 cases), Peru (9,30,267 cases), and South Africa (7,42,394 cases) [3, 4]. India is affected with 86,83,916 confirmed cases with 1,26,668 deaths on 13 November 2020 which is the second largest populated country. The distribution of COVID-19 cases across the globe is given in Fig. 1 [5].

COVID-19's mortality rate tends to be the most severe for people with chronic health problems and for the elderly. The virus is transmitted by coughing, sneezing, respiratory droplets from one human to the other [6]. Laboratory test is time consuming and requires high cost and requires well developed labs for investigation. Computer Tomography (CT) helps us to diagnose in a faster way [6, 7]. Further investigation is required for improving the performance of the radiologist. Early detection of the disease is important, and instant quarantine of the infected because of unavailability of COVID-19 medications. The Chinese Government confirmed the COVID-19 diagnosis

using Real-time polymerase chain reaction (RT-PCR) [8]. Nevertheless, RT-PCR agonizes from false negatives [8, 9]. For certain instances the infected individuals are not recognized and are treated on time. Such people infected with the virus spread to healthy people, as COVID-19 is communicable. Clinical reports show a bilateral change in chest computed tomography (CT) images of infected peoples. So the chest CT can also be preferred as an alternate method to identify the infection instigated by the infectious COVID-19 [10].

The main objective of this paper is to analyse the chest X-ray images for diagnosing COVID-19- infected patients. Deep convolutional neural networks were employed and tested for deep learning models for determining if the patient is affected or not. The suggested CovMnet model is trained by taking COVID-19 patients' chest X-ray images into account. Multifocal, consolidated, patchy, opacity, and a peripheral dispersion of a 'crazy-paved' pattern among COVID-19's superior outcomes on chest images. Many infections, such as measles, severe SARS, and MERS, have ground-glass opacities (GGO). To increase the radiologist's performance, further research is needed. The fundamental goal of this study is to detect COVID-19 using convolutional neural network and to conduct a large-scale experiment to recommend the optimal training using the best classifier.

The main motivation for the development of CovMnet–Deep Learning Model for classifying Coronavirus(COVID-19) and the contributions of the current study is as follows:

- An automated system to diagnose COVID-19 using chest X-ray data is implemented with four compact deep learning architectures such as CovMnet, CovMnet_1, CovMnet_2, CovMnet_3.

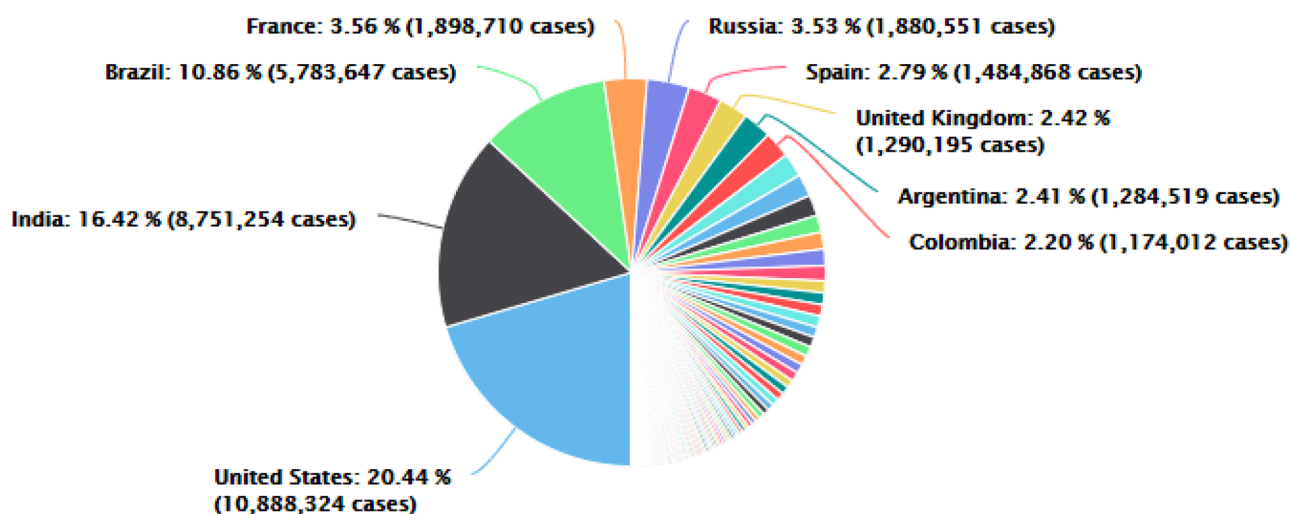


Fig. 1 Distribution of COVID-19 cases across the globe

- The training parameters of CovMnet, CovMnet_1, CovMnet_2, CovMnet_3 are varied using multiple convolution models with effective activation layers and performance for extracting discriminative feature patterns is compared in terms of the classification accuracy.
- The robustness of the proposed CovMnet model is shown in the form of ROC curve, training and validation loss respectively, and the results are compared with other models discussed in the recent literature.

Further the research work is structured as follows: Sect. 2 describes the existing work performed to diagnose COVID-19. An overview of the proposed models, architectures developed is explained in Sect. 3. Experimental analysis and results of the proposed and pre-trained models is detailed in Sect. 4. Finally, conclusion of the work with the future scope is summarized in Sect. 5.

2 Related work

Various machine learning models were carried out to automatically detect corona virus disease using lung X Ray dataset. Deep learning, a successful artificial intelligence (AI) research field, allows the development of models to achieve expected outcomes from the input, Without the need for manual feature extraction. Deep learning models are used effectively to several problems such as identification of arrhythmia, recognition of skin cancer, breast cancer detection, diagnosis of brain disease, pneumonia identification from Chest X-ray images and segmentation of the fundus images. Sousa et al. [11] diagnosed the pneumonia in infants using radiographic images using K-Nearest Neighbor, Support Vector Machine (SVM), and Naïve Bayes where SVM outperformed the other. A novel method is proposed by Tuncer et al. [12] to detect COVID-19 with Residual Exemplar Local Binary Pattern (ResExLBP), using the dataset that included 87 X-ray COVID-19 images which included 26 females, 41 males and 20 are not determined. Deep learning based model proposed by Ardakani et al. [13] used 1020 CT slices from one hundred and eight patients with VGG-16, SqueezeNet, AlexNet, GoogleNet, VGG-19, ResNet-18, ResNet-50, MobileNet-V2, Xception and ResNet-101, where ResNet-101 and Xception outperformed. Chest X-ray images representing the COVID-19 are shown in Fig. 2.

Fang et al. [14] researched RT-PCR sensitivity and chest CT, for COVID-19 detection. By analyzing the travel history and signs of two patients the chest sensitivity of CT has superior detection than RT-PCR. Mahmud et al. [15] proposed CovXNets for identifying the COVID-19 and other pneumonia and achieved 97.4% accuracy. Two datasets were analyzed that includes 5856 images from Guangzhou Medical Center, China and the other dataset included 305

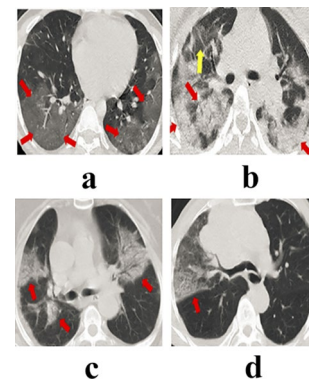


Fig. 2 COVID-19 samples of CT images [13]

X-rays of COVID-19. Panwar et al. [16] projected a deep network technique to analyze COVID-19 using nCOVnet that includes 24 layers and achieved 97.97% confidence during testing also. Berheim et al. [17] analyzed 121 patients' chest CT to identify the relationship between the symptoms. Li et al. [18] fetched features from chest CT using deep learning model COVNet to differentiate pneumonia and other lung diseases.

