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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 identification 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 spreading. Medical imaging techniques has been used for this purpose. The existing works used transfer learning by exploiting different backbones like VGG, ResNet, DenseNet or combine them to detect COVID-19. By using these backbones many aspect can not be analysed like the spatial and contextual information in the images, while these information's can be useful for a better detection performance. For that in this paper, we used 3D representation of the data (video) as input of the 3DCNN-based deep learning model. The Bi-dimensional empirical mode decomposition (BEMD) technique to decompose the original image into IMFs, then built a video of these IMFs images. The formed video is used as input of 3DCNN model to classify and detect COVID-19 virus. 3DCNN model consists of a 3D VGG-16 backbone followed by a Context-aware attention (CAA) modules then fully connected layers for classification. Each CAA module takes the feature maps of different blocks of the backbone, which allows a learning from different feature maps. In the experiments 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. Also, the use of 3DCNN model with contextual information processing exploiting CAA networks helps to achieve better performance.

1. Introduction

Coronavirus (COVID-19) is a contagious respiratory illness identified in December 2019 in Wuhan. As per August 27, 2021 there were 215,612,352 confirmed cases infected by coronavirus "COVID-19" worldwide, 192,807,624 of them recovered and 4,491,204 died [1]. Coronavirus outbreak continues to spread and nobody knows when it will stop. Therefore, from the first day of the virus identification, scientists have launched numerous research projects to understand how the pandemic spreads and how people's immune systems respond to it to prevent, diagnose and treat the disease. For that, medical professionals and research scientists around the world, succeeded to build up a strong understanding of how the novel Covid-19 spreads and affects the body. Therefore, they found that coronavirus attacks mainly the lungs of the patient then spreads into the body and affects other organs such as the kidneys and liver.

The researcher in the other domains are also involved to find some solution of early detection of COVID-19 as well as solutions for ensuring social distancing. From these domains we can find computer sciences, while the techniques of analyzing data have been used especially medical imaging techniques. Using features from CT-scans and X-ray images combined with artificial intelligence (AI) tools and deep-learning-based frameworks, the proposed method achieved high accuracies with a min computational time. Also AI techniques have been used to mitigate the spread like early detection algorithms, drones , mask detection.

In this research paper, we propose deep learning (DL) based framework that combines 3D convolution neural network (3DCNN) and context-aware attention network on BEMD features of X-ray images to detect the virus from X-ray images. In our proposal, we used the BEMD technique to decompose each original image into four new images, a finite number of intrinsic mode functions (IMFs), and then apply the 3DCNN to classify and detect Covid-19. The use of 3D data can be more efficient for any model to extract the useful information than using one image. We used a dataset that was gathered by Islam et al [2]. Accordingly, the paper presents a set of contributions that can be summarized as:

- Extraction of three component from the original images using BEMD decomposition technique. Then, creating a video of the extracted component to be used in 3DCNN proposed model.
- 3DCNN model proposed, which consists of a backbone for features extraction followed by two context-aware attention (CAA) modules that takes the feature maps of two different block of the backbone. The concatenation of CAAs modules outputs is used for classification using folly connected layers.
- An evaluation of the obtained results on two dataset with different sizes which demonstrate the effectiveness of the proposed method on the two datasets with an accuracy of 99.99%.

The research paper is organized as follows: In section 2, we present a summary of the recent research works related to this study. whereas, in section 3, we present a description of the proposed methodology and in section 4, we describe the experiments and results with the related dataset collec-

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tion and preparation. Finally, in section 5 we concluded the paper.

