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Analysis and Design of Artificial Intelligence System for the Prediction of Pulmonary Diseases

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Abstract: Report generated by radiologists using chest X-rays has significant potential to improve clinical patient care. Diagnosing chest X-rays can be challenging and sometimes more difficult than diagnosis via chest CT imaging. Lack of availability of well-trained radiologists and delayed report generation results in long waiting time which indeed leads to delayed medical assistance. As the interpretation of chest X-rays is time consuming, we propose a system that assist the medical professionals in doing the same job within minimum time. In this work, the proposed system can detect heart and pulmonary diseases such as pneumonia and enlargement of heart from chest radiographs at a level equal to the knowledge and skill set of practicing radiologist. The system employs artificial intelligence techniques. Using such techniques improves a patient's overall treatment with less hospital time and can also be used to deliver high-quality and cost-effective care. Its focus is to produce accurate disease profiles to power downstream tasks such as diagnosis and care providing.

Keywords: Machine Learning, Deep Learning, Recurrent Neural Network, Image augmentation, Reinforcement Learning.

I. INTRODUCTION

Patient with a particular disease are often misdiagnosed with other disease leading to delay in the correct diagnosis as well as exposure to inappropriate medication. In recent years respiratory diseases have become the leading source of death and disability in the world. It is reported that about sixty-five million people suffer from pulmonary diseases and three million die each year, making it the third leading cause of death worldwide. Inability to detect the right disease at the right time is life threatening. Chest X-rays are one of the most commonly accessible medical imaging techniques for screening and diagnosis of many pulmonary diseases. Even if more sophisticated tests are required, an X-ray would be taken first. Also, X-rays are cheaper compared to all other diagnostic imaging techniques. It uses deep learning and machine learning methods to produce a mapping from input radiographs to desired output. With the advent of large datasets and increased computing power, this model can perform exceptionally. Detection of pulmonary diseases from chest radiographs automatically at the level of expert radiologists would not only have tremendous benefits in clinical settings, it would also be of great importance in delivery of healthcare to population with inadequate access to diagnostic imaging specialists.

In this paper, section two briefly summarizes the related works. Section three presents the objectives. Section four describes the proposed system. Section five provides results followed by conclusion and future scope.

II. RELATED WORKS

There are various AI tools to analyze the pulmonary related problems from the digital radiographs of chest. In this work [1] the authors provide detailed analysis of deep learning techniques used in various applications to provide an extensive reference for the researchers in deep learning and its algorithms, implementation techniques and applications used in recent technologies. This work also highlights new research areas and advancements of technology. The main motive of this survey is to give valuable insights to apply deep learning techniques in MRI based area. For the high-performance automated binary classification of chest radiographs using the Convolutional Neural Networks (CNNs) were proposed by the author [2].The data set was used to train Convolutional Neural Networks to classify chest x-rays as normal or abnormal before evaluation on a held-out set of 533 images hand-labelled by radiologists. By using standard binary classification metrics, the effects of development set size, training set size, initialization strategy, and network architecture on end performance were assessed and detailed error analysis, including visualization of CNN activations, was also performed.

The author presented a domain-aware automatic chest X-ray radiology report generation system which first predicts the topics that will be discussed in the report, then conditionally generates sentences corresponding to these topics [3]. Then the system is fine-tuned using reinforcement learning, considering both readability and clinical accuracy, as assessed by the proposed Clinically Coherent Reward, Verified the system on two datasets, Open-I and MIMIC-CXR, and demonstrated that the model offers marked improvements on both language generation metrics and CheXpert assessed accuracy over a variety of competitive baselines.

A semi-supervised Reinforced Active learning for pulmonary nodule detection in chest X-rays were proposed by the author [4]. This model is tested on a U-Net segmentation network (U-Net is a convolutional neural network that was developed for biomedical image segmentation) for pulmonary nodules in chest X-rays. To improve the performance of deep neural network, the pulmonary nodule detection task in chest radiographs using the U-Net segmentation network showed that the approach can effectively leverage unlabeled data. In this work [5] authors used probabilistic approach for automated region of interest ROIs detection using convolutional neural networks (CNNs). The proposed algorithm is simple and can be divided into regions and features can be extracted for the divided regions. They have also proposed a preprocessing algorithm based on CNN and RNN that automatically classifies ROIs that are finely adjusted through image standardization based on TW3. The result is 20%-40% more accurate than those obtained using the conventional method. The author proposed a system to detect and predict lung cancer using Multiclass SVM (Support Vector Machine) classifier [6]. Multi-stage classification was used for the detection of cancer. The system can also predict the probability of lung cancer. In every stage of classification image segmentation and enhancement should be done separately. For image enhancement Image scaling, color space transformation and contrast enhancement have been used. For segmentation threshold and marker-controlled watershed-based segmentation has been used. SVM binary classifier were used for classification purpose.

