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Chest disease radiography in twofold: using convolutional neural networks and transfer learning

Prakash Choudhary[1] · Abhishek Hazra[2]

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Abstract
Computer-aided diagnosis and design in the medical province is an exciting domain owing to drastic growth in Medical images. Earlier handcraft feature learning techniques failed to achieve the targeted result in practical aspects. In this paper, we have adopted a deep learning artifice to reduce the semantic gap which exists between the low-level information captured by imaging devices and high-level information preserved by a human. The proposed work has twofold: first, we propose convolutional neural network architecture consisting of five types of layers, convolutional layer, an activation layer, Pooling layer and Fully connected layer followed by a Softmax layer which gives the probability of the output for every genre. The second contribution towards this paper is to find the solution of an unsolved problem in medical image analysis: "Uses of a pretrained model with adequate fine-tuning to eliminate the extra effort of making a new CNN architecture from scratch". To address this puzzle, we employed a pretrained VGG-16 model (a famous CNN architecture trained on Image Net dataset) to train the same dataset. Grad-CAM is used for visualizing the model performance with respect to a test image. The proposed methods are evaluated on famous publicly available NIH dataset called Chest X-Ray 14 and have created a new benchmark performance that has achieved state-of-the-art results 83.671% (scratch CNN) and 97.81% (transfer learning), which are much higher as compared to the other methods. Moreover, we also introduce in-depth comparison with the current existing works.

Keywords Deep learning · Classification · Chest diseases · CNN · Chest X-Ray · Medical images

1 Introduction

According to the World Health Organization (WHO) (https://www.cdc.gov/healthcommunication/toolstemplates/entertainmented/tips/ChronicRespiratoryDisease.html), chronic diseases are the primary cause of death and disability worldwide. India is the second largest country concerning population, more than 1.324 billion (census 2011, https://www.census2011.co.in/) people from the different region and different community are living together. And, the country is experiencing many chronic diseases. As per WHO reports, in the coming next ten years, more than 16 million people will die due to critical illnesses, and it also increases by 18% every year. Different survey (http://cancerindia.org.in/cancer-statistics/) projected that death due to cancer is almost 8% and chronic diseases are nearly 15%. One of the main reasons for these diseases is overweight and uses of tobacco. Men and women both are affected in this twenty-first century. Statistics show that in 2005, 22% men and 21% of women were overweighted, and in the year 2015, 31% men and 29% female were overweighted. WHO says proper diet and avoidance of tobacco can reduce at least 8% heart diseases, diabetes, and 40% cancer. According to the Centers for Diseases Control and Prevention (https://www.who.int/respiratory/en/), the top three cause of death in India is ischemic heart diseases 12%, chronic obstructive pulmonary diseases 11% and stroke 9%. These are the main motivation and inspiration of fusing deep learning technology into Medical Science Research.

In the late 1990s, neuroscience researchers observed one exciting thing that the visual representation of the brain can follow two paths in the brain: spatial path and object path. Position, motion and activity such kind of information follow the spatial path and the info of detection, color, difference,

✉ Prakash Choudhary
pc@nith.ac.in

[1] Department of Computer Science and Engineering, National Institute of Technology Hamirpur, Hamirpur 177005, India

[2] Department of Computer Science and Engineering, Indian Institute of Technology (ISM) Dhanbad, Jharkhand 826004, India

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size, etc. follow the object path. In the 1950s, Hubel and Wiesel (1968) examined that visual cortex in the brain can react by sensing light. The instinct of this discovery, Le et al. (1990) first discovered a computer system which can learn, understand and detect handwritten characters. These learning techniques in the late 1920s succeeded to create lots of attention from the AI research community. In the current milieu, artificial intelligence based systems are latest trend research. By the discovery of X-ray and storage systems, researchers tried to improve the computational capabilities in the medical domain. In 1980s researchers analyzed the medical images with the help of low-level features. Later in 1990s feature extraction based learning systems were generalized. In 2000s Machine Learning based feature learning techniques were adopted (Vo and Sowmya 2010). However, in recent days uses of deep learning (Deng and Yu 2014; Wan et al. 2014; Anthimopoulos et al. 2016; Yan 2016; Simonyan and Zisserman 2015) based approaches are getting popularity because of its end to end learning capability.

In the paper Wang et al. (2017), the authors have presented their dataset and used NLP to label eight diseases. They demonstrated that these diseases could be detected by weakly supervised learning techniques and the system level performance can be further improved by using deep learning techniques. Labeling of clinical datasets is a critical issue in medical science, and paper Yao et al. (2018) introduced an LSTM based technique to label 14 different Chest X-Ray images. They experimentally verified that with a standard baseline model, label interdependencies could be ignored. Khobragade et al. (2016) proposed ANN-based technique for lung image segmentation, future extraction, and classification on three different diseases. In Lessmann (2018) authors used multiple CNN techniques for automatic classification on three different chest diseases. They separately trained and analysed their model on both soft reconstruction and soft-sharp reconstructions. CheXNet (2017) proposed a 121 labeled Deep CheXNet for classifying the NHI Chest X-Ray dataset. A group of medical pathologists manually annotate the test dataset, and CheXNet succeeded to beat human-level performance on detecting and localizing different chest diseases. Song et al. (2017) applied CNN, DNN, and SAE on benign and malignant lung CT images for lung cancer classification. They applied their model on LIDC-IDRI image datasets to show the effectiveness of deep learning techniques on medical image analysis. Anthimopoulos et al. (2016) proposed a simple CNN architecture for classifying the Interstitial Lung Diseases. They evaluated their model on 120 CT scan images. The author demonstrates that medical science can be benefited by using deep learning models. Similar to Medical domain several other fields (Hou et al. 2019; Zhu and Fei 2018; Fang et al. 2019; Fei and Yan 2014) also using neural network for improving their model's performance.