2. 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. Therefore, the development of detection and recognition techniques capable of automating the process without needing the help of skilled specialists is needed. From these techniques, we can find computer vision based techniques that help in detection using images and videos. Islam et al. [2] the authors introduced Deep Learning (DL) technique that combines convolution neural network (CNN) with the Long Short-Term Memory (LSTM) to detect COVID-19 virus from x-ray images. They used in their system 4575 x-ray images, 1525 of them were COVID-19 positive cases. In the same context, Carrer et al. [3], discussed a method to detect automatically the pleura line of lungs and extract the characteristics of its geometry and intensity. The pleura lines extracted and modeled were given as input to the supervised support vector machine (SVM) classifier to identify covid-19. Farooq et al. [4] used the infrared thermography technology (IRT) ,a medical diagnostic tool that detects heat patterns and measure quantitative temperature data of the human body, with the machine learning (ML) techniques, to diagnose COVID-19 virus. They also, illustrated and explained a generic comprehensive block diagram to represent the thermal imaging, using computer aided diagnosis (CAD) system. 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 virus Covid-19. Study [5], demonstrated how deep learning could be utilized to detect COVID-19 using images no matter what is the source, X-Ray, Ultrasound, or CT scan. They built 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 better results in ultrasound images compared to CT scans and x-ray images. They used VGG19 network as backbone in their detection model. Coronet novel techniques were explained [6] to detect Covid-19 from x-ray images. They used 1251 images 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. Horry et al. [7] proposed pre-trained model to detect COVID-19. The system consists of four pre-trained models such as VGG, Xception, Inception and Resnet. The dataset includes 100 COVID-19 images, 100 pneumonia, and 200 normal cases. They used 80% for training and 20% for testing purposes. Iteratively pruned deep learning is capable to detect COVID-19 pulmonary signs from X-rays images. CNN was used to train the data and evaluate the model [8].

In the same context, Roy et al.[9] used Deep Learning (DL) techniques on lung ultrasonography (LUS) images by analysing this type of images using fully-annotated dataset.

The authors in another study [10] confirmed 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 models used which have the potential for COVID-19 detection. Techniques to detect COVID-19 using the concept of transfer learning were proposed with five variants of CNNs. They tested VGG-19, MobileNetv2, Inception, Xception , and ResNetv2 in their first experiment and MobileNetv2 in a second assay [11]. Waheed et al. [12], proposed GAN-based model named CovidGAN or Auxiliary Classifier Generative Adversarial Network (ACGAN) to find covid-19. Minaee et al. [13] 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. SqueezeNet technique gave them the best performance in their experiment.

In another research project, Moutounet et al. [14] developed DL schema to differentiate between COVID-19 and other pneumonia from x-ray images. They tested VGG-16, VGG-19, InceptionResNetV2, InceptionV3, and Xception techniques in their diagnosis. They partitioned the dataset using 5 fold cross validation technique. The best performance was obtained using VGG-16. Recently, the authors in [15] developed a CNN variants schema to detect COVID-19 from X-Ray images. They divided the dataset into two sets, 80% for training and 20% for testing purposes. They proved that the VGG-19 and DenseNet were the best to detect Covid-19. In another study [16], conceptual structures and platforms were investigated for their capability 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 identify COVID-19, Maguolo and Nanni [17] tested the AlexNet technique with 10 fold cross validation for training and testing. In the same context, Oh et al.[18] talked about the importance of Artificial Intelligence (AI) in the diagnosis of COVID-19 using x-ray images. They proposed a CNN method with a small number of trainable parameters to detect COVID-19 virus. In another study, Wang et al. [19] developed a COVID-19 detection scheme named COVID-Net from x-ray images whereas other researchers [20] used a pre-trained models of CNN and SVM to detect COVID-19. They utilized eleven CNN pre trained models to extract features then applied the SVM for the classifications. In their experiment, they found that Resnet50 with SVM gave better accuracy and results.

Shi et al [22] demonstrated the importance of medical imaging using CT-scan and x-Ray which can help in COVID-19 diagnosis. Exploiting the new technologies like Artificial intelligence (AI) for analysing these type of images, helps in detecting Covid-19. X-ray images with COVID-19

Table 1
Summary of techniques and datasets used for COVID-19 detection from X-ray

