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Diagnosis of Covid-19 in X-ray Images Based on Convolutional Neural Network (CNN)

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Abstract

A number of studies focus on the early diagnosis of COVID-19 to reduce the spreading of this virus in the communities in order to support the health system and economy. This paper proposes a Convolutional Neural Network (CNN) model based on row X-ray chest images to detect the COVID-19 disease. In addition, an augmentation technique was employed on these images to increas the dataset and reduce the overfitting inside the CNN. This system bases on x-ray images of the chest. The proposed system contains three stages, the first stage is the pre-processing that starts by resizing the x-ray images into equal size (224 x 224), converting X-ray images into Grayscale images, and enhances the resulting image using Histogram Equalization(HE) technique. The second stage features extraction using CNN after applying augmentation on the dataset. The classification is the last stage for detecting the test sample only if is infected with Covid-19 or not, where the SoftMax function were used to classify patients. The results showed high accuracy in the classification process of the test images Furthermore, specificity, sensitivity, accuracy, and F1-score are used as criteria to estimate the classification efficiency of the proposed CNN model, where the accuracy of the model is 100% in the test dataset (220 X-ray images).

Key words:
Chest X-Ray (CXR), Convolutional Neural Network (CNN), COVID-19 (Coronavirus), Data Augment (DA), Histogram Equalization (HE).

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i. Introduction

Currently, coronavirus is considered a central problem because it critically affects the economy and worldwide health systems. The first claim of the virus (COVID-19) has been raised in Wuhan, China, in December 2019 [1]. Therefore, a standard symptomatic procedure of inverse transcription-polymerase chain reaction is accepted worldwide to diagnose or detect viral nucleic acid of suspected individuals.

The X-Ray of Chest or/and CT scan images technologies can be employed to COVID19 suspected individuals because the PCR test takes time compared to the spreading of the virus in the community. Moreover, time taken by RT-PCR test, false-positive errors, and shortage of test kits compared to coronavirus infected persons makes it inefficient. Usually, the Chest X-Ray (CXR) method is the best option because it helps the radiologists identify the chest pathology without introducing the patient to high CT scan radiation. [2-5]. As a result, an automatic detection method must be implemented as a rapid replacement diagnosis option to avoid COVID-19 from extending between people who use machine learning applications. Various AI applications in data processing have altered predictions by achieving human-level accuracy in several functions, like medical image analysis, due to deep learning, which includes such "Convolutional Neural Network (CNN)" [6] .As a result, CNN was employed in this paper since it eliminates the need for manual feature extraction in addition, weight sharing, and a local connection.These two characteristics significantly decreased the amount of parameters in the network, resulting in a reduction in training time[7].The major goal of this paper is to improve the accuracy of the deep learning model over current approaches by utilizing fewer parameters and therefore requiring less processing resources.

ii.Related Work

Hemdan and et al. in (2020) [8] utilized VGG19 and Dense-Net models to discover the COVID-19 based on X-ray images. The highest accuracy achieved was 80% in the VGG19 and 90% in the Dense-Net models for the classification.

Asmaa and et al. in (2020) [9] classified the COVID-19 based on chest X-ray images by adopting of DeTraC deep convolutional neural network with an accuracy of up to 95.12%.

Sahinbas and et al. in (2020) [10] employed VGG16, VGG19, ResNet, DenseNet, and InceptionV3 models based on X-ray images to detect the virus, their research shows that the accuracy approaches 80%, 60%, 50%, 60%, 60% respectively.

Khan et al. in (2020) [11] they used Xception CNN model, that is pre-trained on the ImageNet dataset. This model is trained on a dataset that is collected by the researchers from online available datasets. Their results are (89.6%) accuracy, (93.0%) precision, and (98.2%) recall for four classes of lung diseases. And for three classes they achieved (95.0%) accuracy.