Google's Google Health team, its DeepMind unit, and London's Imperial College used a triad of three different deep learning neural networks, consisting of, Facebook AI's "RetinaNet," combined with Google's "MobileNetV2," at the top, followed by ResNet-v2-50 in the middle section, and ResNet-v1-50 on the bottom layer. Each one selects suspicious-looking areas of a mammogram in different ways, and the information is added up to reach a probability decision about cancer or no cancer. This is an important work in terms of AI tools that will be very useful to doctors.

This work [7] lists the basic types of machine learning algorithms and examples of each type. The authors have also discussed the typical problems encountered with machine learning approaches. In this paper the author developed an algorithm that exceeds practicing radiologists which can detect pneumonia from chest X-rays [8]. The algorithm, CheXNet, is a 121-layer convolutional neural network which is trained on ChestX-ray14, currently the publicly available chest X-ray dataset, containing over 100,000 frontal-view X-ray images with 14 diseases. Four practicing academic radiologists have annotate a test set, on which compare the performance of CheXNet to that of radiologists and they found that CheXNet exceeds average radiologist performance on the F1 metric. It extends CheXNet to detect all 14 diseases in ChestX-ray14 and achieves state of the art results on all 14 diseases. He also introduced MURA [9], a large dataset of musculoskeletal radiographs containing 40,561 images from 14,863 studies, where each study was manually labeled by medical experts as either normal or abnormal. To evaluate models and to get an estimate of radiologist performance and collection of additional labels from six board-certified Stanford radiologists on the test set, consisting of 207 musculoskeletal studies. On this test set, the majority vote of a trio of three radiologists serves as gold standard. Train a 169-layer DenseNet baseline model to detect and localize abnormalities and the system achieved an AUROC of 0.929, and an operating point of 0.815 sensitivity and 0.887 specificity.

The author presented a model using LSTMs to leverage inter dependencies among target labels in predicting 14 pathological patterns from chest x-rays and establish futuristic results on the largest publicly available chest x-ray dataset from the NIH without pre-training [10].

A novel method is proposed by the author using Convolutional Neural Network (CNN) deals with unbalanced, less category X-ray images are available for the faster Tuberculosis analysis [11]. This method improves accuracy for classifying multiple TB manifestations by a large margin. In the training network the system have explored the effectiveness and efficiency of shuffle sampling with cross-validation and find an outstanding effect in medical images classification. The purpose of this work [12] was to provide an effective and accurate image description of an unknown image by using deep learning methods. The authors have proposed a novel generative robust model that trains a Deep Neural Network to learn about features in images after extracting information about the content of images, for that the used the novel combination of CNN and LSTM. The model was trained on MSCOCO dataset, which also had set of annotations for a particular image, and after the model was fully automated, it was tested using raw images as inputs.

This study [13] proposed a fast algorithm to automatically estimate cardiothoracic ratio (CTR) indices based on chest x-rays. The algorithm has three main steps: first step is model based lung segmentation, followed by estimation of heart boundaries from lung contours, and finally computation of cardiothoracic indices from the estimated boundaries. The authors have extended a previously used lung detection algorithm to automatically estimate heart boundaries without using ground truth heart markings. The two sets of datasets used includes a dataset with 247 images which is publicly available, and the other dataset was a clinical dataset with 167 studies from Geisinger Health System. The models of lung fields are learned from both datasets. The lung regions in a given test image are estimated by registering the learned models to patient CXRs. Then, Harris operator was used to estimate heart region this was done by applying the operator on segmented lung fields to detect the corner points representing the heart boundaries. The algorithm calculates three indices, CTR1D, CTR2D, and cardiothoracic area ratio (CTAR). The method was tested on 103 clinical CXRs and had average error rates of 7.9%, 25.5%, and 26.4% (for CTR1D, CTR2D, and CTAR respectively) were achieved. The proposed method outperforms previous CTR estimation methods without using any heart templates.

Brighton and Sussex University Hospital presented a work to improve access to healthcare in remote areas where medical services are of poor quality. They developed a new Machine Learning methodology that can be implemented into mobile devices to help the early detection of a number of life-threatening conditions using X-ray images. By using the latest developments in fast and portable Artificial Intelligence environments, they developed a smartphone app using an Artificial Neural Network to assist physicians in their diagnostic.