Method	Dataset size (images)			Techniques used
	COVID-19	Pneumonia	Normal	
Islam et al. [2]	613	1525	1525	CNN-LSTM
HORRY et al. [5]	140	322	60361	VGG19
Khan et al. [6]	284	327	310	CoroNet (CNN)
Horry et al. [7]	100	100	200	VGG16,VGG19,ResNet50,InceptionV3,Xception
Apostolopoulos et al. [11]	224	714	504	VGG19,MobileNetv2,Inception,Xception, Inception,ResNetv2
Minaee et al. [13]	71		5000	ResNet18,ResNet50,SqueezeNet, DenseNet-121
Moutounet-Cartanet al. [14]	125	50	152	VGG16,VGG19,Inception,ResNetV2, InceptionV3,Xception
Hemdan et al. [15]	25	-	25	VGG19,DenseNet121, InceptionV3, ResNetV2, InceptionResNet-V2,Xception,MobileNetV2
Maguolo et al. [17]	144	339	-	AlexNet
Chowdhury et al. [24]	423	1485	1579	SqueezeNet, Mobilenetv2, ResNet18,ResNet101, VGG19, DenseNet201
Rahimzadeh wt al. [25]	180	6054	8851	Concatenated CNN
Loey et al. [37]	69	79	79	GAN, Alexnet, Googlenet, Resnet18
Rahimzade et al. [38]	180	4575	4575	Xception,ResNet50V2,Concatenated CNN
Ucar et al. [39]	45	1591	1203	Bayes SqueezeNet
Bukharia et al. [40]	89	96	93	ResNet50
Ozturk et al. [41]	127	500	500	DarkNet
Punn et al. [42]	108	515	453	ResNet,Inception-v3, Inception, ResNet-v2, DenseNet169, NASNetL
Narin et al. [43]	50		50	ResNet50,InceptionV3, InceptionResNetV2
Ozcan et al. [44]	131	148	200	GoogleNet, ResNet18, ResNet50
Li et al. [45]	239	1000	1000	DCSL
Mukherjee et al. [46]	130		130	Shallow CNN
Luz et al. [47]	152	5421	7966	MobileNet, ResNet50, VGG16, VGG19
Farooq et al. [48]	68	931	1203	ResNet50
Khobahi et al. [49]	89	8521	7966	TFEN, CIN

were applied to an SOFM network to search and classify patients sickness. Their work showed that unsupervised learning could extract features from x-rays images [23]. Chowdhury et al. [24] 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 , it was proposed [25] a modified CNN to detect coronavirus from x-ray images. They combined Xception, ResNet50-V2 techniques and applied 5-fold cross-validation techniques on 180 COVID-19 images, 6054 pneumonia images, and 8851 normal images. In another study it was mentioned that the fundamentals of BEMD is based on using the extrema of the original image and using it for the decomposition. [34] The technique is to find the extrema and the minima in the image and then finding the distance between extrema that provides details to characterize the image on intrinsic length scales. Algorithm 1 summarizes 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. [37] presented pre-trained models of CNN with deep transfer learning and a Generative Adversarial Network (GAN) to detect COVID-19. Three techniques were tested, Alexnet, Googlenet, and Resnet18. The experiment showed that Googlenet technique was the best. Furthermore , the authors in [38] 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. In another study, Ucar et al. [39] used Bayes-SqueezeNet to develop a schema named COVIDiagnosis-Net to detect coronavirus using x-ray images. They partitioned the dataset into three sets, 80% for training, 10% for validation, and 10% for testing purpose without reaching high results compared to other studies.

In another study [41] the authors, presented a network called DarkCovidNet based on CNN technique to detect COVID-19 virus using x-ray images. The proposed solution used DarkNet with 17 CNN layers for the classification of 1127 images partitioned in 5-fold cross-validation. In another study, Punn et al. [42] used ResNet, Inception-v3, Inception ResNet-v2, DenseNet169, and NASNetLarge as a pre-trained CNN to detect COVID-19 virus from X-Ray images. In their experiment, they used 1076 images divided into three sets; 80%

