Learning Through One Shot: A Phase by Phase Approach for COVID-19 Chest X-ray Classification

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2020 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES) | 978-1-7281-4245-6/21/$31.00 ©2021 IEEE | DOI: 10.1109/IECBES48179.2021.9398761

***Abstract*—Today globally, coronavirus disease (COVID-19) has infected over more than 81 million people and killed at least 1771K. This is an infectious disease caused by a newly discovered coronavirus. As a result, scientists and researchers around the globe are now trying to find out the path to battle this disease in the most effective way. Chest X-rays are a widely available modality for immediate care in diagnosing COVID-19. Detection and diagnosis of COVID-19 chest X-rays would be more precise for the current situation. In this paper, a phase by phase approach using the concept of one shot learning is introduced for effective classification of chest X-ray images. The proposed method utilizes the application of Entropy for selecting best describing images for effective learning purposes. The proposed model is evaluated on a publically available large dataset of size 24614 images comprising of three classes viz COVID-19, Normal and Non-COVID. The obtained results are promising and encouraging.**

***Index Terms*—One shot learning, Corona virus, Chest X-Ray, Probabilistic Neural Network, Entropy, Classification.**

I. Introduction

Recent past, the world has witnessed nearly 81 million positive cases and around 1771K deaths due to novel Corona Virus disease (COVID-19) as on 28.12.2020 [1]. Fever, dry cough, headache, pneumonia and breathing difficulties are the common symptoms of this disease. Recent week's new type of symptoms are also pooped up and one such symptom is purple or red lesions on the toes named "COVID toes". It is very much essential and required to combat the spreading of COVID-19. In such situation, effective testing methodologies and immediate medical treatment are much required. Most commonly used tests include NAAT, which detects the SARS-C0V-2 virus responsible for the disease and serological test which detects antibodies present in the blood serum. These techniques are much complicated, time consuming and manual with positivity rate of 63% [9]. CT/Chest X-ray are other diagnosis tools of COVID-19. One of the major challenges with typical x-ray images is categorizing with various viral pneumonias and COVID-19 since they have similar features. Researchers are now focusing on developing some AI models to overcome the issues related to this [29]. Recently many researchers have developed algorithms and system to detect COVID-19 using chest X-ray / CT images.

Pereira et al. [1] developed a multi-class and hierarchical classification framework for identifying the covid-19 disease using texture features and pre trained CNN model. The different types of texture features are extracted in phase 1, early fusion technique is applied in phase 2, data resampling technique is employed in phase 3 and finally, phase 4 results the classification of multi-class and hierarchical scenarios. Wang and Wong [2] proposed a Covid-Net concept based the deep convolutional neural network technique to detect the Covid-19 disease in chest X-ray images. The human observational factors are also incorporated in CovidNet to predict as like clinicians. Zhang et al. [3] introduced a Confidence-Aware Anomaly Detection (CAAD) Model to detect the Covid-19 disease. The anomaly detection network is incorporated to learn a one class description model from the large-scale negative data and finally, confidence prediction network is built upon the shared feature extractor for the purpose of binary classification. Abbas et al. [4] presented a Decompose, Transfer, and Compose (DeTraC) deep convolutional network to classify Covid-19 chest X-ray images. Rajaraman et al. [5] developed the iteratively pruned deep learning model for identifying pulmonary manifestation of COVID-19. The iterative process improves the performance of the prediction model by reducing trainable parameters. The weighted averaging ensemble of the pruned models precisely localize the defected region in the given chest X-rays. Brunese et al. [6] implemented a model with VGG-16 deep learning network to detect presence of pneumonia in the chest X-ray. Finally, the model is aimed to localize the areas in the X-ray symptomatic of the COVID-19 presence. Das et al. [7] introduced an automated Deep Transfer Learning-Based approach for identifying the COVID-19 infection in Chest X-rays. Deep transfer learning network is designed to train the weights of networks on large datasets and also it is used to fine tune the weights of pre-trained networks. Khalifa et al. [8] identify the pneumonia chest x-ray using Generative Adversarial Networks (GAN) with a fine-tuned deep transfer learning. The GAN positively affects the model robustness and made it immune to the overfitting problem. Recently, an elegant method on one shot cluster based approach for the detection of chest X-ray is proposed in [11]. The proposed model is a multi-class classification model as it classifies images of four classes viz., pneumonia bacterial, pneumonia virus, normal and COVID-19. The model is based on ensemble of Generalized Regression Neural Network (GRNN) and Probabilistic Neural Network (PNN) classifiers at decision level. Some of the interested papers on recent detection methods can be seen in [12]–[15].

