An Artificial Intelligence Based Technique for COVID-19 Diagnosis from Chest X-Ray.

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***Abstract*—The COVID-19 pandemic had a catastrophic impact on world health and economic. This is attributed to the unavoidable delay in the diagnosis process, due to limitation of COVID-19 test kits. Thus, it is urgently required to establish more cheap and affordable diagnostic approaches. Chest X-ray is an important initial step towards a successful COVID-19 diagnose, where it is easily to detect any chest abnormalities (e.g., lung inflammation). Furthermore, majority of hospitals have X-ray devices that can be used in early COVID-19 diagnosis. However, the shortage of radiologists is a key factor that limits early COVID-19 diagnosis and negatively affects the treatment process. This paper presents an artificial intelligence based technique for early COVID-19 diagnosis from chest X-ray images using medical knowledge and deep Convolutional Neural Networks (CNNs). To this end, a deep learning model is built carefully and fine-tuned to achieve the maximum performance in COVID-19 detection. Experimental results on recent benchmark datasets demonstrate the superior performance of the proposed technique in identifying COVID-19 with 96% accuracy.**

***Index Terms*—Artificial Intelligence, Convolutional Neural Networks, Deep Learning, COVID-19, Pneumonia, Chest X-ray.**

I. Introduction

The world health organization declared a *public health emergency of international concern* (PHEIC) on January 2020, in relation to the Coronavirus disease 2019 (COVID-19) world-wide spread. Human coronaviruses (CoV) belong to order Nidovirales, family Coronaviridae, subfamily Coronavirinae [1]. The subfamily Coronavirinae contains viruses that can be divided into four types α, β, γ and δ. CoVs (α, β, γ and δ) mainly infect the respiratory and gastrointestinal tract of a wide range of animal species including mammals and birds. At the end of 2019 a novel class of β-coronavirus appeared, which known as SARS-CoV-2 (COVID-19). COVID-19 is extremely infectious, and in serious cases may result in acute respiratory distress or multiple organ failure [2].

The number of positive cases increases exponentially everywhere in the world and till today the virus has infected more than 5 million persons. Health systems of several countries has come to the point of collapse because of this fast growth rate in the infected cases [3]. Now, most countries face shortage of ventilators and testing kits. The medical situation is complex due to the limitation of available diagnostic tools, where many countries are only able to apply a limited COVID-19 tests [4]. Thus, there is an urgent need to find a speedy low-cost tool for effective detection and diagnosis of COVID-19.

Attempts have been conducted to find an adequate and fast way to detect infected patients at early stage. Usually, the disorder is verified by a reverse transcription polymerase chain reaction (RT-PCR). The RT-PCR sensitivity might not be strong enough for early identification and diagnosis of suspected patients [5]. This is the reason for the high death rate around the world. However, X-rays, as a non-invasive imaging techniques, can identify these characteristic manifestations in the lungs [6]. Thus, X-rays could be used for early track of COVID-19 and other forms of pneumonia. Fig. 1 depicts normal and COVID-19 positive sample chest X-ray images with their clinical diagnosis to highlight the difference. The chest X-ray of COVID-19 cases shows bilateral lung infiltrate (areas marked with green) and depicts a homogeneous opacity of the infected lungs (i.e., mostly pneumonic opacity).

On the other hand, Artificial Intelligence (AI) based solutions has increased rapidly in many areas of computer vision [7]. AI based techniques can process huge amounts of data at inconceivable speed outperforming humans in terms of accuracy. This is attributed to the power of AI that can inspect and inference hidden patterns and features with almost no human intervention [8]. Furthermore, modern medicine is facing the challenge of acquiring, analysing and applying a large amount knowledge needed to solve complex clinical problems. This situation can benefit from AI potential to exploit meaningful relationship within data to assist in the diagnosis, treatment and predicting outcome in many clinical scen arios [9]. Thus, medical practice and healthcare systems had received a great share of AI solutions [10]. Example medical applications are drug design and discovery [11] and patient monitoring [12], improving the diagnostical capability of clinicians [13] and medical image analysis [14].