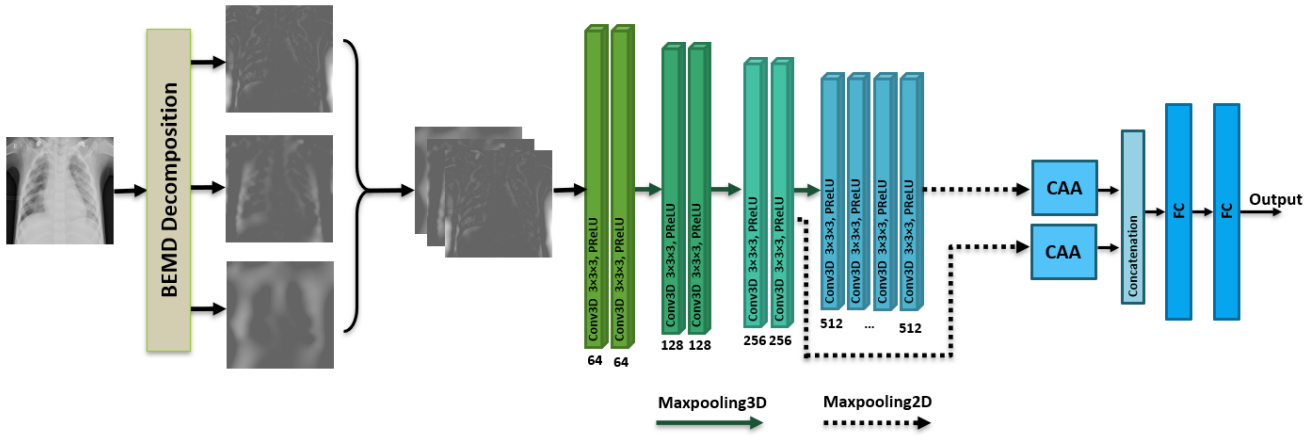


Figure 1: Flowchart of the proposed system.

for training, 10% for testing and 10% for validation purposes. Narin et al. [43] used pre-trained models with InceptionV3, ResNet50, Inception-ResNetV2 to detect COVID-19 virus with 5-fold cross-validation in the dataset partition. The authors of another research work [44] combined three pre-trained models of CNN, ResNet18, ResNet50, and GoogleNet. The grid search technique was used to select the best hyperparameter and the pre-trained models were used to extract features and do the classifications. They divided the dataset into 50% for training, 30% for testing and 20% for validation purposes. On the other hand Li et al. [45] proposed the discriminative costsensitive learning (DCSL) technique to detect COVID-19. The dataset used was partitioned using 5-fold cross-validation technique.

In another study, [48] the authors proposed a deep learning technique with 50 layers using ResNet50 to detect COVID-19. Within 41 iterations only, their system achieved 96.23% of accuracy. Khobahi et al. [49] used a semi-supervised deep learning technique based on Auto-Encoders named CoroNet to detect COVID-19. The dataset was divided into two sets; 90% for training and 10% for testing.

3. Proposed method

During the last two years, many methods have been proposed for COVID-19 detection using different deep learning architectures on x-ray images, as presented in the literatures. The majority of the proposed techniques succeed to identify COVID-19 from x-ray images reaching the accuracy of 99%. 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 a 3DCNN network with context-aware attention (CAA) module trained on BEMD data extracted from the original x-ray images. First, we used the BEMD technique to extract four Intrinsic Mode Functions (IMFs) from each original image while the size of the images used is 512×512. 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. Also the use of CAA module allows a good learning from different features. 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.

3.1. Bidimensional Empirical Mode Decomposition (BEMD)

As it was mentioned in [34], 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) as presented in Algorithm 1 [36] 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.

