Annexure-1 (A typical Specimen of Title Page)

By using Chest X-ray performing pneumonia detection

A Project Work Synopsis

Submitted in the partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

IN

Artificial Intelligence and Machine learning

Submitted by:

Anmol Chopra

Ishika Goyal

Ayushi Gupta

Asmi Zutshi

Jai Mehta

19BCS6069

19BCS6048

19BCS6065

19BCS6078

19BCS6089

Under the Supervision of:

Prof. Pooja Verma

CHANDIGARH UNIVERSITY, GHARUAN, MOHALI - 140413, PUNJAB,

August 2022

Table of Contents

Abstract

Pneumonia is a respiratory infection caused by bacteria or viruses; it affects many individuals, especially in developing and underdeveloped nations, where high levels of pollution, unhygienic living conditions, and overcrowding are relatively common, together with inadequate medical infrastructure. Pneumonia causes pleural effusion, a condition in which fluids fill the lung, causing respiratory difficulty. Early diagnosis of pneumonia is crucial to ensure curative treatment and increase survival rates. Chest X-ray imaging is the most frequently used method for diagnosing pneumonia. However, the examination of chest X-rays is a challenging task and is prone to subjective variability. In this study, we developed a computer-aided diagnosis system for automatic pneumonia detection using chest X-ray images. We employed deep transfer learning to handle the scarcity of available data and designed an ensemble of three convolutional neural network models: GoogLeNet, ResNet-18, and DenseNet-121. A weighted average ensemble technique was adopted, wherein the weights assigned to the base learners were determined using a novel approach. The scores of four standard evaluation metrics, precision, recall, f1-score, and the area under the curve, are fused to form the weight vector, which in studies in the literature was frequently set experimentally, a method that is prone to error. The proposed approach was evaluated on two publicly available pneumonia X-ray datasets. The results were superior to those of state-of-the-art methods and our method performed better than the widely used ensemble techniques.

1 INTRODUCTION

1.1Problem Definition-

Pneumonia is a life-threatening disease, which occurs in the lungs caused by either bacterial or viral infection. It can be life-endangering if not acted upon at the right time and thus the early diagnosis of pneumonia is vital. Pneumonia is considered the greatest cause of child fatalities all over the world. Approximately 1.4 million children die of pneumonia every year, which is 18% of the total children died at less than five years old. Globally, overall, two billion people are suffering from pneumonia every year. Pneumonia is a lung infection, which can be caused by either bacteria or viruses. Luckily, this bacterial or viral infectious disease can be well treated by antibiotics and antivirals drugs. Nevertheless, faster diagnosis of viral or bacterial pneumonia and the consequent application of correct medication can help significantly to prevent deterioration of a patient's condition, which eventually leads to death. Chest X-rays are currently the best method for diagnosing pneumonia. X-ray images of pneumonia are not very clear and are often misclassified to other diseases or other benign abnormalities. Moreover, the bacterial or viral pneumonia images are sometimes miss-classified by the experts, which leads to wrong medication being given to the patients and thereby worsening the condition of the patients. There are considerable subjective inconsistencies in the decisions of radiologists reported in diagnosing pneumonia. There is also a lack of trained radiologists in low resource countries (LRC), especially in rural areas. Therefore, there is a pressing need for computer-aided diagnosis (CAD) systems, which can help the radiologists in detecting different types of pneumonia from the chest X-ray images immediately after the acquisition.

