Predicting Covid-19 Based on Chest X-ray Image Using Attention Guided Contrastive CNN

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ABSTRACT:

The COVID-19 pandemic continues to disrupt healthcare systems around the world. Across numerous countries, the 2nd surge is veritably severe. The World Health Organization (WHO) declared this contagion as a global epidemic after it contagion numerous people and claimed in numerous lives around the world. An infection caused by Covid19 illness wreaks annihilation on the mortal pulmonary system, leading to several organ failures and, in the worst-case script, death. Multiple deep learning literacy CNN architecture were used to extract features from chest X-ray, which were also classified as Covid19, Pneumonia, using the chest X-ray as input. Affordable and rapid testing and diagnosis is essential to combat communicable diseases. Currently, testing for Covid19 is expensive and time consuming. A chest x-ray (CXR) may be the fastest, most scalable and non-invasive system. Existing methods are hampered by the limited number of CXR samples available in Covid19. Therefore, inspired by the limitations of open source work in this area, we propose a center of attention contrast CNN for Covid19 detection in CXR images. The proposed system uses contrast loss to learn powerful and important features.Also,the proposed model gives further significance to the infected regions as guided by the attention medium. We compute the sensitivity of the proposed model over the publicly available Covid-19 dataset. It is observed that the proposed AC-Covid-Net exhibits very promising performance ascompared to the existing model even with the less training data sets.

Keywords: Pneumonia, COVID-19, Deep Learning, CNN (Convolutional neural network), Open CV

INTRODUCTION:

Newly imported virus known as coronavirus will have wreaked havoc on every industrialized and developing country on the planet. Infectious coronavirus 2019 (Covid19) emerged very quickly as a health-threatening disease has affected the world. It is caused by a novel coronavirus that causes symptoms similar to pneumonia, including coughing, fever, and/or difficulty breathing. The Covid19 coronavirus is a completely new strain that has never been seen in humans before. The infection was observed to spread through surfaces that could be contaminated in to infected people. Once the rate of spread increases, it becomes out of control due to a chain reaction similar to the spread of an infection. Covid-19, on the other hand, is presently rapidly spreading from human to human. By January 2022, it had afflicted 4.29 billion individuals worldwide, with the number of cases linked to mortality continuing to rise on a daily basis.

The spread of Covid19 is divided into several stages. Stages 1 and 2 mean small-scale diffusion, and after stage 3 means large-scale diffusion due to a chain reaction. According to the World Health Organization (WHO), COVID-19 was first reported in Wuhan, China on December 31, 2019.Many countries had been declared a Public Health Emergency of International Concern on 30*th* January 2020. the Covid has a long incubating season of 4-14 days. Heartbreakingly, the secondary effect simply appears following 5-6 days. Because they keep meeting and occasionally the symptoms do not show the longer the time span, the greater the risk of Covid-19 spreading to others.

Covid19 pandemic is being witnessed as the toughest time of the century during April May 2021 due to its 2nd wave which has already entered into stage3/stage4 (i.e., community spread) of Covid19 infection spread. As per the Covid19 data released by WHO on 23rd April 2021, the total number of confirmed cases has reached 143,445,675 with 3,051,736 deaths globally as of 22nd April 2021.Consequently, both the time period and the patients with no symptoms make Covid acknowledgment essentially more irksome, and the conceivable outcomes of transmission spread grow radically.

The pandemic has led to a huge burden on the healthcare systems across the world. To prevent the growth of the virus illness, it is critical to identify people who are infected on a regular basis. As suggested by various professionals and healthcare agencies, the most efficient way to tackle this problem is to adapt mass testing, contact tracing, and isolation. Covid19 pandemic is being witnessed as the toughest time of the century during April May 2021 due to its 2nd wave which has already entered into stage3/stage4 (i.e., community spread) of Covid19 infection spread. As per the Covid19 data released by WHO on 23rd April 2021, the total number of confirmed cases has reached 143,445,675 with 3,051,736 deaths globally as of 22nd April 2021.Consequently, both the time period and the patients with no symptoms make Covid acknowledgment essentially more irksome, and the conceivable outcomes of transmission spread grow radically.

