COSC 2673 - Assigment 4

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I. Literature Review

Polymerase chain reaction (PCR) [1] is the prime screening method used for detecting covid-19 cases. It is very sensitive in nature thus require large amount of manual process that are highly complex in nature. X-ray or CT is the alternative, which contains visual indicators of SARS-CoV-2 viral infection that can be inferred by a radiologist [2]. Patients show deformity in chest radiography images that are in character of those infected with COVID-19 [3], thus we invest on the hypothesis that Patterns of COVID-19 lung disease can be inferred on conventional chest X-rays. Computer-Aided Diagnosis (CAD) is the system that recognises use of Machine Learning techniques to classify medical images [4].

A. ML techniques for medical image diagnostics

Deep learning techniques are most widely used in computer vision, natural language processing, speech recognition and object recognition, and has led to the awakening of the artificial intelligence using deep learning, to solve these issues effectively and provide with an end-to-end model that can provide us with categorical classification from raw pixels of sophisticated medical images.

A range of ML techniques are used for medical image diagnostics like for classifying a skin lesion, Jeremy Kawahara, Ghassan Hamarneh [5], proposed a CNN architecture that's based on tracts, and each CNN tract which works on single resolution is converted to work on multi-resolution, the entire network is fine-tuned with auxiliary loss function. This model performed better than state-of-the-art multi scale approaches, over skin lesion dataset. The major issue with this approach is that model is confined to just single resolution images, but medical images like CT scans have multiple resolutions, thus multi-view CNNs could resolve this issue. Setio, Ciompi,Litjens and team [6], proposed a CAD system for pulmonary nodules using ConvNets. The architecture has multiple streams if 2D ConvNets and the outputs are combined by using a devoted fusion method which provides the ultimate classification, thus ConvNets-CAD proved to be a effective measure to screen lung cancer.

The current issue in intensity-based 2-D/3-D registration technology is the slow computation and slow capture range , Miao, Wang and Liao [7] proposed a CNN regression approach which is used the information embedded in the appearances of a digitally re-establishment radiograph and X-ray images and uses CNN regressors to train on local zones and apply this in a hierarchic manner to break down the complex regression task into multiple simpler sub tasks that can be learned separately. This mitigate the issues in 2-D/3-D registration technology.

Spotting appropriate lesions in medical images is vital for correct diagnosis and is mostly the toughest and labour intense work in clinical study. Various ML methods are in place to help with this. Diabetic retinopathy (DR) is the prime cause of preventable blindness, the earliest symptoms, is red lesions, these tendons are mostly detected using a fundus photograph, Orlando , Prokofyeva , Fresno , and Blaschko [8] proposed a method for red lesion detectio built on integrating deep learned and domain knowledge. they used CNN to train the model and incorporate features and then did augmentation by incorporating tailor-made features. Finally, a random forest classifier was used to recognize true lesion candidates. Kooi,Litjens and team [9], provided a head to head comparison of a state-of-the-art in mammography CAD and a CNN and as a result CNN showed better performance in low sensitivity that CAD system and almost equal performance in high sensitivity, end result was a system that can read mammograms independently.

Accurate segmentation of medical images is a vital step for contouring during radiotherapy planning [10] .They act as a pre-processing step for computer-aided diagnosis systems, or for human diagnosis, study of segmentation on brain tumours, sclerosis lesion are vital tasks in image processing, current techniques are specific to application, imaging modality and type of body part to be studied. Therefore, this is one of the most researched and studied field and almost on all study about segmentation in medical images CNN model is used. Wang, Gong [11] proposed an automatic brain tumour segmentation methodology using Deep Neural Networks (DNN) which is costumed to glioblastomas depicted in MR images their unit is a scalable accelerator architecture used for large-scale deep learning using field-programmable gate array (FPGA) as a hardware prototype. The CNN used local features and global contextual features at the same time, and also used a final layer that is a fully connected convolution layer that had a 40-fold speed.