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Basu and et al. in (2020) [12] Deep Learning for Screening COVID-19 using Chest X-Ray Images, was proposed a new concept called domain extension transfer learning (DETL), with a pre-trained deep convolutional neural network. The overall accuracy was measured as 90.13%.

iii.METHODOLOGY

The proposed system is divided into three stages, the first of which is image preprocessing which involve: resizing the x-ray images to a (224×224) pixel scale would improve processing efficiency, Also, transforming a x-ray image into a gray scale x-ray image would decrease processing time, Moreover, the Histogram Equalization technique that was used to enhance the contrast and show the features of the x-ray image, and Data Augmentation was applied to increase dataset and reduce the overfitting, which increase the accuracy of the proposed system. in the second stage, a Convolutional Neural Network (CNN) based on multi-Image augmentation technique, was used as a deep feature extraction technique The extracted feature will be the entrance to the classification stage. Third stage, classification for the diagnosis of Covid-19 infected cases, features of chest x-ray images are used to correctly classify the patients whether they refer to the infected state or not. According to the extracted attribute, classification is used to introduce diagnosing prediction (Covid-19 Positive, Covid-19 Negative).

A. Dataset

X-ray images were gathered for this study from Dr. Joseph Cohen's open-source GitHub repository with different type (jpeg, png, jpg) [13]. Lung X-ray/CT scans of main patients with acute respiratory distress syndrome (ARDS), COVID-19, “Middle East Respiratory Syndrome (MERS),” pneumonia, and “severe acute respiratory syndrome (SARS)” are included in this dataset. Since this study is focused to Covid-19, only Covid-19 images are selected besides the normal healthy lung images. the dataset contains 360 X-ray images (180 COVID-19 positive X-ray images and 180 COVID-19 negative X-ray images). The datasets are split into two categories: training data (250 X-ray) and testing data (110 X-ray). Data Augmentation technique was used on this dataset because of its small size, which increase the dataset. TABLE 1 shows the distribution of training and testing datasets after using augmentation technique.

TABLE.1 The distribution of training and validation datasets.

	COVID-19	Non-COVID-19	Total
Train set	250	250	500
Test set	110	110	220
Total	360	360	720

B. Preprocessing

Preprocessing is used to improve data images in order to avoid unwanted distortions or to improve some important image characteristics.

1. Image Enhancement

One of the most important phases in medical image discovery and analysis is image enhancement, which improves the quality and accuracy of images from a human perspective by removing noise and blurring, increasing contrast, and revealing image features. In this phase, the Histogram equalization (HE) technique is used to preprocess X-ray images. Using the Histogram Equalization (HE) approach, the data set's histogram may be improved. The histogram of the output image closely identifies a specific histogram and represents a consistent distribution of intensities since this approach expands the range of the image histogram. The HE method improves the look of an enhanced image by replacing each pixel with a new intensity value based on the previous intensity value using the Equation (1) [14]:

$$G_i = \left[\sum_{j=0}^{i} N_j\right]\left(\frac{\max\ intensity\ level}{number\ of\ pixels}\right) \qquad i = 0.1.\dots.L-1 \qquad (1)$$

Where G represent The histogram equalized image, and N number of pixel at intensity j.

2. Data Augmentation

The dataset given in Section (A) is insufficient since many machine learning algorithms, notably deep learning, require adequate data for the training and testing sample.

The data augmentation (DA) approach was utilized in this paper to overcome the problem of a little dataset being available, which was hurting the performance of the suggested CNN. DA is an effective and significant method for training any algorithm that deals with media (images, audio, video), as it is very useful to increase media data to enhance the efficiency of any algorithm. In this study, two types of DA methods (Flip horizontal and Rotation) will be used to reduce the issue of overfitting exposure and improve the efficiency of the proposed system for precise assessment, and the network will be able to generalize to hidden data [15].

In FIGURE 1, the observed impact of two common DA techniques on the original dataset has been presented.

1. **Flip horizontal:** The X-ray images will be horizontally reversed by setting the Boolean expression in the parameter horizontal flip to true. (as shown in FIGURE 1 (b))
2. **Rotation range:** The degree angle can be calculated and applied to a large dataset. In this approach, a slight angle (15 degrees) is chosen such that the rotation range variable has little effect on the form of the X-ray image. (as shown in FIGURE 1(c))