The pandemic has put a great strain on the global healthcare system. Regular identification of infected people is important to prevent the growth of viral diseases. According to various health professionals and agencies, the most effective way to address this problem is to coordinate mass testing, contact tracing, and isolation. Currently, RTPCR testing is robust, but time consuming, requires large infrastructure, is expensive, and is limited to test suites. This is a major barrier to effectively contain the spread of the virus, resulting in low testing rates in many countries. However, one disadvantage of this technology is that it takes a long time to test and is expensive. These defects can be overpowered by using radiographic methodologies, for instance, chest X-ray pictures, which have exhibited to be a fruitful strategy for recognizing Covid impacts on bronchi on schedule. The chest X-shaft is an essential and shrewd procedure. In the present situation, there is an urgent need to discover other ways of Covid-19 testing which might be more efficient, fast, and scalable.

The capacities of a couple advanced pre-arranged CNNs were perused up for the perpetual assessment of Covid19 including chest X-ray images in this audit. By using a little plan of photos, move learning (TL) was picked to achieve high accuracy results. To perceive Covid19 patient X–ray of lung from sound chest x-shaft analyses, different CNN models were attempted. Moreover, perceive individuals People with pneumonia and those with Covid19. Researchers have been trying to explore AI-powered deep learning methods for Covid19 detection, such as COVIDNet, COVIDAid, COVIDCaps, COVXNet, Dark COVIDNet, and the Convolutional Neural Network (CNN) ensemble. The lack of sufficient data to train and test the model is a major challenge in developing deep learning models to detect Covid19 in CXR images. Therefore, it is important to develop deep learning-related models that can learn unique features from limited data. To study distinct and localized features, we propose a center of attention contrast CNN (ACCovidNet) for Covid19 recognition in CXR images.

LITERATURE REVIEW:

In this paper, Predicting Covid with X-ray Lung Images Using Hara Lick Texture Features: The author proposes a unique method for classification & identification of normal and infected lungs by pneumonia by extracting 14 hara lick texture features. The dataset contains a complete of twenty-two chest X-ray images, out of which 11 images belong to normal (healthy) lungs, and remaining 11 images were of pneumonia infected lungs. After hara lick feature extraction from normal and pneumonia X-ray images, the difference between these feature values is being computed and thought of for identification. Author observed that out of 14 computed features, 3 features (variance, sum average, and sum variance) are of most concern because the remainder 11 features were almost just like one another. Covid-19 Identification Technique Using ML Classifier with Histogram of Luminance Chroma Features: The proposed method is especially divided into two phases: training and testing phase. After color space conversion, three different feature vectors are being computed by considering different color space combinations. within the testing phase, the computed feature vector of the sample chest X-ray image is supplied to already trained individual machine learning classifiers. Identification of COVID-19 from Chest Radiography Images using Deep Residual Network: Residual Networks (also called Res Nets) are formed by stacking several Residual Blocks together and thus forming deep architectures that yield fruitful results and assure reduction in training error with the rise within the number of layers.

Detection of COVID-19 from Chest X-ray Images using Convolutional Neural Network-Gaussian Mixture Model: The GMM-based regression successfully predicts the spread of pandemic using the required parameters like mean and covariance of the distribution. Further research is being disbursed considering the high-resolution computed tomographic scan imaging for multi-class classification of various bacterial infections together with the COVID-19. The researchers' goal is to create a facial recognition system using a machine learning algorithm and principal component analysis (PCA). Multilayer perceptron, linear discriminant analysis the support vector machine and naive bayes are used to Face recognition is being tested. Further utilizing PCA and linear discriminant analysis, Author has reached recognition accuracy of 97 percent and 100 percent.

Iris recognition is on the popular biometric identification technology that has a wide range of uses. Because of benefits such as self-directed learning, great generalization ability and high accuracy a number of deep learning algorithms have recently been developed. It is used in biometric identification Despite the depth. The convolutional neural network (CNN) is the most often used type of neural network. It is a widely used image processing method.

The picture categorization has a low anti-noise capacity and is Minor disruptions have a quick impact. For training purposes, A huge number of examples is also required by CNN. The newly developed capsule network is not only functional but also attractive. However, it can improve recognition accuracy in categorization tasks. They can learn part-whole correlations, which will improve the memory. The model's sturdiness can also be taught with very little equipment.

We present a deep learning solution for iris recognition based on the capsule network architecture in this research. To make this technique work with iris the network structure is updated after identification. We also provide a new routing algorithm that is based on two capsule layers have dynamic routing. Even Migration occurs when the number of samples is limited required by CNN.

