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A unique deep-learning-based model with chest X-ray image for diagnosing COVID-19

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ABSTRACT

Later innovative advancements cleared the way for deep learning-based methods to be used in the therapeutic field due to its exactness for the detection and localization of different illnesses. Recently, the coronavirus widespread has put a parcel of weight on the health framework all around the world. Reverse transcription- polymerase chain reaction test and medical envisioning are both possible and effective techniques to determine the coronavirus infection. Since coronavirus is highly infection and reverse transcription- polymerase chain reaction is time-consuming, determination utilizing a chest X-ray to early diagnosing the infection is considered secure in different situations. A preprocessing step is done first to balance classes inside the dataset and increase the training data. A deep learning-based method is proposed in this study to determine some human lung infections and classify coronavirus from other non-coronavirus diseases accordingly. The proposed model is used for multi-class classification which is more complicated than binary classification especially in the medical image due to the inter classes' large similarity. The proposed procedure effectively classifies four classes that incorporate coronavirus, lung opacity, normal lung, and viral pneumonia with an accuracy of 97.5%. The proposed strategy appears excellent in terms of accuracy when compared with later strategies.

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1. INTRODUCTION

The coronavirus infection, commonly known as COVID-19, widespread started firstly in Wuhan, China, where the first official case was recorded, in December 2019, and got to be a serious public health issue around the world [1], [2]. It started to spread more and more all over the world, till a pandemic term was declared by the World Health Organization (WHO) in March 2020. Right today, the genetic test reverse transcription polymerase chain reaction, commonly known as (RT-PCR), is the major test to diagnose coronavirus infection correctly [3]. On the other hand, the PCR test is considered a costly and time-consuming test. So, neither all people able to perform it nor all health cases can wait for it. Accordingly, the radiography scanning image, such as a chest X-ray, is a good choice to diagnose coronavirus infection which is much faster and more economical than the RT-PCR test, and it is available nearly in every hospital and clinic [4]-[10]. The only detected challenge in chest X-ray based detection of coronavirus infection is the absence of radiologist experts at specific times due to their preoccupation with the huge number of injuries. Computer vision in medical diagnosis is considered a good alternative solution for that purpose to reduce the medical staff workload and increase diagnosing reliability at the same time [11], [12]. Accordingly, computer-aided diagnosis (CAD) of human lung injuries can be detected efficiently using deep learning techniques. Using deep learning techniques in a medical field can significantly help medical staff to early diagnose the disease efficiently and avoid human errors. Deep learning has recently emerged as one of the strategies for image processing problems. It has been discovered to have major effects in a variety of disciplines, including medicine, gesture recognition, agriculture, and remote sensing. It is utilized in the medical field for the diagnosing of many diseases, such as skin diseases, various forms of cancer, and ulcers [13].

Recently, using deep learning techniques in the medical field for diagnosing numerous diseases is a state-of-the-art strategy followed today. Since COVID-19 is the latest disease that has emerged at present and has spread widely and increasingly and more medical staff need to diagnose the disease early to take the necessary measures and save the largest possible number of virus outbreaks. Most recent studies at present have directed to take advantage of the deep learning capabilities early detect the virus infection using chest X-rays [14]-[18] or computed tomography scan, CT-scan, of the chest area [19]-[21].