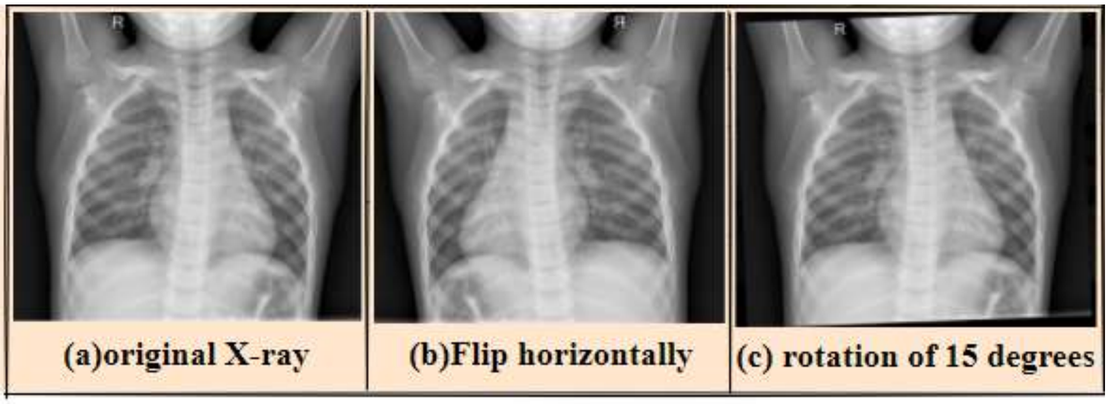

FIGURE 1. X-ray images of COVID-19 for two DA techniques: (a) The Original of X-ray, (b) flip horizontally, (c) rotation of 15 degrees.

C. Feature Extraction

For features extraction, CNNs are extensively used for feature extraction of X-ray image datasets in order to detect COVID-19. The study affirms that CNN-based networks can precisely identify COVID-19 disease. The proposed CNN model consists of 6 layers. The first layer of the model is convolutional layer (Conv2D). At the same time, the max-pooling layer is chosen to be the second layer of the model. However, the third layer is another convolutional layer with different filters than the first layer. The 4th layer is also considered another max-pooling layer and identical to layer second in the model. The flattening layer is assigned to be the 5th layer in the model, and Finally, the 6th layer is considered the fully connected layer (Dense layer).

The proposed system use images with dimensions of is (224, 224, 1) as input to the CNN model. In all Convolutional layers, a kernel size (3, 3) and strides (2, 2), however, the padding equals same. At the first convolutional layer, 32 filters have been used to learn from input, and the 2nd layer of convolutional uses 64 filters. The max-pooling is used after each convolutional layer. Moreover, the output images of the max-pooling layers (4th layer) are mapped into vectors by the flattening layer. These vectors are employed as an input of the dense layer. To update weights, An Adam optimizer with a learning rate of 0.001, and a sparse categorical cross-entropy loss function have been utilized. FIGURE 2 is a representation of the CNN architecture.

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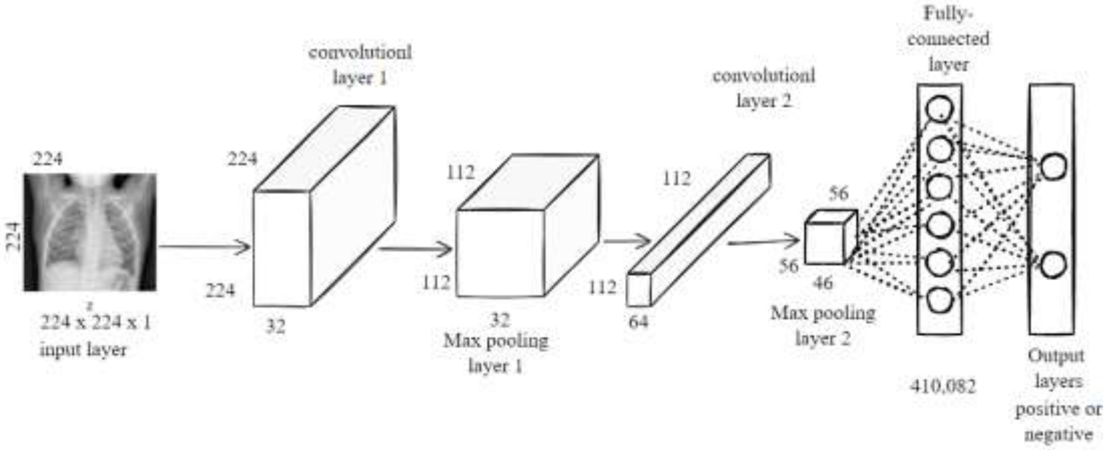


FIGURE 2. CNN model architecture.