Deep learning techniques (van Tulder and de Bruijne 2016; Moeskops 2016) has created a remarkable performance in medical image analysis (Li et al. 2014). The revolution of this field was started in 2015 and every year the number of conferences, journals and articles are increasing exponentially. This paper aims to use deep learning techniques to reduce the semantic gap that exists between the low-level information captured by imaging devices and high-level information preserved by the human. In this work, we have proposed a convolutional neural network architecture to classify the abnormalities in Chest X-Ray images. Here we have taken a different route of evaluation and the research work is carried out for detection of chest diseases on a well-known publicly available NIH dataset called Chest X-Ray 14 (Anthimopoulos et al. 2014) which is twofold. First, we propose a unique convolutional neural network (CNN) architecture from scratch. The proposed CNN architecture consists of five types of layers, convolutional layer, an activation layer, pooling layer and fully connected layer followed by a softmax layer which provides the likelihood of the output for every class. Finally, Grad-CAM is used for visualizing the model understanding with respect to a test image and has achieved a new benchmark performance which is 5% more accurate than earlier approaches.

Our Second contribution towards this paper is to discover the explanation of an unsolved problem in medical image analysis i.e. “The use of a pretrained model with adequate fine-tuning can eliminate the extra effort of making a new CNN architecture from scratch”. To address this problem, we contribute our research methodology to this domain. We use a pretrained VGG-16 model (A popular CNN architecture trained on ImageNet dataset (Krizhevsky et al. 2012)) to train the similar NIH Chest X-Ray dataset. We have observed that by using a pretrained model we can achieve breakthrough performances, 14% better than making a unique CNN architecture from scratch. Though there are several other recent deep learning architectures which give state-of-the-art (Krizhevsky et al. 2012) learning performance in several domains (Bhagat and Choudhary 2018). But as we are in the preliminary stage of our implementation and our main objective here is to understand the working principle of CNN architecture. Thus, we have created simple CNN architecture, analyze its advantages over traditional methods and limitations on big datasets. We also take a standard base architecture called VGG-16 and examine its performance over shallow networks. Finally implementation of visualization techniques on top of the CNN architecture to show the transparency of deep learning models.

Rest of the paper organizes as such: Sect. 2 discusses some of the essential deep learning techniques. In Sect. 3 we introduce our proposed Convolutional architecture. Experimental analysis and learning process of the CNN presented in Sect. 4. Finally, the conclusion and feature direction are presented in Sect. 5.

2 Related work

The idea of deep learning has a very old history. In 1980s back-propagation was introduced and till now it is widely used. Deep learning approaches in medical image analysis is one of the achievements of Artificial Intelligence. One of the main implementation issues with traditional machine learning techniques (Sorensen et al. 2010) is the handcraft feature extraction technique which requires experienced expertise. Another research issue is with the selection of appropriate classifier. Linear Discriminator (Xu et al. 2014; Delorme et al. 1997), Bayesian Classifier (Sluimer et al. 2003; Uppaluri et al. 1999), Nearest Neighbor (Xu et al. 2006; Sorensen et al. 2010; Korfiatis et al. 2010; Foncubierta-Rodríguez 2012), ANN (Uchiyama et al. 2003), Fuzzy sliding mode control (Zhu and Fei 2018), Fuzzy-Neural-Network (Hou et al. 2019; Fang et al. 2019; Fei and Yan 2014), Random Forest (Anthimopoulos et al. 2014), Support Vector Machine (Zhao et al. 2013; Li et al. 2013), Polynomial (Song et al. 2013), RBF (Gangeh et al. 2010), Geometric Measure (Uchiyama et al. 2003), Histogram (Song et al. 2013), Local Binary Classifier (Sorensen et al. 2010),Feature Based (Li et al. 2013; Song et al. 2013), Texture-Based (Depeursinge et al. 2012), Wavelet Transformation (Bentley and McDonnell 1994) based techniques were used for analyzing the medical images.