The main objective of this work is to design and develop an efficient model of learning through one shot. The main contributions of this work are:

- A phase by phase learning approach for effective detection of chest X-ray images.
- A statistical measure of randomness namely, Entropy is introduced as selective process of images.
- Experimented on very large database comprising of 24614 images and compared with well existing algorithms.

II. Proposed Methodology:

The block diagram of the proposed phase by phase approach is shown in figure 1 and 2. The detail explanation about the methodology is outlined in the following subsections.

A. *Learning through one shot and Neural Networks*

The main intent of one shot learning is to mimic the way humans learn in order to make classification or prediction on a wide range of similar but novel problems. The need for one-shot learning is obliviated by following key considerations: (i) Learning to Learn: Usually learning happens only with few examples in humans and also can relate new concepts to already learned concepts. This suggests that model building in humans is a continuous process right from early stages of birth which gets refined by new experiences over a period of time. (ii) Scalability constraints with deep learning: No doubt deep learning has set new benchmarks in performance for specific learning tasks like object recognition, language understanding & machine translation. The main disadvantage of these algorithms is a need for millions of training examples to build which is computationally very expensive. The application of reverse engineering can help to overcome the scalability challenges faced by deep neural networks. (iii) Domains with sparse data: In certain domains, availability of data for training the model is a big challenge. In such applications, getting large number of training examples has practical constraints and recognition needs to be performed with only a few available data points. In such specialized domains, deep learning cannot yield the expected generalization performance. For N-way K-shot learning, suppose we are given with a set of labeled images, $S_{Label} = \{(X_i, Y_i)\}_{i=1}^{N*K}$, where X_i is the image, $Y_i \in$ class set, N is the number of classes in S_{Label} and K is the number of images per class in S_{Label}. For one-shot learning, $K = 1$.

In order to test the significance of each sample in the dataset and contribution towards the success, each sample in the database is considered for training and remaining samples are used for testing. The main idea behind this experiment is to know the contribution of each sample for the success towards designing a better model.

For wide range of applications including regression, forecasting and prediction, classification, and many more, Artificial Neural Networks (ANNs) are considered to be one of the important parts of Artificial Intelligence. In recent past, Probabilistic Neural Networks (PNN) has shown in wide range of applications to solve real world problems. PNN has few advantages compared to other neural architectures. PNN networks usually faster to train, often more accurate and relatively insensitive to outliers and also, PNN approaches Bayes classification thus predicates accurate target probability scores. In this work, we have used PNN for classifying the COVID-19 chest X-ray images.

B. *Texture Feature Extraction:*

The process of finding the best performing samples on larger dataset is expensive and time consuming. In order to overcome this, the application of PNN is performed on the subset of the large dataset considered. In this connection, we selected one best performing image from each category for our next level processing. In machine learning, it is common to quantify the expected amount of information associated with stochastic events, and to quantify the similarity between probability distributions. In both cases, Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. The Mathematical formula for Entropy is as follows:

$$E(S) = \sum_i -p_i log_2 p_i \tag{1}$$

Where ‘p’ contains the histogram counts of an image.