Presently, ongoing research efforts have been made to develop new diagnostic approaches for COVID-19 based on AI algorithms [15]. More specifically using Convolutional Neural Networks (CNN), which brought a revolution in several fields of science [7] by introducing non-traditional and efficient solutions to many image-related problems that had long remained unsolved or partially addressed [16].

The aim of this paper is to benefit from the current AI

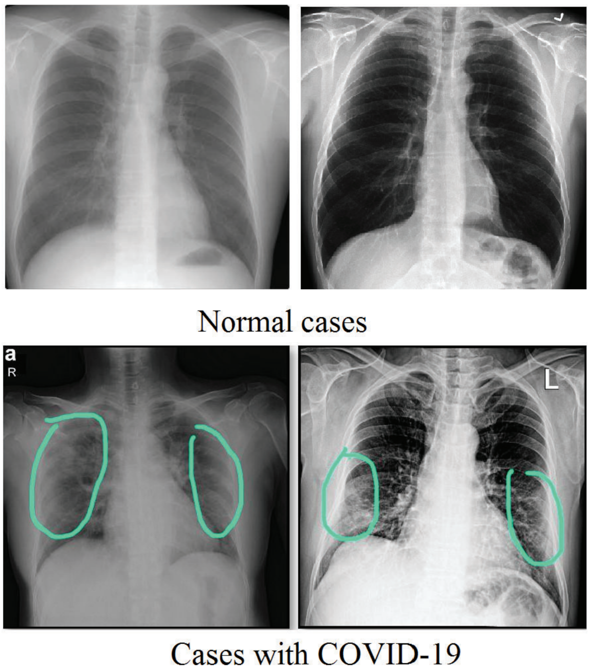

Fig. 1: Samples of normal scans chest X-rays versus ones diagnosed with COVID-19.

advance and develop a robust COVID-19 detection technique from chest X-ray. This will be achieved using deep learning based methods, which is the state-of-art in pattern recognition. Finally, this research results provide a cheap and solid start-up in the battle against COVID-19. This is highly beneficial, especially when doctors are required to examine a lot of cases in a short time period.

The rest of the paper is organized as follows. The proposed CNN model is introduced in Section II. Section III presents the experimental results and discussion. Finally, the paper is concluded in Section IV.

II. The Proposed Method

CNN is a feed-forward artificial neural network that are widely used in image/video analysis [16]. These CNNs use relatively less pre-processing compared to other feature extraction and classification algorithms. This means that the network is fully responsible for developing its own filters in the unsupervised learning. This is not the case with other traditional algorithms that relies on selective pre-processed hand-crafted features. The start-up without initial parametrization and human intervention is a major advantage of CNNs. The core of deep learning work is convolutional operations for input images and stacking layers. The convolution operation is described as:

$$(X \circledast K)(i,j) = \sum\sum K(m,n)X(i-m,j-n) \qquad (1)$$

Where, X is the input image and K is a 2D convolution matrix and $\circledast$ represents the discrete convolution operation. The K matrix slides over the input matrix with stride parameter. The generic full deep learning architecture for COVID-19 detection is illustrated in Fig. 2, and the framework algorithm steps are depicted in Table I.

INPUT:
IMG = Chest X-ray image to be diagnosed;
DS = Dataset of COVID-19 labelled chest X-ray images;

OPERATION:
1. **PREPARE DS** Using Data Augmentation Steps;
2. **Initialize** TensorFlow CNN Network Parameters;
3. **SPLIT** DS to 70% Training and 30% Testing;
4. **BEGIN Training**
5. **Iterate** Through **DS** with Full Training Epochs;
6. **Evaluate** Accuracy At Each Epoch Till Convergence;
7. **END Training**

OUTPUT: Diagnosis (IMG);

TABLE I: The proposed COVID-19 diagnosis algorithm.

The layers implementation details of the proposed COVID-19 detection CNN is depicted in Table. II. Practically, there are two core factors that control the proposed network performance and any CNN network in general. The first is the convolution filter size, which is selected to be (5×5). Although this filter size is slightly larger than common size of CNN filters [18], however, it allows finding lung abnormalities occurring in larger areas compared to normal image classification problems. The second factor is the activation function at the last fully connected layer. The sigmoid function Eq. (2) is selected, as it restricts the $\Phi(x)$ value from a large scale to within the range $[0:1]$. This suits the covid-chestxray multi-class classification problem as it contains 9 diagnosis for the depicted cases.

$$\Phi(x) = (1+\frac{1}{e^x})^{-1} \qquad (2)$$

TABLE II: The proposed COVID-19 detection CNN architecture with full layers implementation details.