2.1 Deep learning

In the context of deep learning, learning is the process of improving behavior based on experience. Deep learning is a subfield of Artificial Intelligence which is used to improve the performance of many Machine Learning applications. Gradient-Based (Lecun et al. 1998) deep architecture with multiple processing units attempts to model high-level abstraction present on the data, having linear and nonlinear transformational function (Deng and Yu 2014). Started in 1965 but it has affected recent decades with the acceleration of GPU based computing power and non-linearity which allows deeper networks for better utilization (Glorot and Bengio 2010). Deep architecture with many hidden layers increases the performance of the artificial neural network. Early invention of backpropagation in the 1980s until today, it is still used to retain the neural network (Wan et al. 2014). Standard backpropagation algorithms are commonly used in image classification tasks. Current studies show that deep learning techniques are most successful in the medical engineering field (Li et al. 2014). Recently classification of the medical images is one of the challenging and interesting tasks for researchers. Deep learning techniques also used to classify the Interstitial Lung Diseases (ILDs) in Anthimopoulos et al. (2016). They work for seven diseases among which six are infected tissue. In van Tulder and de Bruijne (2016), Restricted Boltzmann Machine was used to analyze the Lung generated tomography (CT) diseases. They have introduced two different techniques for two datasets: texture classification and airway detection. In Moeskops (2016), multiple kernels based CNN network was used to classify the brain organs. In Yan (2016), double instance framework was used, in the first phase CNN was used for extraction and in the second phase extracted features were used for classification of images. They used a database using 12 classes of images having CT and MR images. Some remarkable performances in medical imaging like lesion detection or segmentation (Liskowski and Krawiec 2016; Yuan et al. 2017; Roth et al. 2015; Fu et al. 2018; Fu et al. 2017), identification of diseases (Anthimopoulos et al. 2016; Kumar et al. 2017; Rajpurkar et al. 2017; Wang et al. 2017) annotation (Albarqouni et al. 2016; Xu et al. 2014; Simonyan and Zisserman 2015) regression (Liao et al. 2017) registration (Yang et al. 2015)etc. Though there are several machine learning techniques which have popular uses in image analysis, but they are not useful for analyzing the medical images.

2.2 Convolutional neural network

The convolutional neural network (CNN) is a feed-forward neural network mainly inspired by the human brain. CNN is capable of doing extraction and classification altogether (Gu et al. 2017) CNN combines four types of layers: convolutional layer, an activation layer, pooling layer and fully connected layer. A typical convolutional layer takes input and produces feature maps with the help of kernel. Different neuron connection overlapping with one another increases the performance of better representation of images. Moreover Sharing of weights reduces the number of parameters in the neural network. Each convolutional layer connected with a nonlinear activation layer to accelerate CNN for understanding more complex functions. Pooling is a subsampling technique which often used to avoid overfitting and also reduces the number of parameters required. Finally, one or a number of the fully connected layer gives the classifying result. In this paper, we propose deep end-to-end learning for chest diseases recognition. This work also shows the extensive capability of CNN. Different authors follows different architecture of CNN (van Tulder and de Bruijne 2016; Yan 2016)and many researchers also show the level of difficulties with deep network (Glorot and Bengio 2010) In here, we follow a basic and straightforward architecture which was described in LeNet-5. By modifying some layers, kernels, cost function, optimizer and hyperparameters we train our model. In the proposed model one convolutional layer is composed of several kernels which compute the different feature maps followed by an activation layer and pooling layer. The main reason to use the convolutional layer is to learn more complex functions. Theoretically the number of convolutional layer increases the system capability. But in our model, we use only three convolutional layers. The last fully connected layer contains the encoded features of the input image. Let (p,q) be a location in the input image X^l_{pq} and i is the number of features maps of the l^{th} layer. The feature map Z^l_{pqi} can be calculated as shown in Eq. (1):

$$Z^l_{pqi} = W_i^{l^T} X^L_{pq} + S^l_i \tag{1}$$

In Eq. (1), W^l_i is the weight vectors and S^l_k be the bias of each filter in the lth layer. The sharing of weights in every layer gives more power to the neural network for training. The nonlinear activation function denoted by $\lambda(\cdot)$ is used to understand the complex functions. The activation layer takes input features generated by the convolutional layer procedes it and pushes into the pooling layer. In this model, we use the ReLU activation function. This activation function can be derived as shown in Eqs. (2), (3) and (4) as:

$$\lambda^l_{pqi} = \lambda Z^l_{pqi} \tag{2}$$

$$\lambda^l_{pqi} = max(W_i^T X_{pq} + S_i, 0) \tag{3}$$

$$Z^l_{pqi} = pool(\lambda^l_{abi}) \forall (a, b) \in R_{pq} \tag{4}$$

In Eq. (4), R_{pq} is the nearest neighbor of location (p, q) the last fully connected layer is feed-forwarded through a softmax activation layer which gives the probability of the output for each and every class corresponding to the input. The outcome of the softmax activation can be calculated as Eq. (5):

$$s^l_{pqi} = \frac{e^{z^{[l]}}}{\sum_{n=1}^{N} e^{z^{[l]}}} \tag{5}$$

Training a neural network is one of the challenging tasks. By selecting the best set of hyper parameter and training with appropriate cost function one can reduce the cost of the network, the cost of the neural network can be calculated as shown in Eq. (6):

$$\delta = \frac{1}{N} \sum_{b=1}^{N} l(\theta; Z^{(b)}, D^{(b)}) \tag{6}$$

In Eq. (6), θ is the set of all the parameters used in the neural network and Z^b denotes the targeted output label whereas N is the output of the CNN. In this model, we use Adam optimizer (Kingma and Ba 2014) to train the neural network

In this paper, our primary research problem is to recognize the chest Infiltration diseases from Chest X-Ray datasets which consist of fourteen diseases such as: Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Consolidation, Edema, Emphysema, Fibrosis, Pleural Thickening, Hernia and one no finding diseases.

3 Methodology

The significant growth of Machine Learning techniques stimulates Medical Image research at its highest peak. Though there are thousands of machine learning techniques in the literature but most of the traditional (Gangeh et al. 2010; Anthimopoulos et al. 2014) methods are either very simple or suffer from low accuracy. In this work, we try to make a CNN architecture as shown in Fig. 1, by using a simple technique which is computationally cost-effective and also performs well for diseases identification. This section first introduces the dataset used for this case study and the identification of the dataset on a CNN architecture explained further.