In phase two of our approach, we calculate the Entropy for the best performing image obtained from each category and keep as threshold. We select images greater than the Entropy of the best performing image in each category of the database. By doing so, we form a cluster of images for each category that may represent the similar property of best performing image. Again we apply PNN on the obtained set of images and we select best performing samples for our final training purpose. Perspectives of one shot learning can be categorized into (i) Data (ii) Model (iii) Method. The proposed method is one way of learning techniques that falls under the category of data and model. Using one shot, we tried to extract similar property feature images into one cluster. Total of 300 images are considered for training (5 images from category 1(COVID-19), 95 from category 2(Normal) and 200 from category

3(Non-COVID)) and fed to PNN for classification purpose.

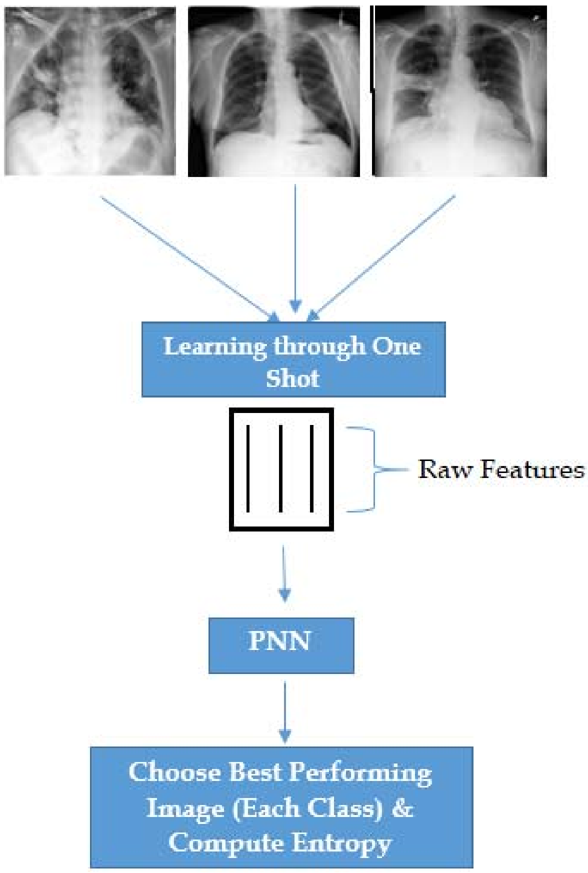

Fig. 1. Phase 1 of the proposed method.

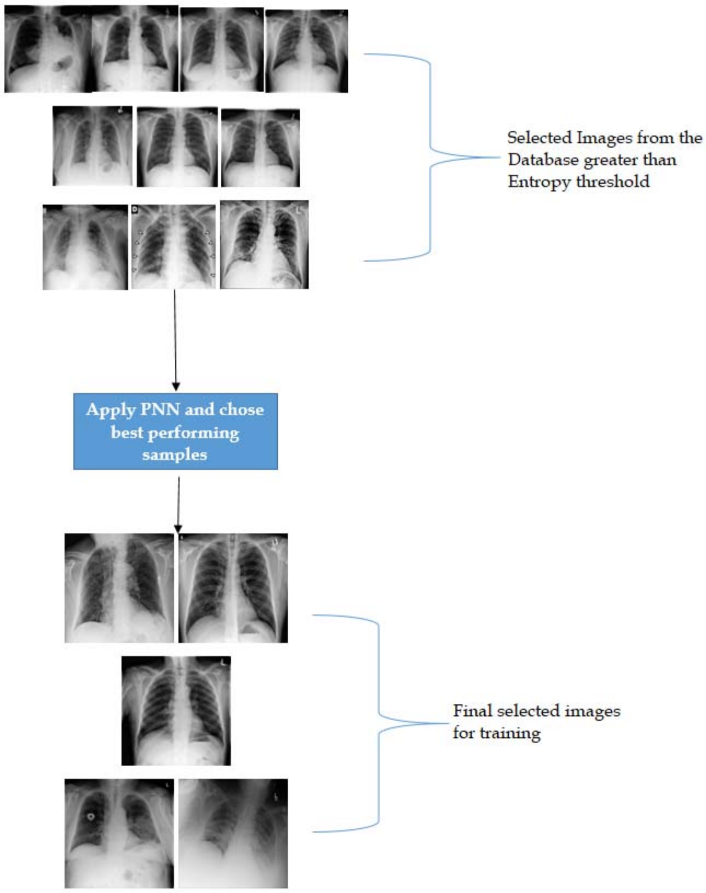

Fig. 2. Phase 2 of the proposed method.