B. AI systems to diagnose COVID-19 and related respiratory diseases

The conventional methods used for processing medical images used features like shape, colour, texture and/or a combination of all of these to create a model. These models have poor generalization ability. Different Ai systems using deep learning techniques are in play to classify x-ray images into categories like healthy patient, ill with pneumonia and infected with covid-19. K Sethy and K Behera [12] proposed a deep learning based AI model to detect covid-19 infected patients from there X-ray images, the model is a classification model which uses a combination of ResNet 50 and support vector machine, this support vector machine is used that classifies the covid-19 affected patients X-ray images from others using deep features. This model gained a F1 score accuracy of 95.52% , however the major limitation was that the model creation was done on just 25 covid infected x rays and 25 healthy patients x ray which itself was divided in a ratio of 60:20:20 for training, validation and testing action. Feature extraction was carried out using deep learning architectures, like ResNet18, GoogleNet and

AlexNet and ResNet50. These features are then classified using SVM. Fig. 1 shows the flow of the model. ResNet50 proved to produce optimum results, coupled with svm.

Ozsahin, Onyebuch and Sekeroglu [13] created a model which differentiates COVID-19 from other types of pneumonia using CNN. For model creation they conducted a 2-class- and 3-class-experiment which was performed using different convolutional neural network architectures. Variations of different convolutional layers and fully connected layers were used. Unlike K Sethy and K Behera [12] model, the modelling was done using 225 covid-19 infected patients X-ray, 1,583 healthy patients X-ray, 2780 bacterial pneumonia and 1493 viral pneumonia chest X-rays. Although a larger dataset is used here, but major problem arises in biased spread of the data which would produce models that are more inclined towards categories, containing a upper hand weightage of data distribution, although data augmentation was done on the images of covid-19 X-Rays to help produce better results . In the 3-class experiment where all three cases were parallelly tested and modelled on, a F1 Score of 95.79% and 94.59% accuracy was obtained for a CNN4 model which had two convolutional layers with 64-32 filters and two fully connected layers with 128 and 8 neurons and the input dimension of images used was 80*40.

S. Luz,L. Silva [14] there model used a flat classification and hierarchical classification . In the hierarchical analysis, there were no remarkable gains in categorizing the covid-19 cases but did better with major classes containing higher data. The data set available here of covid-19 infected patients x-rays was quite limited thus techniques like data augmentation and transfer learning and care was taken that semantics of images is not lost. The pre-processing of data was done via simple intensity normalization of pixels to bring in range of [0,1]. Four CNN models were evaluated EfficientNet, MobileNet, VGG and ResNet . A common trend found in the model was that the higher the complexity of the model, lower is the performance accuracy of minority class , here being the covid-19 X-rays. EfficientNet B0 proved to be the better of the lot in terms of efficiency although there was a small trade-off in terms of sensitivity metrics. This model brought in immediate improvements as compared to the baseline work and had a accuracy of 93.9%, Covid-19 sensitivity of 96.8% and a positivity prediction of 100% on the "Covid-19 Image Data Collection" [15].

The need of a model is fully automated with an end-to-end structure for classifying covid-19 cases from X-ray of patients led Ozturk, Talo, Yildirim and team [16] to come up with an auxiliary diagnostic tool having 17 convolutional layers and different filtering on each layer, Adam optimizer was chosen for weight updates, cross entropy loss function and selected learning rate as 3e-3, learning model contains 1,164,434 parameters. Darknet-19 is the initial model chosen, which has a layer layout as follows. C_1-M_1-C_2-M_2-C_3-C_4-C_5-M_3-C_6-C_7-C_8-M_4-C_9-C_{10}-C_{11}-C_{12}-C_{13}-M_5-C_{14}-C_{15}-C_{16}-C_{17}-C_{18}-C_{19}. C = convolutional layer and M=Maxpool layer. The processing was done in two portions, first binary in which covid cases is checked against non covid cases for which it produced a 98.08% accuracy and then multi-class function where covid cases is evaluated against pneumonia and no finding cases, for which it produced a 87.02% accuracy. The model was trained with 125 chest X-rays. The architecture of this model is shown in Fig 2 [16].

C. Problems in applying ML to medical Images

The major problem encountered across vast number of papers is the lack of suitable dataset. A large number of ML models would have performed much better if it was trained using uniform weighted datasets. A solution to this is the collection of data in a common repository world wide as done in "Covid-19 Image Data Collection" [15].

