International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 5 Volume No.7 September - October – 2023
DOI:10.46647/ijetms.2023.v07i05.048 ISSN: 2581-4621

Artificial Intelligence Exposure of COVID-19 fromX - Ray Images using Deep Learning Techniques

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ABSTRACT

The new coronavirus (COVID19) is contagious the epidemic was declared a pandemic in March 2020.Therefore, easy and quick infection, the corona virus has caused thousands of deaths worldwide. Hence the development of new systems Accurate and rapid detection of COVID19 is becoming crucial. x-ray imaging is used by radiologists to diagnose the coronavirus. However, this process requires a lot of time. Therefore, AI systems can help reduce the pressure healthcare systems. In this article, we propose CoviNet a Deep Learning Network to automatically detect the presence of COVID19 on chest X-rays. The proposed architecture is based on of Adaptive Median filter, Histogram Smoothing and a Convolutional Neural Network(CNN). It is trained end to end a publicly available dataset. Our model achieved accuracy 98.75% in binary classification and 95.77% in multiple classification Because early diagnosis can limit the spread of the disease virus, this framework can be used to help radiologists first diagnosis of COVID19.
Keywords—Coronavirus, COVID19, Deep Learning, Convolutional Neural Network, Chest X-rays , Adaptive Median Filtering

1. Introduction

Since December 2019, the coronavirus disease (also known as COVID19) spread rapidly, causing panic everywhere in the world By June 12, there were more than 7.5 million infected worldwide and causes 25 out of 100 cases death [1]. This infection is easily transmitted from person to person to a person by sneezing, coughing or respiratory droplets. The virus is usually accompanied by cough, fever and weakness and it can cause pneumonia, multi-organ failure and death [2]. Given the lack of a vaccine or therapeutic treatment of the new coronavirus, early diagnosis is essential. Because they contain useful information diagnosis, chest X-ray, including chest X-ray (CXR) and computed tomography (CT) are important in the early detection and treatment of this disease [3]. However, the rapid increase in the number of patients during a pandemic it is difficult for doctors to carry out the diagnostic process a limited time It is in this context that artificial intelligence can emerge an accurate, fast and affordable tool for COVID19 diagnosis. Recently, deep learning as part of machine learning artificial intelligence recognized its superiority over classical AI approaches (artificial methods), in various fields of medicine photo assignments It has been used for many problems such as such

Deep Learning becomes an obvious choice in CXR diagnosis. The main purpose of this article is to provide an effective framework for automatic diagnosis of COVID19. For this Our goal is to

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offer a comprehensive learning model based on end-to-end convolutional neural network (CNN) architecture without using any manual extraction method. In our study the pre-processing stage is very important in image processing before feeding them into the CNN model. Although our goal is we detected the presence of COVID19 in the images, we worked two scenarios, the first of which is binary classification (covid19 vs. normal) and the other is a multi-class classification (covid19 vs discharge vs normal). Examples of images of an object each category is shown in Figure 1. In our study, we tried improve overall accuracy using low computational cost and a smaller number of parameters.

(a) (b) (c)
Fig. 1. Examples of Chest X-Rays. (a) Normal. (b) Effusion affected lungs. c) COVID-19 positive

2. Related Work

The use of machine learning methods in automatic diagnosis in the medical field has recently become important tool for clinicians [5]– [8]. Several recent studies are based on deep learning, has been widely used in chest radiography discover a new corona virus. In this section, we describe some notable works about it in the literature theme in [9] Khan et al. launched CoroNet, Convolutional Neural Network based on Xception (Extreme Start) containing 32 layerspretrainedwithImageNet,data set the accuracy of the proposed model was 87%. to detect COVID19. Sethy and Behra [10] showed ResNet50 model combined with SVM classifier improve detection of COVID19. [11] presented a comparison between seven different known depths learning network architectures. They used a small data set 50 images in their tests and they reported that VGG19 and DensNet201 performed best. In [12], Authors proposed a new CNN architecture (the COVID Network) that was designed to classify CXR images into pneumonia, normal and COVID19. The model was validated with a large dataset contains 13,800 images. It achieved overall accuracy 92. %. Wang and Wong [12] proposed a deep model Detection of COVID19 (COVID-Net), which achieved 92. percent accuracy in detecting normal, non-COVID pneumonia, and Courses on COVID-19. Ioannis et al. [13] applied in depth training model using 22 images of COVID-19. There the model obtained a precision of 98.75% and 93. 8° for the two and three classes respectively.