Index	Layer Type	Output Shape
1	2D Convolution	[196×196×64]
2	Average Pooling	[65×65×64]
3	2D Convolution	[61×61×32]
4	Average Pooling	[20×20×32]
5	2D Convolution	[16×16×8]
6	Flatten	[2048]
7	Fully Connected	[128]
8	Fully Connected	[64]
9	Dropout	[64]
10	Fully Connected	[32]
11	Fully Connected	[10]

III. Experiments and Results

This section investigates the performance of the proposed CNN model for COVID-19 detection. It outlines the covid-chestxray dataset used in the experiments as well as highlights the network training phase details, followed by the obtained experimental results and their discussion.

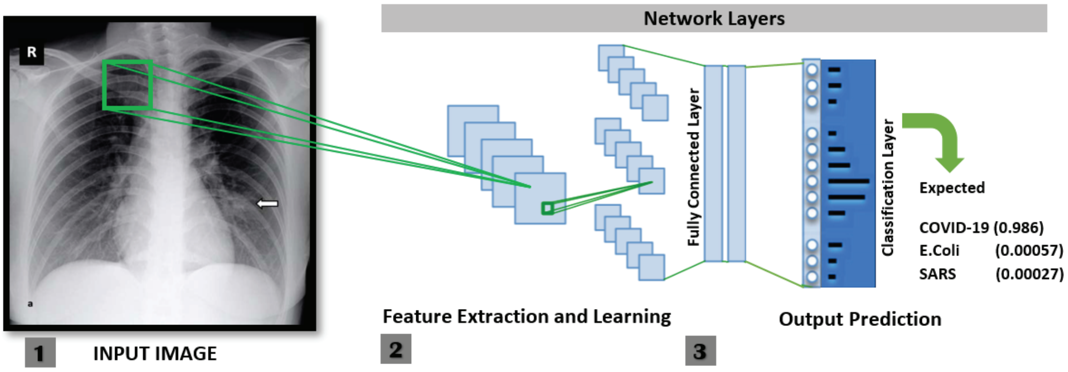

Fig. 2: Abstract pipeline of the proposed deep learning COVID-19 diagnosis framework. The depicted example is real positive COVID-19 case from the covid-chestxray dataset [17], which is correctly classified by the proposed network.

A. Chest-Xray dataset

A public dataset of pneumonia chest X-ray cases [17] is used in this paper. The dataset depicts 9 types of pneumonia (e.g., COVID-19, MERS, SARS, ARDS) in addition to some normal X-ray images. The 9 different pneumonia cases depicted in the dataset helps pretty much in reducing the underfitting of the proposed model, as the model needs to learn several variations among the 9 pneumonia cases. For illustrative purpose, example images from the dataset are shown in Fig. 3. The dataset is constantly updated with images from various open access sources. Till now, the dataset reached 316 chest X-ray images. There are 176 males and 104 females, while the rest are missing the gender information. (The size of the dataset is tripled following the data augmentation step, i.e., section III-B). The minimum and maximum cases ages are 12 and 87 years respectively. 253 of the cases are COVID-19 positive, while the remaining are either normal or depict other pneumonia types.