Gozes et al. [19] performed AI based tool to test COVID-19 which attained 98.2%, 92.2% sensitivity and specificity. Shan et al. [20] developed a VB-net deep learning model to segment the infection sites in the chest CT images. Liu et al. [21] discriminated pneumonia and influenza-viral pneumonia using a Convolution Neural Network (CNN) based prediction model based on deep learning techniques and achieved 86.7% accuracy. A modified inception transfer learning model is used by Wang et al. [22] achieved 89.5% prediction. Automatic deep convolution neural network based prediction is performed by Narin et al. [23] using chest X-ray images where ResNet50 achieved 98% accuracy. Features are [24] extracted through deep learning techniques from the chest X-ray images and are classified using SVM and achieved 95.38% accuracy. COVIDX-Net deep learning model proposed Hemdan et al. [25] diagnosed COVID-19. Wang et al. [26] proposed COVID-Net to classify multi classes and achieved 98.75% accuracy for two class classification. Apostolopoulos and Mpesiana [27] achieved an accuracy of 98.75 using deep learning model using 224 COVID-19 images. Song et al. [28] achieved an accuracy of 86% using modified Inception model for CT images. 3D CNN detected COVID-19 and reported 90.8% accuracy by Lawrence et al. [29].

Ozturk et al. [30] accurately diagnosed binary and multi class classification and attained 98.8% accuracy for binary classification and 87.02% accuracy for multi class using DarkNet. Cohen [31] performed an optimized CNN where fine tuning of CNN parameters is performed using evolution algorithm. Sergio and Melin [32] performed experiments

to analyse the classification of COVID dataset with other lung disease. This analysis was performed on the Computerized Tomographic images. The texture features are generated from the images and are further analysed using feature based feed forward neural network. This process attained a classification accuracy of 94.30% and an AUC of 0.930. Sun and Wang [33] analysed a model for Heilongjiang Province in China collected data from March to May 2020 to make an alert. This newly trained escaper model identified many infections in this province. This also identified a large number asymptomatic pool that was not identified earlier.

Boccalletti, Boccalletti et al. [34] detailed about the COVID-19 pandemic which is a global crisis after second world war. The awareness and advances has been discussed about the pandemic that has changed the habits, relations, and political organisations. This paper also discussed the role of virologists, mathematicians and epidemiologists and the communist scientist to incorporate AI and DL models to generate predictive models. Castillo and Melin [35] performed an intelligent approach using fractal theory and fuzzy logic to forecast COVID-19. The fractal dimension measures the dynamics of every countries time series and the uncertainty is represented using the fuzzy logic. This hybrid approach includes few fuzzy rules to integrate the fractal dimensions both linear and nonlinear.

Castillo and Melin [36] also analysed an intelligent fuzzy based system to predict the confirmed and death cases of 11 countries. Similarly, the COVID-19 forecasting was performed for four countries by Kumar [37] and Jawahar et al. [38] using statistical Modelling that includes ARIMA and deep learning techniques. Melin et al. [39] were able to analyse the COVID-19 spread using self-organizing maps by performing the clustering of the similar affected countries. Publicly available dataset was used for analysis purpose and suggested that spatial aspect is more important to fight against pandemic. Alowibdi et al. [40] analysed the emotional feelings of the people's expression in twitter about COVID-19. The sentimental analysis showed that fear, gratitude and mixed feelings are spread through their tweets. Sedik et al. [41] diagnosed the COVID-19 using convolutional long short-term memory in two datasets that includes CT images and X-ray achieving an accuracy of 100%. Sarivougioukas and Vagelatos [42] tested a ubiquitous computing to dynamically changing context for medical applications. Deep neural network based model is developed for large set of fused data and complex set of information thus improving the quality of decision making.

Rahman et al. [43] and Masud et al. [44] proposed a deep neural network to identify COVID-19 from CT and Xray images along with RT-PCR test data there by providing higher dimension results for diagnosis. In order to control the pandemic created by COVID-19 Internet of Medical Things (IoMT) is proposed for doctors to perform a digital

analysis. The control and monitor of the patients are performed where the security of the data is very important. A secure Physical Unclonable Functions (PUF) is embedded to enhance the security features like authentication, confidentiality, integrity, and anonymity.

Bekhet et al. [45] Used medical expertise and deep Convolutional Neural Networks, for early COVID-19 detection from chest X-ray pictures (CNNs). To get the best performance in COVID-19 identification, a deep learning model is carefully constructed and fine-tuned. Experiments on existing data sets show that the suggested technique outperforms in detecting COVID-19 with a 96% accuracy rate. Bekhet et al. [46] suggested a method for early COVID-19 detection based on medical experience and light-weight Convolutional Neural Networks (CNNs) that does not require special hardware. To produce a light-weight attribute that can operate on a regular CPU, the suggested deep learning model is carefully designed and fine-tuned by removing all superfluous parameters and layers (0.54 percent of AlexNet parameters). This model is especially useful at detecting COVID-19 with 96 percent accuracy on a few more benchmark datasets.

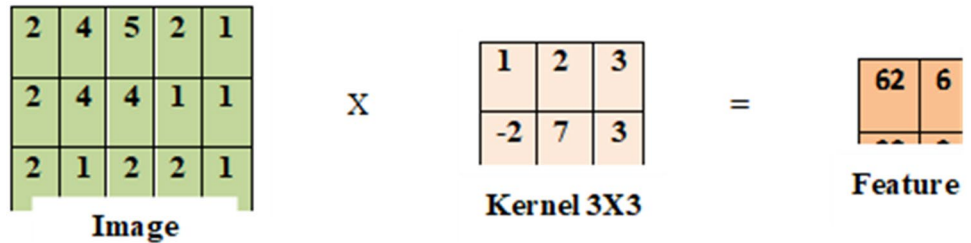
Ali et al. [47] proposed an attention-based convolutional neural network for brain tumour segmentation as a reliable and efficient neural network variation. A pre-trained VGG19 network serves as the encoder component of the UNET, which is followed by adjacent decoder parts with an attention gate for segmentation noise induction and a denoising method to avoid overfitting. Bhattacharya et al. [48] described the state-of-the-art research for COVID-19 medical image processing using deep learning techniques. Also included is a detailed introduction of deep learning and its uses in healthcare during the previous decade.

Various works has been carried out in recent years in classifying the COVID-19 using the Lung X-ray images. It's a challenging task challenging due to its inherent texture variations and similarity towards other diseases like pneumonia. Several studies have developed for classification COVID-19 based on computer vision algorithms.

2.1 Convolution Network

Convolutional network is influenced by biological processes [49–52], where the pattern of communication between neurons resembles the response of a neuron in the visual cortex to a specific stimulus. Individual neurons respond to stimuli for its field of receptive zone. Multilayer perceptron's typically mean networks that are completely connected. Convolution Neural Networks (CNN) [53] is used extensively for the classification of images where the hierarchical structure and the extracted features make the CNN a dynamic model for image classification. A convolution neural network includes various layer (input, output and hidden). The

Fig. 3 Convolution operator with Stride 2 and Kernel Size 3



hidden layers include a series of convolution layer that convolve with an operation. These layers are called convolutions by convention only but technically, it's a sliding dot product or a cross-correlation.

The convolution layer is designed as structures of three dimensions: width, height and depth. Convolution layer includes convolution kernels (height and width), number of input and output channels and the convolution filters depth similar to the feature map. The problems like exploding gradient and vanishing gradient seen in conventional neural networks during backpropagation are evaded through regularized weights. [54, 55]. The convolution operation is given in Eq. (1)

$$F_{cov}(x, y) = (D * F)(x, y) = \sum_i \sum_j D(x + i, y + j)F(i, j) \quad (1)$$

where D refers the input matrix representing the input 2D filter F of size x and y and F_{cov} is output feature map. $D * F$ represents the convolution operation. CNN performs multiple pooling operations and convolutions to evaluate and generate possible features. Convolution networks include layers of local or global pooling to minimizing data dimension. Local pooling performs on 2×2 samples where global pooling acts on all complete samples [56, 57]. Average pooling computes average value of each cluster [58–60]. Minimum pooling uses the minimum value of each cluster of neurons. The ReLU activation function is used to learn complicated functional mappings between inputs and response variables [57, 61]. The mathematical representation of ReLU is given in Eq. (2).

