Transfer learning for decision support in Covid-19 detection from a few images in big data

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Abstract*—The novel coronavirus (Covid-19) has spread rapidly amongst countries all around the globe. Compared to the rise in cases, there are few Covid-19 testing kits available. Due to the lack of testing kits for the public, it is useful to implement an automated AI-based E-health decision support system as a potential alternative method for Covid-19 detection. As per medical examinations, the symptoms of Covid-19 could be somewhat analogous to those of pneumonia, though certainly not identical. Considering the enormous number of cases of Covid-19 and pneumonia, and the complexity of the related images stored, the data pertaining to this problem of automated detection constitutes big data. With rapid advancements in medical imaging, the development of intelligent predictive and diagnostic tools have also increased at a rapid rate. Data mining and machine learning techniques are widely accepted to aid medical diagnosis. In this paper, a huge data set of X-ray images from patients with common bacterial pneumonia, confirmed Covid-19 disease, and normal healthy cases are utilized for AI-based decision support in detecting the Coronavirus disease. The *transfer learning* approach, which enables us to learn from a smaller set of samples in a problem and transfer the discovered knowledge to a larger data set, is employed in this study. We consider transfer learning using three different models that are pre-trained on several images from the ImageNet source. The models deployed here are VGG16, VGG19, and ResNet101. The dataset is generated by gathering different classes of images. We present our approach and preliminary evaluation results in this paper. We also discuss applications and open issues.

Keywords*—*AI, big data mining, Covid-19, decision support, E-health, image recognition, transfer learning

I. Introduction

Deep learning techniques have made breakthroughs in the past decade. Image recognition using deep learning techniques, specifically Convolutional Neural Networks (CNN) have facilitated robust image recognition in computer vision tasks. There are many applications of deep learning in conjunction with computer vision. The task of image classification finds its way in our daily lives with X-ray images in order to detect illnesses such as cancer, classify handwritten digits, and conduct face recognition [1]. Computer vision has many other applications including object detection, object segmentation, image reconstruction, and image synthesis. In our paper, we consider image classification for decision support in E-health.

Covid-19 has imposed tremendous physical and mental strain on society. Fig. 1 depicts an overview of Covid-19 cases worldwide. This disease has spread exponentially across the world and has become an international concern. Hence, there has been a need to maximize efforts to conduct accurate testing. It has led to the use of CNN (convolutional neural networks) and image recognition techniques to label large-scale chest X-ray images. This provides the motivation for our work in this paper.

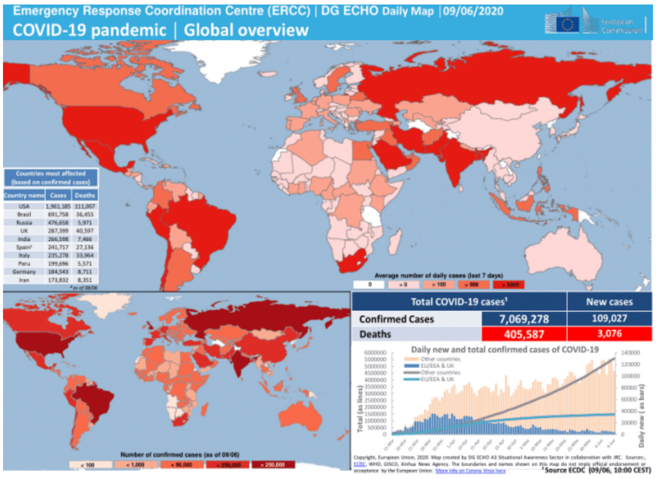

Fig. 1. Covid-19 global overview [2]

In this study, we address the challenging problem of decision support in automated Covid-19 detection based on image data in E-health applications. It is to be noted that some Covid-19 symptoms can be analogous to the symptoms of another infectious disease, i.e. pneumonia, however there is a clear difference between these two diseases as known in the field of medicine. Therefore, it is significant to be able to distinguish Covid-19 cases from pneumonia cases while conducting automated detection. Based on this background, we define our problem as follows.

- Given chest X-ray images, classify them as being *Covid-19 positive, pneumonia positive* or *normal* (i.e. negative for both cases)
- Provide the classification such that images cannot overlap and should only fit into one class each

The data source for our work is ImageNet, which has publicly available chest X-ray images on these two diseases, as well as normal X-rays, i.e. those of people who tested negative for both these diseases. This pre-labeled data with adequate diagnosis serving as the notion of correctness, forms the training data in our problem. In other words, the labeled chest X-ray images for Covid-19 and pneumonia allow us to differentiate between the two and hence aim to obtain accurate classification for Covid-19 by learning via existing data.

Image data on chest X-rays in public repositories in general is vast, ranging from gigabytes to higher orders. It is also complex with significant variations. Inferences drawn from the data are crucial and need to be verified with adequate testing to ascertain their validity as per medical diagnosis. Hence, this problem deals with three of the *Vs* of big data, namely, *volume, variety* and *veracity.* Since we are addressing big data in our work, we deploy deep learning paradigms for mining the data in order to propose a solution to the problem of automated Covid-19 detection. More specifically, we consider the technique of transfer learning. We provide a prequel to our proposed approach herewith.

Transfer learning involves storing knowledge gained while solving one problem and applying it to a different but related problem [3]. An example of transfer learning is that the knowledge gained from recognizing cars could also be applied to recognize trucks [4]. According to a recent study on transfer learning, the detection of various anomalies in small medical image datasets is an achievable target, often yielding remarkable results [5]. There are other studies in this area as explained in our literature survey section.

