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Accurate Diagnosis of COVID-19 Based on Deep Neural Networks and Chest X-Ray Images

التشخيص الدقيق لمرض فيروس كورونا المستجد باستخدام الشبكات العصبية العميقة وصور أشعة-X للصدر

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EYWORDS:

COVID-19; Chest X-ray Images; Deep Learning, CNN

الملخص العربي:- **انتشر مرض فيروس كورونا المستجد مع نقطة انطلاقه في ووهان، الصين، بسرعة في جميع أنحاء العالم تقريبًا مع أكثر من 11.5 مليون حالة وأكثر من 500.000 حالة وفاة وفقًا، لإحصاءات منظمة الصحة العالمية. يلعب التشخيص الدقيق والسريع لحالات الإصابة بفيروس كورونا المستجد المشتبه فيها دورًا مهمًا في الحجر الصحي والعلاج السريري في الوقت المناسب، ويعد الكشف والتشخيص للحالات المصابة باستخدام صور الأشعة السينية للصدر خطوة أساسية لمنع انتشار هذا المرض، حيث تظهر على المرضى في هذه الصور سمات دالة على المرض، تكون مميزة للأشخاص المصابين بـالفيروس، وللحصول على القدرة على التشخيص السريع والمبكر للحالات المصابة، تم تنفيذ خوارزميات باستخدام التعلم العميق تعتمد على الشبكات العصبية التلافيفية باستخدام صور الأشعة السينية لتشخيص الإصابة بالفيروس، حيث تم تعديل أبعاد الصور أولاً ثم معالجتها مبدئيا لزيادة الحدة والتباين والوضوح، وتم إدخال الصور في شبكة عصبية عميقة للتنبؤ باحتمال الإصابة بـالفيروس، وكانت النتائج متميزةحيث تم الحصول على مساحة تحت المنحنى 0.9888 وحساسية 96.2٪ ودقة 98٪ مما يتيح استخدام هذه التقنية منخفضة التكاليف لتشخيص لإصابة بفيروس كورونا المستجد بكفاءة عالية.**

Abstract*— The present study aims at preventing spread out of COVID-19 by early detection of infected cases using chest X-ray images and convolutional neural networks. Covid-19 chest X-ray dataset were collected from public sources as well as through agreements with hospitals and physicians with the consent of their patients. A deep learning algorithm based on convolutional neural networks (CNN) was implemented utilizing X-ray images to diagnose COVID-19. ResNet50, short for Residual Networks, is a classic neural network that was used as a backbone for the classification task. It accelerates the speed of training of the deep networks and reduces the effect of vanishing gradient problems. Images were first resized and then pre-processed to increase sharpness, contrast, and clarity. Images were fed into a deep neural network to predict the probability of COVID-19 infectious. The deep learning calculation acquired an area under the curve (AUC) of the receiver operating characteristics (ROC) of 0.9888, 96.2% sensitivity, 98% accuracy, and 100% specificity. Moreover, the algorithm can be easily modified to add extra images (normal and COVID-19) to improve performance. The proposed system introduces a great help to all nations to screen and diagnose COVID-19 as a faster alternative compared with conventional method that uses PCR.

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I. INTRODUCTION

A PNEUMONIA of obscure reason appeared in Wuhan, China was first announced on the last day of 2019. WHO does all best to collect and interpret data, advise people and countries, arrange with partners, help nations plan, and increment supplies. The flare-up was reported a public health crisis of global importance on 30th January 2020 [1].

COVID-19 pandemic keeps on devastatingly affecting the wellbeing and prosperity of worldwide populace, caused by

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the infection of individuals by Severe Acute Respiratory Syndrome Corona Virus 2 (SARS-CoV-2). The most important issue in fighting COVID-19 is fast and accurate detection of infected cases, such that these cases can be isolated to get rapid treatment and care, to reduce the spread of the virus. The principal diagnostic method for COVID-19 is polymerase chain reaction (PCR) testing using nasopharyngeal or oropharyngeal swabs [2].

