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Chest Disease Detection through X-Ray using Machine Learning

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ABSTRACT

Chest disease have majorly affected man lives around the world.There are many chest disease such as pneumonia, asthma, tuberculosis and many more lung diseases. If these diseases are not diagnosed in time they can turn deadly.Chest radiography (chest X-ray)is a effective way of recognizing and the problem and cost effective at he same time. But due to lack of professional radiologist the application of the method hasn't reached it peak. In this paper, we will explore the possibility of designing a computer aided diagnosis for chest X-rays using deep convolutional neural networks. Using a real-world dataset of 118055 chest X-rays with natural language diagnosis reports, we can train a multi-class classification model from images and preform accurate diagnosis, without any prior domain knowledge. Chest X-ray (CXR)is commonly used for the diagnoses of such lung diseases. Computeraided diagnosis (CAD)was developed for the radiologist to achieve the desired result in short period of time.

Keyboard: - CAD, CXR, CNN, multi-label classification, problem transformation method, deep learning, image classification, image feature extraction.

I. INTRODUCTION

Medical X-rays are used to diagnose several disease in a short period of time.Medical professionals use this technique to identify different fractures and abnormalities in different ares of the body.This is because X rays are very effective and does not cause any harm to the body in any ways.Chest diseases can be shown in CXR images in the form of cavitation, consolidations, infiltrates, and small broadly distributed nodules. By analyzing the X-ray's the doctors can diagnose different diseases such as effusion, pneumonia, bronchitis, infiltration, nodule, cardiomegaly, pneumothorax, fractures, and many others. In this work, we diagnose the lung diseases at a much quicker pace than the radiologist. Chest X-Ray, is one of the most common types of radiology examination for the diagnosis of lung diseases.

However, radiologist involve the decision under uncertainty Therefore, a clear output cannot be taken out[1]. Therefore, Computer- Aided Diagnosis was developed to get the result effectively with easy and in short amount of time.CAD systems are not here to replace doctors rather help them get a second opinion for the overall diagnoses. Over the past few years we have been working on use of Computer-Aided Diagnosis and Artificial Intelligence for classification of the image and through the classification acquiring the accuracy .

The first step towards classification is to extract the features from the images which in turn will act as input to the second step for training[2]. The accuracy completely speedy on the training of the dataset.Therefore, we are using the best model for the classification which is called as the Convolutional neural network in deep learning.This model provides the highest accuracy after training the dataset. This model was introduced in 90's for human visual perception of recognizing things. The best known architecture in Convolutional neural net is the LeNet architecture that was used to analyze the zip codes, digits, etc. [3]. But due to it property of being data hungry researchers had to introduce more generalized methods in deep learning [4].In multiclassification instances are introduced for the training of the dataset by transforming problem into more single labels. The given paper introduces a model which will use multiclassification and deep learning technique for the detection of different chest diseases.The Ian concept is to change the multi-classification design into a single label concept as mentioned below. The following is achieved using a publicly available dataset called NIH-Chest X-ray.

II. KEY FEATURES

- Recognize the disease of the chest by feeding the images to the machine learning model.
- Machine learning model is flexible and can be trained for any type of diseases and different kinds of chest diseases.
- Real-time images are provided to the app which in turn is integrated with Machine learning model and output disease is predicted.

- Information about each chest disease is available on the app such as different term description related to chest or lung diseases.
- Model which is built for detecting disease can be integrated with any app because the model is converted to API and requests can be made to the endpoint URL of the API.
- I
t is hosted globally so anyone can access the API and integrate it with the app.

III. RELATED WORK

Using the publicly available dataset called ChestXray14 dataset many models have been introduced[19].In that we have used three different CNN models and classified there uses.[20]Present a two-staged model with recurrent neural network acting as a decoder. While [21]analyses is done about which function is more suitable for the working of CNN model. The feasible works of ChesXNet [22] that tells us about DenseNet-121 on the chest X-ray images, which has a modified last fully- connected layer and [23] that proposes a guided two-branch convolutional neural network for chest disease classification. The model consist of both the global and publicly evaluated model for the training and gives us the best result possible.