3.1 Dataset

Examination of Chest X-Ray is one of the cost-expensive techniques, however with the advances of computing

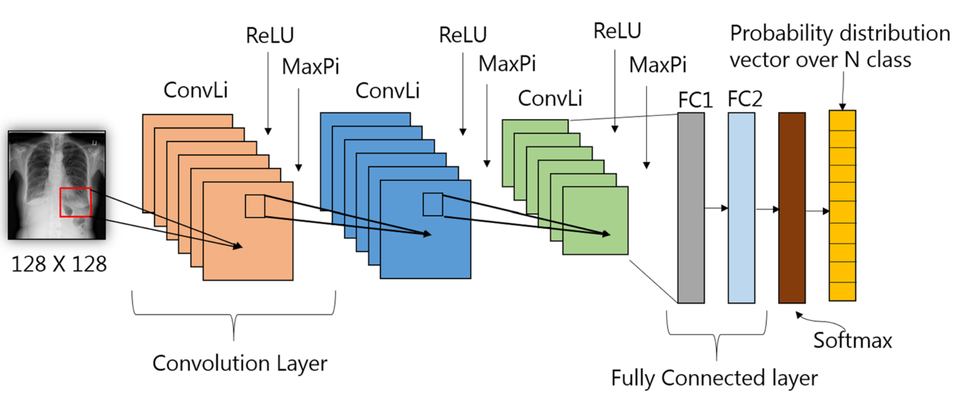


Fig. 1 Proposed CNN architecture for abnormality detection in chest diseases

power, storage and capturing devices in clinical diagnosis the pathology image datasets are also increasing in number. Open-I is the actual source of this dataset. The dataset which was used to validate our model is Kaggle (Wang et al. 2017), a random sample of NIH Chest X-Ray (Open-i http://openi.nlm.nih.gov, Wang et al. 2017) dataset. This dataset contains 5606 sample images of 14 different diseases and no finding diseases with 1024×1024 pixels each. The original dataset comprises 112,120 images which are taken from 30.805 different patients. The labeling of the dataset is > 90% exactly and most suitable for lazy supervised algorithms. In our experimental work we uses total 15 (14 diseases and one No Finding diseases) classes and the number of images in each class are respectively: Atelectasis: 508, Cardiomegaly: 141, Effusion: 644, Infiltration: 967, Mass: 284, Nodule: 313, Pneumonia: 62, Pneumothorax: 271, Consolidation: 226, Edema: 118, Emphysema: 127, Fibrosis: 84, Pleural Thickening: 176, Hernia:13 and No Finding: 3044 sample images.

3.2 Proposed CNN architecture

Convolutional neural network is one of the state-of-the-art learning algorithms (Rajpurkar et al. 2017) for classifying the images in the computer vision field. Our proposed CNN architecture consists of a total of six layers: three convolutional layers, two fully connected layers, and one softmax layer. We consider Convolutional (ConvLi) layer, activation layer (ReLU) and Maxpooling (MaxPi) layer consist of one Convolutional layer. ConvLi and MaxPi denote the convolutional layer and a max-pooling layer respectively where i defines the number of layers in CNN. FC1 and FC2 determine the first and second level of the convolutional layer. At first convolutional layer takes information of a small patch from the input with the help of several featured maps. These featured maps are passed through a nonlinear activation function which gives acceleration to CNN models for understanding complex functions. Here, we use ReLU non-linear activation function. ReLU is used to clip all negative elements into 0 and keep positive samples as they are. Training a neural network with a large number of parameters is one of the standard problems. Pooling is a subsampling technique which can address such kind of difficulties. In this model, we use three Convolutional layers to increase the depth of the neural network. Two fully connected layers which summarize the special learnable information which is useful for a further level of analysis. These fully connected layers are computationally expensive, increases trainable parameters exponentially. Finally, the output of the last fully connected layer is passed through a softmax classifier which gives the probability distribution of every output class corresponding to each input image.

3.3 Training

Training a neural network and selection of the best set of hyperparameters is one of the challenging issues and requires a lot of experimental expertise. In this segment, we justify our selection of the best set of hyperparameters, and we also introduce a comparison with some of the previous experiments. At first, we divide our data into two subgroups: training (4484) and testing (1122) images each with pixel size 128×128. We consider the batch size of 16 and the number of epochs is 100. For implementation simplicity in every layer of the convolutional layer, we use kernel size 3×3 and for max-pooling size 2×2 fixed. ReLU nonlinearity is used as an activation function for all the cases. In the first level of the convolutional layer, we use 32 filters, in the second layer 64 filters and in the third level we use 128 filters. A fixed of 50% neurons are dropped after each convolutional layer. For final activation Softmax function is used and the model was trained by Adam optimizer (Kingma and Ba 2014) where learning rate is 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and decaying rate is 0.0. We have discussed in previous sections, our diagnostic problem is a multilevel classification problem. Hence we used categorical cross-entropy to minimize the cost of the network and is defined as:

$$\delta\left(\frac{X_i}{Y_i}\right) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log P_i(y_i/Y_i) + (1 - Y_i) \log P_i(y_i/Y_i)]$$

where, Y_i is the actual output value and P_i is the predicted value after applying the softmax classification layer. $P_i(\frac{y_i}{Y_i})$ represents the estimated probability of an output image sample X corresponding to level i.