3. Methodology

We propose a new deep learning framework automatically detects the COVID19 virus on a 2D chest X-ray image picture Our system is also dedicated to differentiation COVID19, Outbreak and Common Cases. Network based already in receptive convolutional neural networks processed and filtered images (with an adaptive median filter and histogram smoothing). We value performance model and retrained it by changing the architecture and hyperparameters until the best possible accuracy score was obtained. Picture. Figure 2 illustrates the general workflow of the proposed CoviNet.

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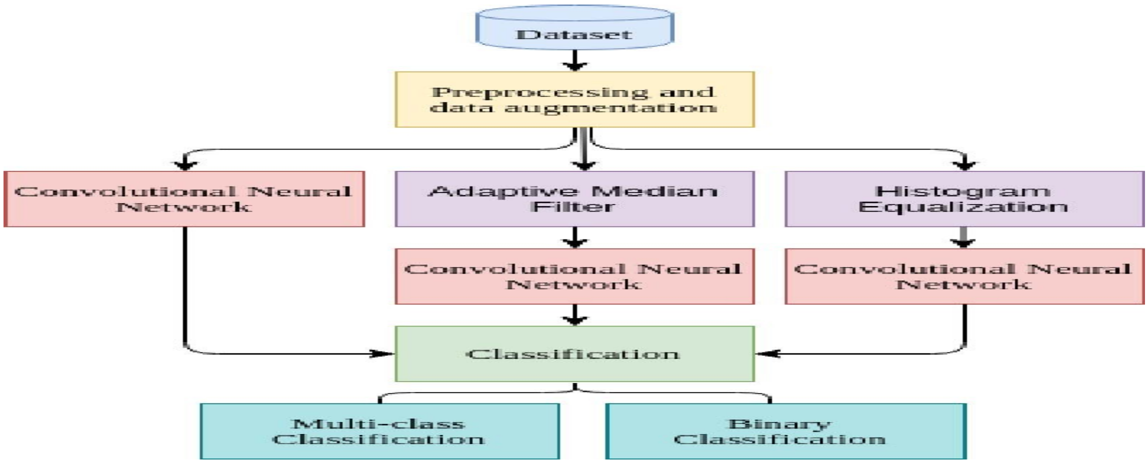

Fig. 2. The overall framework of the proposed CoviNet.

1. Pretreatment The pre-processing stage involves many activities, including:
- Dataset image labelling: 0 for normal, 1 for COVID19 virus and 2 for effusion disease.
- Resize all images to a single size of 256x256.
- Saving images in a one-dimensional model (in grayscale).
- Solve a problem of imbalance of class data with activity data techniques (mirroring, vertical rotation and random rotation). Statistics for the newly received dataset are shown in Table 1.