PCR testing is considered as the most recommended methodology of COVID-19 detection due its high sensitivity and acceptable accuracy. However, it is a time-consuming test which requires special tools and kits. As reported from recent studies, patients with COVID-19 have shown abnormalities in chest radiographic images [3]. Thus, an alternative approach for COVID-19 detection is based on the use of either X-ray or computed tomography (CT). Resulting images are analyzed to search for visual markers related with COVID-19 infection. This technique provides a faster method which can be adopted as a companion to PCR testing in moderate infection situations. In emergency situations, with large population of infected patients, X-ray imaging can be trusted as a means of accurate detection of infectious cases. The major challenge confronted is the need of professional radiologists to read X-ray images.

The present work is utilized to overcome the lack of specialized radiologists as well as to increase the diagnosis speed and accuracy. Fast improvements in digital image processing and artificial intelligence have shown great applications in the medical field, especially in computer-aided diagnostic (CAD) systems. Deep learning algorithms, with the high capability of nonlinear modeling, have wide set of applications in the medical field. They have been proposed in recent studies to detect corona virus using X-ray and CT images preciously [4]. In the present paper, a deep convolutional neural network (CNN) is utilized for COVID-19 detection using chest X-ray images. The image set is available for researcher use in [5].

The present article starts with section 2 that introduces presents the methods including dataset, and pre-processing. Section 3 suggests the theory and architecture of the proposed CNN. Section 4 introduces the experimental results of both the training set and the test set. Section 5 summarizes the concluded remarks and suggestions for the future work.

II. METHODS

Since X-ray images in the dataset differ in size and contrast, they are resized and pre-processed. The processed images are utilized for training of CNN. After that, CNN is employed to the test set. The present study aims at classifying the X-ray image of the patient into normal or infected with COVID-19. Figure (1) shows a block diagram for the suggested system.

a. Dataset

Thanks to Dr. Joseph Cohen [5], for making chest X-ray dataset available to researchers. His team had built a public database of pneumonia cases with chest X-rays, especially, COVID-19 cases. Data were collected from public sources as well as through agreements with hospitals and physicians with the consent of their patients. Data were divided into 2 folders; normal cases and COVID-19 cases. Each folder contains 25 images with 'jpeg' format and variable size ranging from 700*630 up to 3342*4095.