3.4 Comparative analysis

There is a minimal scope of direct comparison with existing literature works because the dataset we are using is entirely different and has several limitations compared to other datasets. Each dataset has its limitations and also has a specific purpose of implementation. This dataset has a fair number of samples, and moreover, it is a multilevel classification problem and most of the previous works are done based on multiclass classification. Though it is not possible to make a direct comparison with the previous work. However, at first, we are obliged to make a simple comparison with a similar kind of implementation and then we will introduce our model evaluation. In Wang et al. (2017), authors used natural language processing for labeling CNN for classifying the diseases. They provide a class-wise result for validating their model. Yao et al. (2018) proposed an LSTM based deep learning techniques and achieved 79% of diseases identification accuracy. Literature Khobragade et al. (2016) and Lessmann (2018) worked with convolutional neural network on three different diseases and they succeeded to achieve higher detection accuracy. also be found in Li et al. (2014), Rajpurkar et al. (2017) and Ciompi et al. (2016). In Tajbakhsh et al. (2015) author succeeded to achieve 83% of test accuracy on CTPA pulmonary image datasets. Slightly different kind of work can be found in Sorensen et al. (2010), Anthimopoulos et al. (2014, 2016), Angelov and Xiaowei (2018), Sargano et al. (2017) and Hyde et al. (2017), by using several traditional feature learning techniques they succeeded to classify 73%, 78% and 96% of accuracy. In Table 1, we presented a compact summary of previously existing works and made a comparison with our model. Comparison Table 1 clearly shows that our proposed CNN based architecture performs better as compared to various remaining works for both detection and localization of several chest diseases.

3.5 Visual formulation

Discriminative gradient based class activation mapping (Grad-CAM) is a "VISUAL EXPANSION" model which is mainly initiated for crystalline large scale deep learning architectures (Selvaraju et al. 2017). This technique is widely used for visualizing and analyzing the predicted classes. A large number of applications can also be found in classification with localization, video analysis and analysis of diseases affected regions. To make our CNN model more transparent, we have used weighted gradient based class activation mapping. Grad-CAM produces heatmap to the effective interested region in an image. The beauty of Grad-CAM is that it can highlight a wide range of multiple interests of regions. CNN models generally contain eminent feature information is in its last convolutional layers and last fully connected layers summarizes these special information to provide explicit eminent features. To generate the heatmap, Grad-CAM compute the gradient y^c from last convolutional layer corresponding to the output class C i.e.$\delta y^c/\delta A^K_{ij}$, where A^K_{ij} represents the featured map obtained from convolutional layer of the location (i,j). Then it summarize the information using global-average-pooling from featured map K of the corresponding class c to calculate the weights w^c_k of the neurons as:

$$W^C_{(K-pool)} = \frac{1}{z}\sum_i \sum_j \frac{\delta y^c}{\delta A^K_{ij}} \tag{7}$$

$$L^c_{G-CAM} = ReLU\left(\sum_k W^C_{(K-pool)} A^K\right) \tag{8}$$

These weighted combinations are finally passed through nonlinear ReLU activation layer. It is also notable that the primary intuition behind using ReLU is that it has a high influence of positive pixels only and normalize negative pixels to zero. Figure 2 shows how we can implement gradient based activation mapping on top of the CNN architecture.

4 Experimental performance

This section mainly focuses on performances of the proposed model. Our experimental strategy is to divide the whole dataset into three sets: training, validation, and testing. We train our model on 80% of the total image dataset, among the training data 20% is used for validating the training accuracy and rest 20% of original data was used for testing the model. The model performs an average efficiency of 83.15% of trained accuracy and 83.67% of test accuracy. From Fig. 2, it is also clear that validation loss is fluctuating in a certain range and the training loss is going down with the increase in the number of epochs.

While testing, our CNN model initially takes the input image, then process the input image and predicts the output class with the help of softmax function. Then the model stores the featured map concerning output class C from the last fully connected layer and summarizes all the information by using global average pooling. These features are then normalized concerning weights to generate the heatmap. Finally, a nonlinear activation is used for obtaining the positive pixels because we want actual pixels which are responsible for classifying the output class. The generated heatmap directly applied on the input image to show the region of interest of the proposed model. Figure 3 shows the diagrammatic workflow of our proposed model. Table 2 exemplifies the performance assessment of the proposed model with different test samples and Table 3 shows the visualization of interest of region by using Gradient-based Class Activation Mapping.

Our research query also exploits the solution of one unsolved problem i.e., "what are the best possible ways of training a neural network?" For finding the answer to the question, we examine some breakthrough performances and general intuitions for understanding a neural network. We found out that there are mainly two ways we can train one neural network: first is by creating our own neural network architecture from scratch and the second is by using transfer learning. In the previous section, we examined some unique deep learning architecture. Now, we try to understand transfer learning (http://cs231n.github.io/transfer-learning/add), (Shin 2016) techniques.

There are mainly three ways of using a pre-trained model and train neural network.