Given this background, motivation and prequel, the main contributions of our paper are as follows:

- Deep transfer learning models are used to classify Covid-19 and pneumonia infected patients by considering chest X-ray images, in order to provide decision support for Covid-19 detection in E-health.
- Learning occurs efficiently through a few images with low training time (using data augmentation with suitable models) after preprocessing big data on chest X-rays from a benchmark open dataset.
- High accuracy is obtained in classification for the symptom recognition that could promote automated medical diagnosis, as evident from our experiments.

The remainder of this paper is organized as follows. Section II presents a literature survey of related work in the area. Section III describes our proposed approach and its implementation based on deep transfer learning for Covid-19 and pneumonia detection. The preliminary evaluation with discussion is summarized in Section IV. Conclusions along with open issues for future work are presented in Section V.

II. LITERATURE SURVEY

There is much work in the joint area spanning medical research and artificial intelligence, incorporating data mining and machine learning techniques. Some of this is the general realm of E-health while some of it focuses specifically on the recent Covid-19 pandemic. In a study by Apostolopoulos et al. [5], a dataset of X-ray images from patients with common pneumonia, Covid-19, and normal healthy cases are collected for the automatic detection of the coronavirus. Their study aims to evaluate state-of-the-art CNN architectures for medical image classification. The models used in this study are VGG19, Mobile Net, Inception, Xception, and Inception ResNet v2. Among these, VGG19 and MobileNet achieve the best classification accuracy. Our study is fairly orthogonal to such work and is focused on different models, in order to aim for high accuracy with fewer images by deploying transfer learning on big data.

In other related works on medical diagnosis, physicians manually analyze chest computed tomography (CT) images of patients in search of abnormalities [6]. The algorithm here follows three main steps: scale space particle segmentation to isolate vessels; 3-D CNN to obtain the first classification of vessels; and graph-cuts' optimization to refine the results. It achieves an overall accuracy higher than that of other CNN architectures but has certain limitations, including much manual intervention. We aim to minimize this in our work.

In the area of pathological brain image classification ranging from classical methods to deep learning with CNN, much research has been conducted [7]. Features extracted by CNN strongly depend on the training data set size. If the size is small, CNN tends to overfit. Hence, deep CNNs (DCNN) with transfer learning have evolved. Our paper takes a significant step in this direction pertaining to data size and accuracy, our focus being on Covid-19 and X-rays.

The results of another study [8] indicate that a deep learning model applied to chest X-rays can be helpful in diagnosing Covid-19. Collection of Covid-19 images is the most important task in this research towards effectively answering the question of whether chest X-rays can be truly useful for fast, accurate and relatively inexpensive diagnosis of the disease. The drawbacks of this work are the lack of information on: the stage of the disease, the outcomes, and the types of chest X-rays.

Recently, a deep learning system [9] has achieved good performance using patients' current and prior CT volumes to predict the risk of lung cancer. This system has outperformed human radiologists where prior CT scans were not available, and equaled human radiologist performance where historical CT scans were available. Although X-ray is the current reference diagnosis for pneumonia, some studies point that CT outperforms X-ray as a diagnostic tool for pneumonia, albeit at a higher cost. We use X-rays in our work since they are more widely used and are more cost-effective.

Hemdan et al. [10] investigate Covid-19 classification with seven different deep CNN architectures. In their experimental studies, they work on two different categories, Covid-19 and non-Covid-19. They reportedly achieve better results with the VGG19 and DenseNet201 models. Ghoshal and Tucker [11] propose a drop weights-based Bayesian CNN model and test it for four different classes: normal, bacterial pneumonia, non-Covid-19 viral pneumonia, and Covid-19. Sethy and Behera [12] extract features from X-ray images using pre-trained models. They collect their dataset from GitHub, Kaggle, and Open-I repositories. As per their results, features from ResNet50, subsequently classified with SVM (support vector machines) are better than other models. A deep learning based anomaly detection model for Covid-19 detection from X-Ray images is proposed by Zhang et al. [13]. It achieves a sensitivity of 90.00% and specificity of 87.84% but incurs threshold based limitations.

Narin et al. [14] propose a transfer learning based CNN model for detection of Covid-19. They use ResNet50, InceptionV3, and Inception-ResNetV2 pre-trained models for learning. According to their results, the ResNet50 model records the best results. This motivates us to look further into other ResNet models. The CIFAR-10 retrained in another paper [15] achieves an accuracy of 70.1% better than earlier models, but it has variations in accuracy/confidence scores.

On another note, Boulos et al. [16] illustrate a range of practical online/mobile GIS and mapping dashboards and applications for tracking the 2019/2020 coronavirus epidemic and associated events as they unfold globally. Dashboards are popular in understanding the spread of the SARS-CoV-2 coronavirus. Communication through map-based dashboards offers accessible information to people around the world, eager to protect themselves and their communities.

Jinia et al. conduct a review [17] to explore active sterilization with recommendations from the CDC (Center for

Disease Control) and FDA (Food and Drug Administration) of the USA. They assess limits of sterilization techniques and identify applications where ionizing radiation may hold the most promise. Their findings can provide methods to sterilize PPE (Personal Protective Equipment). Lower radiation doses (< 10 kGy) allow hospitals to operate safely without worrying about high dose delivery to staff and patients.