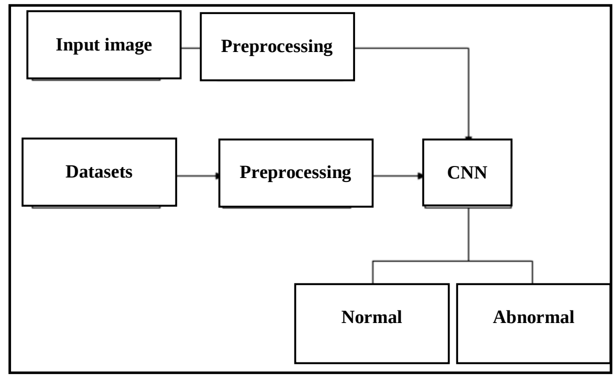


Fig. 1 Block Diagram of the Proposed System

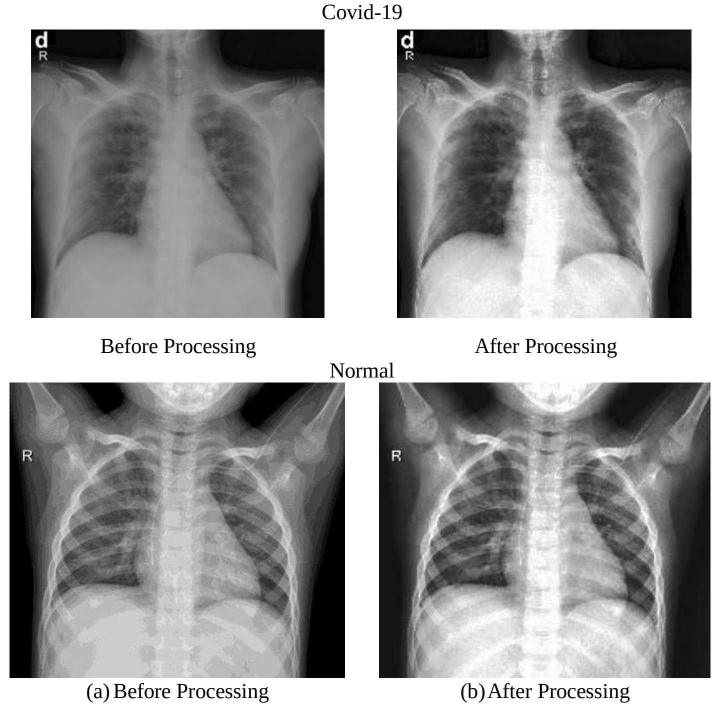
b. Preprocessing

Some images were observed to be 3-dimensional. As a first step, they were transformed into gray scale. To normalize dataset, images were resized to 400*400. Histogram equalization was utilized to enhance the contrast of all images for better detection. Figure (2) shows an example for two images before and after contrast enhancement.

c. Data Augmentation

The sampling distribution of COVID-19 cases and normal cases is equal. There are 25 images of both classes which represents an equal distribution with no class imbalance. Data augmentation techniques, including random rotation [-5º 5º], random reflection, random shear operation, were applied on original dataset to enhance the dataset size and to prevent over-fitting.

Covid-19



Before Processing After Processing

Normal

(a) Before Processing (b) After Processing

Fig. 2 Processing of original dataset

Data were split into 15-folds for analysis. This means 15 different algorithms would be trained using different set of images from the dataset. This had given a better performance compared with the hold-out validation method which had been tried previously. In the hold-out validation, the number of folds is equal to the number of instances in the data set and the learning algorithm is applied once for each instance, using all other instances as a training set and using the selected instance as a single-item test set.

III. Convolutional Neural Networks (CNN)

The basic CNN architecture contains an input layer, an output layer, and a set of hidden layers. Hidden layers consist of convolution layer(s) followed by pooling layer(s) and fully connected layer(s) as shown in Fig. (3). the convolution layer determines the most important kernels that are relevant to the application. The pooling layer allows dimensionality reduction by obtaining the mean or maximum of the image patches. CNN end with fully connected layers ending with a tensor which is converted to a vector [6].

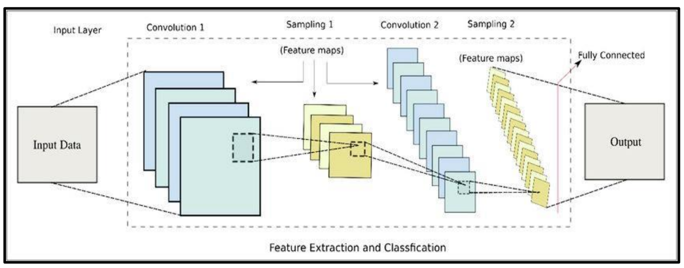


Fig. 3 General architecture of CNN

a. CNN Training Process

The ResNet was built by several stacked residual units and developed with many different numbers of layers: 18, 34, 50, 101, 152, and 1202. However, the number of the operations can be varied depending on the different architectures. For all of the above, the residual units are composed of convolutional, pooling, and layers. ResNet is similar to VGG net, but ResNet is about eight times deeper than VGG. ResNet 50 contains 49 convolutional layers and a fully-connected layer at the end of the network. For saving computing resources and training time, ResNet 50 was chosen for the development of the present work. A CNN with the ResNet-50 architecture is shown in Fig. (4). It was utilized to obtain the most important features from all input images [7]. As the ResNet-50 is defined, the number of categories is specified, the new learnable layer is obtained, and then, last layers are replaced with new ones. The training parameters were chosen by continuous trials as follows:

- Learning rate 10^{-5} (It gives the best loss without sacrificing speed of training)
- Minimum batch size 8 (A batch size of 32 was chosen as a start point, then the size was reduced to 16, and finally it was set to 8 to reduce memory space needed)
- Maximum epochs 40 (A maximum number of 100 epochs was tried, then 50, and finally it was found that 40 epochs were enough to get the acceptable error rate)

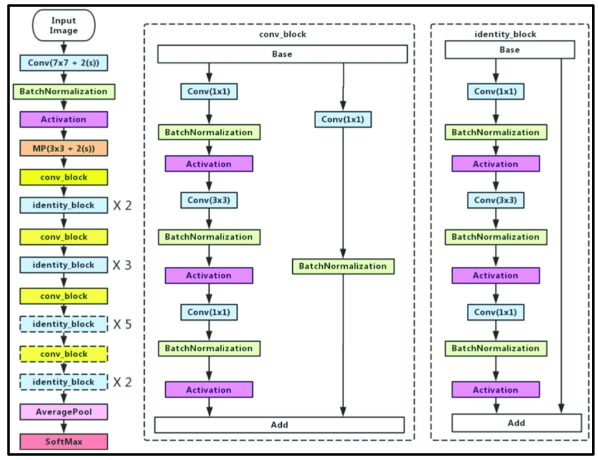


Fig. 4 The ResNet-50 architecture [7]

Training images are then scaled to 224*224 to be compatible with ResNet architecture. After training, testing images are resized also to 224*224. Figure (5) shows an example for the training process.

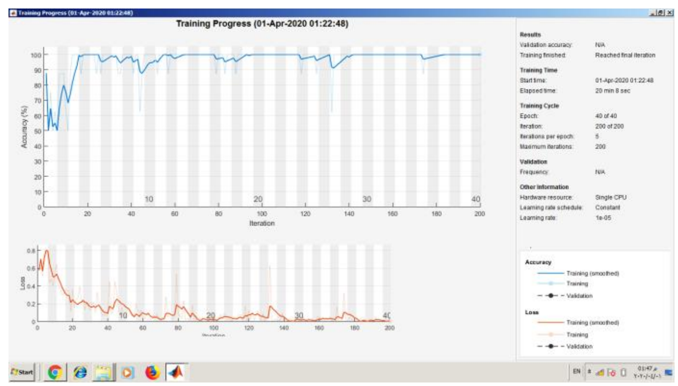


Fig. 5 An Example of The Training Process

IV. RESULTS

The confusion matrix gives false positive (FP), false negative (FN), true positive (TP), and true negative (TN) cases. False positive means that normal cases were misclassified and represented as infectious cases. True positive corresponds to the correctly detected COVID-19 cases. True negative means that normal cases were correctly classified as being non-infectious. The worst possibility is the false negative case which means that COVID-19 cases were misclassified as normal. Figure (6) shows the confusion matrix. It can be used to get sensitivity, precision, accuracy, specificity, and negative predictive value [8].

$$Sensitivity = \frac{TP}{TP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$Negative\ Predictive\ Value = \frac{TN}{TN+FN} \quad (4)$$

The suggested algorithm has given 96.2% sensitivity, 100% precision, 98% accuracy, 100% specificity, and 96% negative predictive value.

Results had shown that the accuracy of the proposed method is 98% which ensures that true results, either true positive or true negative, are fairly high. The high accuracy is a must in the COVID-19 diagnosis. Moreover, the sensitivity of 96.2% is acceptable as it guarantees low false negative results which constitute the major source of infection. The proposed method is suitable also for real-time applications. The processing time was about 0.56 seconds on a machine with Core i7 processor and 8 GB RAM. This makes the proposed method reliable for clinical application.