Asif and Wenhui [22] Utilized deep learning strategies in the medical field and proposed a CNN-based inception V3 pre-trained model for classifying human lung disease from chest X-ray as normal, viral, and COVID-19 cases. The used dataset is a composition from different sources such as the GitHub repository, SIRM dataset, and COVID-19 radiography dataset. Based on the chest X-ray, A. In Narin *et al.* [23], the authors aimed to detect COVID-19 using five pre-trained CNN-based models. These models named Inception-ResNetV2, InceptionV3, ResNet152, ResNet101, and ResNet50. They used binary classification with three different datasets of four classes, pre-trained ResNet50 model returned the best binary classification results among other pre-trained models for the used datasets which are acquired from Kaggle, GitHub repository, and other normal lungs chest X-ray datasets with the infected ones acquired from different sources, the obtained accuracy is about 96 %. In the work proposed by Das *et al.* [24], a deep learning-based method was used to detect COVID-19 infection from chest X-ray images. They used InceptionV3, Resnet50V2, and DenseNet201 models. They used a weighted average technique to combine the independently trained models individually. The used collected chest X-ray images from different publicly available open-source images of normal and COVID-19 infection chest X-ray, the binary classification accuracy obtained using the proposed technique with the proposed dataset is about 91.62%. Mahesh *et al.* [25] Developed a binary classification deep learning model to classify human lungs from the chest X-ray image as normal or infected with COVID-19. They utilize the features learned from a pre-trained model to classify the images as normal cases or infected with COVID-19. They used a composite dataset from the GitHub repository for the COVID-19 images and Kaggle for the normal images with the developed model to obtain about 98 % validation accuracy result. In Khan *et al.* [26], the authors depended on a deep-learning-based method with the help of chest X-ray to classify COVID-19 using pre-trained models. The pre-trained named MobileNetV2, NasNetMobibe, and EfficienNetB1 are used and fine-tuned in this study. As more as, hyper-parameters are also fine-tuned to improve the fine-tuned model's performance. EfficientNetB1 outperforms best results among other models for multi-class classification of four classes dataset, the composition of multiple sub-dataset, acquired from Kaggle with 96.13% accuracy.

The unusual COVID-19 begins to spread in Wuhan, China in December 2019 and has since spread to several other nations across the world. Early diagnosis of this disease could be extremely helpful in limiting its spread. One of the most important challenges is the rare number of human experts compared with a sudden huge number of COVID-19 infection states, on the other hand, a costly and time-consuming RT-PCR test is another challenge. Multi-class lung disease classification is another challenge that faces the learning systems due to the large similarities among medical image classes, especially X-ray imaging. Accordingly, the main contribution of this study is:

a) To address the costly and time-consuming RT-PCR test challenge with a faster, more economical, and high-accuracy replacement test using medical images called X-ray imaging for the chest region.
b) Developing an artificial intelligence method based on deep learning used as an assistance for the radiologist experts for detecting COVID-19 infections to reduce the number of human expert requirements.
c) Classifying four types of lung diseases, multi-class, rather than the binary classification of COVID-19 positive/negative at a time when the multi-class classification may have weak capabilities yet and need further improvements. Feature extraction and classification are done using a novel architecture developed for this purpose in an end-to-end deep learning technique that eliminates the need for traditional hand-crafted techniques. It has improved its performance and superiority over other models.
d) The imbalanced classes challenge was also addressed by generating a new version of the already existing image via geometric augmentation for the low data classes as a pre-processing step before augmenting the overall trained image features.

The proposed method provides about 97.5% accuracy for the clinical diagnosing of lung diseases as an assistance for the human experts and early diagnosing of the disease using chest X-ray images with a multi-class classification method. The remainder of this paper is organized as follows: Section 2 describes the proposed model architecture and algorithm in detail. Section 3 describes the data acquisition and the preprocessing of the dataset images to address unbalanced classes and generate a final dataset. As more as feature extraction using the proposed architecture and classification method are also clarified in the same section. Section 4 discusses the results obtained by the proposed method using curves and a confusion matrix. Section 5 concludes the paper.

2. THE PROPOSED ARCHITECTURE AND ALGORITHM

The proposed architecture, which automatically augments features from dataset images, was the best one among the numerous architecture experiments. As more as, all images are resized into 100 pixels for each width and height before training. The classification process diagnosing the lung disease according to the predefined labels of the trained data. Two dense layers are completely connected layers with sizes of 128 and 4 (number of classes), respectively. The softmax function is utilized to activate the last fully connected layer, and the optimizer used in this study is Adam. After the first fully connected layer, the dropout (0.5) layer is used to generalize the model and avoid overfitting. The proposed architecture model is discussed briefly in Table 1 and visualized in Figure 1 respectively. The algorithm of the overall proposed method is clarified in Algorithm 1 step by step.