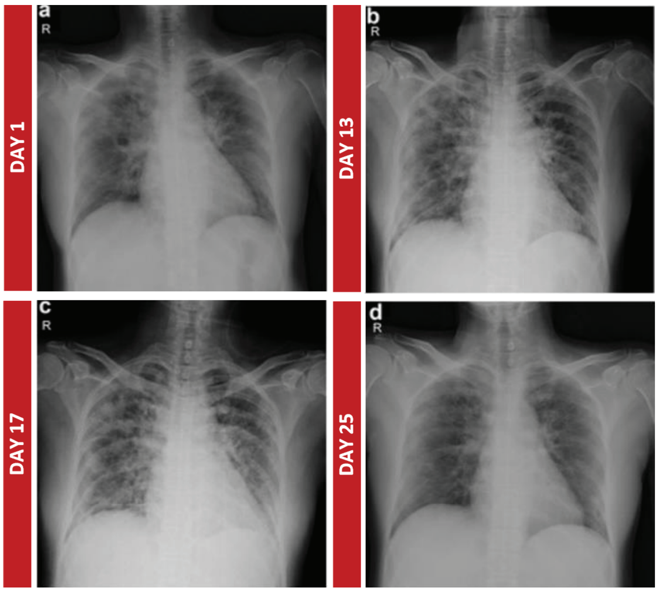

Fig. 3: Example X-ray images from the covid-chestxray dataset. The images shows COVID-19 progress on a recovered 55 year old female. The figure is adapted from [17]. Day 1 chest X-ray shows an early changes in the form of bilaterl peripheral lung infiltrates. Day 13 and 17 chest X-ray changes become more sever and obvious in the form of sever lung infiltrates and reticular shadows. On day 17 there is a prevalence of ground glass Opacity. Day 25 chest X-ray signs start to improve than before and infiltrates start to disappear.

B. Network training phase

The proposed CNN model takes advantage of data augmentation to reduce the effects of overfitting [19]. Before presenting an example image to the network, all dataset images are preprocessed by randomly translating in [-30,30] range and randomly reflecting. The random translation step is necessary to avoid the positional bias in the data. These preprocessing steps are applied consistently to all images to artificially increase the dataset size using label-preserving transformations [20]. The performance of the proposed network model during training and validation phase is depicted in Fig. 4.

The model was trained using a stochastic gradient descent with a batch size of 10 examples, momentum of 0.9 and weight decay of 0.001. The training and results were obtained using an Intel Core i5, 2.9 GHZ with 8GB of RAM. The network architecture was implemented using TensorFlow framework [21]. The next section presents and discuss the network performance for the targeted problem.

C. Results and discussion

This section discusses the procedure in setting up tests to evaluate the proposed network model and documenting the obtained results. Following the common experimental setup, the dataset was randomly splitted by assigning 70% of the images to training and 30% to validation. The split in this case does not affect the results, since there is no established test-set split for the chest-xray-images dataset. Regarding the quantitative evaluation, the standard Accuracy measure is used

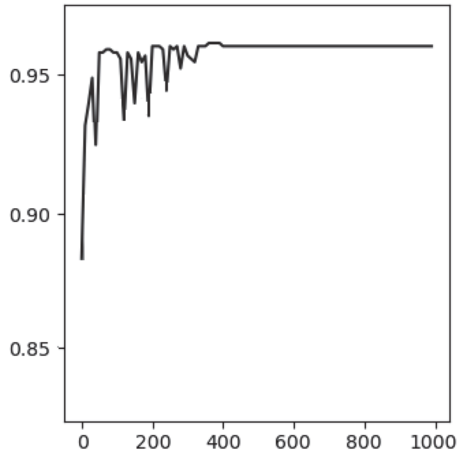

Fig. 4: The proposed CNN model accuracy performance in the first 1000 epochs. The graph depicts a performance stability after the first 500 epochs, with 96% accuracy.

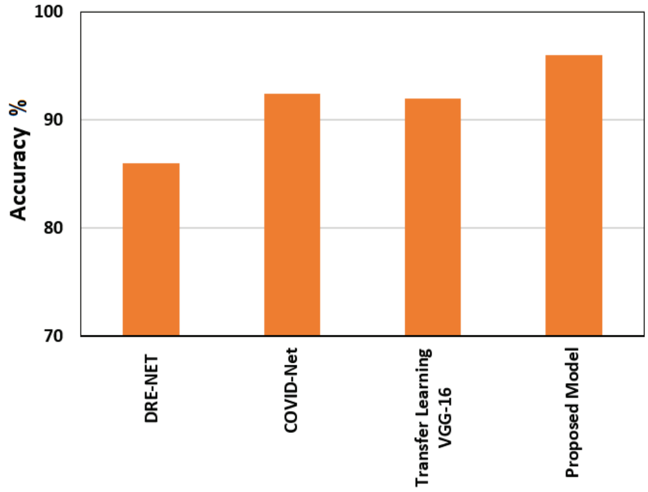

Fig. 5: A performance comparison of the proposed CNN COVID-19 detection model against DRE-NET [23], COVID-Net [24] and Transfer Learning (VGG-16) [25].