$$R_{cov}(x) = \max(0, x) \quad (2)$$

It is a linear function that if it is positive, produces the input directly; otherwise it will produce zero. Extracted features are used and assessed the likelihood of objects in the image [53]. In order to create non-linearity and reduce overfitting, the activation function and dropout layer are typically used [29]. Figures 3 and 4 shows the convolution and max pooling operations. A Softmax function that measures the distribution of probability of the ‘m’ classes are specified as

$$S^{Cov} = \frac{G^{Y^m}}{\sum_{j=1}^k G^{Y^k}} \quad (3)$$

where Y refers to the input feature vector and S denotes the output. Always the sum of the outputs equals to 1 and the loss function used is the cross entropy defined as

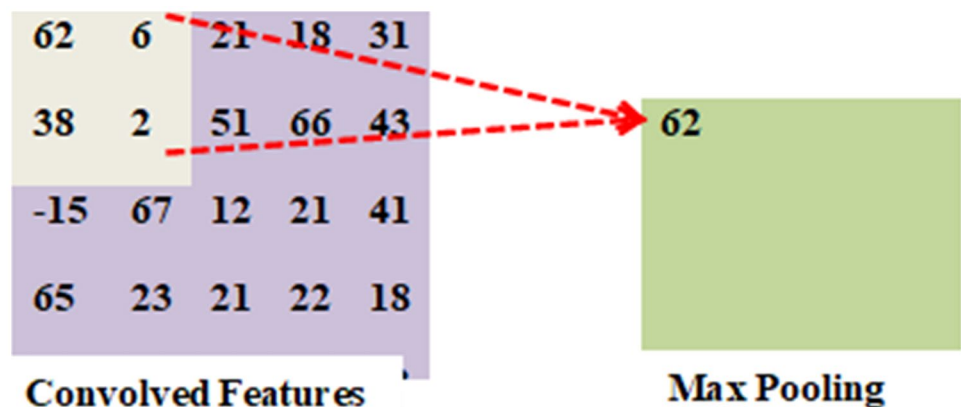
$$L(DV) = -\sum_i D_i \log(V_i) \quad (4)$$

The trade-offs between depth and filters (s) plays a major role in enhanced results represented as $n_{i-1}(s||i) * (s||i)n_i$. The time complexity of all convolutional layers are given as Eq. (5).

$$O\left(\sum_{l=1}^d n_{l-1}s_l^2n_l m_l^2\right) \quad (5)$$

where l is the layer index, d is the number of layers (convolution + pooling), n_l is the number of filters in layer l, m_l is the spatial size of l (spatial map) and S_l is the spatial length

Fig. 4 Max Pooling Operations



of the filter [62]. Deep learning schemes are performed to expose the data set features that are concealed in the data sources, like image and video. For this function, the CNN is used to retrieve features and is been used tremendously in medical image processing, which offers great support in advancing medical research. CNN processes high data volumes and achieves high accuracy with lower computation. In this research X-ray images are used to diagnose COVID-19 and were preprocessed by converting it to greyscale and resized all images to 224×224 .

3 Proposed architecture

In this research work, a custom CNN model is presented to predict corona virus using the chest X-ray image. The proposed work includes four variant folds of CovMnet model of which the last version gives the best results. The overall flow structure of the suggested COVID-19 classification model is given in Fig. 5. The X-ray images are converted into grayscale and are pre-processed using Wiener filter. Subsequently, features are extracted using the convolution layers followed by the pooling layers resulting in dimensionality reduction. The proposed models are hyper tuned to achieve good classification accuracy.

The proposed model ‘CovMnet’ is a modified deep learning model with learning rates indicating the model adaptation to extract the features, number of iterations i.e. the training epochs and the hyper parameters tuning. The model framework comprises 22,621,569 parameters with three convolution layers, max pooling and ReLU activation at each convolution layer. Initial convolutional layer used 64 filters

of size 3×3 on the input in Conv1, where max pool layer is applied with 2×2 filters. The second and third convolutional layer also included 64 filters of size 3×3 . In each convolution layer ReLU activation function is applied. The output of the convolution layers is converted into single dimensional array using two flattens layers. Two fully connected layers with 512 neurons followed by another dense layer with 256 neurons are used. Furthermore, to avoid overfitting and to reduce the complexity of the model two drop out layers is used at the end. Finally, the output layer uses softmax classifier that triggers one neuron to classify the COVID-19 and normal classes.

Algorithm Table 1 shows a model tried to achieve a good accuracy for the taken dataset. The algorithm starts with the top layer convolution layer adding more layers to the head layer. The layers are improvised using initial weights, max pooling layer with pool size of 2×2 , activation function ReLU where the function overcomes the problem of the disappearing gradient, models can learn faster and perform better. Dropout refers to spontaneously dropping out units during the neural network training process, or omitting them. Both weight thinning and dropping units cause the same form of regularisation, and when referring to weight dilution, the term dropout is also used. Next, layer flattens which transforms the 2D feature map to a vector to be fed into a completely connected classifier of the neural network. Features are converted into vectors and are fed to the fully connected layer with ReLU and 64 units. Threshold of 0.5 is set to enhance the output dropout. The dropout layer simply ignores those units (neurons) that take into account the threshold value given. Finally, the output layer predicts COVID-19 and Non COVID-19.

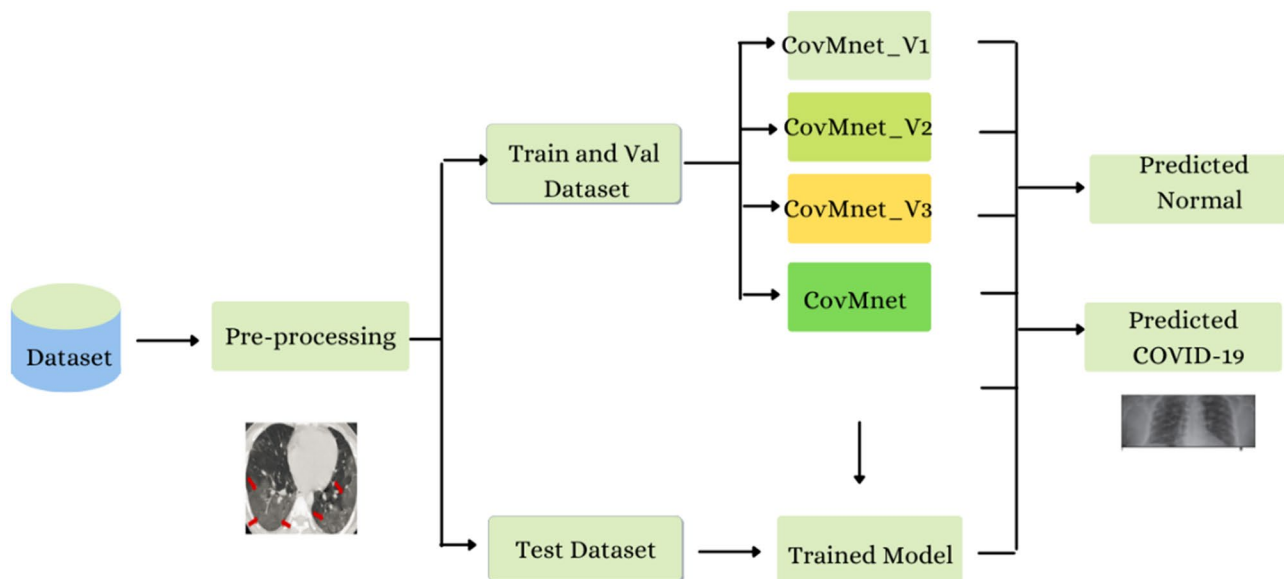


Fig. 5 Proposed COVID-19 classification model for chest X-ray images

Table 1 Optimized classification of CovMnet algorithm

Algorithm: Optimized Recognition and Classification of COVID-19

Input: Chest X-Ray dataset: Training and Testing data set

 β —> Learning Rate ∞ —> Iteration or Epochs

Output: Classified Results COVID-19 or Not

Begin:

1. Set the base layer of the CNN architecture
 2. Set the CNN_{MaxPooling}, CNN_{DropOut}, CNN_{ReLU}, CNN_{BatchNormalization}, CNN_{Flatten}, CNN_{Dense}
 3. Initialize the hyper parameters (β , ∞)
 4. Preprocess the image
 5. Train the CNN, initialize the strides, padding
- For $\delta = 1$ to ∞ do
6. Randomly select a batch of layers
 7. Compute the loss function
 8. Perform Back propagation and update the weights with Adam optimizer
- End

3.1 CovMnet_V1 model

The two-layer convolution network (CovMnet_V1) is built where convolution and activation function ReLU, MaxPooling followed by a Drop Out are stacked together as first layer followed by convolution, activation and MaxPooling are stacked as second layer. Final convolutional layer output is flattened and is given as the input to fully connected network of three dense layers, activation function ReLU and Dropout. The achieved training accuracy is 93.88% and validation accuracy 92.59%.