The convolutional layer obtains a function map by computing the matrix's multiplication (the kernel filter and the receptive domain). Behind every convolutional layer is inserted an activation function (such as Rectified Linear Unit (ReLU)). It is a Nonlinear function. It substitutes all negative image pixels in the activation map by zero (as shown in FIGURE 3) [16].

$$\mathbf{R(z) = max\ (0, z)} \qquad \mathbf{(2)}$$

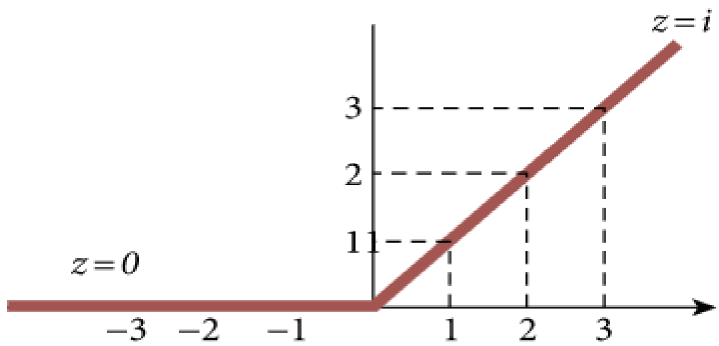


FIGURE 3. The ReLU function demonstration.

In this paper, the technique of downsampling a collection of neighboring pixels into a single pixel is known as the pooling layer (also known as subsampling or downsampling). After the convolution layer, the pooling layer was used to decrease the size of the image activation maps. pooling layer have various types the following is common Max and average, etc. as illustrates in FIGURE 4, The Max-pooling chooses a spatial area (sub-region) such as a 2x2 window and chooses the largest value from each window's corrected activation maps. Downsampling reduced the size of the activation maps image from 4 × 4 to 2 x 2. On the other hand, average pooling gives the average value for each part of the region. Overfitting may be solved by pooling layers, and Max Pool has proved to be the most effective [17].

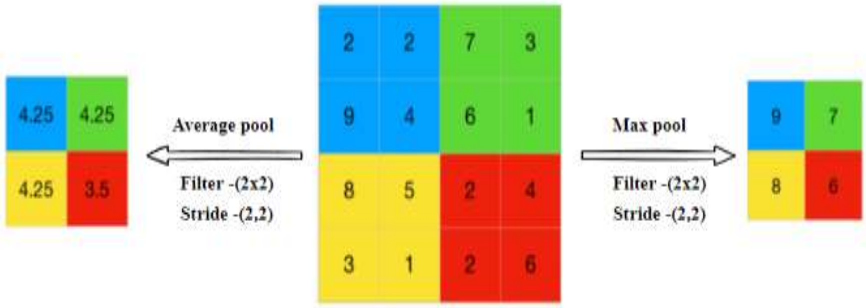


FIGURE 4. shows Max Pool with 2×2 kernel size and stride 2.

The trained CNN is then used to improve the extraction of X-ray images features. This stage provides the general characteristics of the X-ray images.

D. Classification

Features of chest X-ray images are utilized to accurately identify patients whether they are infected or not for the diagnosis of Covid-19 contaminated cases. Classification is utilized to introduce diagnostic prediction based on the retrieved characteristic (COVID-19, Non-COVID-19). After the Flatten layer, and there is one Fully Connected layer of the dense architecture, SoftMax was utilized as the activation function for the dense layer for classification. Because softmax ranges are between 0 and 1 and have the number 1 if all the characteristics are applied using the following formula, the SoftMax function is frequently used to assess probabilities and perform multiclass classifications.

$$\boldsymbol{SoftMax}(\mathbf{X}_i) = \mathbf{exp}(\mathbf{X}_i) \sum_{j=0}^{n} \mathbf{exp}(\mathbf{X}_j) \qquad \textbf{(3)}$$

Where j denotes the number of classes and Xi is the production associated with class [15].

iv. Results and Evaluations

To evaluate the model's performance, many criteria are used [18]:

1. The accuracy checks the number of correctly classified instances, whether positive or negative instances.

   Accuracy (Acc) = “T P + T N / T P + T N + F P + FN”. (4)

2. Sensitivity is the rate at which positive samples are identified Correctly.

   Sensitivity (Sen) = “T P / T P + FN”. (5)

3. Testing the proper true positive from the anticipated positives determines the accuracy of the performance of the model.

