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Deep Learning based Automated Pneumonia Detection from X-ray Images

1st Sunil Kumar Aithal S
Department of Computer Science and Engineering
Nitte (Deemed to be University), NMAM Institute of Technology
Nitte, India
sunilaithal@nitte.edu.in

2nd Rajashree
Department of Computer Science and Engineering
Nitte (Deemed to be University), NMAM Institute of Technology
Nitte, India
rajashree@nitte.edu.in

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***Abstract*—Artificially Intelligent (AI) based systems possess the capability of successfully realizing the insights from frequently available huge datasets. Various health care and medical imaging applications have been significantly benefited for making accurate decisions for improving the health conditions of the patients. Nowadays, medical science area have witnessed enormous advancement with the effective utilization of AI and deep learning (DL) techniques for various applications namely automated patient monitoring, prescribing medications, in-depth analysis of severe disease patterns and performing laser based surgeries based on the observations of the disease patterns occurring in the medical based digital images. Most of the automated medical oriented digital images are generated using MRIs, X-rays and CT scans which makes the processing of such images by numerous modern AI and DL algorithms efficient and highly accurate for critical decision making and medical treatment diagnosis. Conclusively, human based expert system is replaced by various AI and DL based systems which has fast processing and accurate reporting capabilities especially in medical science domain. Thus, our article proposes the utilization of AI and DL based techniques to efficiently propose diagnosis for patients suffering from pneumonia based on the gathered X-ray images. Precisely, our article focuses upon the effective utilization of DL based modified convolutional neural network (CNN) and visual geometry group (VGG-16) for accurately classifying the chest X-ray images into normal and pneumonia categories. Proposed model based on the recognition of the pattern changes in the chest X-ray images have the ability to classify the disease into either a normal or a pneumonia case with an overall training and validation accuracy of 97% respectively.**

Keywords*—*Medical Science, Deep Learning, Pneumonia Detection, Chest X-ray digital images, Neural Networks.

I. Introduction

Most common disease that is threatening infants, children and old age people is popularly known as pneumonia which affects the lungs of the affected patients severely. Several forms of pneumonia exists depending on the severity of the lung infection. As the lungs filled up with liquid type of fluids or pus kind of matter immediate diagnosis prevents the further damage to the affected lungs. Bacteria, fungus and virus are the main source of different forms of pneumonia which cause affected person to suffer breathing and fever. Also, symptoms also includes wheezing, heart rate variation, coughing and severe chest pain depending on the spread of the disease. The disease has the potential of spreading to other people through cough, usage of objects that was in contact of pneumonia affected person and direct communication. Different forms of pneumonia exist namely fungus, viral, bacterial and walking types which can be further distinguished into type 1 and type 2. Medical field has been witnessing greater success due to the advancement of AI and application of DL based automated techniques for vast applications of healthcare domain as compared to conventional human based techniques. In our research article, deep learning based CNN is utilized for automated classification of normal or pneumonia case based on the features or patterns observation occurring in the gathered digital X-ray based images. We utilize data augmentation technique for enhancing the training X-ray samples which also reduces the over fitting overhead. Also, for extracting accurate lung region patterns CNN is utilized and for effective classification custom baseline model is fabricated using public dataset focusing on dropout and fully connected layers. Fine tuning of parameters using random based search strategy depending on the learned patterns is adjusted for enhancing the overall accuracy of the proposed work.

II. LITERATURE REVIEW

Bandar Almaslukh in their research work suggested DenseNet-121 backbone based CNN architecture for detecting pneumonia disease from chest X-ray samples. Fine tuning is performed using dense neural network with random search based strategy for effective classification of the pneumonia symptoms [1]. Luka Racic et al., proposed CNN based model for recognizing the pattern changes in the chest X-rays for pneumonia detection. Nvidia GeForceRTX 2060 based GPU lesser than one and half hour time duration was observed for training. ReLu based CNN model detects effectively pneumonia case from digital image samples [2]. Pranav Rajpurkar et al., proposed CheXNet dense CNN consisting of 121 layers experimented upon chest X-ray 14 dataset generated by Wang et al [3]. Dataset consist of fourteen pathalogies for automated pneumonia detection task [4]. Khalid El Asnaoui in their article suggested transfer learning based ensemble framework consisting of ResNet V2, 50 and

MobileNet V2 fine-tuned versions of architectures for experimenting upon X-ray images [5].