Considering E-health in general, there are several interesting studies. Tancer et al. [18] consider the use of the Medical Markup Language (MML) for storing Electronic Health Records (EHR) to facilitate information retrieval and data mining. The incorporate issues such as cloud versus server storage, security, privacy and accessibility that are crucial in dealing with sensitive healthcare data. Du et al. [19] predict air quality based on fine particle pollutants PM2.5 (particulate matter, diameter < 2.5 µm), incorporating health standards of the widely accepted EPA (Environmental Protection Agency) of the USA. They conduct data mining on worldwide multicity road traffic data obtained from WHO (World Health Organization). They also perform opinion mining of tweets posted by the public in response to actions taken by government agencies to combat air pollution in certain regions. Sentiment analysis occurs here to assess public reactions on health-related matters.

Given the plethora of medical research with AI-based approaches that address E-health in general, our paper contributes the two cents to this broad arena. As stated earlier, our contributions include deploying deep transfer learning on the big data of chest X-rays on Covid-19, pneumonia and normal cases, by using a few images from benchmarked open datasets and making comparisons with well-known pre-trained models. We aim to minimize number of data samples and the time for learning, yet achieving high classification accuracy by using different models and data augmentation with transfer learning on the big data. We survey the literature in detail in order to derive motivation from earlier studies, obtain useful inputs, and understand the limitations of some works, in order to proceed with our own research.

III. Approach and Implementation

Our proposed approach for decision support in automated AI-based detection of Covid-19 and pneumonia cases from chest X-rays has three main steps as depicted in the framework in Fig. 2. These are:

- Image acquisition for suitable dataset generation from big data with preprocessing
- Deployment of transfer learning models along with data augmentation for data mining
- Classification pipeline development to help in the diagnosis of new patient cases

In the first step, images are acquired and saved in three folders: Covid-19, pneumonia, and normal (healthy) cases. The next step entails extracting automated features by deploying pre-trained architectures of CNN and the newly trained layers, where different transfer learning models are investigated and data augmentation is performed. In the last step, a classification pipeline is built in order to aid the diagnosis of new patient cases as Covid-19, pneumonia and normal healthy cases. These are based on the corresponding three classes in the image acquisition step, using the knowledge discovered by transfer learning. We explain the details of this approach in the subsections herewith.

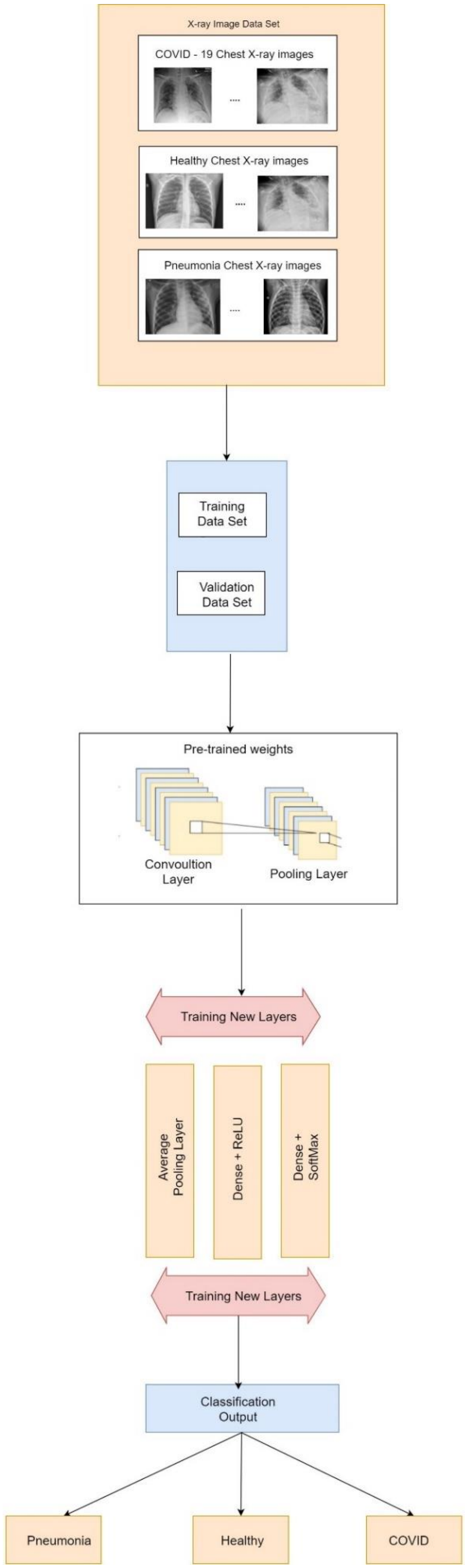

Fig. 2. Framework of proposed approach based on transfer learning

A. Image Acquisition for Dataset Generation

The first step of our approach involves generating a suitable dataset in order to proceed with the learning. The images for this dataset are acquired from the publicly available repository ImageNet. The ImageNet source is a large image database often used to train highly efficient models (including the transfer learning models used in this study). The dataset consists of numerous X-ray images, and is thus subjected to numerosity reduction by selective sampling methods in data mining. The resulting images are combined to generate a sizeable dataset of 1GB, yet small enough to conduct efficient learning from the original big data consisting of several GB. The classes in this dataset are: confirmed Covid-19, confirmed pneumonia, and healthy chest X-ray images (as seen in the respective thumbnails of images in Fig. 2).

The images in the dataset are mapped to a CSV (comma separated variables) file with the correct labels and metadata: marked *0* if the patient is *Covid-19 positive*, *1* if *pneumonia positive,* and *2* if *normal*. Using these labels, a program is coded in Python to map and move all the images of each class into a separate folder. Creating a separate folder for each class allows us to differentiate between the classes and the input. Combining, labeling, and separating the images are crucial steps in the overall process, allowing us to gather a large number of images.