1.2 Project Overview-

The project aims to automatically detect bacterial and viral pneumonia using digital x-ray images. It provides a detailed report on advances in accurate detection of pneumonia and then presents the methodology adopted by the authors. Four different pre-trained deep Convolutional Neural Network (CNN): AlexNet, ResNet18, DenseNet201, and SqueezeNet were used for transfer learning. A total of 5247 chest X-ray images consisting of bacterial, viral, and normal chest x-rays images were preprocessed and trained for the transfer learning-based classification task. In this study, the authors have reported three schemes of classifications: normal vs. pneumonia, bacterial vs. viral pneumonia, and normal, bacterial, and viral pneumonia. The classification accuracy of normal and pneumonia images, bacterial and viral pneumonia images, and normal, bacterial, and viral pneumonia were 98%, 95%, and 93.3%, respectively. This is the highest accuracy, in any scheme, of the accuracies reported in the literature. Therefore, the proposed study can be useful in more quickly diagnosing pneumonia by the radiologist and can help in the fast airport screening of pneumonia patients.

1.3 Software Specification

The minimum software requirements that will be used in making this are:

1. Windows or linux operating system
2. Python3 should installed on the system
3. These libraries should also be installed: Tensorflow, Keras, Numpy, OpenCV, Flask

1.4 Hardware Specification

1. Dual Core CPU
2. Minimum 256 MB RAM
3. Minimum 200 MB storage

2 LITERATURE REVIEW

2.1 Literature Review Summary

Table 2.1: Literature review summary

Authors	Method Used	Dataset	Advantages	Challenges
Abiyev et al.	CNN, CpNN, and BpNN	Chest X-rays	Accuracy= 92.4%, CpNN(80.04%), BPNN(89.57%)	Accuracy needs improvement, CNN converges slower than CPNN
Stephan et al.	CNN with four convolution layers.	Pediatric chest X-rays	Less computationally complex model, accuracy=93.7%	Non-standard division of dataset, no performance metrics other than accuracy were evaluated.

2.2 Proposed System

Pneumonia detection using chest X-rays has been an open problem for many years, the main limitation being the scarcity of publicly available data. Traditional machine learning methods have been explored extensively. Chandra et al. segmented the lung regions from chest X-ray images and extracted eight statistical characteristics from these regions, which they used to classify them. They implemented five traditional classifiers: multi-layer perceptron (MLP), random forest, sequential minimal optimization (SMO), classification via regression, and logistic regression. They evaluated their method on 412 images and achieved a 95.39% accuracy rate using the MLP classifier. Kuo et al. used 11 features to detect pneumonia in 185 schizophrenia patients. They applied these features in a large number of regression and classification models, such as decision trees, support vector machines, and logistic regression, and compared the results of the models. They achieved the highest accuracy rate, 94.5%, using a decision tree classifier; the other models fell short by large margins. Similarly, Yue et al. used 6 features to detect pneumonia in chest CT scan images of 52 patients; the best AUC value they achieved was 97%. However, these methods cannot be generalized and were evaluated on small datasets.

An optimal algorithm for pneumonia detection from Chest X-rays is proposed in this project. Data augmentation techniques were deployed to increase the size of the limited dataset. Pre-trained ResNet50 architecture is fine-tuned for the pneumonia classification task. Then, the scaling up of ResNet50 architecture is done using compound scaling. First, the input images were resized to train the model. Effective training of the neural net requires a large dataset. When the deep networks are trained on a smaller dataset, then the networks cannot generalize and hence poor testing accuracy. Data augmentation is one of the solutions to this problem and utilizes the existing dataset in an efficient manner and expands it. Scaling of CNNs can be done across three dimensions: depth, width and resolution. The depth of a CNN is equivalent to the number of layers it has, width refers to the number of channels in the convolution layer and resolution refers to the resolution of the image passed to a CNN. Scaling can be used: to achieve greater performance for a particular task and to create more efficient models. ResNet50, which was pre-trained on ImageNet dataset is used as the base architecture.

PROBLEM FORMULATION

The ensemble learning model helps incorporate the discriminative information of all its constituent models, and thus, its predictions are superior to those of any of its constituent base learners. Weighted average ensembling is a powerful classifier fusion mechanism. However, the choice of the weights to be allocated to the respective base learners plays a pivotal role in ensuring the success of the ensemble. Most approaches in the literature set the weights experimentally or based solely on the accuracy of the classifier. However, this may not be a good measure when a class imbalance exists in the dataset. The use of other evaluation measures, such as precision, recall (sensitivity), f1-score, and AUC, may provide relatively robust information for determining the priority of the base learners. To this end, in this study, we devised a novel strategy for weight allocation, which is explained in the following.