III. Experimental Results

In this section we describe about the dataset collection and experiment results. To create this database, we have utilized several publicly available scattered and different format databases and repositories. RSNA pneumonia detection challenge dataset [20] is comprised of about 26,684 chest X-ray images, where 8,851 images are normal, while rest of them are abnormal X-ray images. All images are in DICOM format, a popularly used format for medical imaging. Padchest dataset [21] includes more than 160,000 images from 67,000 patients that were interpreted and reported by radiologists at Hospital San Juan (Spain) from 2009 to 2017, covering six different position views and additional information on image acquisition and patient demography. Paul Money has released an X-ray database of 5,232 chest X-ray images from children, including 3,883 characterized as depicting pneumonia (2,538 bacterial and 1,345 viral) and 1,349 normal, from a total of 5,856 patients [22]. In this study, we used 7000 normal images from RSNA database, 4000 normal images from Padchest database and remaining 1000 X-ray images were from Kaggle database, which is a child database. Therefore, the designed 12K normal and 12K Non-COVID images are of different age group, gender and ethnicity. COVID-19 dataset is comprised of 614 positive COVID-19 chest X-ray images. As mentioned earlier, these are collected and formatted from different public databases and repositories, some duplicate, over-exposed and low-quality images were identified and removed in the pre-processing stage. 183 X-ray images of COVID-19 patients were from a Germany medical school [23], 431 X-ray images were collected from public repositories: Italian Society of Medical and Interventional Radiology (SIRM), Github, Kaggle & Tweeter [24]–[28].

Table 1 shows the detection accuracy of the proposed method. From the table it is observed that average recognition accuracy of the proposed approach is 96.4%. Under COVID-19 and Normal classes, we achieved 100% recognition accuracy and under non-COVID category 89.38% is reported. We also compared our method with well known existing approaches and average recognition accuracy under different datasets are reported. From the table is it observed that a very few images (nearly 1.2%) are used for training the system and a total of 24314 images are used for testing. Certainly the proposed idea of learning through one shot using phase by phase approach has considerable impact when compared to existing deep learning models.

TABLE I
RECOGNITION ACCURACY OF THE PROPOSED AND EXISTING APPROACHES

Methods	Accuracy	Training Samples	Testing Samples
RANDGAN [13]	77%	12,381	1719
GraphXCOVID [12]	94.6%	13,675	1579
Infection Map [16]	98.69%	20070	3099
4S-DT [17]	97.54%	43475	6525
Ecovnet [18]	97%	14914	1579
ReCoNet [19]	97.48%	13624	1510
Proposed Approach	Precision:0.964 Recall:0.968 F-Measure: 0.96 Accuracy: 96.4%	300	24314

IV. DISCUSSION & CONCLUSION

Recent past, the world has witnessed nearly 38 million positive cases and around 1114K deaths due to novel Corona Virus disease (COVID-19). To distinguish COVID-19 from other viral pneumonias is quite challenging and difficult for radiologists. Wrong diagnosis may sometime lead to a non-COVID viral pneumonia being falsely labeled as highly suspicious of having COVID-19. There are few limitations exist in particular fields for getting more data for analysis. At this situation it will be more convenient to learn from few examples / data. Hence, the present work has concentrated on experimenting the learning through one shot. The proposed method utilizes the application of Entropy for selecting best describing images for effective learning purpose. The proposed model is evaluated on publically available large dataset of size 24614 images comprising of three classes viz COVID-19, Normal and Non-COVID. An average accuracy of 96.4% is reported with training only 300 samples and testing more than 24000 samples. This is an initial effort in understanding the behavior of the existing learning models. No doubt, there is still long run exists to understand and analyze more on the perspective of one shot learning especially on data, models and algorithms.

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