Table 1 Dataset Distribution

Dataset	Normal	Effusion	COVID-19
Original dataset	1005	120	350
Balanced dataset	1005	1005	1005

2. Adaptive median filter The adaptive median filter [1] is a non-linear digital filter a filtering technique often applied to images to remove them noise and make images clearer and easier to distinguish. The Adaptive Median Filter (AMF) changes the noise region the window detects noisy pixels in the vicinity. If the noise points are detected, they are replaced by the median pixel value and if not, the original pixel value is retained. Advantage an AMF is an option to save details while debugging pulseless noise that is not produced by a traditional median filter.
3. Network Architecture CoviNet is based on the CNN architecture, which includes of different layers and consists of two stages: automatic function separation and classification part. As shown in Figure 3, the proposed CNN has four convolutional layers with filters size 3x3, number of filters in three convolution modes there are 32 layers. The fourth layer uses 6 filters. After each convolutional layer, ReLU is used as an activation function. recipient reduces computational complexity and space size max-joining layers are used after the resulting feature maps two twisted layers of window size 2x2 and 2-pixel step length. The combined product is then flattened and eaten the first fully connected layer with 128 neurons. Stop [15] is used as an adjustment technique to avoid overfitting problems

4. Experimental Results

In this section, we describe the main dataset used here study We also present the experimental setup and results we decide on both binary and multi-class classification part with a comparison with modern methods. A. Data set There are two different publicly available sub-databases in this study used to create one dataset:

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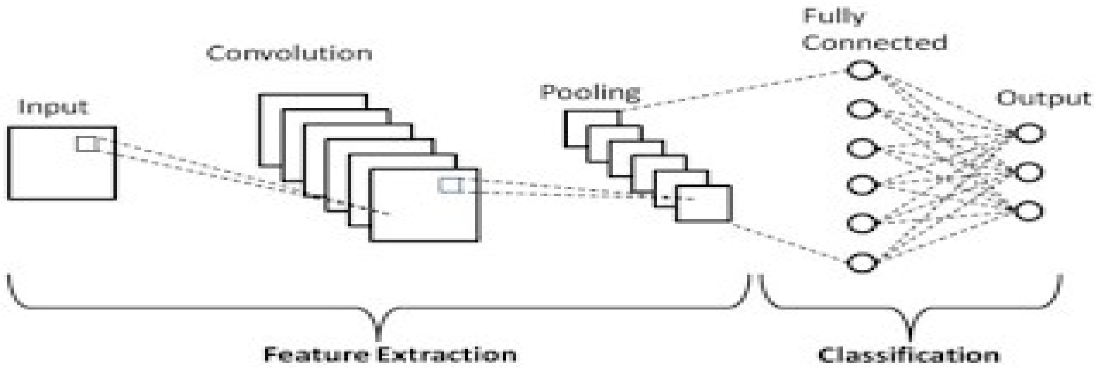

Fig. 3. The CNN model architecture.

4.1 Experimental Environment:

Our model is developed with Python and Sphere library with TensorFlow backend Intel core (TM) i7 Gen GHz processor. Experiments were performed using Graphics processor (GPU) NVIDIA GEFORCE GTX 1050 Ti and RAM 8GB and GB respectively. To the train models, we specify the number of epochs, the set size and learning rate 120, 00 and 0.001. We used cross entropy as a loss function (binary, categorical) and Adam optimization of the cross-entropy function

4.2 Evaluation Process:

Evaluate the performance of our trained model calculation accuracy, sensitivity, specificity, accuracy and F1- score TP is the number of true positive patterns, FP represents the number of false positive patterns, TN is the number of true negative patterns and FN is the number false negative patterns

Accuracy = (T P + T N)/(T P + F P + F N + T N) (1)

Sensitivity = (T P)/(T P + F N) (2)

Specificity = (T N)/(T N + F P) (3)

Precision = (T P)/ (T P + F P) (4)

F1 – score = 2 × (Recall × Precision)/(Recall + Precision) (5)

Sensitivity and specificity give the portion of positives and negatives that well classified, respectively

4.3 Model Performance:

We conducted experiments to classify and identify COVID19 using chest x-rays in two different scenarios. United States, first trained CoviNet to classify deep learning networks CXRs into two categories COVID19 and normal. In the second in the scenario, the model was taught to distinguish between three categories COVID19, normal and effusion.

