BEMD-3DCNN-Based Method for COVID-19 Detection

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ABSTRACT

Coronavirus outbreak continues to spread around the world and none knows when it will stop. Therefore, from the first day of the virus detection in Wuhan, scientists have launched numerous research projects to understand the nature of the virus, how to detect it, and search for the right medicine to help and protect patients. A fast diagnostic and detection system is a priority and should be found to stop COVID-19 from expanding. The purpose of the study is to combine the bi-dimensional empirical mode decomposition (BEMD) technique with 3DCNN to detect COVID-19. BEMD is used to decompose the original images into IMFs and from there built a video then apply the 3DCNN to classify and detect COVID-19 virus. In our experiment we used 6484 X-Ray images, 1802 of them were COVID-19 positive cases, 1910 normal cases, and 2772 pneumonia cases. The experiment results showed that our proposed techniques achieved the desired results on the selected dataset. It reached the accuracy of 100%.

Introduction

Coronavirus (COVID-19) is a contagious respiratory illness discovered in December 2019 in china, specifically in Wuhan, the city where the new coronavirus was first detected. As per December 26, 2020 there were 80,288,455 confirmed cases infected by coronavirus "COVID-19" worldwide, 56,564,649 of them were recovered and 1,759,351 died[1]. The coronavirus outbreak continues to spread and nobody knows when it will stop. Therefore, from the first day of the virus detection, scientists have launched a numerous research projects to understand how the pandemic disease spreads and how people's immune systems respond to it to prevent, diagnose and treat the disease. Few months later, medical professionals and research scientists around the world, succeeded to build up a strong understanding of how the novel Covid-19 spreads and influences the body[2]. Therefore, they found that coronavirus attacks mainly the lung of the patient then spreads into the body and affects other organs such as the kidneys and liver.

In this research paper, we proposed deep learning (DL) based framework that combines the 3D convolution neural network (3DCNN) with the BEMD to detect the virus from X-ray images. In our proposal, we used the BEMD technique to extract four images from each original image by decomposing the original image into a finite number of intrinsic mode functions (IMFs), and then apply the 3DCNN to classify and detect Covid-19. In this research, we used the dataset gathered from different sources by Islam et al.[3]. A preprocessing was performed to diminish the noise and augmentation was applied to the collected images.

The research paper is organized as follows: In section 2, a summary of the recent research works related to this study. In section 3, we presented a description of the proposed methodology. In section 4, we described the experiment and results including the data set collection, the preparation, and experimental results. Finally, in section 5 we concluded the paper.

1 related works

Early work in COVID-19 detection is to extract images on patient lungs using the ultrasound technology, a technique to identify and monitor patients affected by viruses, this method needs a trained and qualified staff. The development of recognition techniques and strategies capable to automate the process without needing the help of prepared specialists is still not advanced. In[3] the authors introduced the DL technique that combines CNN with the LSTM to detect COVID-19 virus from x-ray images. They used in their system 4575 x-ray images, 1525 images of them were COVID-19 positive cases. Carrer et al.[4], discussed a method to detect automatically the pleural line of lungs and extract the characteristics of its geometric and its intensity. They also presented images about the classification of each Lung Ultrasound (LUS) in terms of score. The pleural lines extracted then modeled and given as input to the classifier. They use a supervised Support Vector Machine (SVM) classifier in their study. Farooq et al.[5], introduced the Infrared Thermography Technology (IRT) a medical diagnostic tool to detect heat patterns and

Table 1. SUMMARY DATASET AND TECHNIQUES USED TO DETECT COVID-19 FROM X-RAY IMAGES

Method	Dataset size (images)			Techniques used
	COVID-19	Pneumonia	Normal	
Islam et al.[3]	613	1525	1525	CNN-LSTM
HORRY et al.[6]	140	322	60361	VGG19
Khan et al.[7]	284	327	310	CoroNet (CNN)
Horry et al.[8]	100	100	200	VGG16,VGG19,ResNet50,InceptionV3,Xception
Apostolopoulos et al.[12]	224	714	504	VGG19,MobileNetv2,Inception,Xception, Inception,ResNetv2
Minaee et al.[14]	71		5000	ResNet18,ResNet50,SqueezeNet, DenseNet-121
Moutounet-Cartan.[15]	125	50	152	VGG16,VGG19,Inception,ResNetV2, InceptionV3,Xception
Hemdan et al.[16]	25	-	25	VGG19,DenseNet121, InceptionV3, ResNetV2, InceptionResNet-V2,Xception,MobileNetV2
Maguolo and Nanni.[18]	144	339	-	AlexNet
Chowdhury et al.[25]	423	1485	1579	SqueezeNet, Mobilenetv2, ResNet18,ResNet101, VGG19, DenseNet201
Rahimzadeh and Attar.[26]	180	6054	8851	Concatenated CNN
Loey et al.[31]	69	79	79	GAN, Alexnet, Googlenet, Resnet18
Rahimzade et al..[32]	180	4575	4575	Xception,ResNet50V2,Concatenated CNN
Ucar and Korkmazb[33]	45	1591	1203	Bayes SqueezeNet
Bukharia et al.[34]	89	96	93	ResNet50
Ozturk et al.[35]	127	500	500	DarkNet
Punn et al.[36]	108	515	453	ResNet,Inception-v3, Inception, ResNet-v2, DenseNet169, NASNetL
Narin et al.[37]	50		50	ResNet50,InceptionV3, InceptionResNetV2
Ozcan et al.[38]	131	148	200	GoogleNet, ResNet18, ResNet50
Li et al.[39]	239	1000	1000	DCSL
Mukherjee et al.[40]	130		130	Shallow CNN
Luz et al.[41]	152	5421	7966	MobileNet, ResNet50, VGG16, VGG19
Farooq and Hafeez2[42]	68	931	1203	ResNet50
Khobahi et al.[43]	89	8521	7966	TFEN, CIN