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The deep learning method can be applied with learning. As a result, three cutting-edge pretrained models are introduced: VGG16, InceptionV3, and ResNet50. They used three networks which are divided into series of subnetwork architectures. These architectures are based on the number of primary constituent blocks. Instead of a single convolutional layer in the capsule network, they are used as the convolutional component to extract primary features. To investigate the performance of different network architectures, we used three iris datasets: JluIrisV3.1, JluIrisV4, and CASIA-V4 Lamp. The proposed networks are then put to the test in simulated high and low light scenarios, revealing that networks with capsule architecture are more resilient than those without.

PROPOSED SYSTEM:

1. We propose an attention guided contrastive CNN for Covid-19 recognition, named as AC-Covid Net. The proposed model relies on the popular COVID-Net model. It heavily uses light weight residual projection expansion projection extension (PEPX) mechanism, Attention Gate. The contrastive loss facilitates the network to extend the space between the learnt representation of the classes the maximum amount as possible.
2. Projection-Expansion: The idea of this module is to project features into a lower dimension using the primary two conv1x1 layers, then expand those features employing a depth wise convolution layer (DWConv3x3) and project into lower dimension again using two conv1x1 layers.
3. We use attention gates within the proposed AC-Covid Net model at various layers as depicted. Features are from multiple layers and those are more responsible conv1x1x1 and are added together.
4. The following are the main components of the proposed CNN model. Encoder network, It is the CNN model as discussed above after removing the last three layers which form the classifier network. The encoder network maps the input image into a vector of size 1024. Projection network, This network projects the output of the encoder network into a vector of size 128. This is a multilayer perceptron with input size of 1024, one hidden layer of length 512, and an output vector of size 128. This network is used while training the encoder and later discarded. Classifier network, this is the last three layers of CNN that take a 1024 length output of the encoder as the input and produces an output of size c = 3 (corresponding to the classes, Normal, Pneumonia, and Covid-19).

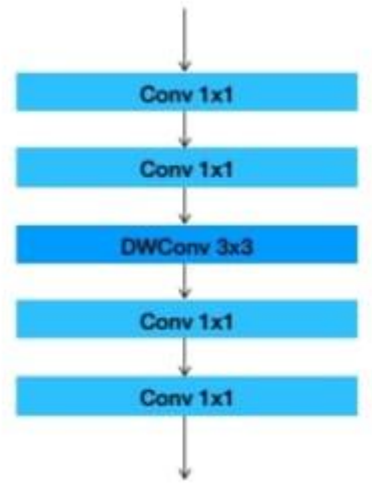

Fig1: Proposed Model

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OBJECTIVES:

In this model we have used supervised contrastive learning method to train the encoder network for feature extraction. We train the classifier network using the cross entropy loss function after freezing the encoder network.

Contrastive loss is most commonly used in unsupervised and self-supervised learning. In order to adapt this method to supervised learning and take advantage of the labels available, the supervised contrastive learning has been investigated. This loss is used to train the encoder network of the proposed CNN model.

Cross entropy loss is used to train the classifier which takes input from the feature extractor. It produces the output probability corresponding to three class from the softmax activation function.

METHODOLOGY:

Data Set:

The Kaggle repository provided the data for this investigation. And the X-ray scans of patients are the dataset that is being considered for this investigation. X-ray scans are critical in the medical field for detecting any type of lung disease. Training, testing, and validation are the three subfolders that make up the dataset. Each sub folder contains four sub folders, one for each of the four types of lung disease: Covid19, Pneumonia, Tuberculosis, and Normal. The dataset has Three categories that must be classified: Covid19, Pneumonia, and Normal. A total of 1756 X-ray images are included in the dataset, which cover all three types of disease listed above.

Inception net:

Inception Net's inception block performs convolution on an input using three different filter sizes. Additionally, maximum pooling is used. The results are then combined and passed to the inception module. A 1x1 convolution is used before the 3x3 and 5x5 convolutions to limit the number of enter channels. Despite the fact that including a larger operation appears to be more complex, 1x1 convolutions are much less expensive than 5x5 convolutions since the number of channel inputs is reduced. However, keep in mind that the 1x1 convolution happens after the max pooling layer, not before it.