3.2 CovMnet_V2 model

A Four-layer convolution network (CovMnet_V2) is built where convolution is include in the first layer followed by convolution, MaxPooling, Dropout stack together as second, third and fourth layer. The output of the final layer is flattened and fitted to two dense layers of fully connected neurons, with Dropout. The achieved training accuracy is 96% and validation accuracy 94.30%.

3.3 CovMnet_V3 model

Later the model is redefined with a two-layer convolution block(CovMnet_V3) where convolution and activation function ReLU are stacked together as first layer followed by convolution with two Max Pooling layers stacked as second layer. Final convolutional layer is flattened and connected to fully connected layer of three dense layers. Sigmoid activation function is used, resulting 0 or 1 (normal or COVID-19). The most suitable loss function binary_crossentropy is used along with RMSprop (Root Mean Square Propagation) as error function and 0.001 as

learning rate is used as the optimizer. The measurement metric uses accuracy as the metrics to achieve the prediction accuracy rate on each epoch.50 epochs are used in the training process. The achieved training accuracy is 95% and validation accuracy 95.16%.

3.4 CovMnet model

A Three-layer convolution network (CovMnet) is built where all the layers included convolution layer along with activation function ReLU and MaxPooling. The output of the final convolutional layer is flattened and fit to fully connected neurons of four dense layers, activation layer and Dropout. The achieved training accuracy is 97% and validation accuracy 95.16%. Figure 6 shows the flow diagram of CovMnet model. Different parameters are explored and the results are reported in Tables 2. The learning rate is initialized as 0.001 and the number of epoch is considered to be 50. Three convolution layers with activation function Relu followed by Max pooling is constructed in the CovMnet model. The 3×3 kernel size is used in the Max pooling layer resulting in a dimensionality reduction. Now in order to prevent the network from overfitting, 30% drop is performed to the less contributing neurons which in turn help to lower the generalization error.

Flatten layer is stacked which acts as a utility layer for converting the output into a vector followed by the dropout to avoid overfitting. Finally, the flattened output is fed to a feed-forward neural network with three dense layers, one with 512 neurons and ReLU activation function and the other with 256 neurons with ReLU followed by one neuron with softmax as an activation function. ReLU maintain the sparsity and reduces the likely-hood of vanishing gradient that is more likely to happen in the dense model. Last layer

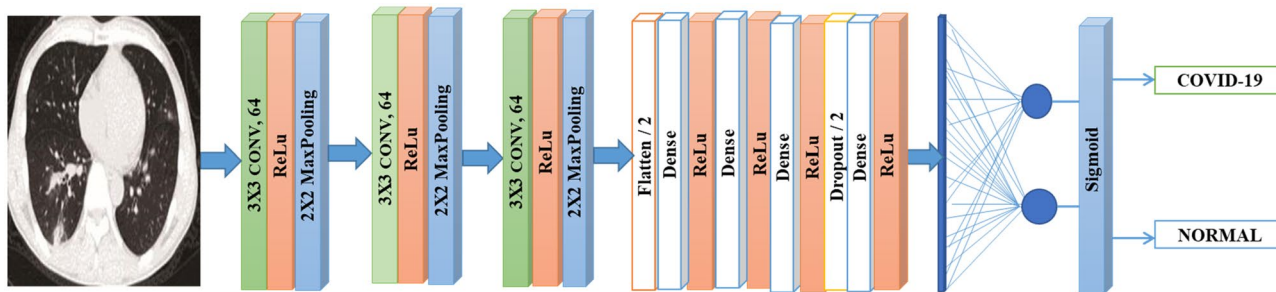


Fig. 6 Schematic structure of the proposed CovMnet

includes sigmoid activation function to overcome dying ReLU problem that prohibits further learning. In order to prevent the network from overfitting, 50% drop is performed to the less contributing neurons which in turn help to lower the generalization error between these two dense layers. This model results in classification accuracy of 95.15%.

4 Experiment results and discussion

A comprehensive view of the database, development, experimentation, training, and validation is presented in this section. This section also provided a performance analysis of the proposed approach with the existing works.

Table 2 Parameters obtained for CovMnet model for COVID-19 diagnosis

Layer	Stride	Filter	Pool Size	Padding	Depth	Output Shape	No. of Parameters
Input Layer					2		0
Cov1	1	3X3		Same	64	(None, 222, 222, 64)	1792
ReLU					64	(None, 222, 222, 64)	0
Max Pooling			2X2		64	(None, 111, 111, 64)	0
Conv2	1	3X3		Same	64	(None, 109, 109, 64)	36,928
ReLU					64	(None, 109, 109, 64)	0
Max Pooling			2X2		64	(None, 54, 54, 64)	0
Conv3	1	3X3		Same	64	(None, 52, 52, 64)	36,928
ReLU					64	(None, 52, 52, 64)	0
Max Pooling			2X2		64	(None, 52, 52, 64)	0
Flatten					43,264	(None, 43,264)	0
Flatten					43,264	(None, 43,264)	0
Dense					512	(None, 512)	22,151,680
ReLU					512	(None, 512)	0
Dense					512	(None, 512)	262,656
ReLU					512	(None, 512)	0
Dense					256	(None, 256)	131,328
ReLU					256	(None, 256)	0
DropOut					256	(None, 256)	0
DropOut					256	(None, 256)	0
Dense					1	(None, 1)	257
ReLU					1	(None, 1)	0
Total parameters							22,621,569
Trainable parameters:							22,621,569
Non-trainable parameters							0

4.1 Data acquisition and pre-processing

Kaggle included images of COVID-19 CT Lung X-ray where there are 219 CT images with 153, 491 and 1853 are the minimum, average and maximum width. These images belong to 216 patients; Also includes 648 COVID-19 negative images. The dataset included the images of various sizes and are not identical, so the images are transformed into a size of 224X224 pixels. Since deep learning requires huge dataset and our data set is small, so data augmentation is performed to increase the images in the dataset. The X-ray images have been horizontally and vertically rotated to greatly increase the size of the data collection. Now this data can be used for both testing and training process.

4.2 Data augmentation

Data augmentation techniques like rotation ‘ θ ’ between 10^0 to 40^0 , width_shift between 0.2 to 1.0, height_shift between 0.2 to 1.0, shear_range between 0.2 to 1.0, zoom_range between 0.5 to 1.0, brightness range between 0.2 to 1.0 horizontal flipping, vertical flipping and filling of missing pixels, are performed to generate the large amount of data for CNN architectures and to reduce over-fitting. The eight transformations are applied to generate and render the augmented samples. The augmented samples are shown in the Fig. 7.

4.3 Hyperparameter tuning

Experiment to set up hyper parameter tuning in the CNN model is as follow: (a) dropout, (b) learning rate, (c) gradient update, (d) number of convolution layers and its kernel size (e) type of pooling (max pool/ average pooling) (f) loss/activation functions. Optimal tuning is accomplished by looking for parameter values within the determined range: To reduce overfitting and to improve the performance, the dropout factor is chosen between 0.5 to 0.8 with 0.1 increment; learning rate as 0.001, beta1 value is set as 0.9, beta2 as 0.999, epsilon to be $1e-08$; ADAM or SGD as gradient optimizers. The learning rate is scaled by using squared gradients in ADAM optimizer which is a result of combined output of RMSprop and SGD with momentum. The weight decay parameter rule with ADAM is shown in the Eqs. (6) and (7).

$$W_t = W_{t-1} - \beta v \quad (6)$$

$$\gamma = \gamma_{norm} \sqrt{\frac{b}{XY}} \quad (7)$$

where X denotes the total number of training samples per epoch (527), Y indicates the total number of epochs (50)

and b denotes the batch size (32). It is found that dropout probabilities of 0.5 towards the output layer and 0.8 near the input grouped and separable convolutional branches respectively resonated well respectively. Different variants of convolution layers of varying kernel size (2×2 , 3×3 , 5×5 and 7×7), pooling layers (average/ max pool) is explored. It is found that the convolution with 3×3 kernel size activated with ReLU function and max pool (2×2) layer gave optimal results.