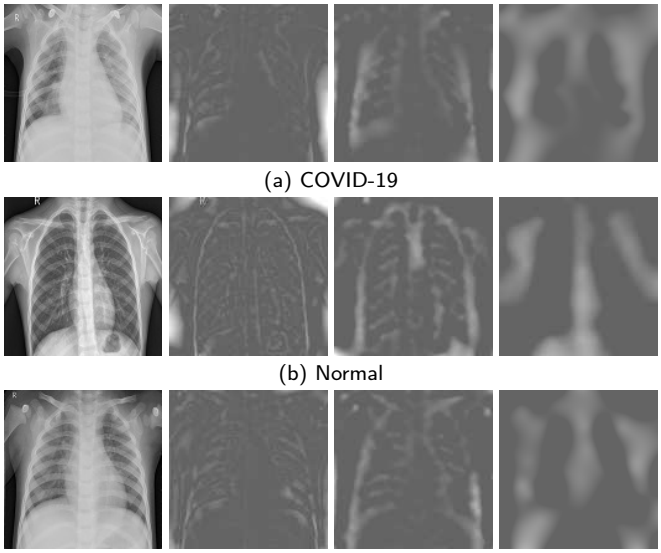
In the pre-processing phase, we took the original images. After that, we applied the bidimensional empirical mode decomposition (BEMD) technique to decompose original images into four IMFs. The latter were then used to generate the video and used as the input for the proposed 3DCNN model, which allows a good learning model from 3D shapes.

3.2. Proposed architecture

Convolutional neural network (CNN), is a deep learning neural network used to process structured arrays like pixels in an image. It becomes important in many applications like image classification, text classification, and pattern recognition [26, 27, 28, 29]. CNN is a feed-forward neural network.

Algorithm 1: BEMD Algorithm [36]

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



(a) COVID-19

(b) Normal

(c) Pneumounia

Figure 2: Some results using BEMD algorithm .

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,hidden layers, activation layers and pooling layers.

Before training the data, BEMD features are extracted and used as input of the proposed 3DCNN backbone follwed bay two CAA modules. The pre-processing 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 the parts of features extraction with convolutional and max-pooling layers followed by two CAA modules then a 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 ten 3D convolutional layers and two fully connected layers. We took layers from VGG-16 that include convolutional and max-pooling layers. After 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 to 2D representation using max-pooling layer, then to flatten data to make the model learns from multi-scale layers also using a complex architecture that performs the learning. Two fully connected layers are of 1024 and 128 respectively.

For the ten 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

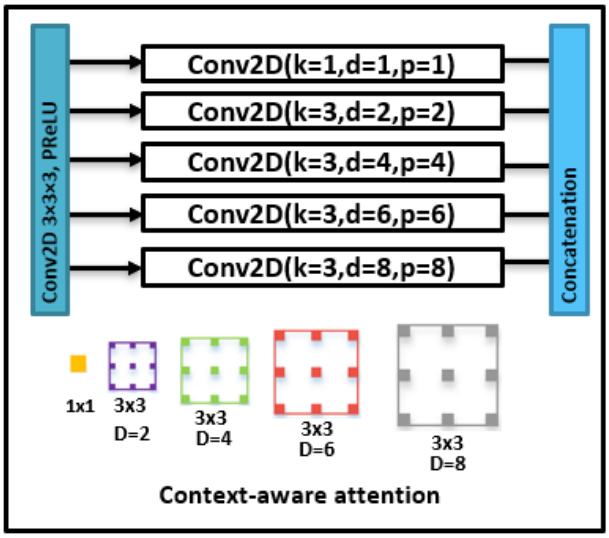


Figure 3: Context-Aware attention module.

values were set to null. The PReLU function is defined as:

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

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 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.

Context-aware Attention module: analyzing the context is the way to extract, recognize segment or classify the content in an image or a video. To do that, the existing deep learning architectures combine multiple convolutional and pooling layers to extract features for learning like in [30]. For image classification from x-ray images, the lung infection can be under the variations of the lung position and scale. The combination of the convolutional and pooling layers cannot be effective for handling all these variations. The authors in [31] attempted to implement a module inspired by SIFT feature extraction method [32] that can extract the features based on the image content. For that atrous convolution [33] is used to extract the features of the same content. For multi-scale features, the use of the output of each convolutional-pooling block can be taken. The same strategy is used for implementing the context-aware pyramid (CP) module shown in Figure 3. Two CAA blocks are used for scale-shape-based extraction. The first one takes the output of the third VGG-16 block as input of the first CAA module while the second one CAA takes the output of the last block of the backbone. Each CAA module is composed of adopted atrous convolutions with a variation of dilatation rate and pending parameters. The outputs of each atrous convolution are concatenated. Then the two CAA modules are combined to get features maps of Context-aware pyramid module then used as input of the next channel-wise attention module.