Table 1. The architecture of the proposed model

Layer	Layer Information	Output Image Shape
Convolution 2D	No.Of filters 32, filter size (3,3)	(100, 100, 32)
Activation	ReLU	(100, 100, 32)
Batch Normalization	Axis=-1	(100, 100, 32)
Max Pooling 2D	Pool size (2,2)	(50, 50, 32)
Convolution 2D	No.Of filters 64, filter size (3,3)	(50, 50, 64)
Activation	ReLU	(50, 50, 64)
Batch Normalization	Axis=-1	(50, 50, 64)
Max Pooling 2D	Pool size (2,2)	(25, 25, 64)
Convolution 2D	No.Of filters 128, filter size (3,3)	(25, 25, 128)
Activation	ReLU	(25, 25, 128)
Batch Normalization	Axis=-1	(25, 25, 128)
Max Pooling 2D	Pool size (2,2)	(12, 12, 128)
Convolution 2D	No.Of filters 256, filter size (3,3)	(12, 12, 256)
Activation	ReLU	(12, 12, 256)
Batch Normalization	Axis=-1	(12, 12, 256)
Max Pooling 2D	Pool size (2,2)	(6, 6, 256)
Convolution 2D	No.Of filters 512, filter size (3,3)	(6, 6, 512)
Activation	ReLU	(6, 6, 512)
Batch Normalization	Axis=-1	(6, 6, 512)
Max Pooling 2D	Pool size (2,2)	(3, 3, 512)
Flatten	/	2048
Dense	128	128
Activation	ReLU	128
Batch Normalization	Axis=-1	128
Dropout	0.5	128
Dense	Number of classes	Number of classes
Activation	Softmax	Number of classes