   Precision (Pre) = (TP / TP + FP). (6)

4. Specificity is the percentage of identification of negative examples Correctly.

   Specificity (Spe) = (T N / T N + FP). (7)

5. For computing a balanced mean output, the F1-score displays a combination of accuracy and sensitivity.

   F1-score = 2*((Precision * Sensitivity)/ (Precision + Sensitivity)). (8)

The parameters of the given model and test x-ray images are:

True Positive (TP) is the positive states that are correctly labeled as positive states. False Positive (FP) denotes the negative states that are incorrectly labeled as positive states. True Negative (TN) represents the right classification of negative diagnosis. False Negative (FN) indicates the positive cases that are incorrectly classified as negative.

As previously stated, the model was evaluated on the dataset (X-ray): (500) of the datasets are used in the training phase, while the remaining (220) are used in the testing phase. Firstly, each X-ray is scaled to a resolution of (224 x 224) pixels. The training sample was employed to train the model (i.e., adjust the weights and biases), the testing sample was used to enhance the hyperparameters to get the best performance for model measures, and the validation sample was used to assess the final model independently. FIGURE 5, shows the confusion matrix of features retrieved using CNN.

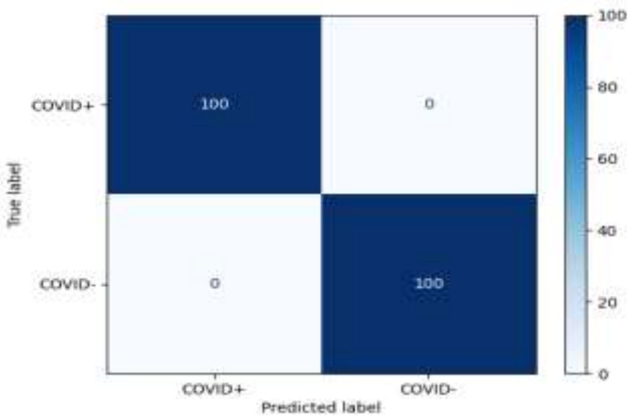
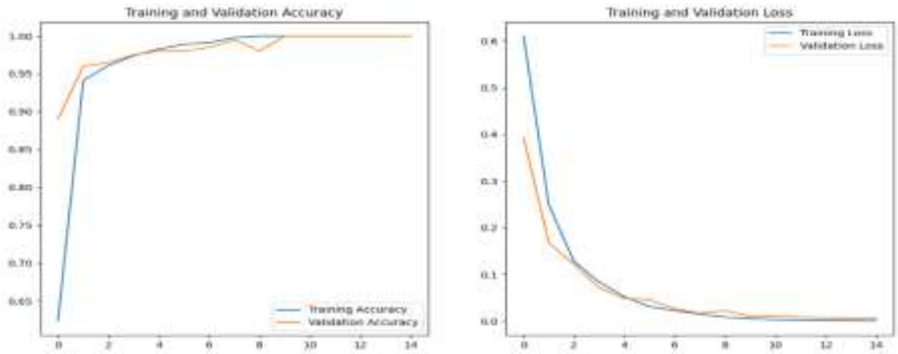


FIGURE 5: The test sample confusion matrix

From the confusion matrix of the test sample, the highest accuracy achieved is 100%, specificity is 100%, sensitivity is 100%, F1-score 100%, precision is 100%.



(a) (b)

FIGURE 6: (a) the accuracy of train and validation on Augmented X-ray (b) the loss of train and validation on the Augmented X-ray image.

Because the loss of training and validation decline to the point of equilibrium, and the difference between the two-loss values is slight, the learning curves (loss of training and validation) plot (Figure 6 (b)) demonstrates the excellent fit condition. Overfitting is an issue that might arise from repeated training of a good fit. The system was checked as shown in the table 4 and it was found that the system is 100% accurate and that these images that was used are real images taken from patients who were actually infected.

TABLE 4. Test the proposed system.

images	Label	Result	Predicted Correctly
	Negative	Negative	Yes
	Positive	Positive	Yes
	Negative	Negative	Yes
	Positive	Positive	Yes
	Positive	Positive	Yes

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TABLE 3, contains a comparison of various deep learning-based Covid-19 diagnostic methods with the proposed system performance that uses the same dataset. It should be noticed that the proposed system accomplished higher performance than the other existing systems.