Computational power and resources is an issue pertaining to use of deep network architectures to process medical images, high end hardware like graphic processing units are required to mitigate this issue. Design of simpler and efficient models are also a solution to a large extent

During designing of models a large quantity of nodes needed to analyse complex relations or patterns that are usually seen in medical images, and can lead to huge number of parameters than need to be optimised during the training phase which is a very complex task and successful tuning is in not possible in such scenarios and also requires large amount of training data.

Also taking ethics consideration, any diagnosis from medical images without 100% accuracy can lead to life threating problems. Thus, intense care should be taken while applying ML techniques on medical images to not give false output.

II. Proposed Methodology

A. Ideology

Effective diagnosis of covid-19 patients from their chest X-ray using ML techniques can provide revolutionary change in fighting against this disease. A radiology expert can diagnose a X-ray successfully but takes significant time, which is an issue when a huge population is sick around the world due to this virus.To showxase the intensity of the situation Fig. 3 depicts the distribution of COVID-19 cases worldwide, untill 11 June 2020 *[17]*.The aim is to use a simple neural network that can produce fast inference and thus will increase its scalability.

B. Data preparation and preprocessing

A multi-class model need to be produced which can classify covid-19 patient X-ray images against pneumonia patients and healthy patient. Also a simple classification can help clinicians to determine further testing is required or not. We assume to have access to a data set containing 200 X-ray images of Covid patients and 300 X-ray images of pneumonia affected patients and another 300 of healthy patients. The presence of the COVID-19 infection can be observed through some opacity (white spots) on chest radiography imaging. In Fig. 4 shows a sample from the dataset showing different conditions and dimensions of the x-ray given in the dataset, which can be produced by random sampling from the dataset.

As a pre-processing set, data augmentation can be done on the COVID-19 cases to bring it on par with other two categories, this will greatly help in having a balanced training set common augmentation techniques that can be done on the dataset are rotation, scaling, and horizontal flip .presence of external devices like pace maker from the images can be identified using edge detection as these devices have clear boundaries and pixel intensity compared to body organs. Normalization of images is done The training process can be very slow if we keep the default pixel value thus to bring it in the form range of 0-1we rescale the value by dividing it with 255, which is the maximum pixel range.

C. Feature Extraction

Feature extraction can be done on the X-ray images using texture as a parameter. Methods like local binary pattern [18] which calculates a binary pattern fir local neighbours from each pixel of the x-ray image. Elongated quinary patterns [19] which uses quinary pattern evaluated different topology patterns for the neighbourhood of the central pixel, instead of considering only the circular neighbourhood, as originally done for LBP and LTP. Due to the presence of x rays that are blurred in nature we apply Local Phase Quantization [20] which takes the coefficients that are responsible for taking the intensity of the image, and a STFT 2D window with a previously defined size is slid over the image.

D. Modelling

k-fold cross validation should be performed, and the training set is divided into k folds and then the model is trained on k-1 parts of the X-ray dataset. For evaluation remaining 1 part as test set is used. This step will be repeated k times and the performance of model is taken by computing the average of k fold predictions. Making use of pre trained model will give us immense opportunity to in cultivate a well-established system and fine tune it according to our needs, thus resnet50 model can be first deployed, it's a CNN model which is 50 layers deep [21] and is pre trained over 1000 categories, fine tuning this model can provide us with valuable model. Resnet adds shortcuts between layers to solve a problem.

Parameter Tuning: the input image size can be rescaled to lower vlue since the complexity if model is pretty high in general the feature map generated by CNN models has many tuneable parameters. Fine Tuning these parameters should provide optimum accuracy model. 1) Size 2) Depth: Depth is determined by number of filters in the convolution 3) Stride: It is the distance to move the input over the centre of each filer. Default value is 1 .4) Activation Function : the most commonly used activation function is "relu" 5) Convolutional kernel value - we can choose values of 16,32 or 64 as the kernel size.We can fine-tune the resnet 50 model by making the number of epoch by 100 and keeping the btch size as 20. Adam optimizer could be used which will optimize the loss function. Another model that we can use is

EfficientNet [22] starts from a high quality yet compact baseline and then uniformly scale each dimensions of itself systematically in a fixed set of scaling coefficients. EfficientNet has three dimentions 1) depth; 2) width; and 3) resolutions. They are comparatively less computational cost, we can keep adding operators block on top to get optimum results also We can copy the weights from the result of resnet50 and add new layers to adapt to the present x-ray dataset condition then define which layer will pass through the new learning process then updating the weights according to the loss function. We use fully connected layers at last for the output layer. Batch normalization is used to constrain the output to a particular range, thus acting as a regularization. Dropout could also be used as regularization which inhibits few neurons in random and hence facilitates training.