- Fixed feature extractor: Fixed feature extractor is one of the early machine learning algorithms. First, use a technique which extracts the features and then apply a

Table 1 Implementation options of convolutional neural network

Author	Database	Technique	Result	Remark
Wang et al. (2017)	NIH Chest X-Ray 8	CNN applied on thorax diseases and uses heatmap to localize the infected area	Result is provided based on their classes	The model trained on 108,948 images and gets average performance
Yao et al. (2018)	NIH X-ray	LSTM network for prediction of 14 diseases	0.798	Its complex implementation limits the proposed method performance
Khobragade et al. (2016)	80 lung images	Neural network applied to X-ray images	92%	Models overfit the target because of its limited data
Lessmann (2018)	NCI	Multiple CNN for detection of 3 different diseases	A table shows performance	Model is tasted on small chest dataset
Taylor et al. (2018), CheXNet (2017)	NIH Chest X-Ray 14	Pneumonia detection technique using Deep CNN	0.435 (F1 score)	It is almost impossible to implement in a low computational system
Song et al. (2017)	LIDC-IDRI	CNN technique is used on CT images to detect lung nodules		Result examined with different implementation points Average performance
Tajbakhsh et al. (2015)	CTPA	Pulmonary Embolism detection mechanism, applied CT images on a CNN network	83%	Traditional Learning technique
Carneiro et al. (2017)	48 images	Deep learning model used to analyze chest CT images	Low accuracy	Few samples on a deep learning model
van Ginneken et al. (2015)	LIDC	Pretrain CNN model is used on CT images to detect pulmonary Nodule	78%	Linear Classifier
Ciompi et al. (2016)	MILD, DLCST	Deep Learning for Lung cancer screening	Different parameters are obtained to get different observations	Low accuracy
Gao et al. (2016)	Reference multimedia dataset	CNN model to classification of Interstitial lung diseases	92.8%	Image segmentation on CT images
Anthimopoulos et al. (2016)	University Hospital of Geneva, Bern University Hospital dataset	2D CNN model is introduced to analyze lung diseases	85.5%	Feature mapping techniques are not implemented properly
Gangeh et al. (2010)	Gentofte University Hospital dataset	Texton-based CT image identification	96.43%	Traditional feature extraction based technique
Sorensen et al. (2010)	COPD	Pulmonary detection using LBP	0.7333	Texture classification based system, Local LBP, joint LBP and intensity histograms low specificity
Anthimopoulos et al. (2014)	TALISMAN data	DCT based future extraction and RF-based ILD Classification	0.7809	Detection of ILD using Fourier transformation
Li et al. (2014)	ILD database	CNN architecture for image classification	0.6705	Comparison done between CNN, SIFTLBP, RBM and highest accuracy is achieved by using CNN
Krizhevsky et al. (2017), Rajpurkar et al. (2017)	NIH Chest X-Ray	121-layers of dense CNN for classification and Cam for localization of the X-Ray images	0.7609	Pretrained Deep CNN networks are used for diseases prediction

Table 1 (continued)

Author	Database	Technique	Result	Remark
Proposed method	5606	CNN	83.67%	
Proposed method	5606	Pretrain VGG-16	97.81%	

classier for predicting levels. Also, the same way we can train neural network at first choose a convolutional neural network trained on big dataset like ImageNet Krizhevsky et al. (2012) and by removing last fully connected layer the network can be treated as a fixed featured extractor. Once the feature is extracted then the neural network trains a classifier for new dataset.

- Fine-tuning the ConvNet: Another important strategy is that it not only retrain as the classier over new dataset but also replace and fine-tune the learning experiences of the neural network. It may also be possible to train all the layers or keep some of the earlier layer fixed and fine-tune the upper layers. One notable thing is to mention the previous layer of convolutional layer which contains more generic low-level information's which can be advantageous for new dataset. Different experiments show that layer-wise fine tuning of a ConvNet for a big data performs better than making a neural network from the scratch.
- Pre-train models: Training a network on a large dataset like ImageNet may take 2–3 weeks for training a GPU based systems. Researchers sometimes release their final work for helping others. Using a pretrained model a fuse of different network sometimes is also beneficial for learning a neural network.

To address this problem and understand the conviction of transfer learning we have done a counter experiment. We have taken the VGG-16 model as shown in Fig. 4 and trained on the same Chest X-Ray 14 dataset. VGG-16 is one of the famous CNN architectures trained on ImageNet Krizhevsky et al. (2012) dataset. We have taken the weights of the pre-trained network and train the new dataset. We replace fully connected layers of 1.000 units with 128 units and replace the last fully connected layer with our 2 class problem. In experimental results, we found out that using a pre-trained neural network for medical image analysis achieved average training accuracy of 98% and test accuracy of 97%, it performs better than our scratch CNN network explained in the previous section. From this experiment we can make a strong observation by using the pre-trained neural network with adequate fine-tune could give us a practical way to reach the final output.