The main reasons for obtaining these achieved results:

A. The Convolutional Neural Network architecture (FIGURE 2) was designed with the Max Pooling layer after each convolutiona layer and big kernels in the early layers to collect more important information.
B. The overfitting problem, was prevented through the use of data augmentation technology, which is the problem that most CNN models suffer.
C. The number of parameters obtained in the model reached (410,082), which is not much compared to the number of parameters of other literature models.

TABLE 3. Comparison of the proposed method with other methods.

Study	Method used	Accuracy	Precision	Recall	F-Score	Specificity
Sahinbas et al.[10]	VGG16	80%	80%	80%	80%	___
Hemdan et al.[8]	VGG19	90%	83%	100%	91%	___
Monshi et al. [19]	CovidXrayNet	95.82%	96.93%	95.43%	96.16%	___
Ozturk et al.[20]	DarkCovidNet	98.08%	98.03%	95.13%	96.51%	95.3%
Proposed System	CNN	100%	100%	100%	100%	100%

V. Conclusion

In this paper, we proposed an CNN model to classify the X-ray images into Covid19-positive and Covid19-negative. The proposed system was used the preprocessing on the X- ray images, where images was resized to (224 x 224) which benefit to decrease the computational cost and improve processing efficiency. In our system, we utilized the Histogram equalization method to effectively increases the contrast of the image, eliminates noise and blurring, to sharpen the features, and showing the details of the image. Moreover, converting x-ray images into grayscale images which decrease processing time. Also, we employed the data augmentation to reduce the overfitting and increase the efficiency of the classification. Hence, after the training of our model under these processinges, we got 100% accuracy of ability to predict who is infected by COVID-19 by using X-ray image.

Conflict of interests.

There are non-conflicts of interest.

References.

[1]. Mackenzie, J. S., & Smith, D. W. (2020). COVID-19: a novel zoonotic disease caused by a coronavirus from China: what we know and what we don't. Microbiology Australia, 41(1), 45-50.

[2]. Ng, M. Y., Lee, E. Y., Yang, J., Yang, F., Li, X., Wang, H., ... & Kuo, M. D. (2020). Imaging profile of the COVID-19 infection: radiologic findings and literature review. Radiology: Cardiothoracic Imaging, 2(1), e200034.

[3]. Liu, H., Liu, F., Li, J., Zhang, T., Wang, D., & Lan, W. (2020). Clinical and CT imaging features of the COVID-19 pneumonia: Focus on pregnant women and children. Journal of infection, 80(5), e7-e13.

[4]. Chung, M., Bernheim, A., Mei, X., Zhang, N., Huang, M., Zeng, X., ... & Shan, H. (2020). CT imaging features of 2019 novel coronavirus (2019-nCoV). Radiology, 295(1), 202-207.

[5]. Chen Nanshan, Zhou Min, Dong Xuan, Qu Jieming, Gong Fengyun, Han Yang, Qiu Yang, Wang Jingli, Liu Ying, Yuan Wei. Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in wuhan, China: a descriptive study. Lancet. 2020;395(10223):507–513. [PMC free article] [PubMed] [Google Scholar].

[6]. Xu, X., Jiang, X., Ma, C., Du, P., Li, X., Lv, S., ... & Li, L. (2020). A deep learning system to screen novel coronavirus disease 2019 pneumonia. Engineering, 6(10), 1122-1129.

[7]. Amyar, A., Modzelewski, R., Li, H., & Ruan, S. (2020). Multi-task deep learning based CT imaging analysis for COVID-19 pneumonia: Classification and segmentation. Computers in Biology and Medicine, 126, 104037.

[8]. Hemdan, E. E. D., Shouman, M. A., & Karar, M. E. (2020). Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images. arXiv preprint arXiv:2003.11055.

[9]. Abbas, A., Abdelsamea, M. M., & Gaber, M. M. (2021). Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. Applied Intelligence, 51(2), 854-864.

[10]. Sahinbas, K., & Catak, F. O. (2021). Transfer learning-based convolutional neural network for COVID-19 detection with X-ray images In Data Science for COVID-19 (pp. 451-466). Academic Press.