4.4 Model training and validation

In this research, the experimentation is carried out using the publicly available COVID-19 lung X-ray dataset comprising 219 COVID-19 X-ray images and 648 normal X-ray images. The dataset is partitioned into 70% training and 15% validation and 15% testing dataset. Four CNN models are deployed for extracting discriminating features from the X-ray images. During CNN experimentation phase, both Adam and RMS prop solver are used for training in each architecture. The value of batch size is set to 10 with the initial learn rate of $1e-4$ and the maximum epochs is set to 50. The number of best epochs is varied according to validation criteria with the validation frequency of 50 iterations. The highest accuracy of best network is achieved up to 97% using the proposed CovMnet. Figures 8 and 9 shows the learning process recorded by the CovMnet model with respect to the number of epochs, model loss, and model accuracy curve respectively.

From Figs. 8 and 9, it can be observed that the CovMnet model training learns consistently as the number of epochs. The variation between the training & validation is less which confirms the potential to predict Covid cases accurately. The proposed CovMnet Model attained 97% training accuracy and 95.16% validation accuracy whereas the other versions achieved lesser than this model. This results a minimum classification error rate that indicates the model classification distinguishability. The Table 4 presents the accuracy and loss for the proposed CovMnet model along with their respective earlier versions.

4.5 Visual interpretation of the trained model features

Table 3 shows the visualization of features extracted by the inner layers of the proposed model CovMNet during the training process. This visualization helps in understanding how a model is interpreting the image internally. Here image represents visualization of the output after

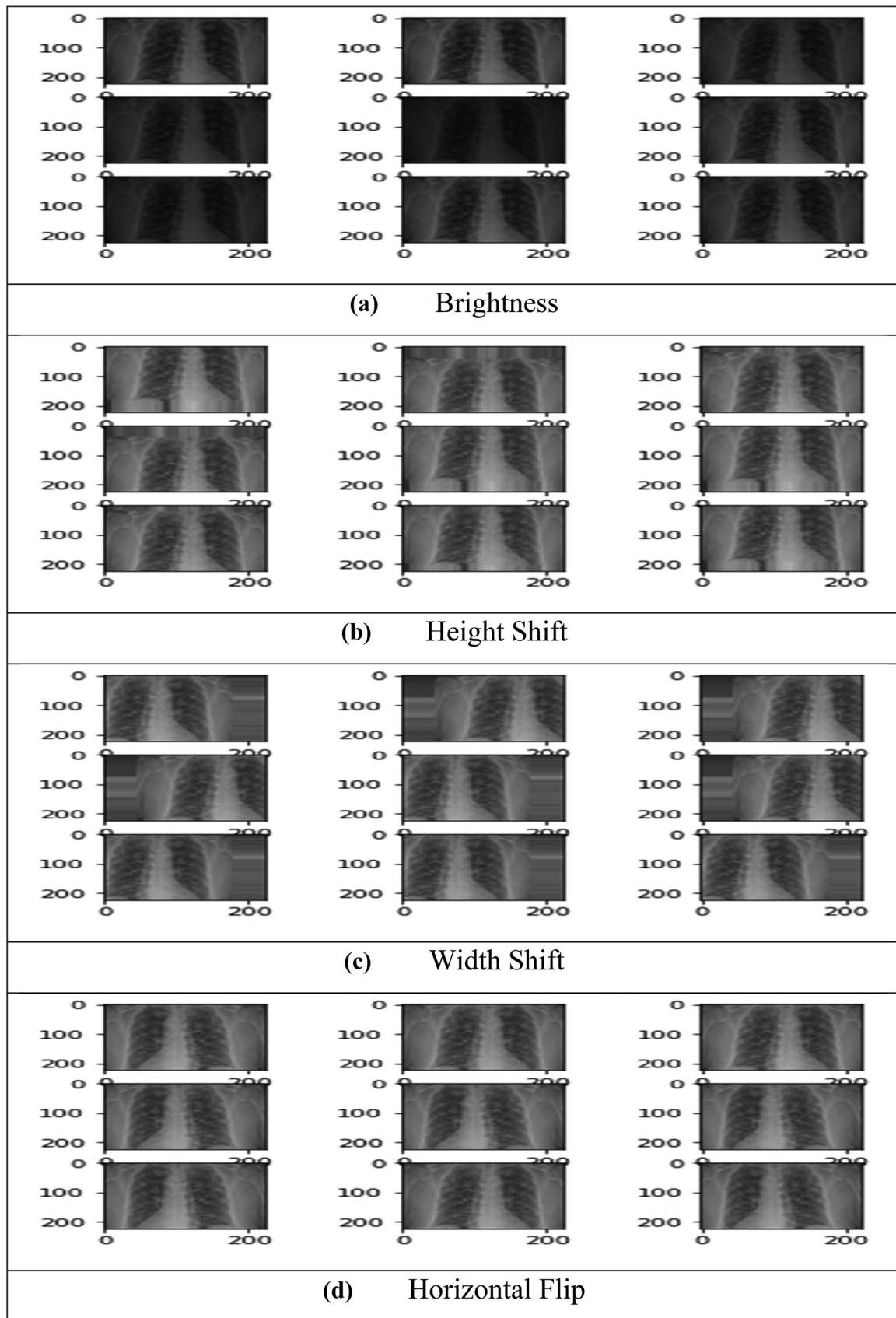


Fig. 7 a–g Different variations of a COVID-19 lung x-ray images after augmentation process