There are certain intuitions when and how to fine-tune a network, choosing a perfect transfer learning technique on a new dataset is a bit challenging task. There are several functions one should take care, but the two important are the size of the new dataset and similarity between old and new datasets. The lower level of ConvNet contains a lower level of generic information and upper level of the network contains more specific information related to the dataset. Some thumb rule for fine tuning (http://cs231n.github.io/transfer-learning/add) the new dataset are:

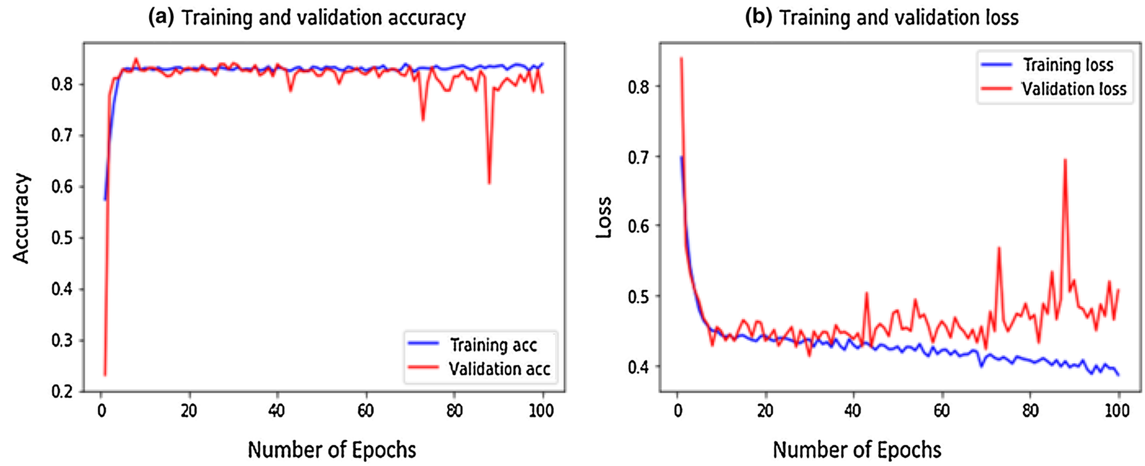


Fig. 2 Comparison of training and validation loss-accuracy with validation and testing samples

Fig. 3 The proposed framework for abnormality detection in X-ray images using convolutional neural network

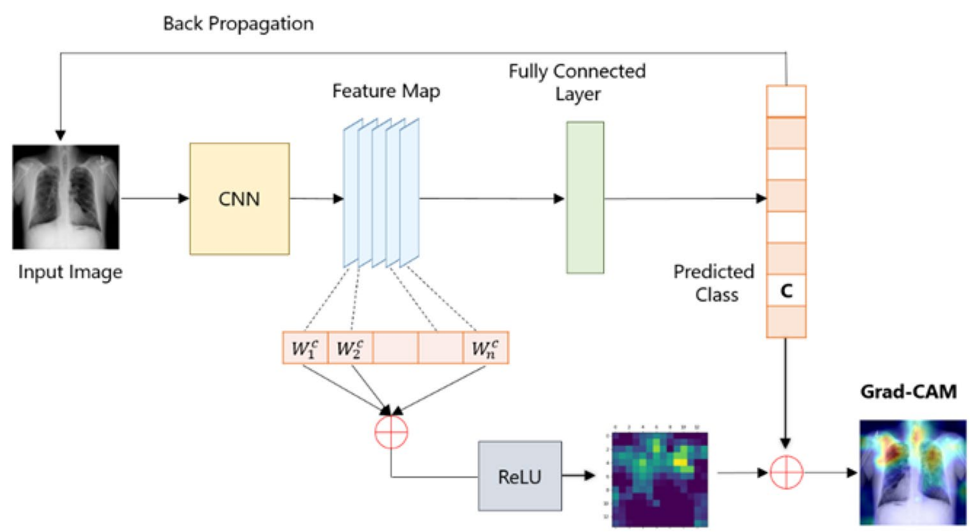
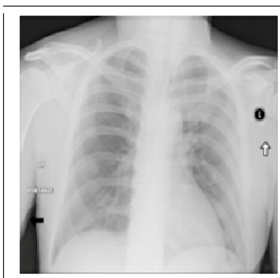
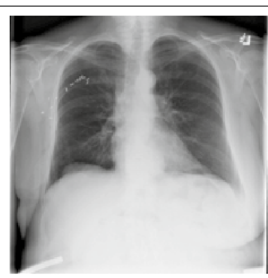
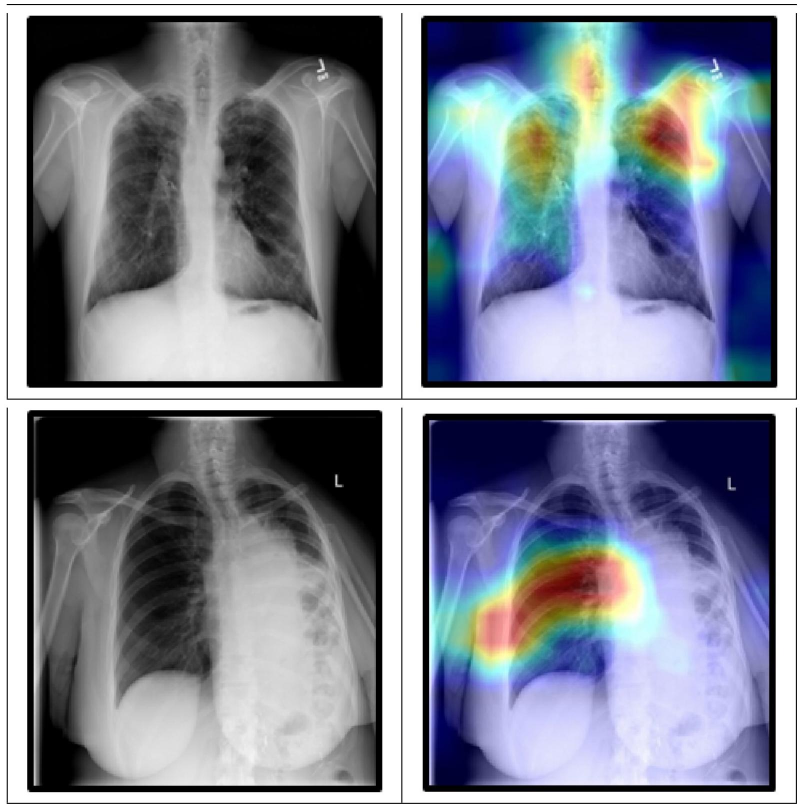