[11]. Khan AI, Shah JL, Bhat MM (2020) Coronet: a deep neural network for detection and diagnosis of COVID-19 from chest X-ray images. Comput Methods Programs Biomed 196:105581.

[12]. Basu, S., Mitra, S., & Saha, N. (2020, December). Deep learning for screening covid-19 using chest x-ray images. In *2020 IEEE Symposium Series on Computational Intelligence (SSCI)* (pp. 2521-2527). IEEE.

[13]. Cohen, J. P., Morrison, P., Dao, L., Roth, K., Duong, T. Q., & Ghassemi, M. (2020). Covid-19 image data collection: Prospective predictions are the future. *arXiv preprint arXiv:2006.11988*.

[14]. Kaur, M., Kaur, J., & Kaur, J. (2011). Survey of contrast enhancement techniques based on histogram equalization. International Journal of Advanced Computer Science and Applications, 2(7).

[15]. Taylor, L., & Nitschke, G. (2018, November). Improving deep learning with generic data augmentation. In 2018 IEEE Symposium Series on Computational Intelligence (SSCI) (pp. 1542-1547). IEEE.

[16]. Singh, D., Kumar, V., & Kaur, M. (2020). Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks. European Journal of Clinical Microbiology & Infectious Diseases, 39(7), 1379-1389.

[17]. Gong, W., Chen, H., Zhang, Z., Zhang, M., Wang, R., Guan, C., & Wang, Q. (2019). A novel deep learning method for intelligent fault diagnosis of rotating machinery based on improved CNN-SVM and multichannel data fusion. *Sensors*, *19*(7), 1693.

[18]. Narin, A., Kaya, C., & Pamuk, Z. (2021). Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. Pattern Analysis and Applications, 1-14.

[19]. Monshi, M. M. A., Poon, J., Chung, V., & Monshi, F. M. (2021). CovidXrayNet: Optimizing data augmentation and CNN hyperparameters for improved COVID-19 detection from CXR. *Computers in biology and medicine*, *133*, 104375 , doi: 10.1016/j.compbiomed.2021.104375.

[20]. Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Acharya, U. R. (2020). Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Computers in biology and medicine*, *121*, 103792 , doi: 10.1016/j.compbiomed.2020.103792.

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تشخيص Covid-19 في صور الأشعة السينية بناءً على الشبكة العصبية التلافيفية (CNN)

الخلاصة

يركز عدد من الدراسات على التشخيص المبكر لـ COVID-19 للحد من انتشار هذا الفيروس في المجتمعات من أجل دعم النظام الصحي والاقتصاد. تقترح هذه الورقة نموذج الشبكة العصبية التلافيفية (CNN) بناءً على صور الصدر بالأشعة السينية للكشف عن مرض COVID-19. بالإضافة إلى ذلك ، تم استخدام تقنية تعزيز البيانات (augmentation) على هذه الصور لزيادة مجموعة البيانات وتقليل فرط التدريب داخل شبكه CNN. يعتمد هذا النظام على صور الأشعة السينية للصدر. يحتوي النظام المقترح على ثلاث مراحل ، المرحلة الأولى هي المعالجة المسبقة التي تبدأ بتغيير حجم صور الأشعة السينية إلى أحجام متساوية (224 × 224) ، وتحويل صور الأشعة السينية إلى صور ذات تدرجات رمادية ، ومن ثم عمليه تحسين الصورة الناتجة باستخدام تقنية معادلة الرسم البياني (Histogram Equalization). المرحلة الثانية استخراج الميزات باستخدام CNN بعد تطبيق تقنيه تعزيز البيانات على مجموعة البيانات. التصنيف هو المرحلة الأخيرة للكشف عن عينة الاختبار فقط إذا كانت مصابة بـ Covid-19 أم لا، حيث تم استخدام وظيفة SoftMax لتصنيف المرضى. أظهرت النتائج دقة عالية في عملية تصنيف صور الاختبار علاوة على ذلك، تم استخدام الخصوصية والحساسية والدقة ودرجة F1 كمعايير لتقدير كفاءة التصنيف لنموذج CNN المقترح ، حيث تبلغ دقة النموذج 100٪ في مجموعة بيانات الاختبار (220 صورة بالأشعة السينية).

الكلمات الدالة: اشعه الصدر السينية ، الشبكة العصبية التلافيفية، فايروس كورونا، تعزيز البيانات، تسوية المدرج التكراري