The programming language Python [20] plays a vital role in the completion of this study. We deploy this software to create programs for all the steps of our proposed approach. With its powerful libraries and frameworks for machine learning, yet simplicity of code, Python is a good fit for coding in the implementation of our approach.

B. Transfer Learning Models with Data Augmentation

We already introduced the basic concept of transfer learning briefly in the introduction. While this is well-known to quite a few readers, in this section we outline it in some detail with specific reference to our tasks.

Transfer learning in the broad realm of machine learning is an approach wherein the knowledge mined by CNN (convolutional neural networks) is transferred to solve a different but related task involving new data. The new data is usually integrated with an existing CNN model [21]. In deep learning, this process includes the initial training of a CNN for a specific task (e.g., classification) utilizing large-scale datasets. The availability of data for the initial training is a vital factor for successful training since the CNN learns to extract significant characteristics (features) of the image. Depending on the capability of the CNN to identify and extract the most outstanding image features, it is judged whether the model is suitable for transfer learning.

Next, the CNN is utilized to process a new set of images of a different nature and to extract features obtained during the initial training. There are two commonly used strategies to exhaust the capabilities of the pre-trained CNN.

The first strategy is called feature extraction via transfer learning [21] and refers to an approach wherein the pre-trained model retains both its initial architecture and all the learned weights. Hence, the pre-trained model is used as a feature extractor; the extracted features are inserted into a new network that performs the classification task. This method is commonly used to circumvent computational costs with training a very deep network from scratch or to retain the useful feature extractors trained during the initial stage.

The second strategy has a procedure wherein specific variations are applied to pre-trained models to obtain optimal results. These modifications typically comprise architectural adjustments and parameter tuning. In this manner, only certain knowledge mined from the previous task is retained, while new trainable parameters are incorporated into the network. This requires substantial amount of training on a relatively large amount of data in order to be advantageous. Since we focus on learning from a few images in the big data, we prefer to avoid such exhaustive training. Hence, we focus on the first strategy in our work.

In our approach, transfer learning in the form of computer vision models is applied using the first strategy described here, along with data augmentation as explained later. Transfer learning in computer vision allows us to take the last layers away from a predefined model integrating the pre-trained model (trained on thousands of images) and our image data. The computer vision models used for this study are VGG16, VGG19, and ResNet 101 described as follows.

VGG16: The VGG16 model is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large Scale Image Recognition" [22]. With an accuracy of 92.7%, this model achieves the top 5 test accuracy in ImageNet. The 16 in VGG16 refers to the 16 layers in which weights and bias parameters are learned. With 138 million parameters this is a very large network. VGG16 can be very simplistic, using only 3 x 3 convolutional layers stacked on top of each other, increasing in depth while also reducing the size that is handled by max pooling. An overview of this model's architecture is illustrated in Fig. 3 as seen in the literature [23]. The main intuition behind VGG architecture, with reference to 16 or 19 layers is the multiple 3x3 kernel-sized filters. These small filters lined up in a sequence can mimic the effect of large filters [23]. Due to its simplicity in design and generalization power, the VGG architecture is widely used. Multiple scenarios are tested within the VGG16 model.

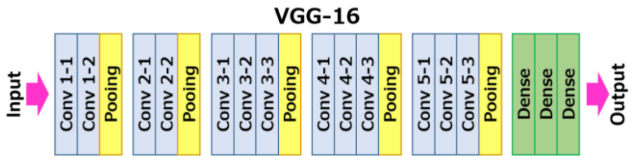

Fig. 3. VGG16 architecture [23]

VGG19: The VGG19 model is also a CNN model and its architecture is essentially the same as that of VGG16, the difference being that VGG19 contains 19 convolutional layers instead of 16 making it a larger system. VGG19 is a competition-winning model that can classify images into 1000 object categories such as a keyboard, pencil, and many different animals [24]. Due to its training experience, this model learns rich feature representations for a wide range of images. The network has an image input size of 224-by-224. We use two variations of the VGG architecture to determine whether the extra layers make a difference in the accuracy. Although VGG models are probable choices for this project, there are some drawbacks with their architecture [23]. They are very slow to train, the weights are very large and they consume substantial bandwidth. It may be feasible to use smaller network architectures depending on the specific classification task at hand. On the other hand, the VGG architecture has demonstrated high accuracy over many highly regarded models. The component of increasing the depth in the VGG architecture makes it a viable option for a high performing model. Fig. 4, as found in the literature [25], portrays the VGG19 architecture.

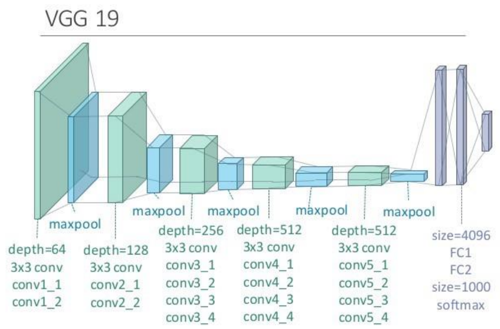

Fig. 4. VGG19 architecture [25]

Res101: The pioneers of the ResNet101 model emphasize that deeper neural networks are more difficult to train and hence present a residual learning framework to ease the training of networks that are substantially deeper than those used previously [26]. To address issues with very Deep Neural Networks, the ResNet model proposes to skip some connections hypothesizing that deeper layers should be able to learn as well as shallow layers [25]. They propose to copy activations from shallow layers and set additional layers to identify the mapping. Fig. 5, observed in the literature [25], displays the skipped connections.