for this part [22]. The accuracy metric is defined in Equation 3, as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

Where TP is true positive, TN is True Negative, FP is False Positive and FN is False Negative. The validation loss is also used to provide an extra measure about the model performance, as it indicates how well the model is generalizing to unseen data Equation 4 depicts the loss function. Where $\hat{y}_i$ is the network prediction with the ground truth values y_i and λ is the individual loss function, i.e., log-loss in the proposed model.

$$J = \sum_{i=1}^{N} \lambda(\hat{y}_i, y_i) \tag{4}$$

The proposed network achieved 96% accuracy on the chest-xray dataset with 0.2 log-loss, as depicted in Fig. 4. This is a very good result considering the limited size of the dataset.

The literature contains a limited published research about the COVID-19 as listed in Table III. This is attributed to limitation of the available test-data for the research community, and the COVID-19 symptoms that vary between countries, and may overlap with other of forms of pneumonia (e.g., SARS). However, there are some research attempts related to the COVID-19 pandemic with some limitations that could be summarized in the following points:

- Some approaches were developed based on the transfer learning [25]–[27] scheme. However, this could be useful in general image classification problems, that could generalize learnt edges and colour blobs features to other image classification tasks.
- Although the COVID-19 situation is a world wide catastrophic, most of the datasets are kept in secrecy from field researchers, causing delays in developing a robust assistive AI techniques for the greater good of the humanity.
- The performance of deep learning based methods is mainly affected by the number of positive samples. However, the majority of literature approaches used an average of 50 COVID-19 positive cases, which is a quite small number to validate the resultant high accuracy.

TABLE III: Summary of key previous literature on COVID-19 detection using deep learning methods.

Methods	Year	Cases	Accuracy (%)
DRE-NET [23]	2020	1485	86
UNet+3D Deep Network [28]	2020	542	90.8
COVIDX-Net [29]	2020	50	90
COVID-Net [24]	2020	5579	92.4
Transfer Learning (VGG-16) [25]	2020	204	92

The proposed network model performance is compared to a group of three benchmark baselines, that represents the most recent work in COVID-19 detection using deep learning methods. The comparison is depicted in Fig. 5 emphasizes the robust performance of the proposed COVID-19 detection CNN model, as it outperformed all of the other baselines with 5.8±3.5%. In addition, the results were validated by an expert medical team, where the same accuracy measure, i.e., Equation 3, was used to quantify this part performance. Each X-ray image that was correctly classified by the proposed network was further exposed to radiologists to manually re-classify it. The obtained medical-based accuracy is 99%, which confirms the effectiveness aspect.

In general, due to the aforementioned reasons, the majority of the literature work is still immature in presenting realistic AI solutions that can help in early COVID-19 detecting from chest X-rays. Furthermore, CNN-based techniques are powerful and suit the job as it combines feature extraction and classification together in a comprehensive end-to-end model that receives the raw input data and produces the final classification results. Conclusively, there is still much room for work to assist in fighting this pandemic and present affordable solutions that could help the humanity in its fight against viruses.

IV. Conclusion

This paper presented an end-to-end fully automated CNN model for COVID-19 detection from chest X-ray images. The proposed CNN model achieved 96% accuracy. Furthermore, the model performance is clinically validated with expert radiologists, which verifies the soundness of the results. The results presented by this paper is promising, where the proposed technique could be used in places that are short of radiologists support. It can help radiologists and clinicians to perform a quick diagnosis for COVID-19 infection, particularly when health systems are overloaded. However, there is still a room to improve the proposed CNN model by considering more X-ray images and adapting the model to CT images as well. The main limitation of this research and all of the COVID-19 related research at this time is the small number of available COVID-19 cases data. Thus, working closely with local hospitals to provide more cases to further enhance the performance is an essential step.

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