First, the probability scores obtained during the training phase by the base learners are utilized to calculate the weights assigned to each base learner using the proposed strategy. These generated weights are used in the formation of an ensemble trained on the test set. This strategy is implemented to ensure that the test set remains independent for predictions. The predictions of the i^{th} model ($\hat{y}_i$) are generated and compared with the true labels (y) to generate the corresponding precision score ($pre^{(i)}$), recall score ($rec^{(i)}$), f1-score ($f1^{(i)}$), and AUC score ($AUC^{(i)}$). Assume that this forms an array $A^{(i)} = \{pre^{(i)}, rec^{(i)}, f1^{(i)}, AUC^{(i)}\}$. The weight ($w^{(i)}$) assigned to each classifier is then computed using the hyperbolic tangent function. The range of the hyperbolic tangent function is [0, 0.762] because x represents an evaluation metric, the value of which is in the range [0, 1]. It monotonically increases in this range; thus, if the value of a metric x is high, the *tanh* function rewards it by assigning to it a high priority; otherwise, the function penalizes it.

$$w^{(i)}=\sum_{x\in A^{(i)}}\tanh(x)=\sum_{x\in A^{(i)}}\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$$

These weights ($w^{(i)}$) computed are multiplied by the decision scores of the corresponding base learners to compute the weighted average probability ensemble, where the probability array (for a binary class dataset) of the j^{th} test sample by the i^{th} base classifier is $p^{(i)}_j=\{a,1-a\}$, where $a \leq 1$ and the ensemble probability for the sample is $ensemble\_prob_j = \{b, 1 - b\}$.

$$ensemble\_prob_j=\frac{\sum_i w^{(i)}\times p^{(i)}_j}{\sum_i w^{(i)}}$$

Finally, the class predicted by the ensemble is compute, where *prediction*$_j$ denotes the predicted class of the sample.

$$prediction_j = argmax(ensemble\_prob_j)$$

4 OBJECTIVES

The proposed work is aimed to carry out work leading to the development of an approach for detecting pneumonia using chest X-rays. The proposed aim will be achieved by dividing the work into following objectives:

1. First developing the deep learning model to detect pneumonia using the convolutional neural networks. The main libraries used here are tensorflow and keras.
2. Now, second part is making the model available through a website which is done using flask which is a web framework for python.
3. At last, the model is deployed and the website is created for use.
4. Now, html and css can be used to make the website presentable and look good.

METHODOLOGY

This section deals with the detailed description of the applied methodology. The proposed pneumonia detection system using the ’Densely Connected Convolutional Neural Network’ (DenseNet-169). The architecture of the proposed model has been divided into three different stages - the preprocessing stage, the feature-extraction stage and the classification stage.

The Pre-Processing Stage

The primary goal of using Convolutional Neural Network in most of the image classification tasks is to reduce the computational complexity of the model which is likely to increase if the input are images.

The Feature-Extraction Stage

Although, the features were extracted with different variants of pre-trained CNN models the statistical results obtained proposed DenseNet-169 as the optimal model for the feature extraction stage. Therefore, this stage deals with the description of DenseNet-169 model architecture and its contribution in feature extraction.

The Classification Stage

After feature extraction, different classifiers such as Random Forest, Support Vector Machine etc. were used for the classification task. But the best results were found to be attained when Support vector Machine was used as classifier for the problem. So, in the best proposed model features extracted from DenseNet-169 were used with SVM classifier to accomplish better results. The description of the parameters and Kernel used with SVM is as follows: Let us suppose a set of training data as (x1,y1),(x2,y2).......(xn,yn) and the data needs to be separated into two set of classes where x_i ε F^d is the feature vector and y^i ε (0,1) represents the label class. A Support Vector machine used for binary classification is able to find the best hyperplane for the above training data presented i.e the one with the maximum margin between the classes and is capable of separating the data points of one class with the other. The performance of SVM highly depends on the selection of the kernel and parameters. We used the Gaussian ’radial basis function’ kernel (rbf).