4.4 Binary classification results the results are described in Table 2. From this table we can see that images are inserted After applying histogram correction (HCNN) to the CNN model, it gives better results for almost most metrics. U.S Note that the best model achieved average accuracy 98.75% and sensitivity, specificity and F1 score were obtained 98.52%, 98.72% and 98.65%. Figure, fig. 5, figure 6 shows the accuracy and loss curve, confusion matrix, respectively and ROC curve for the binary ConviNet model classification

4.5 Multi-class classification:

The triple classification performance of the two models was evaluated and accuracy, precision and recall metrics were calculated. The results are described in Table 3, where it is clearly seen that the model where earlier we applied histogram smoothing to the images feeding them to the achieved convolutional neural network in terms of differences, better results than the other two models' meters, achieving an average accuracy of 95.77 percent with only 9 0 seconds to better confirm the effectiveness of this model, we plot the accuracy curve on the figure. 7. The confusion matrix is also shown in Figure 8 to give us an idea accuracy of each class. From this figure we can notice that the number of cases of COVID19 is projected to be much higher odds than non-Covid cases, which is good allows us to accurately identify positive cases.

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4.6 Comparison with Benchmarks:

In this subsection, we compare the effectiveness of the presented approach in this work based on the latest methods accuracy Table IV describes the results of this comparison, where different types of images are used to detect COVID19: CT and CXR images. As you can see, our method looks better results in both multiclass and binary classification. we can explain this by the importance of proper selection hyperparameters for the problem and also very preprocessing images before uploading them online.

Table 2 Performance of the Two Approaches under the same Dataset for the Binary Classification

Model	Acc %	AUC %	Spe %	Sen %	Pre %	F1-Score %	Time (s)
CNN	98.75	0.99	93.53	98.49	93.77	96.07	223
AMF-CNN	95.5	0.99	95.52	95.47	95.47	95.47	149
H-CNN	98.62	0.99	98.72	98.52	98.77	98.65	705

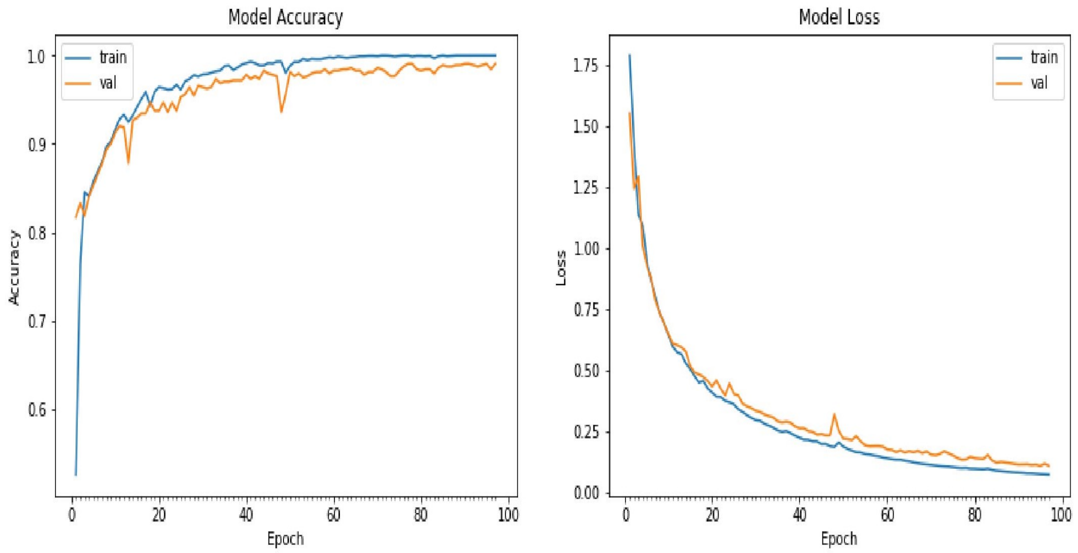

Fig. 4. Accuracy and loss model curves for the binary classification

Table 3 Performance of The Two Approaches for The Same Dataset (3 Classes)