Two important performance measures were evaluated; the receiver operating characteristics (RoC) curve which could help physicians to select the operating region using FP and detection rate and the area under the curve (AUC). This area is important as it doesn't vary with scale. It measures how well predictions are ordered, regardless their absolute values. Moreover, AUC doesn't vary with classification threshold. Figure (7) gives the RoC curve. The AUC was calculated and found to be equal to 0.9888. Table (1) gives a short comparison with other deep learning methods.

TABLE (1)
COMPARISON OF THE PROPOSED DIAGNOSTIC METHOD AND OTHER DEEP LEARNING METHODS

Study	Number of Cases	Method Used	Accuracy
Ioannis et al. [9]	224	VGG-19	93.48%
Wang and Wong [10]	53	COVID-Net	92.4%
Sethy and Behra [11]	25	RESNET50 + SVM	95.38%
Hemdan et al. [12]	25	COVIDX-Net	90.0%
Proposed method	50	RESNET50	98%

Applying a t-test of hypothesis with 5% level of significance had shown that the proposed method had shown significant difference compared with other techniques. It had better performance which made it an accurate method for COVID-19 detection.

V. CONCLUSION

A deep convolutional neural network had been utilized to classify COVID-19 X-ray images in an accurate and simple manner. ResNet-50 had been adopted as it is the most common architecture used in biomedical imaging. The implemented system has shown great performance measures in terms of precision, sensitivity, accuracy, specificity, RoC, and AUC. Moreover, the algorithm can be easily modified to add extra images (normal and COVID-19) to improve performance. The proposed system introduces a great help to all nations to screen and diagnose COVID-19 as a faster alternative compared with conventional method that uses PCR.

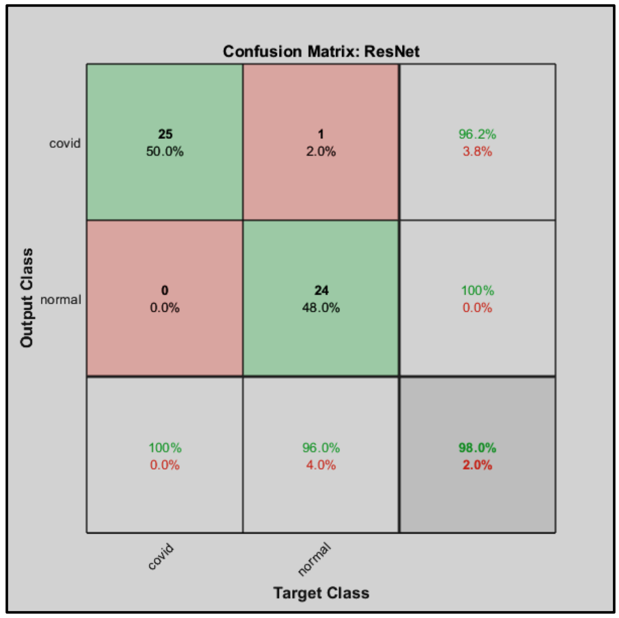


Fig. 6 The confusion matrix for the 2 classes

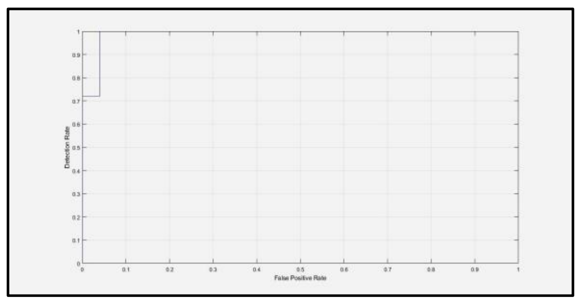


Fig. 7 The RoC curve

ACKNOWLEDGMENT

Thanks to Dr. Joseph Cohen, for making chest X-ray dataset available to researchers.

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