Table 2
Dataset used in our experiment [2]

Data/Cases	COVID-19	Normal	Pneumonia	Overall
Training	1442	1528	2218	5188
Testing	180	191	277	648
Validation	180	191	277	648
Overall	1802	1910	2772	6484

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

4. EXPERIMENTAL RESULTS

In order to evaluate the proposed method for COVID-19 detection from X-ray images, a set of evaluation metrics have been used. Also we attempted to test the proposed architecture on two dataset with diff rents size. To demonstrate the obtained results, we compared using the same metrics with state off the arts methods including Islam et al.[2], Chowdhury et al.[24], Rahimzade et al. [38], Ucar et al. [39], An et al. [40], Ozturk et al. [41] , Punn et al. [42], Narin et al. [43], Ozcan et al. [44], Bukhari et al. [45], and Mukherjee et al. [46]. In this suction, a description of the used datasets, experimental setup of the proposed deep-learning-based model, also a discussion of the obtained results is performed.

4.1. Experimental Setup

For the experiment, we divided the dataset into training,testing and validation sets. The training set contains 80% of the data, the testing and validations sets contains 10% each. For features extraction techniques we used the pre-trained VGG-16 networks, while the adaptation of 3D representation is performed. The decomposition of the images into IMFs has been made using Matlab exploiting the BEMD algorithm. 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, 8GB and 64GB RAM.

4.2. Dataset

In this paper, we used the dataset mentioned by Islam et al [2]. They collected the images from multiple sources then they did some prepossessing on it to reduce the noise. After that, they applied the augmentation technique to get a reasonable number of images to run the CNN. In our study, we tested the performance of our model using two datasets. The first one includes 6484 images divided into two sets, 80% for training and 10% for validation and the same for testing. While, the second one includes 4575 images that was collected by Islam et al [2].The used number of images in training validation and testing are presented in Table 2.

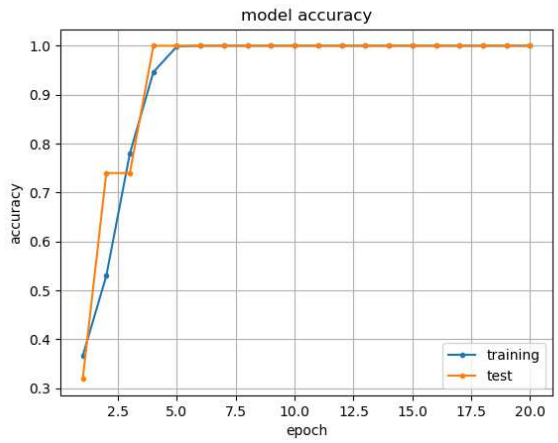


Figure 4: Accuracy graph.

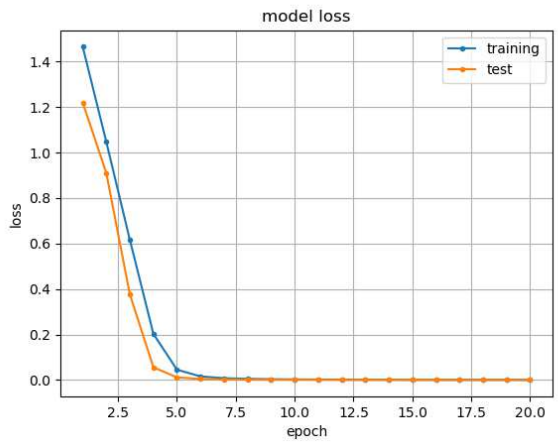


Figure 5: Loss graph.

4.3. Evaluation metrics

To evaluate the image classification method some metrics are exploited including Recall, Precision F1-score, sensitivity, specificity. These metrics computed based on four measures such as True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). While True Positive (TP) denotes the COVID-19 cases that correctly predicted, False Positive (FP) refers 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. Also we used the accuracy of the trained model as a performance metric. These metrics are defined as follows.