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Deep convolutional neural network (CNN) based method is proposed by the authors for thorax disease diagnosis [14]. Firstly, the images are aligned by matching the interest points between the images, and then the dataset is enlarged by using Gaussian scale space theory. Then it makes use of the enlarged dataset in training a deep CNN model and applies the resultant model for the diagnosis of new test data. The following work by the author explored and evaluated different CNN architectures [15]. 5000 to 160 million parameters, and vary in numbers of layers were contained by the studied model. Then evaluate how the dataset scale and spatial image context influenced the performance. Finally examined when and why transfer learning from pre-trained ImageNet (via fine-tuning) can be useful. They studied two specific computer-aided detection (CADe) problems, namely thoraco abdominal lymph node (LN) detection and interstitial lung disease (ILD) classification and achieve the state of the art performance on the mediastinal LN detection, and report the first five-fold cross-validation classification results on predicting axial CT slices with ILD categories.

The author proposed and evaluated a convolutional neural network (CNN), designed for the classification of ILD patterns (The six histopathological patterns of ILD “acute injury, fibrosis, cellular infiltrates, airspace filling, nodules, minimal changes”) [16]. The network consists of 5 convolutional layers with 2X2 kernels and LeakyReLU activations, followed by average pooling with a size similar to that of the final feature maps and three dense layers. The last dense layer has 7 outputs, equivalent to the classes considered: healthy, ground glass opacity (GGO), micronodules, consolidation, reticulation, honeycombing and a combination of GGO/reticulation. To train and evaluate the CNN a dataset of 14696 image patches, derived by 120 CT scans from different scanners and hospitals. This work, [17] examines the strength of deep learning approaches for pathology detection in chest radiographs. The ability of CNN learned from a non-medical dataset is explored to identify different types of pathologies in chest x-rays. The algorithm was tested on a 433 image dataset. The finest performance was achieved using CNN and GIST features. An area under curve (AUC) of 0.87-0.94 was obtained for the different pathologies. The results demonstrated the feasibility of identifying pathology from chest x-rays using deep learning methods based on non-medical learning. In this paper [18] the authors give decomposition implementations for two "all-together" methods. They then compared it's performance with three methods based on binary classifications: "one-against-all," "one-against-one," and directed acyclic graph SVM (DAGSVM).The experiments indicate that the "one-against-one" and DAG methods are more suitable for practical use than the other methods. Results also show that for large problems methods which considers all the data at once in general need fewer support vectors. The basic terminology and concepts of image processing as it applies to x-ray projection radiography are discussed and defined [19]. In general, the processing of an image involves one or more-point, local, global operations. Clinical examples of linear and nonlinear gray-scale and algebraic point operations are presented. Examples are also given of local operations. Included in the latter group are distortion corrections, misregistration corrections, linear filtering, and nonlinear filtering.

III. OBJECTIVES

To develop an artificial intelligence system that can assist radiologists by avoiding misdiagnosis and also reduces the time taken for clinical report generation. It mainly focuses on diseases such as pneumonia and cardiomegaly which can be diagnosed from a chest X-ray.

IV. PROPOSED SYSTEM

The architecture of the proposed system is described in fig 1. It can be used to detect pneumonia and cardiomegaly from chest X-rays.

A. Data Preprocessing

The main purpose of preprocessing is to enhance the quality of the images and make the ROI (region of interest) more obvious. Thus, the quality of preprocessing has a large influence on performance of the subsequent procedures. It deals with preparing input data before it is being fed to the model and is achieved by converting raw data into a more understandable format. Since this project deals with medical data, there will be more tendency to have radiographs with multiple labels. Hence the first important step is to clean data by removing radiographs with multiple labels. Later the image is resized to 224x224 to fit the model.Also since the input to the proposed CNN model are digital chest radiographs, it is necessary to improve their contrast by effectively spreading out the most frequent intensity values. This is done by performing histogram equalisation on radiographs. Inorder to optimise the code, we use inbuilt function equalizeHist() to perform the histogram equalization .Then the resultant image of grayscale format is converted to RGB to match the expectation of the model radiographs with multiple labels. Later the image is resized to 224x224 to fit the model. Also since the input to the proposed CNN model are digital chest radiographs, it is necessary to improve their contrast by effectively spreading out the most frequent intensity values. This is done by performing histogram equalisation on radiographs. Inorder to optimise the code, we use inbuilt function equalizeHist() to perform the histogram equalization .Then the resultant image of grayscale format is converted to RGB to match the expectation of the model.