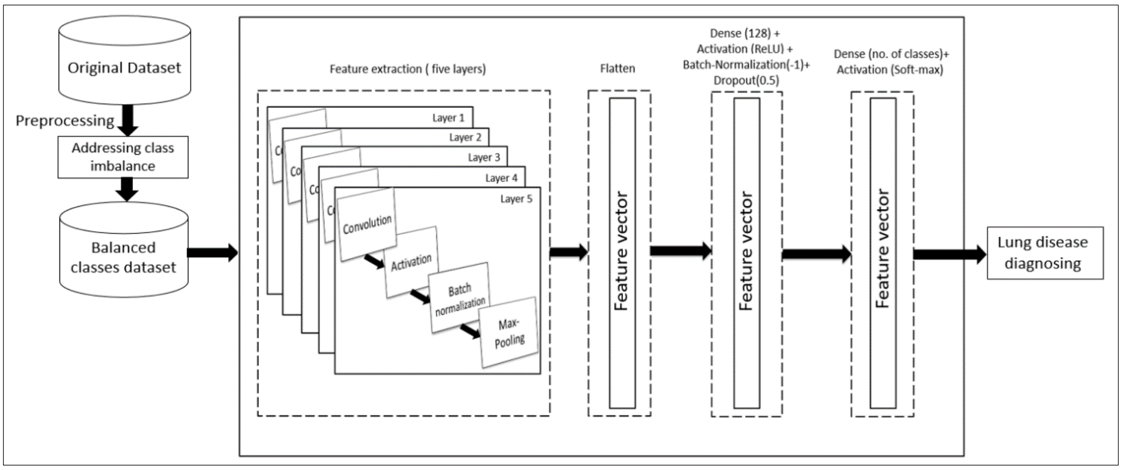


Figure 1. The architecture of the proposed model's visualization

Algorithm 1: The proposed method algorithm

```
// Pre-processing step (data augmentation and class balancing)
For all classes of the original dataset
        Compute the number of data inside each
        Addresses the imbalanced classes issue (Data augmentation)
        Divide into subgroups for training, validation, and testing with 70, 20, and 10
percent respectively
End For

// Training the proposed model
For all training part classes (70 percent of original dataset)
        For all images inside the class
       Train the images of all classes using the proposed model structure
       Save the model weights of the trained data
        End For
End For

// Testing the proposed model
Match specific unseen image weights with the augmented model weights.
Obtain the prediction probability results with all classes
Compare the obtained prediction probability of all classes
Select the largest probability as a system decision for the lung infection diagnosing

// Evaluating the proposed model
For all testing part classes (10 percent of the original dataset)
        For all unseen images inside the class
       Match specific unseen image weights with the augmented model weights.
       Obtain the prediction probability results with all classes
       Compare the obtained prediction probability of all classes
       Select the largest probability as a system decision for the lung infection
       diagnosing
       Check prediction correctness (actual prediction and system prediction)
       If actual prediction equal to system prediction
               Increase the correct decision counter
       End If
        End For
        Compute system accuracy by dividing the number of correct decision images by the
overall unseen images
End For
```

3. METHOD

The proposed method follows two main steps which are data augmentation as a preprocessing step and feature extraction and classification using the proposed model architecture. Before the two main steps are done, data collection must be viewed briefly to generate a general view of the proposed method's original dataset sources and its classes. The overall proposed method steps are shown briefly one by one in the following sub-sections.

3.1. Data collection

The dataset utilized in the proposed technique's training and evaluation is publicly available on Kaggle. COVID-19, lung opacity, normal lung, and viral pneumonia are all part of the mentioned dataset, which is made up of various sub-datasets with four separate classes. It's crucial to go through the composition of the used dataset in-depth because it's made up of multiple datasets. Each class is made up of sub-datasets that have been merged [27], [28]. Table 2 also shows how the dataset composition was put together.

Table 2. The dataset’s composition [27], [28]

No.	Data composition	BIMCV-COVID19+ [29]	German medical school [30]	SIRM, GitHub, Kaggle, and Twitter [31]-[34]	GitHub [35]	RSNA [36]	Kaggle [37]	Total
1	COVID-19	2473	183	560	400			3616
2	Lung opacity					6012		6012
3	Normal					8851	1341	10,192
4	Pneumonia							1345

3.2. Data preprocessing

A multiclass classification technique for chest X-rays goal is to find COVID-19 infections from multiple lung diseases infections that are correctly classified each one using the same method. Although there is a substantial quantity of studies on the binary classification of COVID-19 in the literature, finding information on the multiclass classification of COVID-19 infection is still a significant challenge due to the large similarities among inter-classes. On the other hand, multi-class datasets availability and imbalanced classes, if found, are other major challenges. The proposed method aimed to diagnose the COVID-19 infection in the human lungs and some other lung diseases in multi-class classification using a deep learning technique based on a novel developed convolution neural network model architecture. The significant challenge that faces the deep learning-based models is the class imbalance dataset. To overcome the previous challenge, the proposed technique followed a pre-processing step for augmenting a new version of the already existing images in the low data classes, to be somewhat close to the large data classes. The geometric augmentations used with the low data classes are vertical flipping (mirroring) and resizing (zooming up) the images. The data augmentations applied to each class of the dataset are clarified in Table 3.

Table 3. Type of augmentation to balance the dataset's classes

Classes	Number of the original items	Augmentation	Augmentation type
COVID-19	3616	Yes	Vertical flip
Lung opacity	6012	Yes	Vertical flip
Normal	10192	No	/
Viral Pneumonia	1345	Yes	Vertical flip + Resize

3.3. Feature extraction and classification

Since an unbalanced dataset can cause model training to be biased towards one or more classes, the preprocessing step addressed the class imbalanced issue using the data augmentation method. After this processing, the final dataset is completed and the next step comes to play. The dataset is then divided into three subgroups with 70, 20, and 10 percent of the overall size for training, validation, and testing respectively. The feature extraction is done in an end-to-end process using deep learning with a five-layer convolution neural networks model defined in the previous section Table 1 and Figure 1 with the training part of the dataset. The proposed model architecture consists of five blocks, each one with the same layers inside which are convolution (2D), Activation (ReLU activation function), Batch Normalization (Axis= -1), and pooling (Max Pooling). The batch normalization layer is also used to normalize the output of preceding layers. The batch normalization layer not only speeds up the convergence process but also improves accuracy. Finally, the classification process is done using the convolution neural networks, softmax activation function in the last layer with the number of classes, four classes.