measure quantitative temperature data of the human body. The IRT with the machine learning (ML) techniques, helped a lot in the diagnosis of COVID-19 virus. They also, illustrated and explained a generic comprehensive block diagram to represent the thermal imaging, using Computer Aided Diagnosis (CAD) system. A machine learning (ML) is used to preprocess the images, refine the outputs, train the data and extract features to predict the outputs. The CNN was applied for the training of data and the detection of the disease. In[6], the study demonstrated how deep learning could be utilized to detect COVID-19 using images no matter what is the source either X-Ray, Ultrasound, or CT scan. They build a CNN model based on a comparison of several known CNN models. Their approach aimed to minimize the noises so that the deep learning uses the image features to detect the diseases. Their study showed a better results in Ultrasound images compared to CT scans and x-ray images. They developed a VGG19 model that could be used to find the virus. The authors in[7] explained the role of CNN techniques in their Coronet novel to find corona virus using x-ray images. 1251 images were used in their experiments, 284 of them were COVID-19, 330 bacterial pneumonia, 327 viral pneumonia, and 310 images from normal patients. They divided the collected dataset into two sets, 80% to train the model and 20% to validate the model. The results showed the accuracy of 89.5%. Horry et al.[8] proposed the concept of pre-trained model to detect COVID-19 from x-ray images. Their system consists of four pre-trained models such as VGG, Xception, Inception and Resnet. The dataset consists of 100 COVID-19 images, 100 pneumonia, and 200 normal cases. They used 80% for training and 20% for testing purposes. Their experiment findings showed that their system achieved 80% in the precision, sensitivity, and F1-score using VGG-19 which is measured as the highest performance in the study considering three-class data. In[9], the authors showed that the iteratively pruned deep learning is capable to detect COVID-19 pulmonary signs from X-rays images. They used CNN to train the data and evaluate the model.

Algorithm 1: BEMD Algorithm[29]

Data: Images
Result: IMFs images
Initialization : $r_0(m,n) = f(m,n), k = 1, (m,n) \in [0.M-1] \times [0.N-1]$
for *k=1:K* **do**
  $h_{k,0}(m,n) = r_{k-l}(m,n), l = 1$
  while $SD \leq 0.3$ **do**
    -Envelope surfaces generation $e_{max,l-1}(m,n)$, $e_{min,l-1}(m,n)$ *of* $h_{k,l-1}(m,n)$ *using local maxima and minima are interpolation*
    -Computation of mean envelope surface: $e_{mean,l-1}(m,n) = 1/2[e_{max,l-1}(m,n) + e_{min,l-1}(m,n)]$
    -Update of the original $h_{k,l}(m,n) : h_{k,l}(m,n) = kk, l-1(m,n)e_{mean,l-1}(m,n)], l = l+1$
    -Computation the standard deviation (SD): $SD = \sum_{m=0}^{M} \sum_{n=0}^{N} \frac{h_{k,l-1}(m,n) - h_{k,l-1}(m,n)}{h^2_{k,l-1}(m,n)}$
  end
  $Bimf_k(m,n) = h_{k,l}(m,n)$.
end

In the same context, Roy et al.[10] used Deep Learning (DL) techniques on lung ultrasonography (LUS) images by analysing this type of images using fully-annotated dataset.

The authors in[11] affirmed that the automatic analysis of X-ray images can be presented as a good alternative for COVID-19 diagnosis. However, the accuracy of such method is related to the annotated data by the experts and the deep learning used models which proves it potentials for COVID-19 detection. In[12], the authors proposed techniques to detect COVID-19 using the concept of transfer learning with five variants of CNNs. They tested VGG-19, MobileNetv2, Inception, Xception , and ResNetv2. In their first experiment, 1427 image were used. In their second experiment, they used 224 COVID-19 images, 714 bacterial and viral pneumonia images, and 504 normal images. The dataset was divided using the 10 fold cross validation method. They obtained the accuracy of 96.78% using the second dataset using MobileNetv2. WAHEED et al.[13], confirmed that the correctness of COVID-19 patient identification using X-rays is feasible. CNNs-based method require a large-scale datasets for good learning. Therefore, in their research, x-ray images are used for data augmentation. Also, GAN-based model named CovidGAN or Auxiliary Classifier Generative Adversarial Network (ACGAN) was proposed. They reached 95% of accuracy in their experiment after using CovidGAN. Minaee et al.[14] talked about a technique named Deep-COVID based on the concept of deep transfer learning to detect COVID-19 from x-ray images. They used in their experiment ResNet18, ResNet50, SqueezeNet, and DenseNet121. They collected 5071 images from different sources. Among them, 2000 images were used for training, and the remaining were used for testing. SqueezeNet gave them the best performance in their experiment, 100% for sensitivity, and 95.6% for the specificity.

In another research project, Moutounet et al.[15] developed a DL schema to differentiate between COVID-19 and other pneumonia from X-Ray images. They tested VGG-16, VGG-19, InceptionResNetV2, InceptionV3, and Xception in their diagnosis. 327 x-ray images were used , 152 images where from normal persons, 125 from persons having COVID-19 and 50 images from others having pneumonia diseases. They partitioned the dataset using the 5 fold cross validation technique. The best performance was obtained using VGG-16. They achieved the accuracy of 84.1%. Recently, the authors in[16] developed a schema to detect COVID-19 using the CNN variants using X-Ray images. They used a dataset that contains 50 images, half of them were COVID-19 positive cases and 25 images from healthy persons. In their experiment, they divided the dataset into two sets, one with 80% for training and the rest for testing purposes. They proved that the VGG-19 and DenseNet were the best. They achieved the accuracy of 90%. In[17], the authors studied the conceptual structures and platforms capable for dealing with COVID-19 diagnosis. Different techniques have been developed to detect the pandemic, such as Generative Adversarial Networks (GAN), LSTM, Extreme Learning Machine (ELM), and Recurrent Neural Networks (RNN).