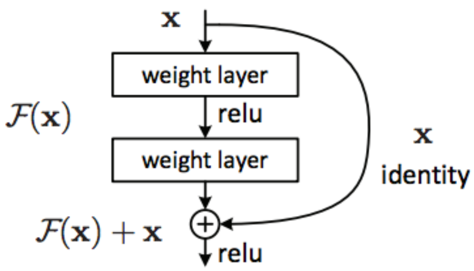

Fig. 5. ResNet101 (skipping connections) [25]

The ImageNet dataset has evaluated nets with a depth of up to 152 layers, i.e. 8 times deeper than VGG frameworks, while also having lower complexity. An ensemble ResNet incures only a 3.57% error rate on the ImageNet test set [26]. With the depth being of central importance in many visual recognition tasks, ResNet provides a refined method of object recognition. As with the VGG models, ResNets also produce solutions with very high accuracy in ImageNet competitions. ResNet offers reformulated layers as learning residual functions with reference to layer inputs, instead of learning unreferenced functions [26]. As per this research, ResNet frameworks are easier to optimize and they gain accuracy from considerably increased depth.

Data Augmentation: Considering these transfer learning models, it is important to dwell on the concept of data augmentation. The data augmentation technique effectively enhances the training set of a network and is used mainly when the training dataset contains only a few samples [27]. Geometric distortions or deformations are often applied to either increase the number of samples for deep network training or to balance out the size of datasets. In the case of microscopic images, shift and rotation invariance, as well as robustness for deformations and grey value, variations are the required modifications applied to each image of the training set [28]. These methods are proven to be rapid, reproducible and consistent. Increasing the number of data samples may efficiently improve the CNN's training and testing accuracy, reduce the loss and improve the network's robustness. However, heavy data augmentation should be carefully considered, as this may produce unrealistic images and confuse the CNN. Since we sample the original big data on images to a smaller dataset of size 1GB, we deploy data augmentation within the transfer learning framework to enhance the effective data available for learning without the overhead of additional storage or added computational complexity, yet positively impacting accuracy.

C. Classification Pipeline to help Diagnosis of New Cases

The classification pipeline in our approach is portrayed in Fig. 6 herewith. It reads in images sorted into subdirectories with the subdirectory name used as the corresponding image class. Images are then randomly split into 80:10:10 for training, testing and validation data subsets respectively. The images are resized into a 224 x 224 pixels array. Image data is augmented with the data augmentation methods of shear, zoom, horizontal flipping and rescaling that are often used in scientific data mining applications [27].

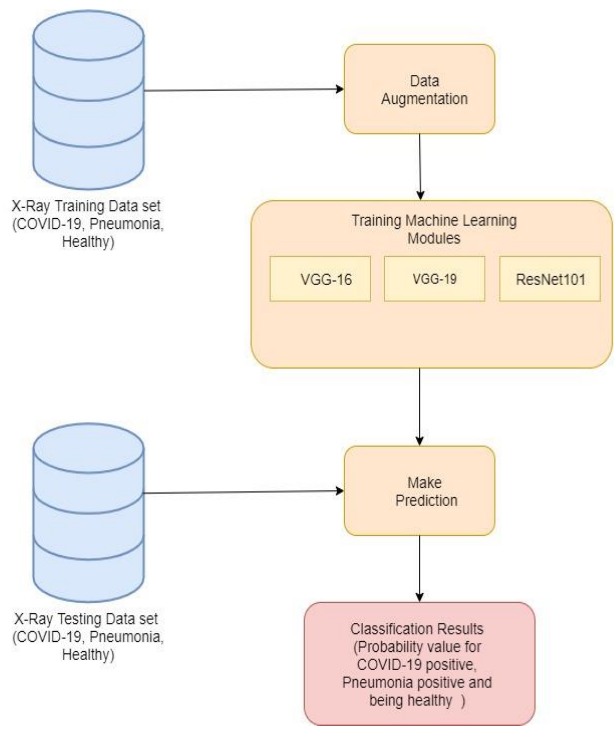

Fig. 6. Classification pipeline - model architecture for decision support

The transfer learning models VGG16, VGG19, and ResNet101 are used for feature extraction. These models learn from the images in our training dataset. All the convolutional layers are activated by the Softmax [29]. The CNNs are compiled by utilizing an optimization method called Adam [29]. The training is conducted for multiple epochs with a suitable batch sizes. After generating the models, we use unseen test data in the form of chest X-ray images for automated detection of new cases, to assist in medical diagnosis. Figs. 7, 8 and 9 show examples of chest X-rays that constitute a Covid-19 positive case, a pneumonia positive case and a normal case respectively. The model makes a prediction on the probability of the three classes as seen in the labels above the respective images. These are useful in the image classification in our pipeline, in order to provide decision support for Covid-19 detection.