4. RESULTS AND DISCUSSION

The techniques implementation used in this study is done using Python development environment, 3.5 version, and PyCharm 2018 IDE. The system settings used are Windows 10 with 64-bit. As more as, Intel with Core i7 processor manufacturer running at 2.00 GHz used with 16 GB of RAM. NVIDIA GEFORCE is also compatible with the proposed system architecture. According to the proposed technique that depends on CNN, the unseen images compared with the weights of the CNN model trained on the training part of the dataset images to achieve lung infection status and type of this infection. The diagnosing results achieved for the sample query image are shown in Figure 2, where Figures 2(a)-(d) are samples from the used dataset with COVID, Normal, Lung Opacity, and Viral Pneumonia cases respectively, and all are predicted and diagnosed correctly using the proposed system with accuracy percents about 99.83%, 99.99%, 100.00%, and 99.9%.

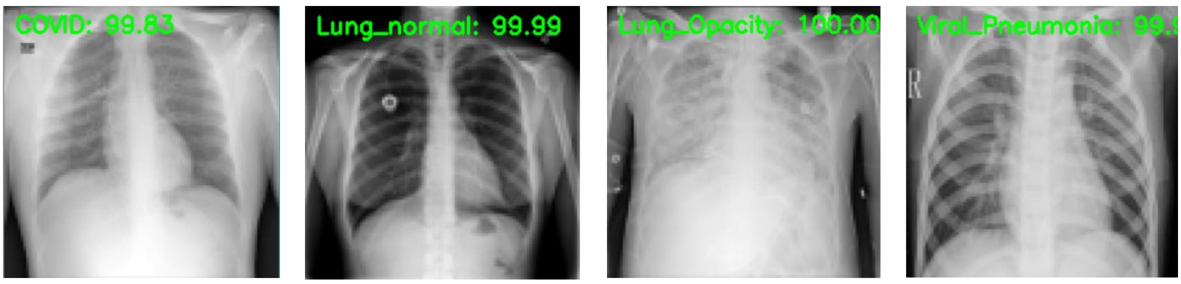
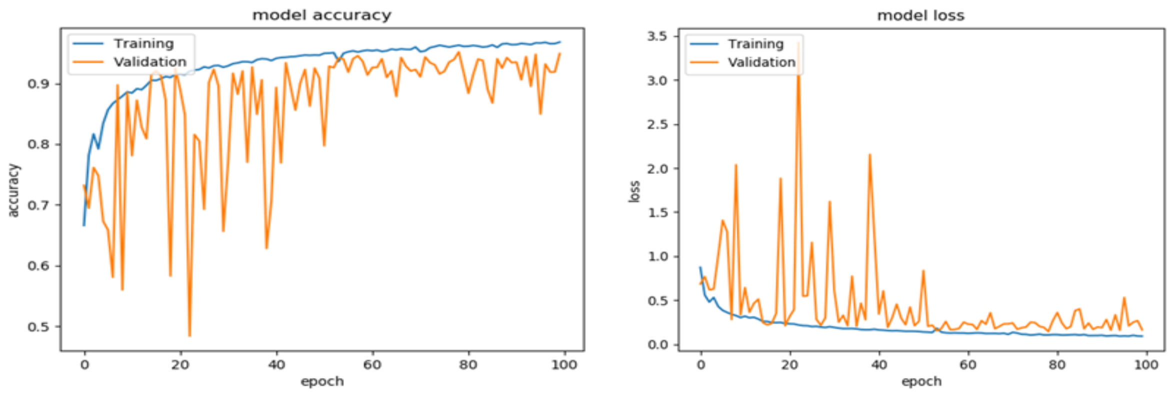