To detect COVID-19, Maguolo and Nanni[18] used AlexNet technique . They used 339,271 images gathered from different data source, 144 of them are COVID-19, 108,948 images of pneumonia and bacteria, 224,316 chest radiographs of bacteria and pneumonia and 5,863 images viral and bacterial pneumonia. They partitioned the dataset into 10 fold cross validation for training and testing. According to their experiment, the system achieved the AUC of 99.97%. Oh et al.[19] talked about the importance of Artificial Intelligence (AI) in the diagnosis of COVID-19 using x-ray images. However, due to COVID-19 nature, the collection of x-ray images dataset necessary for the training is not easy. To solve this problem, they propose a CNN method with a small number of trainable parameters to detect COVID-19 virus. Wong et al.[20] developed a COVID-19 detection schema named COVID-Net from x-ray images. They combined two dataset to obtain 13,800 X-ray images. 90% of images were used

for training and 10% for validation purposes. In ten iterations only, their proposed network reached the accuracy of 92.4%. In another research work, the authors in[21] used a pre-trained models of CNN and SVM to detect COVID-19. They used eleven CNN pre trained models to extract features then applied the SVM for the classifications. They used in their first dataset 50 images; half of them were COVID-19 positive cases whereas the others were normal cases. They also used a second dataset that contains 133 MERS, SARS and ARDS images and 133 normal images. In their experiment, they found that Resnet50 with SVM gave the accuracy of 95.38%. In[22] the authors, confirmed that image segmentation is required when processing medical images. They proposed a method called MPAMFO to segment the images, which demonstrated a good performance in all the tests.

Shi et al[23] demonstrated the importance of medical imaging using CT-scan and x-Ray which can help in COVID-19 diagnosis. Also, exploiting the new technologies like AI for analysing these type of images helps for a fast detection. In[24] they applied x-ray images of COVID-19 to an SOFM network to search and classify patients sick or healthy. Their work showed that unsupervised learning could extract features from x-rays images. Chowdhury et al.[25] used in their research a dataset that contains 423 COVID-19 x-ray images, 1485 viral pneumonia x-ray images, and 1579 normal x-ray images. They used the transfer learning with the image augmentation techniques to train and validate some pre trained deep CNN. Furthermore , the authors in[26] proposed a modified CNN to detect coronavirus using X-Ray images. They concatenate Xception and ResNet50V2 techniques. They applied 5-fold cross-validation techniques on 180 COVID-19 images, 6054 pneumonia images, and 8851 normal images. The results showed the accuracy of 99.50% to detect COVID-19. The authors in[27] mentioned that the fundamentals of BEMD is based on using the extrema of the original image then use it for the decomposition. The technique is to find the extrema and the minima in the image and then find the distance between extrema that provides details to characterize the image on intrinsic length scales. In 2D-images the pixels are denoted by (m,n). Algorithm 1 summarized the basic procedure of the BEMD. After using the BEMD algorithm, four IMFs are obtained and then used to generate the video sequence as an input for the 3DCNN. Some examples for BEMD decomposition are illustrated in Figure 2 for each category.

Loey et al.[31] presented how they used the pre-trained models of CNN with deep transfer learning and the Generative Adversarial Network (GAN) to detect COVID-19. They used Alexnet, Googlenet, and Resnet18 and since the number of COVID-19 images are small, they used GAN to increase the number of samples. They used 307 images with four classes such as COVID19, normal, bacterial pneumonia, and viral pneumonia. The experiment showed that Googlenet is the best, the accuracy obtained was 80.6% whereas both Alexnet and Googlenet achieved the accuracy of 85.2% and 100% respectively when using two classes only. Furthermore , the authors in[32] concatenated Xception and ResNet50V2 and used 5-fold cross-validation techniques on 180 COVID-19 images, 6054 pneumonia images, and 8851 normal images to detect COVID-19 virus. Their experiment results showed an accuracy of 99.50% in the COVID-19 detection. In another study, Ucar and Korkmaz[33] used Bayes-SqueezeNet to develop a schema named COVIDiagnosis-Net to detect coronavirus using x-ray images. They used 1591 pneumonia images, 45 COVID-19 images, and 1203 normal images in their experiment. The dataset was collected from three publicly sources available in the internet. They partitioned the dataset into three sets, 80% used for training, 10% for validation, and 10% for testing purposes. The experimental results showed the accuracy of 98.26%.

In[34] the authors used ResNet50 with 278 X-Ray images in their experiment to detect COVID-19. 89 images from the total were COVID-19 cases, 93 normal cases, and 96 were pneumonia cases. The dataset was splited into two sets; 80% for training and 20% for testing. The experiment results showed the accuracy of 98.18%. Recently, Ozturk et al.[35] illustrated a network called DarkCovidNet using the CNN to detect COVID-19 virus using x-ray images. The proposed solution used DarkNet with 17 CNN layers for the classifications. A total of 1127 images were used and partitioned in 5-fold cross-validation. They obtained the accuracy of 98.08%. In another study, Punn et al.[36] used ResNet, Inception-v3, Inception ResNet-v2, DenseNet169, and NASNetLarge as a pre-trained CNN to detect COVID-19 virus using X-Ray images. In their experiment, they used 1076 images which was divided into three sets; 80% for training, 10% for testing and 10% for validation purposes. The results showed that NASNetLarge performed better and achieved the accuracy of 98%. Narin et al.[37] explained how they used the pre-trained models with InceptionV3, ResNet50, Inception-ResNetV2 to detect COVID-19 utilizing X-ray images. They used 100 X-Ray images in their experiment, 50 images of them are COVID-19 cases while the rest were from healthy persons. They used 5-fold cross-validation in the dataset partition. The best performance was achieved using ResNet50 with precision of 100%, recall of 96%, specificity of 100%, and F1-score of 98%. In[38], the authors combined three pre-trained models of CNN with the grid search strategy. They used ResNet18, ResNet50, and GoogleNet in the pre-trained models of CNN. The grid search technique is also used to select the best hyperparameter and the pre-trained models were used to extract features and do the classifications. The authors used three public datasets that contains 131 COVID-19 images, 242 bacteria images, 200 normal images and 148 viral pneumonia images. They divided the dataset into 50% for training, 30% for testing and 20% for validation purposes. The ResNet50 with grid search performed better and obtained the accuracy of 97.69%. In the other side Li et al.[39] proposed the discriminative costsensitive learning (DCSL) technique to detect COVID-19 utilizing x-ray images. They used 2,239 X-Ray images, 239 from them were COVID-19 images, 1000 bacterial or viral pneumonia images, and 1000 normal images. The dataset was partitioned using 5-fold cross-validation technique. The proposed technique