E. Evaluation Framework

To calculate the efficiency of the designed model we need to take a random set of x ray images from the lot of covid infected or any other two category and feed into the model and check the accuracy and confusion matrix which will provide us with proof of its efficiency in each category of classification. The metrics that should be computed to evaluate the model are F1- score, average area under the curve, precision and sensitivity. The quantitative analysis of the need to calculate the test accuracy and also the sensitivity accuracy. factors to take into consideration are the architectural complexity, test accuracy and computational complexity. As a final step of evaluation we can plot a gradient based class activation map which is used to highlight the important patterns in the X-ray images which the model used for classifying different classes The proposed model can save critical time in diagnostics and can be applied to CT images.

F. Issues and result

The major technical issues that can be faced is the computational time and hardware required for processing such deep neural networks, the optimum solution to it is to take pre trained models that can save significant computational needs, also as mentioned, weight transfer is also a optimum means by which execution starts right from where it was left, on next model . Getting suitable dataset with uniform distribution across all categories in study is essential.

The model used will show tendency to classify images more towards positive covid side, one hypothesis to this could be because pneumonia and covid shares a large number of similar patterns on the x-ray. A bias result towards pneumonia or healthy patient is possible due to the dataset containing more images pertaining to those categories. Presence of external factors like pacemaker machines can hinder the classification process.