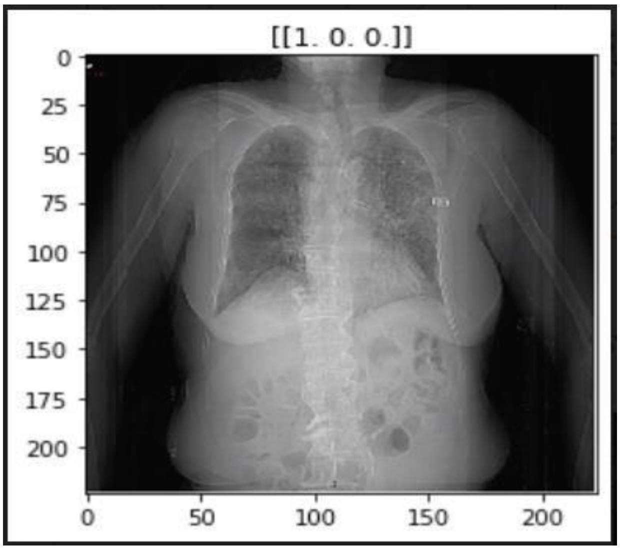

Fig. 7. Model tested on an image with Covid-19 positive case

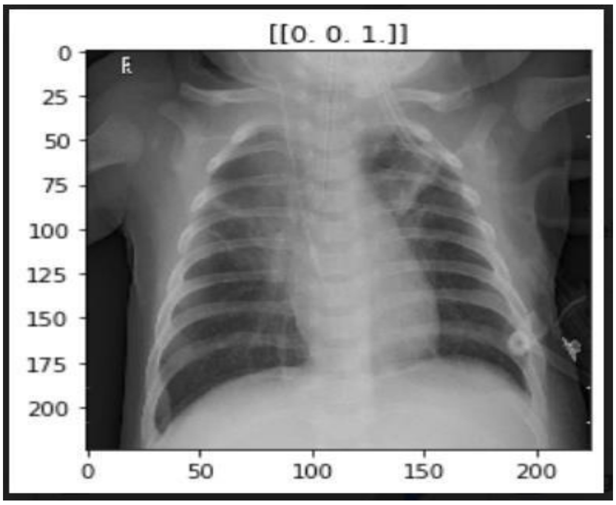

Fig. 8. Model tested on an image with pneumonia positive case

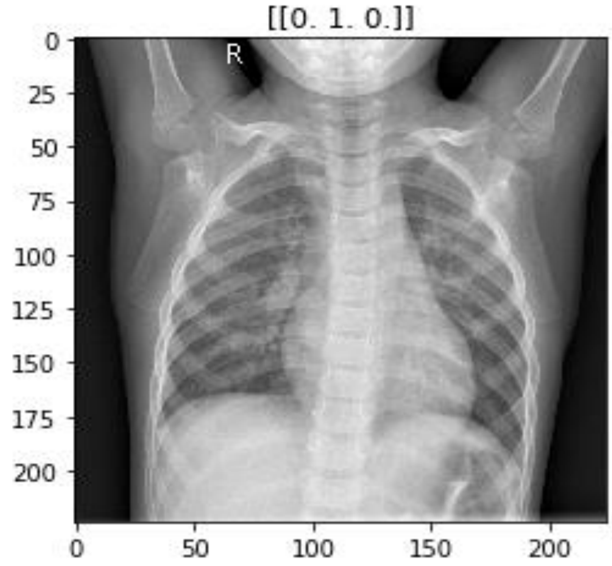

Fig. 9. Model tested on an image with normal / healthy case

IV. Preliminary Evaluation and Discussion

We present a summary of our preliminary evaluation herewith. This is followed by a discussion on the evaluation results, especially considering an application perspective.

A. Experiments and Results

In our initial experiments, the models VGG16 and VGG19 are developed and tested for accuracy over five epochs. ResNet101 is tested over a total of ten epochs since it does not perform too well with fewer epochs. Note that in our learning process, we try to obtain high accuracy with as few epochs as possible.

It is observed that all the models perform well. The *best case training accuracies* are: ResNet101 at 97.46%, VGG16 at 96.47% and VGG19 at 95.32% respectively. While these numbers depict the best case accuracy levels over training sets, the overall accuracy ranges for all the three models using training as well as validation sets are plotted in the figures next. Figs. 10 – 15 shown here depict the ranges of training and validation *accuracy*, as well as *loss* for all the models tested. Accuracy and loss are explained next, as per our work.

Accuracy (A) refers to the fraction / percentage of correctly classified samples. It is calculated as shown in Equation (1) as the number of True Positives (TP) plus True Negatives (TN) divided by the total number of samples in the dataset, i.e. number of chest X-ray images here. For example, a TP here is an image detected as being Covid-19 positive when the corresponding patient actually has Covid-19, while a TN is an image detected as being Covid-19 negative when the patient does not have this disease. Both these constitute correct classifications.

$$A = \frac{(TP+TN)}{D} \quad (1)$$

where TP denotes the number of True Positives, TN denotes the number of True Negatives, and D denotes the number of Data Samples.

Loss (L) refers to cross-entropy loss, or the uncertainty of a classification based on how much the classification varies from the true value. It helps to understand how close the predicted distribution is to the true distribution. The loss, i.e. cross-entropy loss is calculated using Equation (2) herewith.

$$L(\mathrm{p},\mathrm{q}) = -\sum_{x=1}^{c} \mathrm{p}(x)\log q(x) \qquad (2)$$

where p(x) is the correct probability, q(x) is the predicted probability, and c is the number of classes (c=3 here).

In other words, accuracy helps to indicate whether the classification is equal to the true value or nor (correct or wrong), while loss indicates the extent to which it is incorrect, i.e. away from correctness. Based on this, the x-axes on all these figures depict the learning time over the training/ validation sets, while the y-axes depict accuracy / loss as a fraction of the total number of samples as labeled in the respective figures. For example, accuracy = 0.95 implies that a fraction of 95/100 samples were correctly classified in the respective dataset. In all these figures, we can observe high accuracy values and low loss values, indicating good performance of all the models on the training as well as validation sets. Hence, we can infer that our proposed approach works well in detecting Covid-19, pneumonia and healthy cases from chest X-rays.