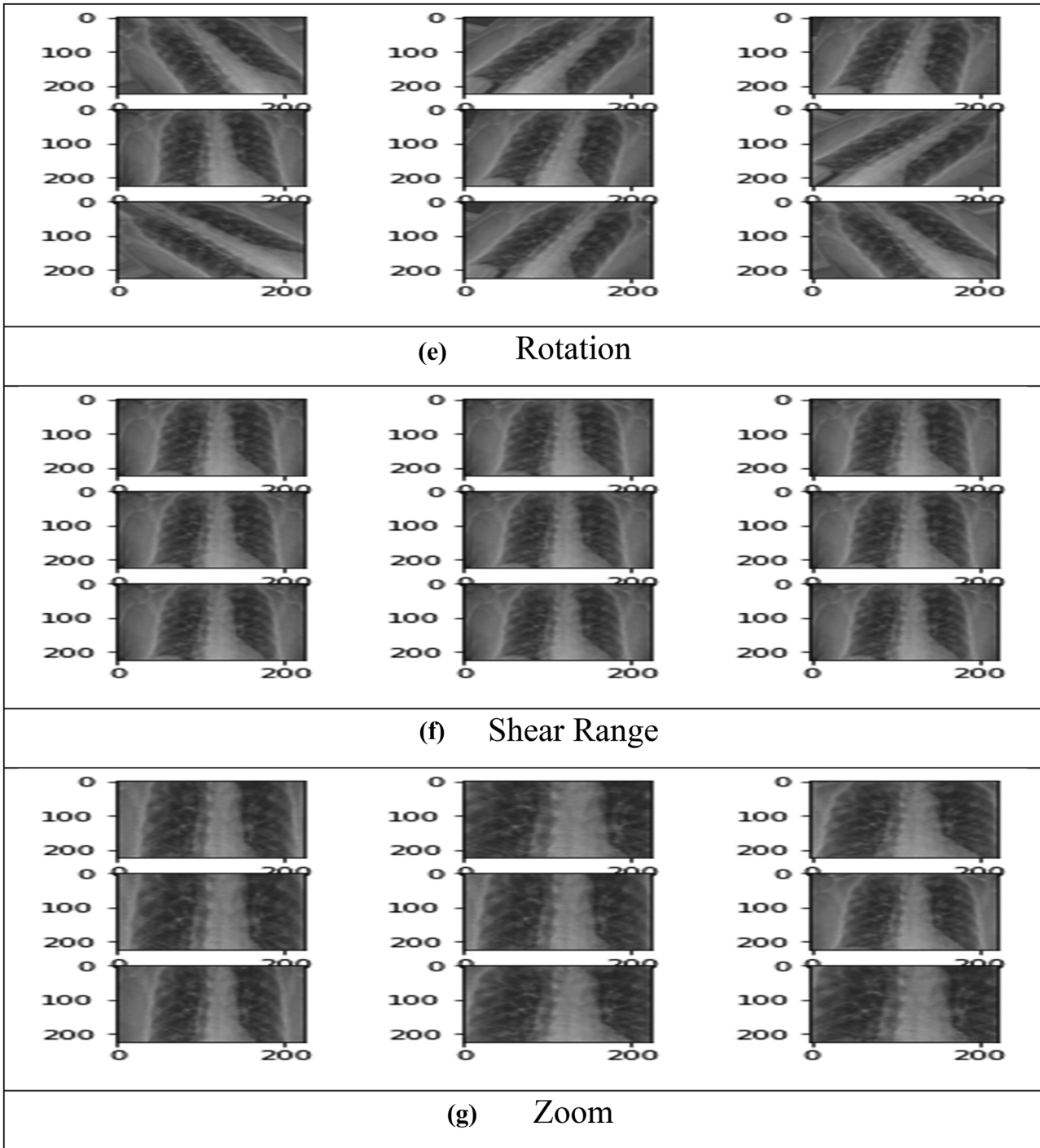


Fig. 7 (continued)

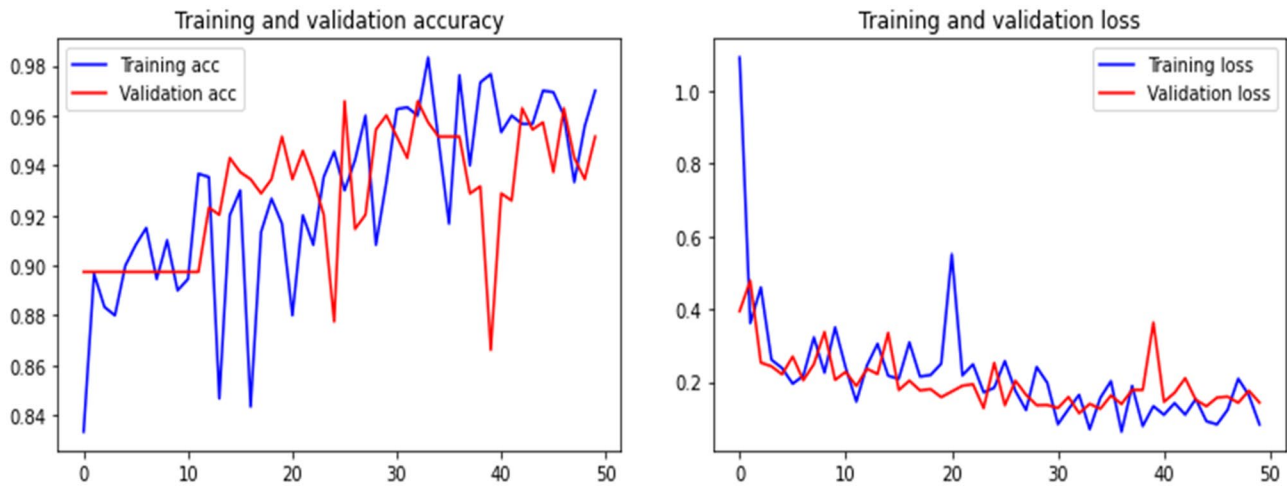


Fig. 8 Observation of the validation and training detailed by the CovMnet Model with respect to number of epochs, model accuracy and loss

applying $32, 3 \times 3$ filters. Followed by image that represents the output after applying max-pooling to each 32 filters. Edges are strengthened as compared to the convolution image features. Similarly, further convolution blocks, which helps in extracting more fine-grained features from the image. Visualization of the features of the proposed CovMnet shows that the network is able to extract both high level (edge features) and small fine-grained features from the lung x-ray images that discriminates the normal and corona disease.

5 Effectiveness of the proposed architecture

Tables 4 represent the compiled performance metric of all the models. The proposed CovMnet model is trained with the chest X-ray images to analyze and evaluate the custom model. The distribution of the samples into training and validation dataset is in 2:1 ratio, with 219 CT images with 153, 491 and 1853 are the minimum, average and maximum width which is further converted into a size of 224×224 pixels dataset. The input size of the training and testing images are $224 \times 224 \times 3$, batch size

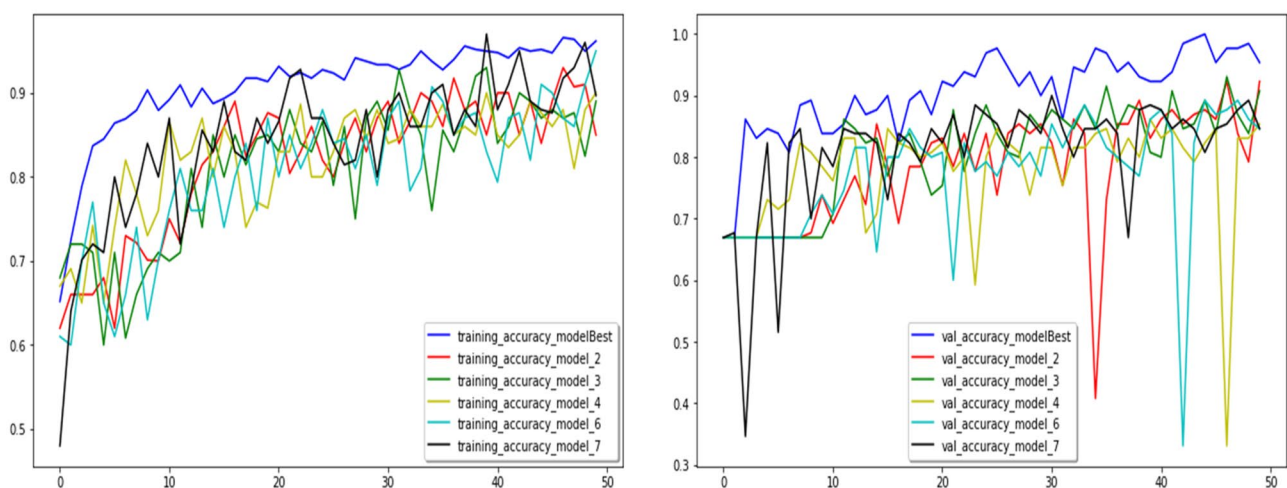


Fig. 9 Observation of the validation and training process detailed by the CovMnet along with the other versions with respect to number of epochs, model accuracy and loss

Table 3 Visualization of features extracted by the inner layers of the proposed model