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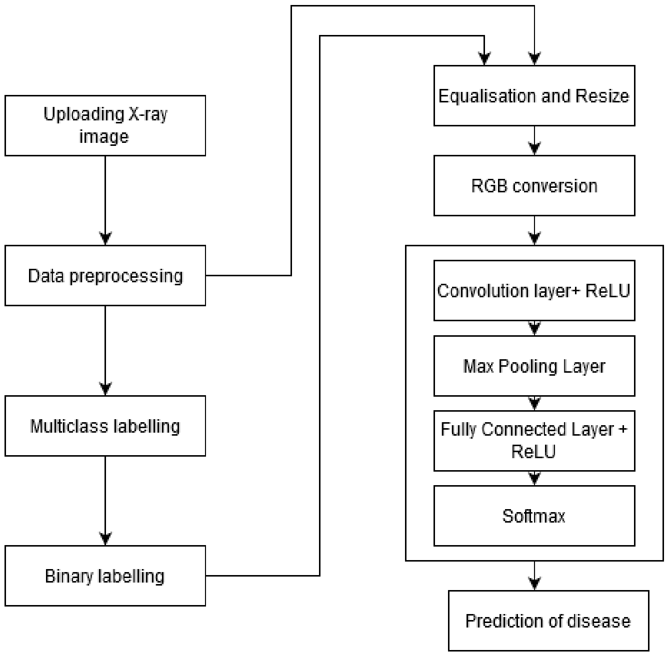

Fig. 1 System architecture

B. Multiclass Labelling

The multiclass labeling module deals with assigning distinct numerical labels to each sample on the available dataset. Here a number within the range 0-14 is assigned with different diseases available in the dataset. Labelling is done on each radiograph based on the disease it shows. It can be done using the Scikit-learn library of python.

C. Binary Labelling

Most of the radiographs are labelled with more than one disease making it a typical multi-label classification problem. Since we are dealing with medical data we need to ensure that only one disease is present in a particular radiograph so as to train the model. Also many diseases can have common features, so binary labeling must be implemented to train the system in a proper way. Binary labeling is done using label binarizer from Scikit-learn library. In binary labeling each images in the dataframe will have four fields, and if the first field is 1 then it will be cardiomegaly, if the second field is 1 then it will be fibrosis, if the third field is 1 then it will be no finding and if the last field is 1 then it will be pneumonia. In general image with label 1000 is cardiomegaly, 0010 is no finding and 0001 is pneumonia. Once labeling completed, pretrained model classify the input radiographs under different categories of diseases based upon the features extracted from them.

D. Training and Testing

Based upon literature survey, it has been found that a deep convolutional neural network (CNN) can be employed to improve the performance of diagnosing chest diseases in terms of accuracy and minimum square error achieved. CNN is one of the most powerful deep networks is the convolutional neural network that can include multiple hidden layers performing convolution and subsampling in order to extract low to high levels of features of the input data. Basically, CNN consists of three layers: convolution layers, subsampling or pooling layers, and full connection layers

In convolution layer, an input image of size R * C is convolved with a kernel (filter) of size a * a. Each block of the input matrix is independently convolved with the kernel and generated a pixel in the output. The result of the convolution of the input image and kernel is used to generate n output image features. Generally, a kernel of the convolution matrix is referred to as a filter while the output image features obtained by convolving kernel and the input images are referred to as feature maps of size i * i. CNN can include multiple convolutional layers, the inputs and outputs of next convolutional layers are the feature vector. There are a bunch of n filters in each convolution layer. These filters are convolved with the input, and the depth of the generated feature maps (n*) is equivalent to the number of filters applied in the convolution operation. Each filter map is considered as a specific feature at a certain location of the input image. After the convolution layer, the activation function can be applied for nonlinear transformation of the outputs of the convolutional layer. Typically used activation functions are sigmoid, tanh, and rectified linear units (ReLUs). ReLU is popularly used in deep learning models due to its help in reducing the interaction and nonlinear effects.

In the pooling layer, they spatially reduce the dimensionality of the features maps extracted from the previous convolution layer. To do so, a mask of size b∗b is selected and the subsampling operation between the mask and the feature maps is performed. Many subsampling methods were proposed such as averaging pooling, sum pooling, and maximum pooling. The most commonly used pooling is the max pooling, where the maximum value of each block is the corresponding pixel value of the output image. This layer helps the convolution layer to tolerate rotation and translation among the input images. Finally, fully connected layer is the

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last final layer of a CNN is a traditional feedforward network with one or more hidden layers. The output layer uses Softmax activation function.