TENTATIVE CHAPTER PLAN FOR THE PROPOSED WORK

CHAPTER 1: INTRODUCTION

This chapter will cover the overview of the whole project.

CHAPTER 2: LITERATURE REVIEW

This chapter include the literature available for the pneumonia detection. The findings of the researchers will be highlighted which will become basis of current implementation.

CHAPTER 2: BACKGROUND OF PROPOSED METHOD

This chapter will provide introduction to the concepts which are necessary to understand the proposed system.

CHAPTER 4: METHODOLOGY

This chapter will cover the technical details of the proposed approach.

CHAPTER 5: EXPERIMENTAL SETUP

This chapter will provide information about the subject system and tools used for evaluation of proposed method.

CHAPTER 6: RESULTS AND DISCUSSION

The result of proposed technique will be discussed in this chapter.

CHAPTER 7: CONCLUSION AND FUTURE SCOPE

The major finding of the work will be presented in this chapter. Also directions for extending the current study will be discussed.

REFERENCES

REFERENCES

[1] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, ‘‘ChestX-ray8: Hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jul. 2017, pp. 3462–3471.
[2] D. S. Kermany, G. Michael, C. Wenjia, C. V. Carolina, L. Huiying, L. B. Sally, and M. E. A. Alex, ‘‘Identifying medical diagnoses and treatable diseases by image-based deep learning,’’ Cell, vol. 172, no. 5, pp. 1122–1131, 2018.
[3] WHO | World Health Organization. Accessed: Mar. 31, 2020. [Online]. Available: https://www.who.int/
[4] O. Stephen, M. Sain, U. J. Maduh, and D.-U. Jeong, ‘‘An efficient deep learning approach to pneumonia classification in healthcare,’’ J. Healthcare Eng., vol. 2019, pp. 1–7, Mar. 2019.
[5] R. Siddiqi, ‘‘Automated pneumonia diagnosis using a customized sequential convolutional neural network,’’ in Proc. 3rd Int. Conf. Deep Learn. Technol. (ICDLT), 2019, pp. 64–70.
[6] M. Mardani, E. Gong, J. Y. Cheng, S. S. Vasanawala, G. Zaharchuk, L. Xing, and J. M. Pauly, ‘‘Deep generative adversarial neural networks for compressive sensing MRI,’’ IEEE Trans. Med. Imag., vol. 38, no. 1, pp. 167–179, Jan. 2019.
[7] A. Oates, K. Halliday, A. C. Offiah, C. Landes, N. Stoodley, A. Jeanes, K. Johnson, S. Chapman, S. M. Stivaros, J. Fairhurst, A. Watt, M. Paddock, K. Giles, K. McHugh, and O. J. Arthurs, ‘‘Shortage of paediatric radiologists acting as an expert witness: Position statement from the british society of

paediatric radiology (BSPR) national working group on imaging in suspected physical abuse (SPA),'' Clin. Radiol., vol. 74, no. 7, pp. 496–502, Jul. 2019.

[8] L. Yao, E. Poblenz, D. Dagunts, B. Covington, D. Bernard, and K. Lyman, ''Learning to diagnose from scratch by exploiting dependencies among labels,'' 2017, arXiv:1710.10501. [Online]. Available: http://arxiv.org/abs/1710.10501

[9] G. Deng and L. W. Cahill, ''An adaptive Gaussian filter for noise reduction and edge detection,'' in Proc. IEEE Conf. Rec. Nucl. Sci. Symp. Med. Imag. Conf., Oct. 1993, pp. 1615–1619.