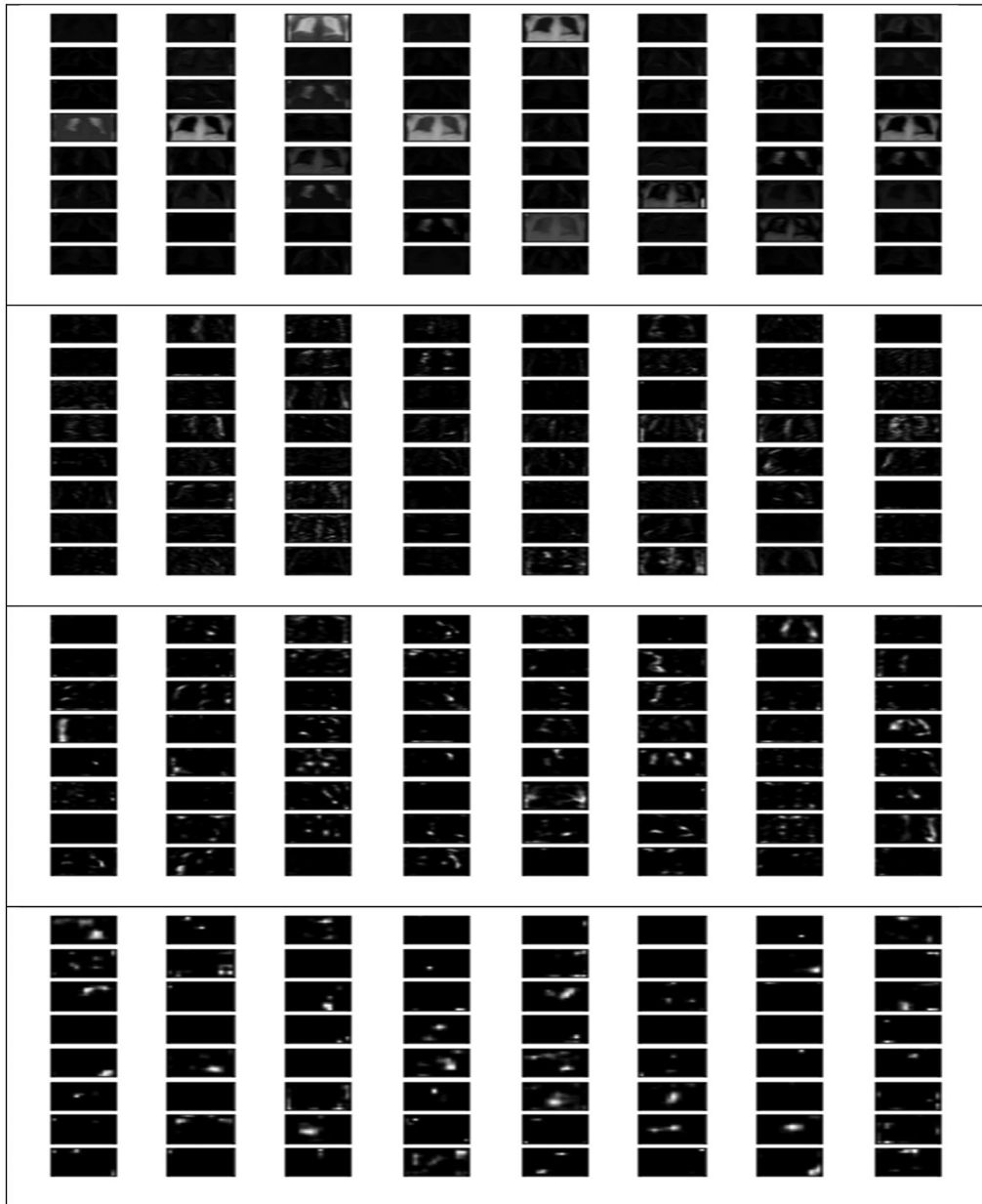


Table 4 Accuracy and Loss values for the proposed CovMnet and its variants

Model	Accuracy	
	Training	Validation
CovMnet	97.4	95.16
CovMnet_V1	93.88	92.59
CovMnet_V2	96	94.30
CovMnet_V3	95	95.16

of 64 is used during the experiment. The models were trained for 50 epochs with early-stopping configuration, i.e. the training stops once the model stops improving performance on the validation set. Table 4 includes the learning process recorded by the CovMnet model with respect to the number of epochs, model loss, model accuracy respectively. The best model for binary classification in the custom model category is CovMnet achieving an accuracy of 97.4%, sensitivity as 100% and specificity as 97.73%. Table 5 shows the performance of the proposed system compared with the existing models.

Table 5 Performance of the proposed system compared with the existing models

Reference	Image Data	Model	Accuracy
Xu et al. [9]	Chest CT	ResNet þ Location Attention Model	86.7
Wang et al. [22]	Chest CT	M-Inception Model	82.9
Sethy and Behera [24]	Chest X-ray	ResNet50 and SVM Model	95.38
Hemdan et al. [25]	Chest X-ray	COVIDX-Net Model	90.0
Wang et al. [26]	Chest X-ray	COVID-Net Model	92.4
Apostolopoulos and Mpesiana [27]	Chest X-ray	VGG-19 Model	93.48
Song et al. [28]	Chest CT	DRE-Net Model	86
Zheng et al. [63]	Chest CT	UNetþ3D Deep Network Model	90.8
Ozturk et al. [30]	Chest X-ray	DarkCovidNet Model	87.02
Singh et al. [64]	Chest CT	Fine-tuned CNN Model	Good accuracy
Proposed	Chest X-ray	CovMnet	97.4

6 Conclusion

This study successfully developed a powerful CovMnet model using convolution neural network architecture to diagnose COVID-19 disease from normal chest lung X-ray images. This study explored four different deep CNN architectures for classifying the COVID-19 lung X-ray images. The objective of this research work is to investigate different deep learning networks and evaluated their performance in terms of model size, ability to extract discriminative features, effect of number of trainable parameters. The proposed CovMnet architecture contains three conv and max pool followed by three dense blocks. CovMnet fully exploits the dense connection, reduces the number of trainable parameters as well as extracts the distinguishing visual patterns and features from the X-ray images with less time complexity. Feature visualization maps of the proposed CovMnet shows discriminative high and low level features extracted from the lung X-ray images. Experimental results show that CovMnet achieved the highest accuracy of 97.4%. CovMnet_V2, CovMnet_V3 and CovMnet_V1 are ranked second, third and fourth in terms of their classification accuracy of 96%, 95% and 93.8%, respectively. A comparative analysis with other CNN architectures demonstrates the effectiveness of the proposed CovMnet in terms of classification prediction accuracy and compactness. Directions for future work include exploring deep learning architecture namely one shot/fewer shot for smaller dataset and to tackle the imbalanced dataset challenge. Further this model can be improved by fusion of CNN and pertained model features to enhance the accuracy. Also, in future multi class classification can be designed to classify among various types of lung diseases. CovMnet can be enhanced for real time dataset using transfer learning models.

Author contributions All authors have equal contributions.

Availability of data and material The data that support the findings of this study are available from the first author upon reasonable request.

Code availability The code is available from the first author upon reasonable request.

Declarations

Ethical approval None.

Consent to participate None.

Consent to publication None.

Informed consent None.

Conflicts of interest The authors declare no conflict of interest.

References

1. Lau H, et al. Internationally lost COVID-19 cases. *J Microbiol Immunol Infect* 2020;53.3:454–458.
2. Zhang JF, et al. SARS-CoV-2 turned positive in a discharged patient with COVID-19 arouses concern regarding the present standards for discharge. *Int J Infect Dis.* 2020;97:212–214.
3. Lippi G, Plebani M, Henry BM, "thrombocytopenia Is Associated With Severe Coronavirus Disease,. (COVID-19) infections: a meta-analysis." *Clin Chim Acta.* 2019;506(2020):145–8.
4. Rodriguez-Morales AJ, et al. Clinical, laboratory and imaging features of COVID-19: A systematic review and meta-analysis. *Travel Med Infect Dis.*2020;34: 101623.
5. Coronavirus Worldwide Graphs available at <https://www.worldometers.info/coronavirus/worldwide-graphs/>.
6. Chung M, et al. CT Imaging features of 2019 novel coronavirus (2019-nCoV). *Radiology.* 2020;295(1):202–207. <https://doi.org/10.1148/radiol.2020020230>.
7. Zu ZY, et al. Coronavirus disease 2019 (COVID-19): a perspective from China. *Radiology.*2020.
8. Ai T, et al. Correlation of Chest CT and RT-PCR Testing in Coronavirus Disease 2019 (COVID-19) in China: A Report of 1014 Cases. *Radiology.*2020;296(2):200642.
9. Xu X, et al. A deep learning system to screen novel coronavirus disease 2019 pneumonia. *Engineering.*2020;6.10:1122–1129.