IV. DEEP LEARNING WITH MEDICAL IMAGE

Deep learning's basically introduced to get the images which have scare and recognize them.It basically uses the a large dataset to get the value and extract the desired knowledge require for the training and testing of the data.

CNN AS FEATURES EXTRACTOR

In order to get the fully featured network we need to get rid of the latest fully trained CNN model. We first have to pre-trained the whole model gained and start with the training and testing of the model.This will help us extract the right features and accuracy in no time.The huge data should be trained and testing in such a way the the accuracy of the model should not be hindered.To get the good CNN model we had to try and test various training models including ResNet [5], VGG-Net [6], and DenseNet [7]. As a result, we chose the DenseNet-121 model which achieved the state-ofthe-art results.

V. MULTI-LABEL CLASSIFICATION (MLC)

Multi-label image classification has gained a lot of attention in the computer vision field and has helped untacking many problem related to images. The binary/multi-class has one label of each image but a multi-label can have multiple image labels. There are different approaches have been proposed to address the problem of multi-label classification; they are mainly arranged into three categories: 64280 VOLUME 7, 2019 I. Allaouzi, M. B. Ahmed: Novel Approach for Multi- Label CXR Classification of Common Thorax Diseases Problem Transformation Methods:

The main idea is to fit data to an algorithm by converting the multi-label classification problem into one or more binary/multi-class sub- problems, and then combine their results to form the multi-label prediction. Representative algorithms include Binary Relevance [8], Random k-Labelsets [9] and Classifier Chains [10].

Problem Adaptation Methods:

The idea is to fit the well know techniques with the multi-label classification model. The algorithms include lazy learning techniques ML-kNN [11], an adaptation of decision tree techniques ML-C4.5 [12], an adaptation of kernel techniques RankSVM [13]. A novel approach called Ensemble methods [14] was developed on top of these two approaches. It converts the problem of multi-label classification into an ensemble of multi-label sub-problems. Representative algorithms include the Random klabELsets method (RAkEL) [15], Ensemble Classifier chains (ECC) [16], and label space partitioning classifiers [17]. In order to find the most suitable approach for our case, we tried to make a comparison between the three above methods.

VI. THE PROPOSED APPROACH

The idea behind our approach is to combine the effectiveness of CNN for image features extraction from a small image dataset and the power of the problem transformation methods in the task of multi-label classification. As shown in Figure 2, the development of the proposed method consists of four parts: data description and exploration, data pre-processing, feature extraction part, and classification part.

A. DATA DESCRIPTION AND EXPLORATION

1) NIH CHESTX-RAY DATASET

The dataset contains 112,120 frontal CXRs from 30,805 unique patients. The images are in PNG format and have a size of 1024 × 1024. CXRs are labeled with 14 common chest diseases including Atelectasis, Consolidation, Infiltration, Pneumothorax, Edema, Emphysema, Fibrosis, Effusion, Pneumonia, Pleuralthickening, Cardiomegaly, Nodule, Mass and Hernia. If the diseases given above are on present in the CXR, then it will be labeled as ‘‘No finding’’. Exploring the image visually helps us gain a lot of information on the size of the image and different faction for formatting it in the way possible

B. DATA PRE-PROCESSING

Data pre-processing is meant resize the images in the way required for the training of the model.This will help us to get the model working for the extraction which is the next stage of the process.With this we normalize the datable subtracting the images as required.

C. FEATURE EXTRACTION

The important part of the CXR is to get the features that will help us classify the images into one or multiple possible classes. We have used the DenseNet-121 model is used as a feature extractor. The Dense Convolutional Network (DenseNet) [8] is a new CNN architecture that is highly competitive object recognition benchmark tasks. The core idea of DenseNet is to connecting all the layer and letting multiple information flow through it that match with it. As shown in Figure 2, this introduces L×(L+1) 2 connections in an L-layer network, instead of just L, as in traditional architectures. A DenseNet is followed by transition layers. Each unit packs two convolutions, each preceded by Batch TABLE 1. The DenseNet-121 architecture.Fixed unit vector is been generated durning the process. The layers between these dense blocks are transition layers which perform down-sampling of the layers features passing the network. A detailed explanation of DenseNet-121 architecture, the DenseNet we used in this work, is shown in Table 1. Motivated by the results obtained by DenseNet-121 on ChestX-ray14 dataset [18], [19], we have trained the DenseNet-121 model on our dataset, using initial weights obtained from the pre- trained network, on ImageNet, which gives a good starting point against random initialization of the weights.