Table 2 Models performance evaluation with different test samples

	
Actual Class: Mass, Nodule	**Actual Class:** Hernia, Infiltration
Predicted Class: Mass(0.45) Nodule(0.38) No Finding(0.16)	**Predicted Class:** Hernia(0.01) Infiltration(0.33) Mass (0.32)

1. If the dataset is small, the fine-tuning a ConvNet over a small dataset will not be a good idea as the network may suffer from overfitting problem. Hence using a linear classifier on a small dataset might be a good idea.
2. If the dataset is large and there is a similarity between two datasets then using a pre-trained model will give more confidence not to be overfitting the network, hence chances of increasing the performance of the network.
3. If the new data is small and differ from original data, then using a linear classifier may not always work, instead use of SVM classifier may be beneficial for new dataset as the network contain data specific information.
4. If the data is large and differ from original data, then fine-tuning a residual neural network sometimes helpful because it concluded that exploring vanishing gradient can lead some problem for weight updating. Even

Table 3 Visualization of interest of region by using gradient based class activation mapping



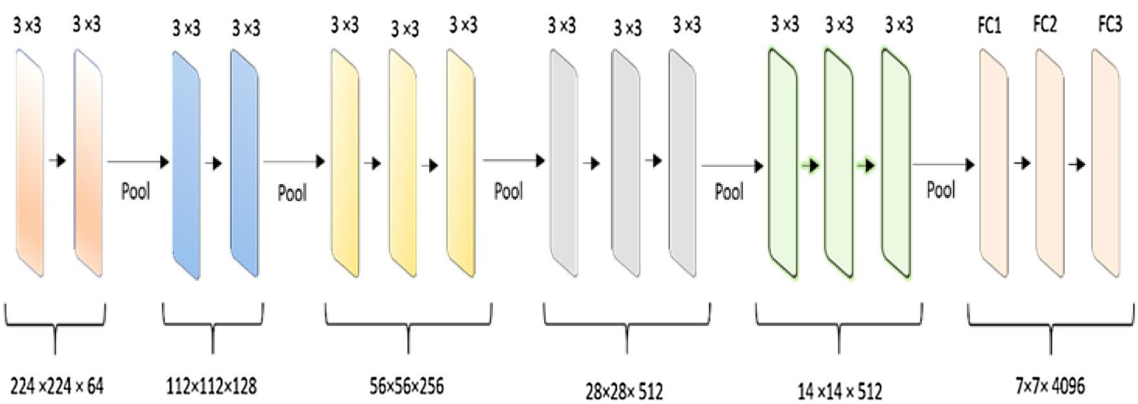


Fig. 4 VGG-16 model architecture

though making a neural network from scratch also works depending on the dataset.

The entire experiment was done on a Windows10 Intel(R) Core i7-4790 CPU @ 3.60 GHz, with 12 GB RAM system. Keras (https://github.com/keras-team/keras.git) is used as the base implementation framework which works on top of the Python programming language. We use Spyder (Anaconda) as our primary integrated development environment (IDE).

5 Conclusion

Deep learning techniques are state-of-the-art learning algorithms (Simonyan and Zisserman 2015) and perform quite well in medical image analysis. In this paper, we have proposed a deep end-to-end convolutional neural network which improves the performance for classifying the chest diseases and localize the region of interest with respect to the infected area. We have evaluated the performance of our model on Kaggle Chest X-Ray 14 dataset. In here we gave our effort to solve several problems which are still cloudy to the research community. We also introduce a broad comparison with existing works and a Grad-CAM based visualization technique which makes CNN networks more transparent. Our CNN consists of several types of layers: convolutional layer, pooling layer, the activation layer, and fully connected layer. We have briefly analyzed the model performance and applied various combinations of hyperparameters for improving model performance. We analyzed the limitations of making random CNN architecture and briefly explained various benefits of applying transfer learning technique. Based on our experimental analysis and expertise, we gave a brief idea to the reviewers, in what way transfer learning techniques can be beneficial in large complex datasets. Moreover, how, where and when to use transfer learning and finally, what types of data are useful for transfer learning is also explained. The training was performed by minimizing the cross-entropy with Adam optimizer. The proposed method validates in the set of images and has the ability to classify the abnormality in chest diseases appropriately. This paper ameliorates the model performance significantly in twofold. Our work is still in progress, in the near future we will surely be able to find all the 14 chest diseases in Chest X-Ray 14 datasets. We will also try to find one unsolvable problem "Big network can be a better solution for analyzing the medical images". We hope that this paper gives a clear understanding to readers and stretch some contribution to Medical Image research.

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