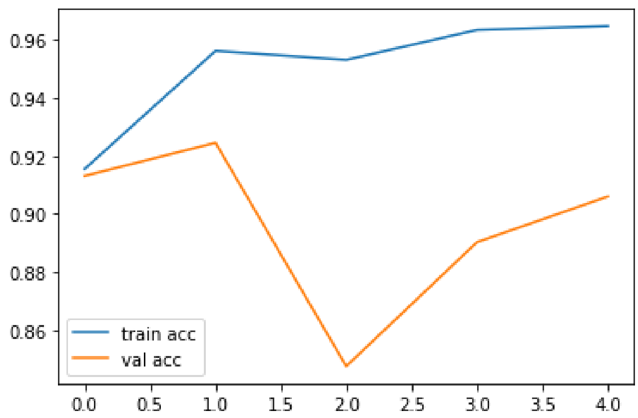

Fig. 10. Results with VGG-16 (training and validation accuracy)

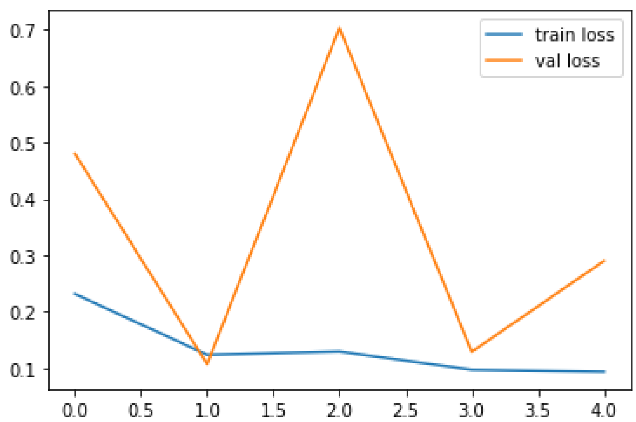

Fig. 11. Results with VGG-16 (training and validation loss)

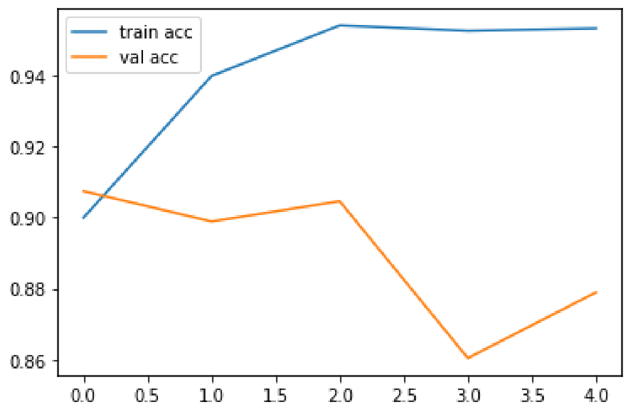

Fig. 12. Results with VGG-19 (training and validation accuracy)

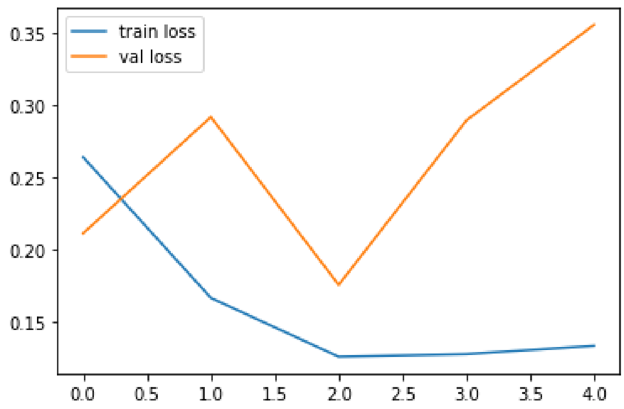

Fig. 13. Results with VGG-19 (training and validation loss)

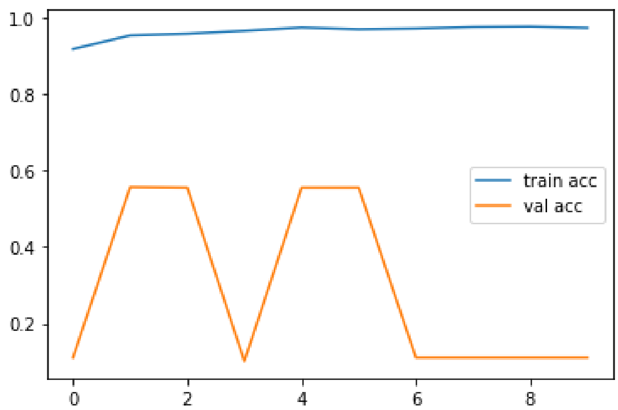

Fig. 14. Results with ResNet101 (training and validation accuracy)

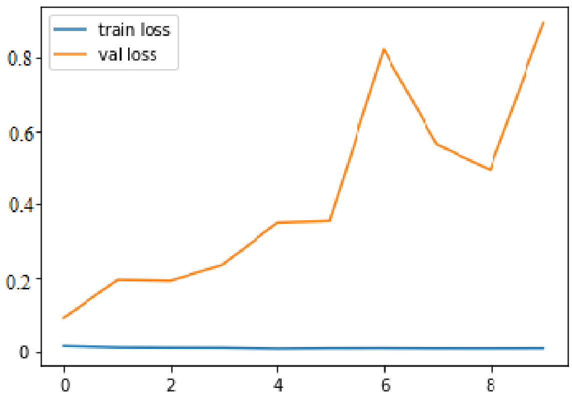

Fig. 15. Results with ResNet101 (training and validation loss)

B. Discussion on Evaluation and Applications

Based on the achieved results, these experiments exhibit that deep learning with CNN has considerable effects in the automated detection and extraction of essential features from X-ray images that are related to medical diagnosis. Utilizing transfer learning and computer vision models generates high accuracy rates in the detection of Covid-19, pneumonia, and normal patients, thus providing decision support in AI-based detection and thereby assisting automated diagnosis of cases.