Layers	Output Size	DenseNet-121
Convolution	112x112	7x7 conv, stride2
Pooling	56x56	3x3 max pool, stride 2
Dense Block 1	56x56	[1x1 conv, 3x3 conv] x 6
Transition Layer 1	56x56	1x1 conv
	28x28	2x2 average pool, stride 2
Dense Block 2	28x28	[1x1 conv, 3x3 conv] x 12
Transition Layer 2	28x28	1x1 conv
	14x14	2x2 average pool, stride 2
Dense Block 3	14x14	[1x1 conv, 3x3 conv] x 24
Transition Layer 3	14x14	1x1 conv
	7x7	2x2 average pool, stride 2
Dense Block 4	7x7	[1x1 conv, 3x3 conv] x 16
Classification Layer	1x1	7x7 global average pool
		14D fully connected, sigmoid

TABLE 1: The DenseNet-121 Architecture

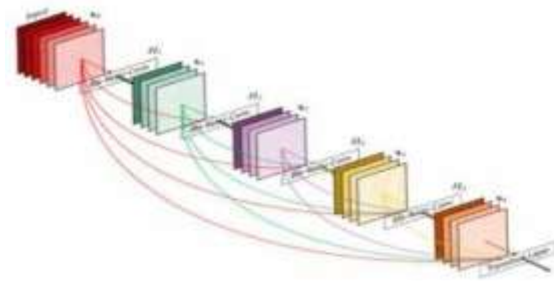

Figure 1: DenseNet with 5

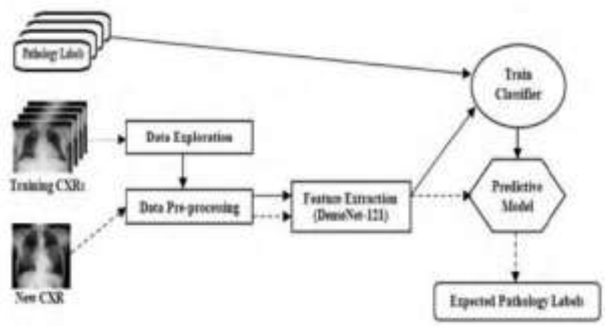

Figure 2: Multi-label classification pipeline

VII. CONCLUSION

In this paper, we propose a new approach that combines the effectiveness of CNN for image feature extraction and the power of supervised multi-label classifiers in order to tackle the task of thorax diseases detection on CXRs. The task has been carried out with a pre-trained DenseNet-121 model as feature extractor and different problem transformation methods. The evaluation process was conducted using performance metrics average AUC. The results showed that our method achieved great results and outperformed current state-of-the-art on ChestX-ray14 dataset. To further substantiate the results of this study, several improvements could be made, such as the use of an attention mechanism to improve CNN's work and train our classifier on a more balanced data set to avoid the problem of imbalance label distribution.

REFERENCES

1. A. Brady, R. Ó. Laoide, P. McCarthy, and R. McDermott, ''Discrepancy and error in radiology: Concepts, causes and consequences,'' Ulster Med. J., vol. 81, no. 1, pp. 3–9, Jan. 2012. [Online]. Available:

https://www.ncbi.nlm.nih.gov/pmc/ articles/PMC3 609674/
2. W. Rawat and Z. Wang, ''Deep convolutional neural networks for image classification: A comprehensive review,'' Neural Comput., vol. 29, no. 9, pp. 2352–2449, Sep. 2017. [Online]. Available: https://www. mitpressjournals.org/ doi/10.1162/neco_a_00990 3. Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, ''Gradient-based learning applied to document recognition,'' Proc. IEEE, vol. 86, no.
11, pp. 2278–2324, Nov. 1998.
4. L. Torrey and J. Shavlik, ''Transfer learning,'' in Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques, E. Soria, J. Martin, R.
Magdalena, M. Martinez, and A. Serrano, Eds.
Hershey, PA, USA: IGI Global, 2009, ch. 11, p. 23. 5. K. He, X. Zhang, S. Ren, and J. Sun, ''Deep residual learning for image recognition,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2016, pp. 770–778.
6. K. Simonyan and A. Zisserman, ''Very deep convolutional networks for large-scale image recognition,'' in Proc. ICLR, 2015, pp. 1–14. [Online]. Available: https://arxiv.org/abs/1409.1556 [7]G. Huang, Z. Liu, K. Q. Weinberger, and L. Van der Maaten, ''Densely connected convolutional networks,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jul. 2016, pp. 4700–4708.
[Online]. Available: https://arxiv.org/abs/1608.06993
8. M. R. Boutell, J. Luo, X. Shen, and C. M. Brown,
''Learning multi-label scene classification,'' Pattern Recognit., vol. 37, no. 9, pp. 1757–1771, Sep. 2004. [Online]. Available: https://www.sciencedirect.com/ science/article/pii/S0031320304001074 9. G. Tsoumakas and I. Vlahavas, ''Random k- labelsets: An ensemble method for multilabel classification,'' in Proc. 18th Eur. Conf. Mach. Learn., 2007, pp. 406–417.
10. J. Read, B. Pfahringer, G. Holmes, and E. Frank,
''Classifier chains for multi-label classification,'' in Machine Learning and Knowledge Discovery in Databases, vol. 5782. 2009, pp. 254–269. doi:
10.1007/s10994-011- 5256-5.
11. M.-L. Zhang and Z.-H. Zhou, ''A k-nearest neighbor based algorithm for multi-label
classification,'' in Proc. IEEE Int. Conf. Granular Comput. (GrC), Jul. 2005, pp. 718–721. [12] A. Clare and R. D. King, ''Knowledge discovery in multi-label phenotype data,'' in Proc. 5th Eur. Conf. PKDD, 2001, pp. 42–53.
13. A. Jiang, C. Wang, and Y. Zhu, ''Calibrated rank- SVM for multi-label image categorization,'' in Proc.
IEEE Int. Joint Conf. Neural Netw. (IJCNN), Jun. 2008, pp. 1450–1455.
14. G. Madjarov, D. Kocev, D. Gjorgjevikj, and S. Džeroski, ''An extensive experimental comparison of methods for multi-label learning,'' Pattern Recognit., vol. 45, no. 9, pp. 3084–3104, Sep. 2012. [Online]. Available: https://www.sciencedirect.com/science/ article/pii/S003 1320312001203
15. G. Tsoumakas, I. Katakis, and I. Vlahavas, ''Random k-labelsets for multilabel classification,'' IEEE Trans. Knowl. Data Eng., vol. 23, no. 7, pp. 1079–1089, Jul. 2011.
16. J. Read, ''A pruned problem transformation method for multi-label classification,'' in Proc. New Zealand Comput. Sci. Res. Student Conf., 2008, pp. 143–150.
17. P. Szymański, T. Kajdanowicz, and K. Kersting, ''How is a data-driven approach better than random choice in label space division for multi-label classification?'' Entropy, vol. 18, no. 8, p. 282, Jun. 2016. doi: 10.3390/e18080282.
18. Q. Guan, Y. Huang, Z. Zhong, Z. Zheng, L. Zheng, and Y. Yang. (2018). ''Diagnose like a radiologist: Attention guided convolutional neural network for thorax disease classification.'' [Online]. Available: https:// arxiv.org/abs/1801.09927.
J. Rubin, D. Sanghavi, C. Zhao, K. Lee, A. Qadir, and M. Xu-Wilson. (2018). ''Large scale automated reading of frontal and lateral chest X- rays using dual convolutional neural networks.'' [Online]. Available: https://arxiv.org/ abs/1804.07839