10. Wang D, et al. Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in Wuhan, China. *JAMA*.2020;323.11:1061–1069.
11. Sousa RT, et al. Comparative performance analysis of machine learning classifiers in detection of childhood pneumonia using chest radiographs. *Prog Comput Sci*.2013;18:2579–2582.
12. Tuncer T, Dogan S, Ozyurt F. An automated Residual Exemplar Local Binary Pattern and iterative ReliefF based COVID-19 detection method using chest X-ray image. *Chemom Intell Lab Syst*. 2020;203.
13. Ardakani AA, et al. Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. *Comput Biol Med*.2020;121:103795.
14. Fang Y, Zhang H, Xu Y, Xie J, Pang P, Ji W. CT Manifestations of Two Cases of 2019 Novel Coronavirus (2019-nCoV) Pneumonia. *Radiology*. 2020;295(1):208–209. <https://doi.org/10.1148/radiol.2020200280>. (Epub 2020 Feb 7. PMID: 32031481; PMCID: PMC7233358).
15. Mahmud T, Rahman MA, Fattah SA. CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization. *Comput Biol Med*.2020;122:103869.
16. Panwar H, et al. Application of deep learning for fast detection of COVID-19 in X-Rays using nCOVnet. *Chaos, Solitons Fractals*.2020;138:109944.
17. Bernheim A, et al. Chest CT findings in coronavirus disease-19 (COVID-19): relationship to duration of infection. *Radiology*.2020.
18. Li L, et al. Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT. *Radiology*.2020.
19. Gozes O, et al. Rapid ai development cycle for the coronavirus (covid-19) pandemic: Initial results for automated detection & patient monitoring using deep learning ct image analysis. *arXiv preprint arXiv:2003.05037*. 2020.
20. Shan F, et al. Lung infection quantification of COVID-19 in CT images with deep learning. *arXiv preprint arXiv:2003.04655*.2020.
21. Liu K-C, et al. CT manifestations of coronavirus disease-2019: a retrospective analysis of 73 cases by disease severity. *Eur J Radiol*.2020;126:108941.
22. Wang S, et al. A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19). *Eur Radiol*.2021;31.8:6096–6104.
23. Narin A, Kaya C, Pamuk Z. Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. *Pattern Anal Appl*. 2021;24(3):1207–20.
24. Sethy PK, Behera SK. Detection of coronavirus disease (covid-19) based on deep features.2020.
25. Hemdan EE, Shouman MA, Karar ME. Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images. *arXiv preprint arXiv:2003.11055*. 2020.
26. Wang L, Lin ZQ, Wong A. Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. *Sci Rep*.2020;10.1:1–12.
27. Apostolopoulos ID, Mpesiana TA. Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. *Physical and engineering sciences in medicine*. 2020;43(2):635–40.
28. Song Y, et al. Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images. *IEEE/ACM Trans Comput Biol Bioinform*.2021;18.6:2775–2780.
29. Lawrence S, et al. Face recognition: A convolutional neural-network approach. *IEEE Trans Neural Netw*.1997;8.1:98–113.
30. Ozturk T, et al. Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Comput Biol Med*.2020;121:103792.
31. Cohen JP. COVID-19 Chest X-Ray dataset or CT dataset. *Git Hub*. 2020.
32. Varela-Santos S, Melin P. A new approach for classifying coronavirus COVID-19 based on its manifestation on chest X-rays using texture features and neural networks. *Inf Sci*. 2021;545:403–14.
33. Sun T, Wang Y. Modeling COVID-19 epidemic in Heilongjiang province, China. *Chaos, Solitons Fractals*. 2020;138.
34. Boccaletti S, et al. Modeling and forecasting of epidemic spreading: The case of Covid-19 and beyond. *Chaos, Solitons Fractals*.2020;135:109794.
35. Castillo O, Melin P. Forecasting of COVID-19 time series for countries in the world based on a hybrid approach combining the fractal dimension and fuzzy logic. *Chaos, Solitons Fractals*. 2020;140.
36. Castillo O, Melin P. A novel method for a covid-19 classification of countries based on an intelligent fuzzy fractal approach. *Healthcare*. 2021;9(2). Multidisciplinary Digital Publishing Institute.
37. Kumar SL. Predictive Analytics of COVID-19 Pandemic: Statistical Modelling Perspective. *Walailak Journal of Science and Technology (WJST)*.2021;18.16:15583–14.
38. Jawahar M, et al. Diabetic Foot Ulcer Segmentation using Color Space Models. 2020 5th International Conference on Communication and Electronics Systems (ICCES). *IEEE*.2020.
39. Melin P, et al. Analysis of spatial spread relationships of coronavirus (COVID-19) pandemic in the world using self organizing maps. *Chaos, Solitons Fractals*.2020;138:109917.
40. Alowibdi JS, et al. Coronavirus pandemic (COVID-19): Emotional toll analysis on Twitter. *Int J Semant Web Inf Syst*.2021;17.2:1–21.
41. Sedik A, et al. Efficient deep learning approach for augmented detection of Coronavirus disease. *Neural Comput Applic*.2021:1–18.
42. Sarivougioukas J, Vagelatos A. Modeling deep learning neural networks with denotational mathematics in UbiHealth environment. *International Journal of Software Science and Computational Intelligence (IJSSCI)*. 2020;12(3):14–27.
43. Rahman MA, et al. A multimodal, multimedia point-of-care deep learning framework for COVID-19 diagnosis. *ACM Trans Multimed Comput Commun Appl*.2021;17.1s:1–24.
44. Masud M, et al. A lightweight and robust secure key establishment protocol for internet of medical things in COVID-19 patients care. *IEEE Internet Things J*.2020;8.21:15694–15703.
45. Bekhet S, et al. An artificial intelligence based technique for COVID-19 diagnosis from chest X-ray. 2020 2nd Novel Intelligent and Leading Emerging Sciences Conference (NILES). *IEEE*.2020.
46. Bekhet S, et al. An efficient method for covid-19 detection using light weight convolutional neural network. *Computers Materials Continua*. 2021;69(2):2475–2491.
47. Ali TM, et al. A sequential machine learning cum attention mechanism for effective segmentation of brain tumor. *Front Oncol*.2021:2129.
48. Bhattacharya S, et al. Deep learning and medical image processing for coronavirus (COVID-19) pandemic: A survey. *Sustain Cities Soc*.2021;65:102589.
49. Fukushima K. *Neocognitron Scholarpedia*. 2007;2(1):1717.
50. Hubel DH, Wiesel TN. The period of susceptibility to the physiological effects of unilateral eye closure in kittens. *J Physiol*. 1970;206(2):419–36.
51. Fukushima K. Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. *Biol Cybernetics*. 1980;36:193–202. <https://doi.org/10.1007/BF00344251>.
52. Matsugu M, et al. Subject independent facial expression recognition with robust face detection using a convolutional neural network. *Neural Netw*.2003;16.5–6:555–559.
53. Zbontar J, Lecun Y. Stereo matching by training a convolutional neural network to compare image patches. *J Mach Learn Res*. 2016;17(1):2287–318.

54. Venkatesan R, Baoxin L. Convolutional neural networks in visual computing: a concise guide. CRC Press. 2017.
55. Balas VE, Kumar R, Srivastava R. Recent trends and advances in artificial intelligence and internet of things. Springer International Publishing. 2020.
56. Ciresan DC, et al. Convolutional neural network committees for handwritten character classification. 2011 International conference on document analysis and recognition. IEEE. 2011.
57. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. *Adv Neural Inf Proces Syst.* 2012;25.
58. Gamage C, et al. GI-Net: Anomalies Classification in Gastrointestinal Tract through Endoscopic Imagery with Deep Learning. 2019 Moratuwa Engineering Research Conference (MERCon). 2019:66–71.
59. Ciregan D, Ueli M, Jürgen S. Multi-column deep neural networks for image classification. 2012 IEEE conference on computer vision and pattern recognition. IEEE. 2012.
60. Mittal S. A survey of FPGA-based accelerators for convolutional neural networks. *Neural Comput Appl.* 2020;32(4):1109–39.
61. Jin KH, et al. Deep convolutional neural network for inverse problems in imaging. *IEEE Trans Image Process.* 2017;26.9:4509–4522.
62. He K, Jian S. Convolutional neural networks at constrained time cost. *Proc IEEE Conf Comput Vis Pattern Recognit.* 2015.
63. Zheng C, et al. Deep learning-based detection for COVID-19 from chest CT using weak label. *MedRxiv.* 2020.
64. Singh D, Kumar V, Kaur M. Classification of COVID-19 patients from chest CT images using multi-objective differential evolution-based convolutional neural networks. *Eur J Clin Microbiol Infect Dis.* 2020;39(7):1379–89.

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