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III. Appendices

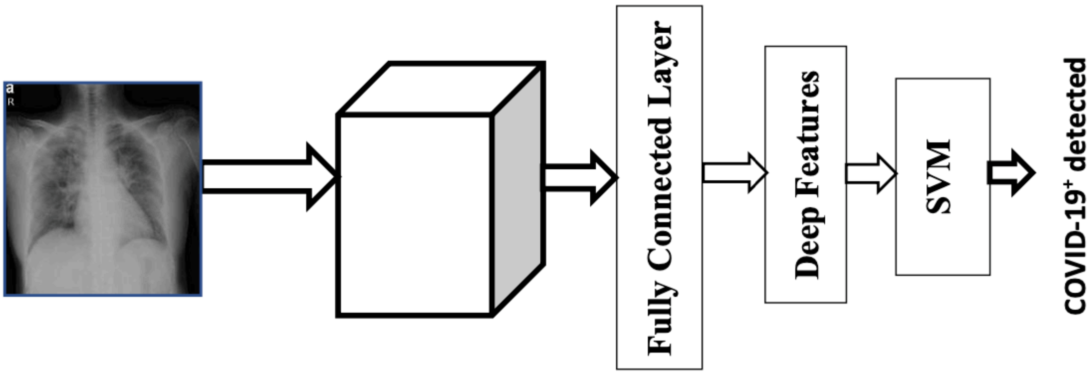

Fig. 1

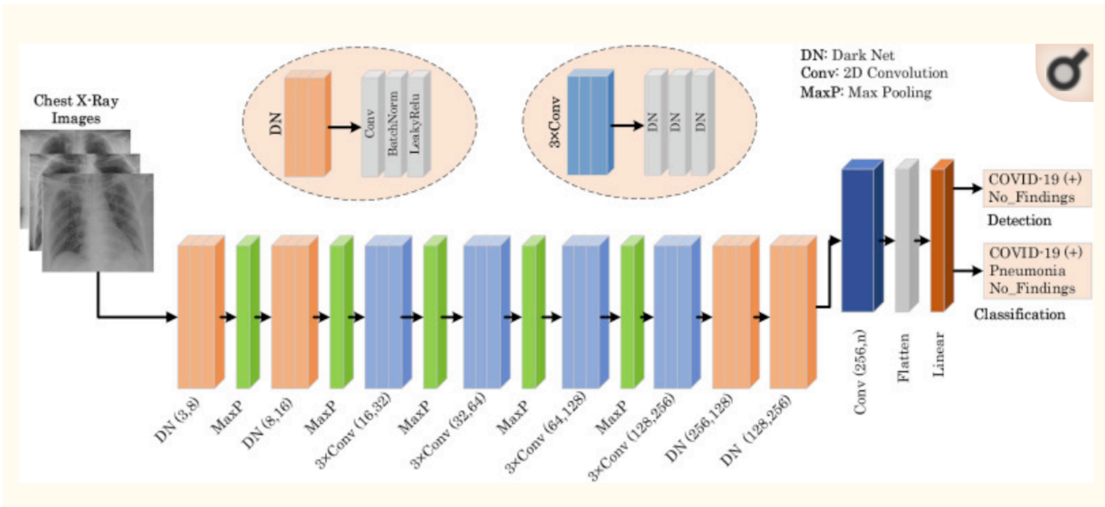

Fig. 2

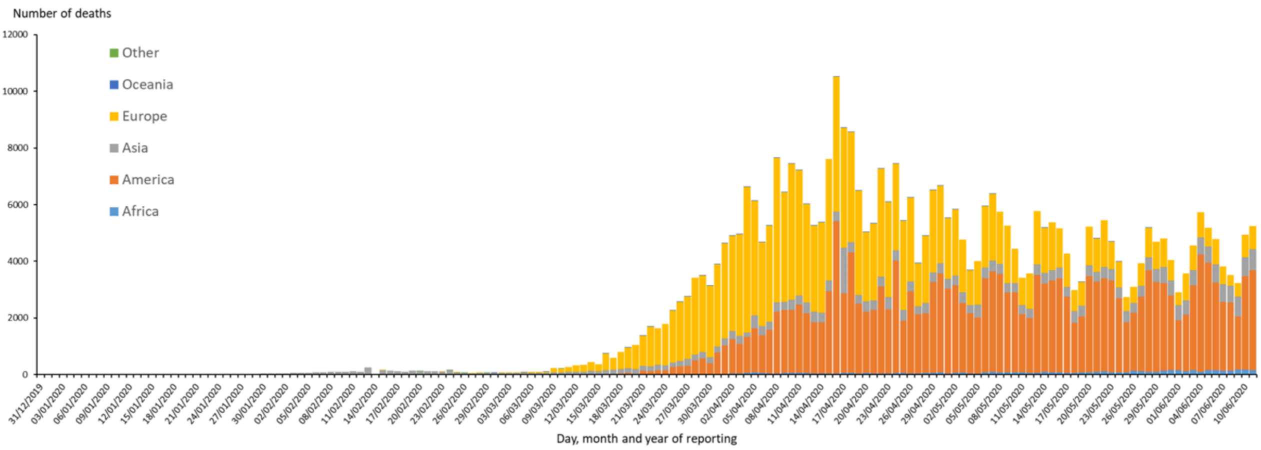

Fig. 3

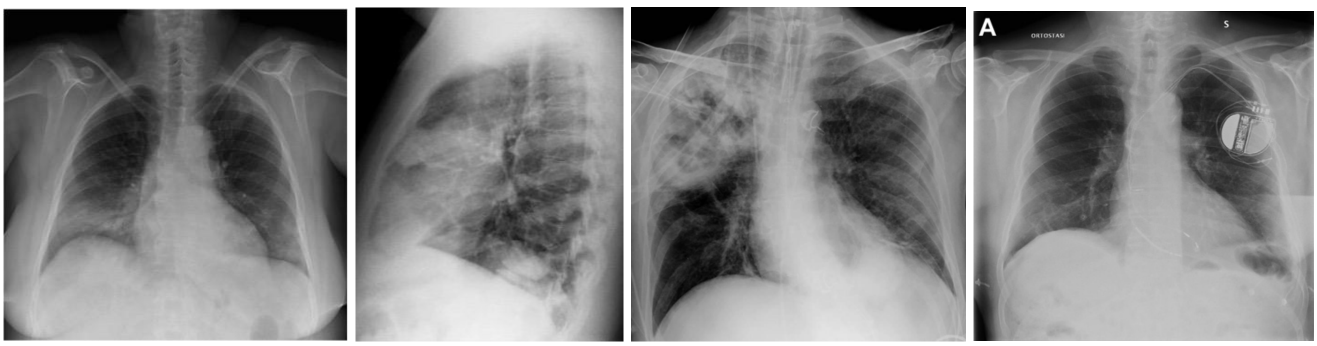

Fig. 4