Vikash Chouhan et al., in their research work unification of GoogleNet, AlexNet, DenseNet, ResNet and Inception CNNs were performed for evaluating upon X-ray images to detect pneumonia [6]. Hafiz Rauf and Ikram Lali proposed time series based sequential recurrent, gated and long short term memory integrated deep learning techniques for predicting future pneumonia case with an average accuracy of over 90% [7]. Nada M. Elshennawy and Dina M. Ibrahim in their research work modified the ResNet and MobileNet V2 architectures for accurately predicting the diagnosis for pneumonia that was predicted using chest X-rays [8].

Muazzez Buket Darici proposed binary form and multiple class based classification of pneumonia and other variations of pneumonia disease occurrence in children utilizing ensemble learning for accurately predicting severity of disease with over 95% accuracy [9]. Tawsifur Rahman and Muhammad Chowdhury implemented augmentation based deep neural network framework for identifying pneumonia categories utilizing kaggle based X-ray samples. The framework also incorporates the data augmentation technique for improving the training speed and overall efficiency of the detection task. Transfer learning based SqueezeNet is incorporated while augmenting the data samples and overcoming over fitting overhead [10]. Vinayakumar Ravi in their research article insisted the automated cost effective approach to pneumonia class identification with the incorporation of deep learning based transfer learning models namely NASNetMobile, DenseNet and others focusing on class imbalance problem. Normalization and scaling strategies makes the CNN models to better perform compared to other straightforward approaches [11].

Thus, various related works discussed in previous section highlights the significance of transfer learning based deep neural networks especially for automated pneumonia and its varieties to be determined accurately using digital X-ray samples collected during the chest scan procedure for infants, children and elderly human beings.

III. PROPOSED APPROACH

Disease diagnosis with radiology is a common practice in medical science that requires doctors to interpret the results from the obtained X-ray images. Day to day patients keep on increasing and also the low availability of specialized doctors necessitates the high demand for accurately monitoring the patient report and prescribe the best diagnosis for the disease by utilizing automation support. Fortunately, modern deep learning techniques have introduced the cost-effective solution for this prevailing problem. In this research work CNN deep learning model is experimented with existing dataset consisting of X-ray images in diagnosing the pneumonia disease. The Fig. 1 demonstrates the overall activities of the proposed research work. Following steps are the key activities that interpret the methodology of our proposed work:

A. Data Collection

Public kaggle dataset which consist of totally 5863 chest X-ray image samples categorized into either pneumonia or normal case. To overcome imbalance issue across the dataset for training, testing and validation process further the chest x-ray samples are fine-tuned along with careful investigation of low resolution, unrecognized and irrelavant patterns in the radiographic samples available in the considered dataset. Thus, fine-tuned dataset with 4684 chest X-ray samples is considered and further categorized into 2480 training, 1102 validation and 1102 testing digital image samples for pneumonia detection task. Here, the public dataset comprising of chest X-ray samples are collected from guangzhou city in china belonging to patients of age group 1 to 5 years children suffering from pneumonia.

B. Image pre-processing

RGB to gray scale conversion and resizing of samples into 150x150 are performed. Normalization of sample pixels is performed to represent them as float form which immensely affects the CNN performance. Images are pre-processed using the hybrid adaptive histogram equalization and gray-level entropy computational based techniques for improving the overall brightness, quality and resolution of the lung regions for effective pneumonia disease identification task [12]. Further, X-ray samples are increased by applying data augmenting techniques such as rotation, scaling, shearing and reflection for overcoming over-fitting issue and improving the overall training and validation accuracy [13]. Finally, pre-processed samples are trained upon transfer learning based VGG-16 modified model and other variations of the CNN such as ElasticNet are further experimented for comparative analysis purpose. CNN models especially updated VGG-16 classifies the considered disease into normal or pneumonia case successfully.

C. Model, Dataset and Evaluation Metrics selection

CNN along with modified VGG-16 is chosen as the baseline models. Incorporation of hyper-tuning, padding, dropout and ElasticNet for experimental analysis is also considered. For effective testing of the CNN models visualization of confusion matrix along with F1 score, recall and precision computations are the promising evaluation metrics. The public dataset is suitably partitioned for various tasks and each sample pre-labelled into either normal or pneumonia category on careful investigation. Further, predicted pneumonia case class either belongs to bacterial or viral category depending on the accuracy of the trained model.

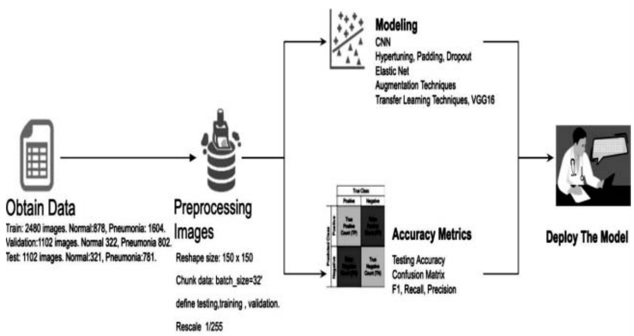

Fig 1. Proposed Methodology Overview.