Our proposed framework for decision support in the automated detection of Covid-19 cases can potentially be employed within a supplementary tool for screening Covid-19 patients in emergency medical support services. Despite the fact that the apt treatment is not determined solely from an X-ray image, an initial screening of the cases would be beneficial, not for actual treatment, but in the appropriate application of quarantine measures for positive samples. This can be viable until a more comprehensive examination and a specific treatment or follow up procedure is implemented.

A few limitations of the study can be overcome in future work. As a higher quality corpus of Covid-19 X-ray image data becomes available, it would be possible to produce models for faster diagnosis of Covid-19. Such a tool would be helpful in the areas where testing kits are unavailable. The data size used is already very large, however having even more data could lead to still higher accuracy in aiding the diagnosis. For future approaches, the focus could possibly be on distinguishing patients that are indicating mild Covid-19 symptoms rather than pneumonia symptoms.

While the whole world is witnessing a lockdown due to the Covid-19 pandemic, persistent efforts are being made to obtain multifaceted solutions to control this pandemic. These include enhancement of research in epidemiology, e.g. [30], development of contact tracing apps, e.g. [31] and others. The application of many advanced AI techniques coupled with radiological imaging can possibly be helpful for the accurate detection of this disease. They can also be assistive to overcome the problem of the lack of specialized physicians in some areas such as remote villages, and overpopulated regions where the doctor to patient ratios are low. In some such places, Information and Communications Technology (ICT) is being used within the field of medicine in order to bridge this gap and provide better healthcare, e.g. [32]. Our proposed approach in this paper can offer decision support in detecting Covid-19 positive, pneumonia positive, or normal healthy cases by using chest X-rays for training using transfer learning. Hence, it could make some feasible contribution here. However, since it only provides decision support, it would still require actual *radiology specialists* devoting the *time* to manually examine each report and use our approach to assist accurate diagnosis. This is one of the highly challenging tasks in the pandemic. It is because compared to the number of cases, there is limited availability of doctors and their time is really precious.

In the future, the use of robots can be considered to overcome this issue, i.e. robots could perhaps be trained to conduct such Covid-19 based medical diagnosis by using the technology in this research and related works. At present robots are being used for simple tasks in Covid-19 care, such as taking the temperature of patients and conducting relevant monitoring [33]. Training medical robots to actually conduct the diagnosis of Covid-19, or to significantly assist human doctors in the diagnosis, is a challenging aspect of future work. Some of this work could involve humans and robots working together in medical decision support for diagnosis. It would incur significant challenges, e.g. incorporation of commonsense knowledge in this process. Some part of this research could potentially benefit from our recent work in commonsense knowledge based human-robot collaboration [34]. Such research on the possible use of robotics within the automated diagnosis of Covid-19 would involve substantial work, calling for further research.

Another aspect of future work could potentially be the development of mobile application (apps) based on some results of this study and related work. These could be health-based apps for easy access on Covid issues. The apps could pertain to symptom information, preventive measures etc. Such work would be orthogonal to other Covid-related apps, e.g. *Covid Alert NY* for contact tracing [35], *MDLive* for telemedicine [36], *Covid Control* for research [37] and others [31, 38]. This work would also be in line with our earlier research on app development in general [39, 40]. The app development pertinent to Covid would help in making further contributions to the paradigm of E-health.

V. Conclusions

The paper contributes to the possibility of a low-cost, rapid and automated diagnosis of the Covid-19 disease via decision support through AI-based detection of Covid-19 symptoms. We propose an approach deploying transfer learning to classify image data from E-health sources on chest X-rays, as Covid-19 / pneumonia / normal cases. We conduct the learning using a few images from the big data on these chest X-rays, by suitably deploying the transfer learning models of VGG16, VGG19 and ResNet101 in conjunction with data augmentation techniques. We also aim to minimize the training time via our experiments by finding the minimal number of training epochs for each model such that it achieves suitable accuracy over training as well as validation sets. Hence, we strive to make the learning process efficient in terms of the number of images and the learning speeds. It is noticed that high accuracy is obtained over all the models in this study despite having few images and low training time.

Since we obtain high accuracy in detection over unseen test data, it indicates that this approach is feasible in assisting the diagnosis of new patient cases. It would thus be useful in decision support for promoting automated medical diagnosis, especially helpful when there are relatively few testing kits and limited medical personnel available. Our approach is orthogonal to existing studies in the literature that address the analysis of Covid-19 with AI-based approaches in machine learning and data mining. This work would be potentially beneficial in ongoing and future Covid-19 diagnostic studies.

Future work includes enhancing the learning by using additional data on Covid-19 cases, and developing suitable applications of the learning framework within the realm of robotics in order to train robots to learn from relevant image data to conduct / assist diagnostics. This could entail further advances in human-robot collaboration. It incurs significant challenges and entails open issues with the scope for further research. Development of apps on various Covid-related aspects could present other avenues for future work. Such research and development would potentially make further contributions to the E-health paradigm.

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