Recall: The recall is the metric of determining the completeness of the classifier. Higher recall indicates lower false negatives, while lower recall indicates higher false negatives. Precision often decreases with an improvement in recall.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Precision: Precision shows how much of the data predicted as positive are predicted correctly. In other words, high precision means fewer false positives.

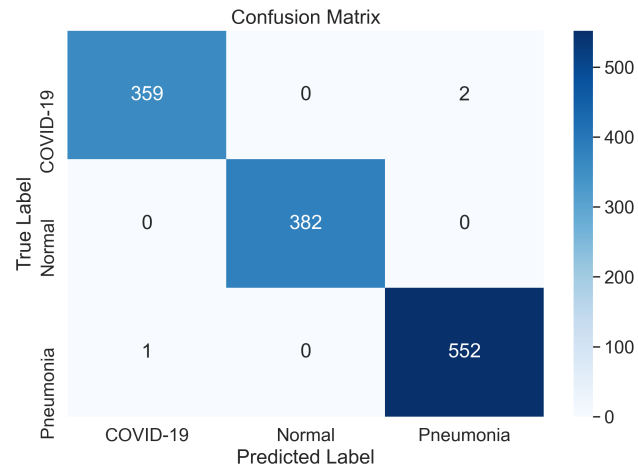


Figure 6: Confusion matrix

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

Sensitivity: Sensitivity, defined as the ratio of correctly detected COVID-19 cases to the total number of detected COVID-19 cases, is computed as:

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

Specificity: Specificity, defined as the ratio of correctly detected non-COVID-19 to the total number of non-COVID-19 , is measured as:

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

F1-Score: To obtain the F1-score, the product of recall and precision is divided by the sum of recall and precision.

$$F1score = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{6}$$

4.4. Evaluation and discussion

In the experiments, we divided the data into 80% for training and 10% for validation, and 10% for testing purposes for training the proposed architecture. Figure 4 and figure 5 show the evaluation metrics accuracy and loss respectively. For these figures, we can observe that the proposed method converges quickly during the training and the reached 1 with the loss graph shows the convergence of it to 0. This is due to the use of 3D representation of decomposed data using the BEMD algorithm, which gives an opportunity to the model to learn from different features. Also, the combination of two CAA modules gives the model the possibility of lean from contextual information contained in the extracted features.

Figure 6 illustrates the confusion matrix of the testing data used for the COVID-19 classification process by the