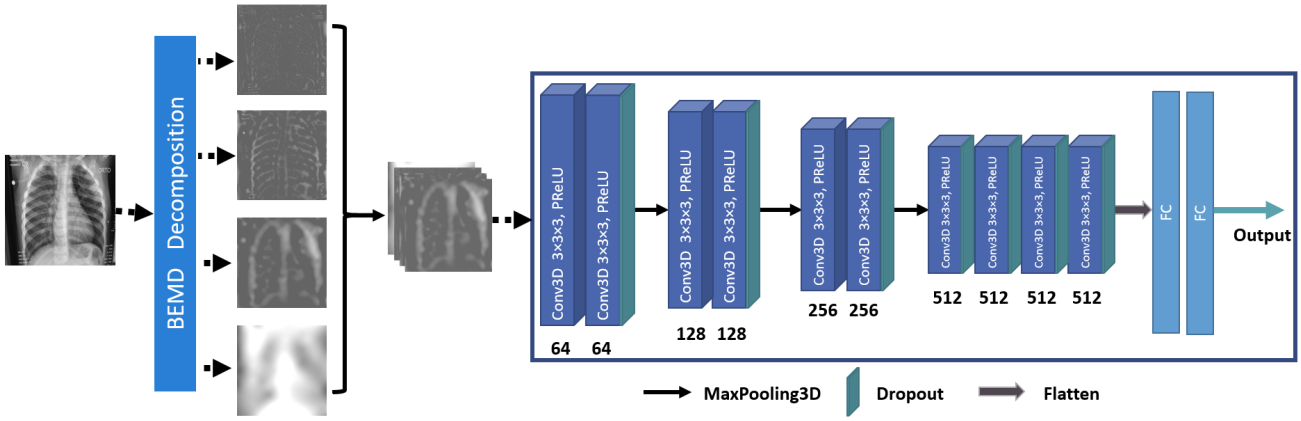


Figure 1. Flowchart of the proposed system.

achieved the accuracy of 97.01%.

In another study, Mukherjee et al.[40] used shallow convolution neural network (CNN) techniques to detect COVID-19 from X-Ray images. In their system, a total of 260 images were used, half of them were COVID-19 images, and half were non-COVID images which includes SARS, pneumonia, MERS, and normal x-ray images. They divided the dataset into 5-fold cross-validation. Their experimental results, showed that their system reached the accuracy of 96.92%. Luz et al.[41] proposed a deep learning method named EfficientNet to detect COVID-19 from X-ray images. The dataset used consists of 183 COVID-19, 16,132 normal images, and 14,348 pneumonia images. Their experiment showed an accuracy of 93.9%. In[42] the authors proposed a deep learning technique with 50 layers using ResNet50 to detect COVID-19. The dataset consists of 13,800 images. Within 41 iterations, their system achieved 96.23% of accuracy. Khobahi et al.[43] used a semi-supervised deep learning technique based on Auto-Encoders named CoroNet to detect COVID-19. A total of 18,529 images were used in their experiment, 99 of them were COVID-19, 9579 were of non-COVID pneumonia, and 8851 images were normal images extracted from healthy persons. The dataset was divided into two sets; 90% for training and 10% for testing. Their experiment results showed the accuracy of 93.50%.

2 Proposed method

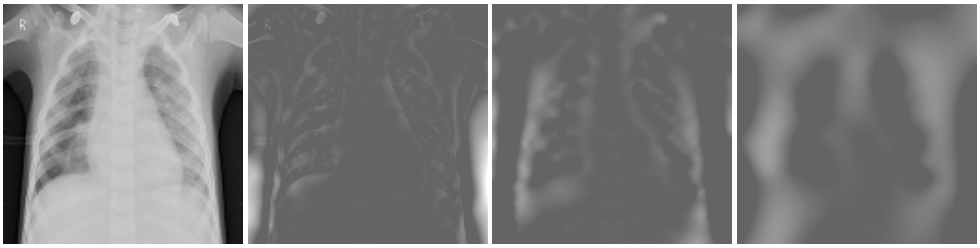
During the last ten-month, many methods have been proposed for COVID-19 detection using different deep learning architectures using x-ray images. The majority of the proposed techniques succeed to identify COVID-19 from x-ray images reaching the accuracy of 99% and more. The number of images used in the data sets was not very large, and every month the number of images used increases which can produce some cases that can be different from the existing ones in terms of appearances of X-ray images and the medical situation of each patient. Therefore, the researcher's attempts follow all these changes to find solutions every time.

In this paper, we propose a novel method to automatically detect COVID-19 from X-ray images. It consists of combining the 3DCNN with the BEMD. First, we used the BEMD technique to extract four Intrinsic Mode Functions (IMFs) from each original image. Then from the extracted IMFs, we created a video. The latter is then used as an input for the proposed 3DCNN model. The utilization of a Video having different features combined with 3DCNN can present good deep learning better than using images as the input of a deep learning model. Figure 1 shows the flowchart of the proposed approach including the extraction of IMFs using BEMD algorithm as well as the proposed architecture of 3DCNN model.

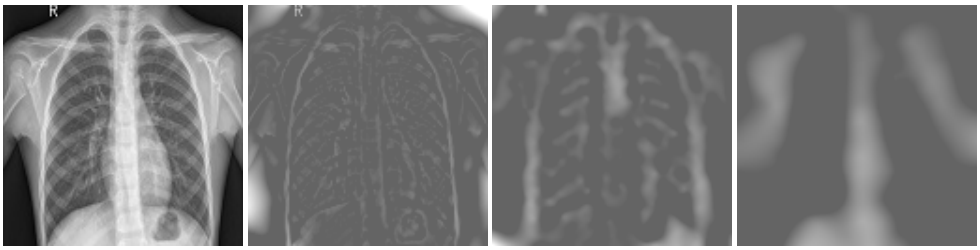
2.1 Preprocessing

Bidimensional Empirical Mode Decomposition (BEMD): As it was mentioned in[27], BEMD is based on using the extrema of the original image then use it for the decomposition. The technique is to find the extrema and the minima in the image and then find the distance between extrema that provides details to characterize the image on intrinsic length scales[30]. In 2D images, the pixels are denoted by (m,n) as presented in Algorithm 1[29] which summarized the basic procedure of the BEMD. After using the BEMD algorithm, four IMFs are obtained and then used to generate the video sequence as an input for the 3DCNN proposed model. some examples of BEMD decomposition are illustrated in Figure 2 for each category.