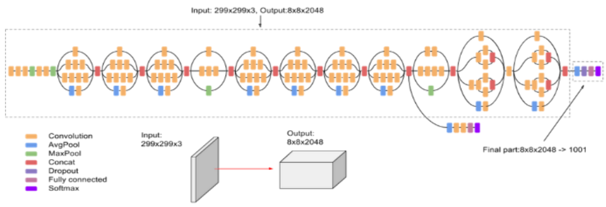


Fig2: Architecture of InceptionNet

Xception Net:

With a modified depth wise separable convolution, XceptionNet is a severe model of Inception. It employs Depth wise Convolution, in which instead of using a convolution of dimension d×d×Cd×d×C, a convolution of dimension d×d×1d×d×1 is observed. To put it another way, we don't compute convolution across all of the channels, but only one at a time. And a Pointwise convolution over the K×K×C volume with measurement 1×1×N. This allows for the expansion of a KKN-like extend. The recordings begin by passing through the entering stream, then through the center float, which is repeated several times, and finally through the leave float. All Convolution and Separable Convolution layers are screened by Cluster. A significance multiplier of 1 is given to all Separable Convolution layers.

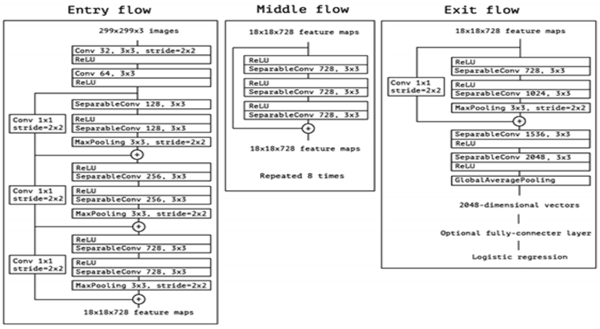


Fig3: Architecture of XceptionNet

Resnet:

Microsoft Research suggested Resnet in 2015. When working with convolutional neural networks, one of the issues is gradient disappearance. To remedy this problem, Resnet added residual blocks, which use skip connections. Each layer of a convolutional neural network is meant to learn various features; however, some of the layers may not learn well or may not extract the feature correctly, resulting in poor model performance or accuracy. To address this issue, Resnet developed skip connections, which allow the model to skip levels that have not learned adequately and transfer the previous layer's output as input to the next layer.

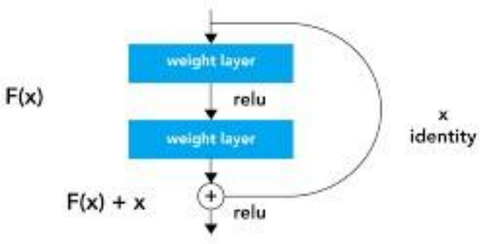


Fig4: Residual blocks

CPT Net:

The CPT Net has ten levels. The first two layers are convolutional layers with a kernel size of 3*3 and a relu activation function, with the first convolutional layer using a 150*150 X-ray image as input. After the first two layers, there is a max pool layer with a kernel size of 2 *2. The fourth layer is a convolutional layer that uses the same hyper parameters as the first two layers. The fifth layer is a convolutional layer followed by a max pool layer with a kernel size of 2*2. The seventh layer, known as the flatten layer, is where all of the retrieved features from the convolution are flattened. The dense layer will receive the output of the flatten layer.

Fig5: Architecture of CPT

Transfer Learning:

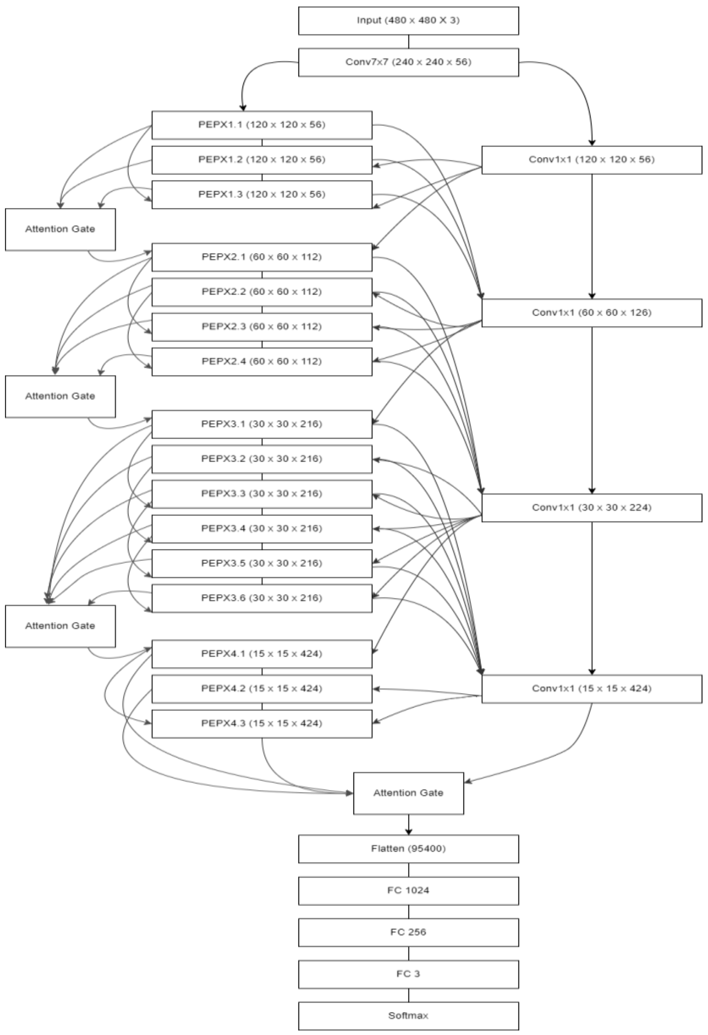
Transfer learning is a method of computer learning in which a mannequin who has completed one project is repurposed for a second layer. We select a pre-trained supply mannequin from among the available models. Many search companies launch styles on large and challenging datasets that are saved in a pool of candidate fashions from which to choose. The pre-trained mannequin can therefore be utilized as a starting point for a mannequin on a 2D project of interest. Depending on the modelling approach employed, this could include using all or parts of the model. Optionally, the mannequin could be modified or sophisticated based on the input-output pair data available for the desired assignment.

ALGORITHM:

Algorithm 1: Training AC-CovidNet

E: Encoder Network, P: Projection Network
C: Classifier Network
$SupCon$: Supervised Contrastive Loss
$CrossEntropy$: Cross Entropy Loss
while $epochs --$ **do**
  `// Stage 1`
  for $batch\ X\ in\ Data$ **do**
    Initialize Z as null;
    for $x_i\ in\ X$ **do**
      $h_i = E(x_i)$;
      $z_i = P(h_i)$;
      $Z.append(z_i)$;
    end
    $\mathcal{L}_{SC} = SupCon(Z_i)$;
    Update E and P to minimise $\mathcal{L}_{SC}$;
  end
end
Discard $P(.)$ and freeze weights of $E(.)$;
Final model, $M(\boldsymbol{x}) = C(E(\boldsymbol{x}))$;
while $epochs --$ **do**
  `// Stage 2`
  for $batch\ X\ in\ Data$ **do**
    $\hat{Y} = M(X)$;
    $\mathcal{L}_{CE} = CrossEntropy(Y, \hat{Y})$;
    Update M to minimise $\mathcal{L}_{CE}$;
  end
end

FLOWCHART:

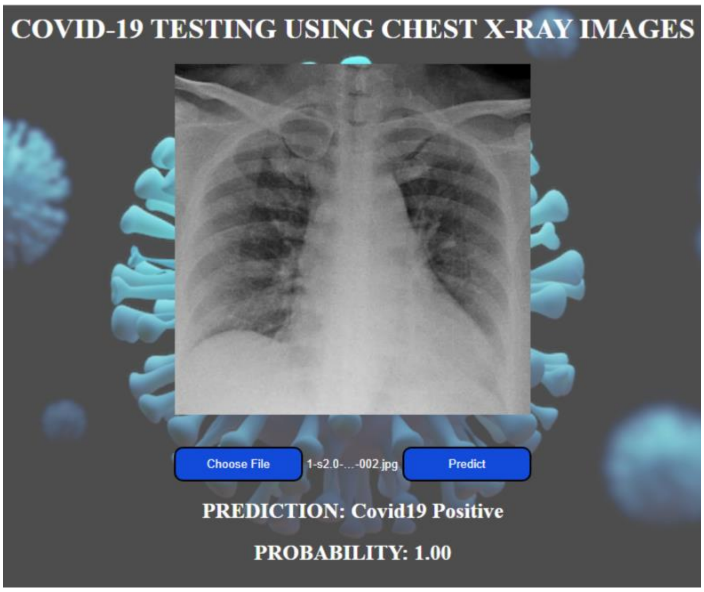


Experimental Results and Analysis:

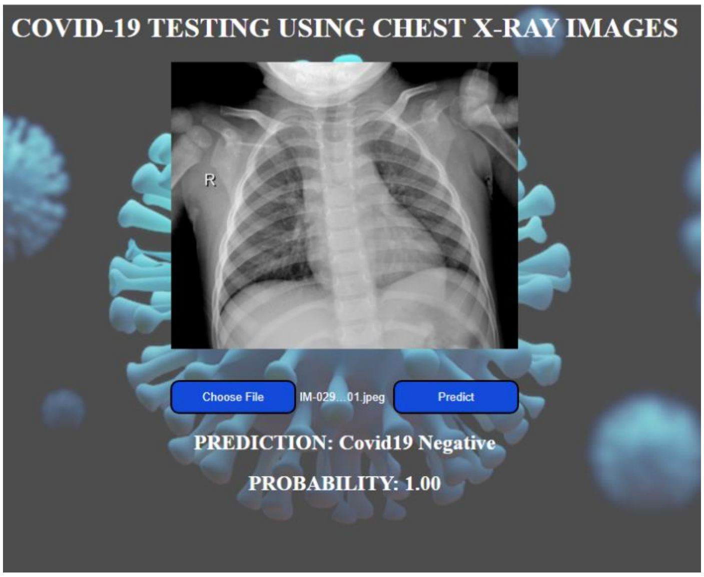
We test the proposed CNN model on all three configurations of the COVIDx dataset and calculate the perceptivity for Covid-19 and other classes. so as to demonstrate the frequence of the proposed model, we also cipher the results using state-of-the-art deep literacy grounded Covid-19 recognition models, like CovXNet, COVID-CAPS, CNN Ensemble, DarkCovid-Net, COVID-Net, and CovidAID. The results in terms of the perceptivity for the Covid-19 perceptivity. The observed Covid-19 sensitivity using the proposed ACCovidNet model is 96%, 96.66%, and 96.5%, independently. It may be observed that the proposed model outperforms the remaining models over all three settings of the COVIDx dataset.

Note that the proposed model is in a position to realize better results than the contrary compared models because the proposed model learns the Covid-19 specific features using the attention module and increases the separation between different classes in point space using the contrastive loss. In the configuration I of the dataset (with 100 test images), the performance of the proposed model is stylish than Cov-XNet, COVID-CAPS, CNN Ensemble, DarkCovidNet and CovidAID models and same as COVID-Net. Therefore, in order to demonstrate the advantage of the proposed model, we compare the results with lower number of guiding samples and future test samples. Principally, it depicts the conception capability of the proposed model.

Corona Positive:



Corona Negative:



CONCLUSION AND FUTURE SCOPE:

In this paper, an AC-CovidNet CNN model is proposed for Covid-19 recognition using chest X-Ray images. The proposed model uses the attention module in order to learn the task specific features by better attending the infected regions in the images.

The proposed system also utilizes contrastive learning in order to achieve the better separation in the feature space by increasing the discriminative ability and increasing performance level. Different deep learning models were exhibited for categorizing the X-Ray images as Covid-19 Positive, Covid-19 Negative, Pneumonia, Normal. The images from the dataset are trained for the feature extraction. Using these trained data sets fresh images are fed into for the detection of the disease, it can identify data as Covid-19 Positive, Covid-19 Negative, normal or pneumonia patients.

Commencement v3, Xception, ResNet, and CPNet are the performance employed. The Above mentioned models, cannot be enforced directly. The current dataset can be used to train multiple deep literacy models to ameliorate the identification of Covid-19 infections. It is noticed that the proposed AC-CovidNet model outperforms the existed models in terms of the perceptivity for the Covid-19 order. It is also observed that the performance of the proposed model is harmonious with a limited training dataset. Whereas, the existed models fail to do so. It shows the better conception capability of the proposed system. The application of recent model in deep learning to break the Covid-19 recognition problem from chest X-Ray images with better performance.

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