Model	Accuracy %	Precision %	Recall %	Time (s)
CNN	93.05	89.88	89.66	537
AMF-CNN	95.47	93.39	93.16	1176
H-CNN	95.77	93.69	93.66	940

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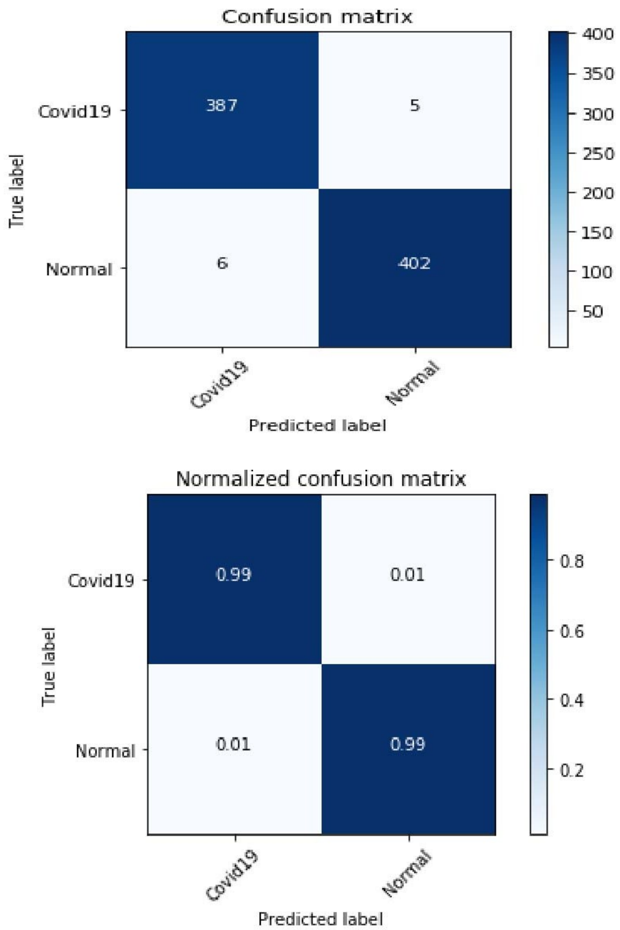

Fig. 5. Confusion Matrix and normalized confusion matrix for the binary classification.

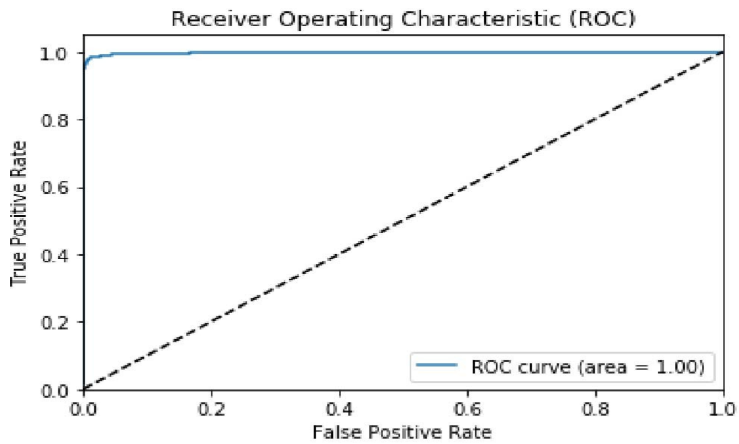

Fig. 6. ROC curve for the binary classification.

CONCLUSION

In this study, we presented a deep learning-based model to classify CXR images as COVID19, normal or discharge our model is fully automated with a complete architecture that does not use a manual method. The CoviNet system is designed with 98.75% and 95.77% accuracy for both binary and multiclass classification respectively. As a future work, we plan to use a wider tilt dataset to better evaluate the performance of our model and also work in the segmentation phase.

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