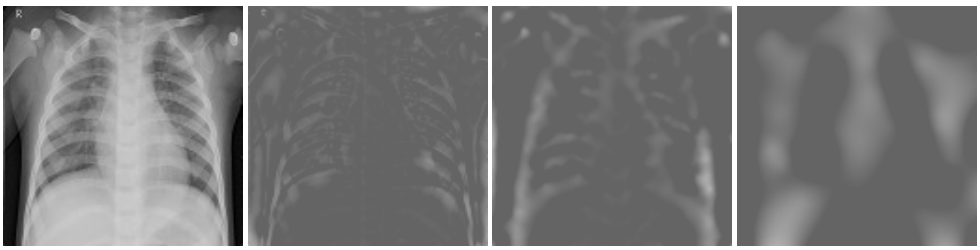
In the preprocessing phase, we took the original images. After that, we applied the bidimensional empirical mode decomposition (BEMD) technique to decompose original images into four IMFs. The latter were then used to generate the



(a) COVID-19



(b) Normal



(c) Pneumounia

Figure 2. Some results using BEMD algorithm .

video and used as the input for the proposed 3DCNN Model, which allows a good learning model from 3D shapes.

2.2 3D Convolutional Neural Network (3DCNN)

Convolutional Neural Network[26], is a deep learning neural network used to process structured arrays like pixels in an image. Convolutional neural networks become important in many applications like image classification, text classification, and pattern recognition. CNN is a feed-forward neural network. The power of CNN comes in from the convolutional layer put on top of each other. The architecture of the convolutional neural network is composed of many layers that form a feed-forward neural network, most of them are hidden, activation layers and the pooling layers.

Before training the data, BEMD features are extracted and used as input of the proposed 3DCNN model. The preprocessing consists of extracting the BEMD features including four IMFS, then collect them to generate the video format. The Proposed 3DCNN model allows a multistage learning technique that permits better learning.

The proposed 3DCNN-based architecture illustrated in Figure 1 consists of features extraction part of convolutional-max-pooling layers followed by the classification block of fully connected layers.

The 3D network is based on VGG16 architecture for generating features and increasing a greater spatial extent. The proposed model contains six convolutional layers, two fully connected layers, three 3D-convolution pooling units, three MaxPooling layers, and one flattened layer. We took 11 layers from VGG16 that includes convolutional and max-pooling layers. After each two consecutive convolutional layers, a dropout layer is added. The output layers consist of three neurons to present COVID-19, pneumonia, and Normal classes. This block allows a transaction from 3D representation to flatten data to make the model learns from multi-scale layers also using a complex architecture that performs the learning.

For the last six convolutional layers, we have used the activation function and the PReLU (Parametric Rectified Linear Unit). PReLU learns the parameters and improves the accuracy and minimizes the computational cost. Positive values are fed into the ReLU activation function whereas negative values were set to null. The PReLU function is defined as:

$$f(y_i) = \begin{cases} y_i \; if \; y_i > 0 \\ a_i y_i \; if \; y_i \leq 0 \end{cases} \tag{1}$$

a_i controls the slope of the negative part. When a_i= 0, it operates as an ReLU; when a_i is a readable parameter, it is referred to

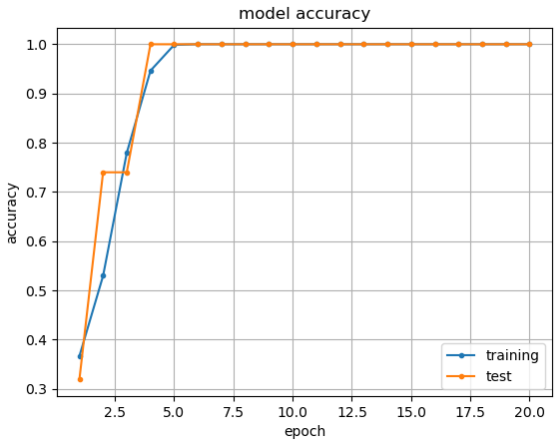


Figure 3. Accuracy graph.

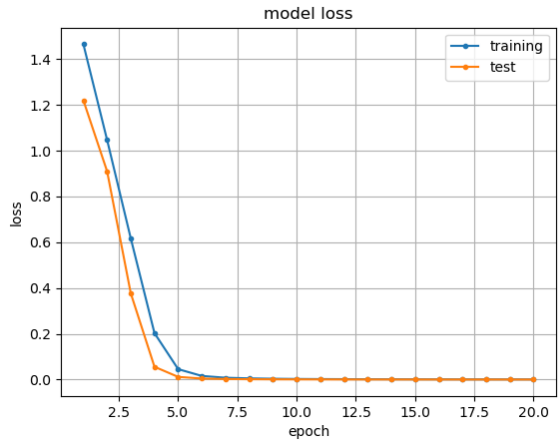


Figure 4. Loss graph.

Table 2. Dataset used in our experiment[3]

Data/Cases	COVID-19	Normal	Pneumonia	Overall
Training	1458	1528	2218	5204
Testing	360	382	554	1296
Overall	1802	1910	2772	6484

as Parametric ReLU (PReLU). If ai is a small value, PReLU becomes LReLU (a_i= 0.01). PReLU can be trained using the back propagation concept.

In the proposed model, some combined COVID-19 datasets were used for training and testing. Also, the use of different features as inputs (IMFs) makes the deep learning model capable of a better learning.

3 Experimental results

In our experiment, we demonstrated and compared the obtained results using the BEMD-3DCNN with some existing methods used to detect COVID-19 such as:[3],[25],[32],[33],[34],[35],[36],[37],[38],[39] and[40].

3.1 Experimental Setup

For the experiment, we divided the dataset into training and testing sets. The training set contains 80% of the data, the testing set contains 20%. The proposed 3DCNN model includes 11 layers divided into nine 3D convolutional layers and 3 Maxpooling layers, as presented in figure 1. the BEMD-3DCNN model is implemented using Pytorch and python on an Intel(R) Core(TM) i7-2.2 GHz processor with a graphical processing unit (GPU) NVIDIA RTX 2070, 8 GB and 64 GB RAM.