After finding output signals, the training of the CNN is started. As a result of training, the parameters of CNN are determined. In this project VGG16, a convolutional neural network architecture named after the Visual Geometry Group from Oxford (who developed it) is used. It was used to win the ILSVRC (ImageNet) competition in 2014. As the name suggests the model has 16 layers,13 convolutional layers followed by fully-connected layers which is used for making predictions. During training, the input to our ConvNets is a fixed-size 224 × 224 RGB image. The image is passed through a stack of convolutional (conv.) layers, having filters with a very small receptive field: 3 × 3. The convolution stride is fixed to 1 pixel, i.e. the padding is 1 pixel for 3 × 3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers. Max-pooling is performed over a 2 × 2 pixel window, with stride 2.All hidden layers are equipped with the rectification (ReLU) non-linearity. The width of conv. layers (the number of channels) is rather small, starting from 64 in the first layer and then increasing by a factor of 2 after each max-pooling layer, until it reaches 512.A stack of convolutional layers is followed by three Fully-Connected (FC) layers: the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer. While loading the given model, the fully-connected output layers of the model used to make predictions are not loaded, allowing a new output layer to be added and trained as per the requirement of the project. Adding the fully connected layers forces users to use a fixed input size for the model (224x224, the original ImageNet format). By only keeping the convolutional modules, the model can be adapted to arbitrary input sizes. Transfer Learning approach is used to decrease the training time for the neural network model.

The dataset is divided into a training set and testing set. 80 percent of the datasets are used for training and rest 20 percent for testing. The training dataset is the actual dataset used to train the model for performing interpretation of chest radiographs. The ongoing development process model learns with various API and algorithms to train the system to work automatically. The model is fitted on the training set followed by the testing set to verify and gives accurate results for observations on validation set.

V. RESULT

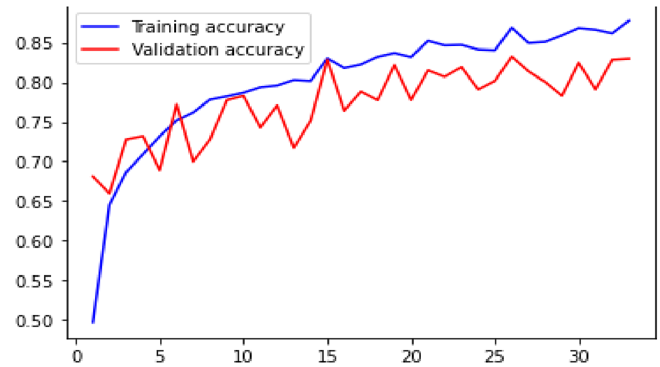

Fig. 2 Training and Validation accuracy

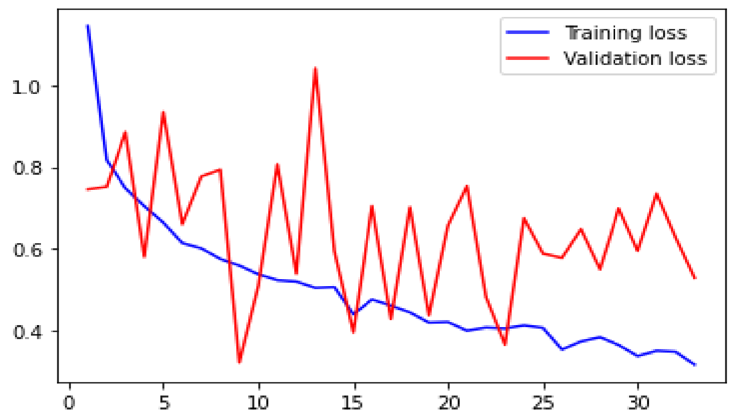

Fig. 3 Training and Validation loss

The graphs shows the accuracy and loss of model after training and validation. The training set consisted of 80% of the data , 20% of data was used for validation. Maximum training accuracy of 83.02% was achieved along with a validation accuracy of 82.84%.

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VI. CONCLUSION

Healthcare is one of the inevitable domains in which artificial intelligence can play a vital role. Currently the medical field faces lack of well-trained radiologists thus the healthcare system is under strain with rising cost and long waiting time. Also radiologists experience heavy workload and find it difficult to provide accurate reports on time which in turn results in misdiagnosis. Initial stage of diagnosis for patients with pulmonary diseases involves reading chest X-rays, this is due to lower cost and demands only less than a minute to take an image compared with other medical imaging techniques. As a result, chest X-rays became the widely used screening tool but it provides a low fidelity view that paves the way to other more sophisticated imaging methods. The ability of radiologists to provide a more accurate diagnosis can be improved by employing artificial intelligence techniques for diagnosing diseases from chest radiographs. Although it is difficult to predict the future, these new technological advancements can bring changes in existing radiology practice in coming years.

Future advancements include extending the system to other imaging techniques like MRI, CT Scan and also increasing its ability to detect all 14 diseases that can be identified from a chest X-ray along with its severity.

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