Figure 2. The result of lung infection diagnosing with diagnosing probability using the proposed model; (a) COVID, (b) Normal, (c) Lung Opacity, and (d) Viral Pneumonia

The accuracy result of multi-class classification obtained from the proposed model on the pre-defined dataset with four classes is about 97.5%. The resulted accuracy and loss curve achieved from training the model on the training part of the databases plot presents in Figure 3, where Figure 3(a) represents the accuracy curve and Figure 3(b) represents the loss curve. To evaluate the system, comparing each unseen digital radiographic image weight with the prediction weights that resulted from training the system using the proposed model. Figure 4 visualizes the confusion matrix of the proposed model. As more as, the performance summary of the related works published in the literature, pre-described works in section 1, and the proposed method are present in Table 4.



(a) (b)

Figure 3. Training/validation accuracy and loss curve of the proposed model (a) training/validation accuracy curve and (b) training/validation loss curve

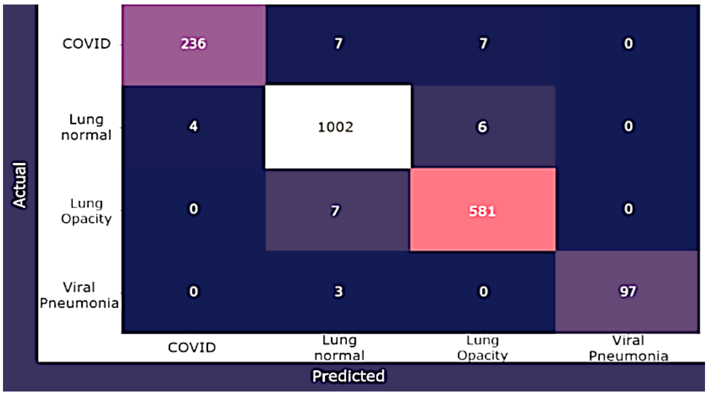


Figure 4. Confusion matrix of the proposed model on the proposed dataset evaluation

Table 4. The proposed method and related work studies summarization

Reference	Year	Method	Classifier	Accuracy
[22]	2020	Deep learning	Multi-class (three)	96 %
[23]	2021	Deep learning	Binary (two)	Database1 = 96.1% Database2 = 99.5% Database3 = 99.7%
[24]	2021	Deep learning	Binary (two)	91.62 %
[25]	2021	Deep learning	Binary (two)	98 %
[26]	2022	Deep learning	Multi-class (four)	96.13 %
Proposed	2022	Deep learning	Multi-class (four)	97.5 %

5. CONCLUSION

It is critical to predicting COVID-19 patients early to prevent the disease from spreading to others. For the classification of various chest diseases, a state-of-the-art deep learning-based technique is proposed in this study as an automated system that can differentiate lung infections. As it was noted from the obtained results, the proposed artificial model system for diagnosing cases of lung infections is equivalent to human diagnosis at a high level that can be relied upon as assistance for humans at a time when cases of infection are increasing in an unprecedented manner compared to the limited number of human experts. In addition, it is clear that the chest X-ray has proven its worth in diagnosing infection at a high level that can be relied upon as assistance or alternative to the costly and time-consuming RT-PCR test. Following the evaluation of chest X-ray pictures, image augmentation is used to address the class imbalance's challenge. It has been noted that image augmentation can significantly increase model accuracy and return a more accurate diagnosis. Despite the great similarities between classes in a multi-class classification method, especially in medical images, it can be clearly noted that the proposed model improved its performance to distinguish between the four classes with high efficiency compared to other similar studies and its proposed methods. This study demonstrates the proposed model's performance with a classification accuracy of 97.5 percent, as well as its superiority in performance when compared to other experimented models. Because of the improved performance, it is expected that these findings would greatly assist radiologists in making clinical judgments.

This research can be expanded in the future to include a larger database with more than four types of classes to classify them. Other deep learning models can also be utilized to reduce the amount of time required for calculation. Furthermore, developing a mobile application that performs the same process in order to help people diagnose their lung infection from the chest X-ray by themselves from any smart mobile device with height performance.

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