3.2 Dataset

In this paper, we used the updated dataset mentioned by Islam and al.[3] in their references. They collected it from multiple sources then they did some prepossessing on it to reduce the noise. After that, they applied the augmentation to get a reasonable number of images to run the CNN. Table 2 summarizes the number of images used for training and testing purposes. We used 6484 images, including the original and the augmented images to train and test the model. Our dataset is bigger than the one mentioned by Islam and al.[3] in their paper this is due to some new images added into the sources.

3.3 Evaluation metrics

To evaluate the image classification method some metrics are exploited. Here, we used True Positive (TP) to refer to the COVID-19 cases that correctly predicted, False Positive (FP) to the samples false classified, TN to refer to the normal cases that are well predicted, and FN for the COVID-19 cases that are miss-classified as normal.

$$Accuracy = (TP+TN)/(TN+FP+TP+FN)s \tag{2}$$

Table 3. Performance of the BEMD-3DCNN network compared to the existing methods

Method	Data	accuracy	Precision	Recall	F1-Score	Loss
CNN-LSTM [2]	4575	99.4%	99.2%	99.3%	98.9%	-
CNN [24]	4575	99.7%	99.7	99.7	99.55 %	-
BEMD-3DCNN	6484	100%	100%	100%	100%	0.000769 ±0.0002

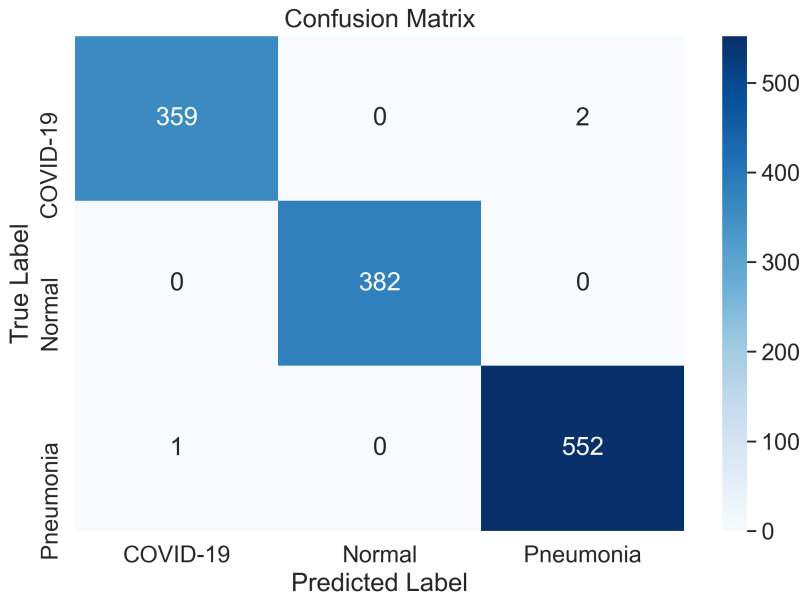


Figure 5. Confusion matrix

$$Sensitivity = TP/(TP+FN) \tag{3}$$

$$Specificity = TN/(TN+FP) \tag{4}$$

$$F1score = (2TP)/(2TP+FP+FN) \tag{5}$$

3.4 Evaluation and discussion

In Our work, we used the dataset that was updated and used by the authors in[3]. It contains the combination of 1802 COVID-19 images, 2772 viral pneumonia images, and 1910 normal X-ray images. We applied the BEMD technique on the original images to obtain four IMFs, then we created a video based on the IMFs and apply the 3DCNN to obtain the classification and detection of COVID-19.

In the experiment, we divided the data into 80% for training and 20% for testing purposes, then we defined the network to include eight conv3D layers and two fully connected layers. We used them as maxpooling3D then to flatten the data. We used Python and Keras to implement 3DCNN network and the BEMD. Figure 3 and figure 4 show the evaluation metrics accuracy and loss respectively.

Our system achieved an accuracy of 100%. Figure 5 illustrates the confusion matrix of the testing data used for the COVID-19 classification process by the proposed BEMD-3DCNN model. From the matrix, we can observe that all the data were successfully classified by the proposed method. It also demonstrates that the proposed method is efficient for COVID-19 classifications with not true negative values.

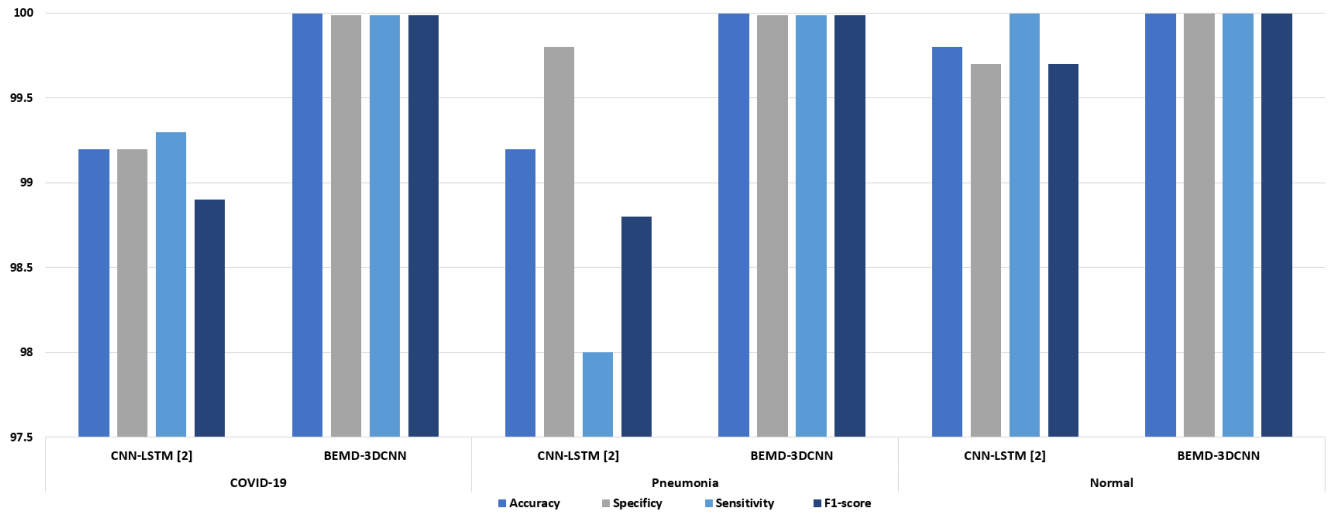


Figure 6. Comparison sensitivity, specificity, and F1-score metrics of the proposed method with state-of-the-art methods