Fig. 2. Train-Test-Validation Data Distribution Statistics.

Obtained X-ray samples are distributed into training, testing and validation samples as depicted in Fig. 2. For evaluating the performance of CNN models various metrics are being utilized namely accuracy (A), precision (P), recall (R) and F1 score which are automatically computed by open source TensorFlow GPU based Keras model. Following equations (1), (2), (3) and (4) are utilized for computing the respective metrics mentioned before for model evaluation. Our proposed model is experimented upon TensorFlow based GPU by using python as interfacing language.

$$A = \frac{TruePositive+TrueNegative}{TruePositive+TrueNegative+FalsePositive+FalseNegative} \quad (1)$$

$$R = \frac{TruePositive}{TruePositive+FalseNegative} \quad (2)$$

$$P = \frac{TruePositive}{TruePositive+FalsePositive} \quad (3)$$

$$F1 = 2 * \left(\frac{Precision*Recall}{Precision+Recall}\right) \quad (4)$$

D. Training and Experimentation of the proposed Modified CNN Model:

Training is performed on the base CNN model by adjusting the tuning of parameters namely padding, augmentation and dropout. VGG-16 and ElasticNet transfer learning are also considered for validation purpose. CNN provides support for convolutional layers, pooling layers, ReLu based activation function and fully connected layers for effective feature extraction and classification task. Fine tuning of base CNN framework is performed for achieving desirable results in the proposed work. Proposed model is experimented for an epoch value ranging from 25 to 30, with batch size 32. Our modified base model, consists of 4 different convolutional layers with max pooling 2 by 2 strategy and further an additional dense layer with 512 neurons are appended. Finally, the output layer consists of one neuron. Depending on the features number of filters doubles from 32 to 64 and from 64 to 128. Max pooling considered decreases the image size from 150x150 to 75x75 and further from 75x75 to 37x37. Thus, max pooling technique reduces the overall image size to 9x9 after the final round of max pooling. We required to achieve the enhancement of features while traversing through the convolutional layers by reduction in the image size.

E. VGG 16 Architecture

VGG (Visual Geometry Group 16) is a deep CNN with thirteen convolutional and three fully connected layers. In our work we use the convolutional base of VGG 16 model and then one fully connected hidden layer is added. Here, 3 by 3 kernel for convolutional and 2 by 2 parameters for pooling process is utilized. VGG 16 final output layer effectively classifies the features extracted from VGG 16 convolutional base. Further, for extracting features and classification tasks pre-trained weights from ImageNet is considered. ImageNet Large Scale Visual Recognition Challenge consists of more than twenty thousand categories of pre-trained object classes which effectively classifies the image samples into normal or pneumonia category. However, conventional VGG 16 suffers over fitting or under fitting issue especially during training process which stimulates the modification of VGG 16 architecture accordingly in our proposed work [14].

IV. RESULTS AND DISCUSSION

In our proposed system the base CNN model miscategorized ten images out of total 1,148 input test images. Consequently, our modified CNN misclassifies overall 41 pneumonia patients as normal category with an error less than 1% and an accuracy of greater than 99% among the overall considered images. Our model witnesses the precision of 87%, recall of 99% and F1-score of 93% which conclusively justifies reliable model for better pneumonia identification and classification task. In our research work tuning of parameters for the base model is performed which predicts the pneumonia case in digital images with precision of 86%, recall of 99% and F1-score of 92% indicating the overall reduction of false negative value. Our model also augmented and regularized with dropout and Elastic Net based adjustment improves the recall value but gradually decreases the overall performance of the pneumonia detection task which is considered drawback of our work. However, with the incorporation of VGG-16 transfer learning based model our model overcomes the fine-tuned model overhead with higher testing accuracy of 95% which surpasses the base CNN model. Finally, CNN modified VGG 16 model is best suitable for pneumonia case identification and classification phenomenon with the highest F1 score of 93% and an overall detection rate of over 99%. However, further performance improvement can be achieved by incorporating robust transfer learning based ResNet architectures for feature extraction task and efficient data augmentation modern algorithms for increasing the number of sample images on demand [15,16]. Recent research investigations have shown the promising results for pneumonia disease identification and classification tasks by reducing the number of convolutional and dense layers of the considered baseline CNN architecture [17]. Various CNNs namely baseline CNN without pre-processor, augmented CNN and modified VGG-16 with pre-processor are evaluated upon TensorFlow based GPU by utilizing public kaggle chest X-ray image dataset for 30 epochs. Summarization of CNN models performance evaluation is illustrated in Table I. which highlights the significance of the proposed method efficiency for pneumonia detection task whereby surpassing the performance of prominent CNNs.