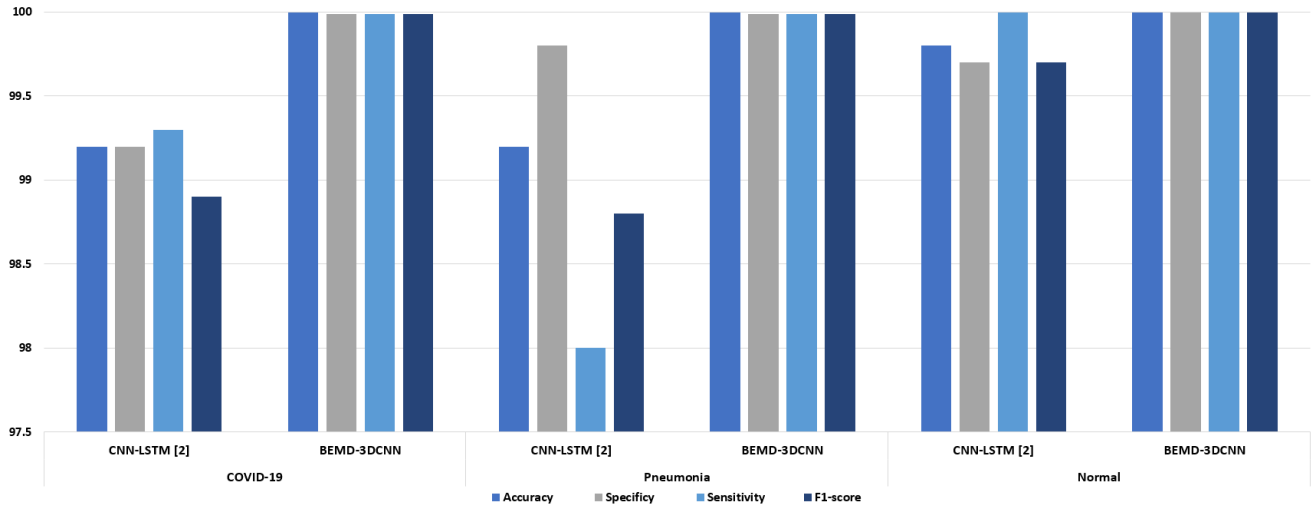


Figure 7: Comparison sensitivity, specificity, and F1-score metrics of the proposed method with state-of-the-art methods.

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

Method	Data	Accuracy	Precision	Recall	F1-Score
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	**4575**	**99.99%**	**99.99%**	**99.99%**	**99.99%**
BEMD-3DCNN	**6484**	**99.99%**	**99.99%**	**99.99%**	**99.99%**

proposed BEMD-3DCNN model using three class including COVID-19 , Normal (non-COVID) and Pneumonia. From the confusion 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 a minimum true negative values.

To demonstrate the performance of each class using the proposed BEMD-3DCNN-based method, we exploited the evaluation metrics shown in figure 7 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 7, we can observe that the BEMD-3DCNN is more accurate and reached 99.99% 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 for COVID-19, Normal and Pneumonia classes.

Using precision, recall and Fa-score the obtained results are presented in Table 3. Due to the fact that each proposed method used specific metrics, we attempted to use all the metrics used in the previous works. For the table, we can observe that the obtained results BEMD-3DCNN method reached the highest values of precision, recall and F1-score, with a difference of 0.8, 0.5 and 1 point comparing with CNN-LSTM method.

Another set of metrics have been used also for evaluating the proposed method against the state-of-the-art methods. These method are respectively sensitivity, specificity. Table 4 Tables 4 summarize the obtained results of some state-of-the-art methods. 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. Form the tables we can find that the proposed method reached the best accuracy value as well as for sensitivity and specificity. While BEMD-3DCNN overcome [2] by a difference of 0.5 for accuracy, 0.6 for sensitivity, and 0.7 for specificity. Also, BEMD-3DCNN outcomes [45] and [46] by 3.6 and 5.7 for sensitivity respectively. As a conclusion, all the proposed method reached good results that exceed 96% in terms of performance accuracy.

5. 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 affected dramatically by the disease because of their limited resources and the large number of infected persons in their areas. Hence, it is necessary to identify as quickly as possible the positive cases during any emergency. We introduced a deep learning model while 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, created a video with these IMFs and then apply the 3DCNN with Context-aware atten-

Table 4
COVID-19 detection techniques (comparison)

Authors	Images	Classes	Partitioning	Accuracy	Sensitivity	Specificity
Islam et al. [2]	4575	3	80%-20%	99.4	99.3	99.2
Chowdhury et al. [24]	3487	3	80%-20%	97.94	97.94	98.8
Rahimzade et al. [38]	180	3	5- fold crossvalidation	99.5	80.53	99.56
Ucar et al. [39]	2839	3	80%-10%-10%	98.26	98.26	99.13
An et al. [40]	278	3	80%-20%	98.18	98.24	98.14
Ozturk et al. [41]	1127	3	5- fold crossvalidation	98.08	95.13	95.3
Punn et al. [42]	1076	3	80%-10%-10%	98	91	91
Narin et al. [43]	100	2	5- fold crossvalidation	98	96	100
Ozcan et al. [44]	721	4	50%-30%-20%	97.69	97.26	97.9
Bukhari et al. [45]	2239	3	5-fold crossvalidation	97.01	97.09	97
Mukherjee et al. [46]	260	2	5-fold crossvalidation	96.92	94.2	100
BEMD-3DCNN(our)	**6484, 4575**	**3**	**80%-10%-10%**	**99.99**	**99.99**	**99.99**

tion (CAA) modules to classify and detect COVID-19. The proposed technique achieved an accuracy of 99.999%. Finally, we achieved excellent results using the proposed techniques that combine BEMD and 3DCNN.

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