Table 4. COVID-19 detection techniques (comparison)

Authors	Images	Classes	Partitioning	Accuracy	Sensitivity	Specificity
Islam et al.[3]	4575	3	80%-20%	99.4	99.3	99.2
Chowdhury et al.[25]	3487	3	80%-20%	97.94	97.94	98.8
Rahimzade et al..[32]	180	3	5- fold crossvalidation	99.5	80.53	99.56
Ucar et al.[33]	2839	3	80%-10%-10%	98.26	98.26	99.13
Bukharia et al.[34]	278	3	80%-20%	98.18	98.24	98.14
Ozturk et al.[35]	1127	3	5- fold crossvalidation	98.08	95.13	95.3
Punn et al.[36]	1076	3	80%-10%-10%	98	91	91
Narin et al.[37]	100	2	5- fold crossvalidation	98	96	100
Ozcan et al.[38]	721	4	50%-30%-20%	97.69	97.26	97.9
Li et al.[39]	2239	3	5-fold crossvalidation	97.01	97.09	97
Mukherjee et al.[40]	260	2	5-fold crossvalidation	96.92	94.2	100
BEMD-3DCNN(our)	**6484**	**3**	**80%-20%**	**100**	**100**	**100**

To demonstrate the performance of each class using the proposed BEMD-3DCNN-based method, we exploit the evaluation metrics shown in figure 6 including accuracy, Specificity, sensitivity, and F1-score for each class. The proposed method as well as the CNN-LSTM classified the classes with high performance, but from figure 6, we can observe that the BEMD-3DCNN is more accurate and reached 100% for all metrics which is a perfect accuracy rate. In our experiment, we used the same metrics used in the existing methods for COVID-19 detection. The proposed method showed the highest and accurate detection of COVID-19 using X-Ray images. Also compared with the other proposed methods, our results are the best in terms of accuracy as well as all metrics.

Table 1 summarizes the dataset and the techniques used by some authors, presented in the literature review in this paper, to detect COVID-19 using X-Ray images. Tables 3 and 4 summarize the results of some methods used to detect COVID-19 from X-Ray images. It shows also, some of the significant factors, like data sources, data partitioning technique, techniques used for diagnosis, number of images, classes, and the performance measures. From the Tables, we can observe that the proposed method is more improved and can classify COVID-19 with a high accuracy of 100% comparing with the stat-of-the-art methods.

4 Conclusion

COVID-19 spreads between people, mainly when an infected person is in close contact with another person. Until now the cases are increasing every day, many countries are still suffering from the disease because of their limited resources and the big number of infected persons in their areas. Hence, it is necessary to identify as quickly as possible the positive case during any emergency. We introduced the BEMD technique combined with the 3DCNN on the X-Ray images to identify the coronavirus

COVID-19. The BEMD was used to decompose the original image into IMFs, and then we created a video with these IMFs and apply the 3DCNN to classify and detect COVID-19. The proposed technique achieved an accuracy of 100%. Finally, we reached excellent results using the proposed techniques that combine BEMD and 3DCNN.

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Author contributions statement

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Additional information

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References

1. "Coronavirus/COVID-19 World Map Data Stats." https://covidstatistics.org/ (accessed.
2. Elharrouss, Omar, Nandhini Subramanian, and Somaya Al-Maadeed. "An encoder-decoder-based method for covid-19 lung infection segmentation." arXiv preprint arXiv:2007.00861 (2020).
3. Islam, M.Z., Islam, M.M. and Asraf, A., 2020. A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images. Informatics in Medicine Unlocked, 20, p.100412.
4. L. Carrer et al., "Automatic Pleural Line Extraction and COVID-19 Scoring from Lung Ultrasound Data," IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, pp. 1-1, 2020.
5. M. A. Farooq and P. Corcoran, "Infrared Imaging for Human Thermography and Breast Tumor Classification using Thermal Images," in 2020 31st Irish Signals and Systems Conference (ISSC), 11-12 June 2020 2020, pp. 1-6.
6. M. J. Horry et al., "COVID-19 Detection Through Transfer Learning Using Multimodal Imaging Data," IEEE Access, vol. 8, pp. 149808-149824, 2020.
7. Khan AI, Shah JL, Bhat MM. Coronet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. Computer Methods and Programs in Biomedicine. 2020 Jun 5:105581.
8. Horry, Michael J., Manoranjan Paul, Anwaar Ulhaq, Biswajeet Pradhan, Manash Saha, and Nagesh Shukla. "X-Ray Image based COVID-19 Detection using Pre-trained Deep Learning Models." (2020).
9. S. Rajaraman, J. Siegelman, P. O. Alderson, L. S. Folio, L. R. Folio, and S. K. Antani, "Iteratively Pruned Deep Learning Ensembles for COVID-19 Detection in Chest X-Rays," IEEE Access, vol. 8, pp. 115041-115050, 2020.
10. S. Roy et al., "Deep Learning for Classification and Localization of COVID-19 Markers in Point-of-Care Lung Ultrasound," IEEE Transactions on Medical Imaging, vol. 39, no. 8, pp. 2676-2687, 2020.
11. R. Sethi, M. Mehrotra, and D. Sethi, "Deep Learning based Diagnosis Recommendation for COVID-19 using Chest X-Rays Images," in 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA), 15-17 July 2020 2020, pp. 1-4.
12. 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 Apr 3:1.
13. A. Waheed, M. Goyal, D. Gupta, A. Khanna, F. Al-Turjman, and P. R. Pinheiro, "CovidGAN: Data Augmentation Using Auxiliary Classifier GAN for Improved Covid-19 Detection," IEEE Access, vol. 8, pp. 91916-91923, 2020.
14. Minaee, Shervin, Rahele Kafieh, Milan Sonka, Shakib Yazdani, and Ghazaleh Jamalipour Soufi. "Deep-covid: Predicting covid-19 from chest x-ray images using deep transfer learning." arXiv preprint arXiv:2004.09363 (2020).
15. Moutounet-Cartan PG. Deep Convolutional Neural Networks to Diagnose COVID-19 and other Pneumonia Diseases from Posteroanterior Chest X-Rays. arXiv preprint arXiv:2005.00845. 2020 May 2.
16. Hemdan, Ezz El-Din, Marwa A. Shouman, and Mohamed Esmail Karar. "Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images." arXiv preprint arXiv:2003.11055 (2020).