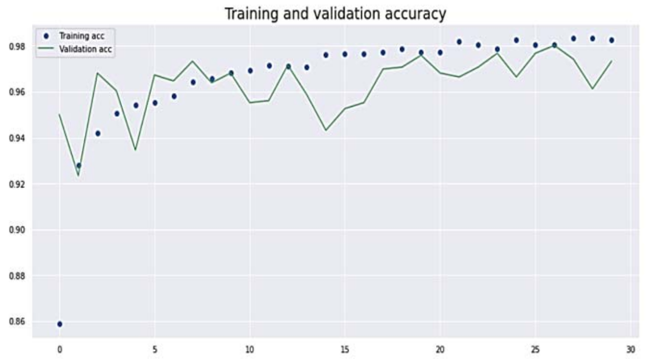

Fig. 3. Training and Validation Accuracy Statistics.

In the Fig. 3 and Fig. 4 the overall visualization of the training accuracy increases with the validation accuracy for the CNN and VGG-16 fine-tuned models is depicted. Also, increase in training loss slightly increases the validation loss. In the Fig. 5 visualization of normal and pneumonia case categorization process is depicted during training, testing and validation phase of our proposed model. As the fluid or pus fills the lungs region as seen in the X-ray samples the pneumonia case is classified accordingly.

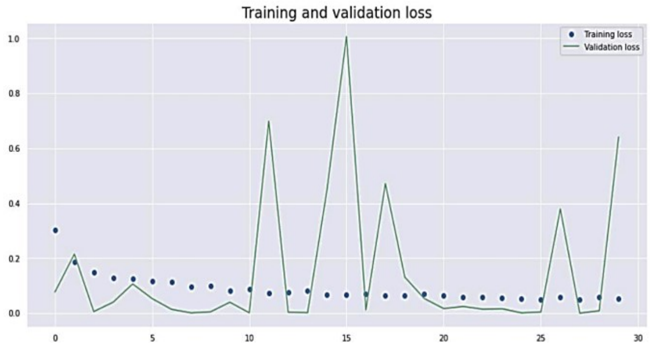

Fig. 4. Training and Validation Loss Statistics.

TABLE I. CNNs Performance Evaluation statistics

Model	Evaluation Metrics (%)		
	Precision	*Recall*	*F1 Score*
BaseLine (CNN)	73	99	85
Augmented CNN	86	91	88
Proposed (Modified VGG 16)	**87**	**99**	**93**

Proposed model achieves an overall F1 score of 93% which indicates the significance of proper fine-tuned

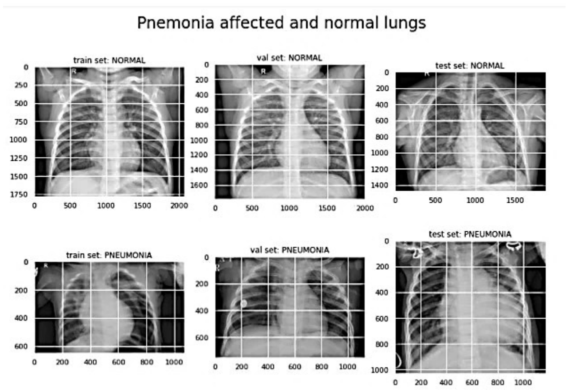

Fig. 5. Chest X-ray Image Classification.

parameters along with relevant dense layers retainment and discarding the irrelevant layers necessarily boosts the training and validation performance whereby effectively improves the overall pneumonia detection task from chest X-ray images.

V. Conclusion And Future Work

In our research work baseline CNN and modified VGG-16 performs better especially for distinguishing pneumonia case from normal case from carefully investigating the kaggle chest X-ray samples dataset. However, the testing accuracy of 95% is observed in updated VGG-16 and the testing accuracy of 88% is observed in base CNN model even though the base model and VGG-16 utilizes the similar sequence architecture with the number of trainable parameters in base CNN model considered as 3.5 million while the number of trainable parameters in VGG-16 considered as 15 million. Our model slightly suffers performance bottle with the fine tuning and augmentation process which needs careful investigation in the future prospect. Conclusively, baseline CNN along with other modern CNNs like VGG-16 with certain fine tuning of parameters improves the performance of reliable pneumonia detection and classification real-world healthcare problems.

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