17. M. B. Jamshidi et al., "Artificial Intelligence and COVID-19: Deep Learning Approaches for Diagnosis and Treatment," IEEE Access, vol. 8, pp. 109581-109595, 2020.

18. Maguolo G, Nanni L. A critic evaluation of methods for covid-19 automatic detection from x-ray images. arXiv preprint arXiv:2004.12823. 2020 Apr 27.

19. Y. Oh, S. Park, and J. C. Ye, "Deep Learning COVID-19 Features on CXR Using Limited Training Data Sets," IEEE Transactions on Medical Imaging, vol. 39, no. 8, pp. 2688-2700, 2020.

20. Wang, Linda, Zhong Qiu Lin, and Alexander Wong. "Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images." Scientific Reports 10, no. 1 (2020): 1-12.

21. Sethy PK, Behera SK. Detection of coronavirus disease (covid-19) based on deep features. Preprints. 2020 Mar 19;2020030300:2020.

22. M. A. Elaziz et al., "An Improved Marine Predators Algorithm With Fuzzy Entropy for Multi-Level Thresholding: Real World Example of COVID-19 CT Image Segmentation," IEEE Access, vol. 8, pp. 125306-125330, 2020.

23. F. Shi et al., "Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation and Diagnosis for COVID-19," IEEE Reviews in Biomedical Engineering, pp. 1-1, 2020.

24. B. King, S. Barve, A. Ford, and R. Jha, "Unsupervised Clustering of COVID-19 Chest X-Ray Images with a Self-Organizing Feature Map," in 2020 IEEE 63rd International Midwest Symposium on Circuits and Systems (MWSCAS), 9-12 Aug. 2020 2020, pp. 395-398.

25. M. E. H. Chowdhury et al., "Can AI Help in Screening Viral and COVID-19 Pneumonia?," IEEE Access, vol. 8, pp. 132665-132676, 2020, doi: 10.1109/ACCESS.2020.3010287.

26. Simonyan, K. and Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

27. An, F.P., Lin, D.C., Zhou, X.W. and Sun, Z., 2015. Enhancing image denoising performance of bidimensional empirical mode decomposition by improving the edge effect. International Journal of Antennas and Propagation, 2015.

28. An, F.P. and Zhou, X.W., 2017. BEMD–SIFT feature extraction algorithm for image processing application. Multimedia Tools and Applications, 76(11), pp.13153-13172.

29. H. Mohammadzade, F. Agrafioti, J. Gao, and D. Hatzinakos, "BEMD for expression transformation in face recognition," in 2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 22-27 May 2011 2011, pp. 1501-1504, doi: 10.1109/ICASSP.2011.5946778.

30. Abbad, A., Elharrouss, O., Abbad, K. and Tairi, H., 2018. Application of MEEMD in post-processing of dimensionality reduction methods for face recognition. Iet Biometrics, 8(1), pp.59-68.

31. Loey M, Smarandache F, M Khalifa NE. Within the Lack of Chest COVID-19 X-ray Dataset: A Novel Detection Model Based on GAN and Deep Transfer Learning. Symmetry. 2020 Apr;12(4):651.

32. Rahimzadeh M, Attar A. A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2. Informatics in Medicine Unlocked. 2020 May 26:100360.

33. Ucar, Ferhat, and Deniz Korkmaz. "COVIDiagnosis-Net: Deep Bayes-SqueezeNet based Diagnostic of the Coronavirus Disease 2019 (COVID-19) from X-Ray Images." Medical Hypotheses (2020): 109761.

34. Bukhari SU, Bukhari SS, Syed A, SHAH SS. The diagnostic evaluation of Convolutional Neural Network (CNN) for the assessment of chest X-ray of patients infected with COVID-19. medRxiv. 2020 Jan 1.

35. Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Acharya UR. Automated detection of COVID-19 cases using deep neural networks with X-ray images. Computers in Biology and Medicine. 2020 Apr 28:103792.

36. Punn NS, Agarwal S. Automated diagnosis of COVID-19 with limited posteroanterior chest X-ray images using fine-tuned deep neural networks. arXiv preprint arXiv:2004.11676. 2020 Apr 23.

37. Narin A, Kaya C, Pamuk Z. Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. arXiv preprint arXiv:2003.10849. 2020 Mar 24.

38. Ozcan, Tayyip. "A Deep Learning Framework for Coronavirus Disease (COVID-19) Detection in X-Ray Images." (2020).

39. Li, Tianyang, Zhongyi Han, Benzheng Wei, Yuanjie Zheng, Yanfei Hong, and Jinyu Cong. "Robust Screening of COVID-19 from Chest X-ray via Discriminative Cost-Sensitive Learning." arXiv preprint arXiv:2004.12592 (2020).

40. Mukherjee, Himadri, Subhankar Ghosh, Ankita Dhar, Sk Obaidullah, K. C. Santosh, and Kaushik Roy. "Shallow Convolutional Neural Network for COVID-19 Outbreak Screening using Chest X-rays." (2020).

41. Luz, Eduardo José da S., Pedro Lopes Silva, Rodrigo Silva, Ludmila Silva, Gladston Moreira, and David Menotti. "Towards an Effective and Efficient Deep Learning Model for COVID-19 Patterns Detection in X-ray Images." CoRR (2020).

42. Farooq, Muhammad, and Abdul Hafeez. "Covid-resnet: A deep learning framework for screening of covid19 from radiographs." arXiv preprint arXiv:2003.14395 (2020).

43. Khobahi, Shahin, Chirag Agarwal, and Mojtaba Soltanalian. "CoroNet: A Deep Network Architecture for Semi-Supervised Task-Based Identification of COVID-19 from Chest X-ray Images." medRxiv (2020).