Pneumonia Detection Using CNN based Feature Extraction

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***Abstract*—Pneumonia is a life-threatening infectious disease affecting one or both lungs in humans commonly caused by bacteria called Streptococcus pneumoniae. One in three deaths in India is caused due to pneumonia as reported by World Health Organization (WHO). Chest X-Rays which are used to diagnose pneumonia need expert radiotherapists for evaluation. Thus, developing an automatic system for detecting pneumonia would be beneficial for treating the disease without any delay particularly in remote areas. Due to the success of deep learning algorithms in analyzing medical images, Convolutional Neural Networks (CNNs) have gained much attention for disease classification. In addition, features learned by pre-trained CNN models on large-scale datasets are much useful in image classification tasks. In this work, we appraise the functionality of pre-trained CNN models utilized as feature-extractors followed by different classifiers for the classification of abnormal and normal chest X-Rays. We analytically determine the optimal CNN model for the purpose. Statistical results obtained demonstrates that pretrained CNN models employed along with supervised classifier algorithms can be very beneficial in analyzing chest X-ray images, specifically to detect Pneumonia.**

***Keywords*—DensetNet, Deep Convolutional Neural Networks, SVM, Transfer Learning, Random Forest, Naive Bayes, K-nearest neighbors, Feature extraction.**

I. Introduction

Over the recent years, Computer Aided Designs (CAD) have become the major research domain in machine learning. The subsisting CAD systems have already been proved to facilitate the medical area primarily in detection of breast cancer, mammograms, lung nodules etc. In the procedure of employing Machine Learning (ML) techniques to medical images, significant features are of uppermost importance. For this reason, most of the previous algorithms used hand crafted features for developing CAD systems based on examining images [1,2,3]. However, the hand crafted features with limitations varying according to tasks were not capable of supplying much meaningful features. Employment of Deep Learning (DL) models particularly Convolutional Neural Networks (CNNs) revealed their self-potential of extracting useful features in image classification tasks [4,24]. This process of feature-extraction demands transfer learning methods where pre-trained CNN models learn the generic features on largescale datasets like ImageNet which are later on transferred to the required task. Availableness of pre-trained CNN models like AlexNet [5], VGGNet [6], Xception [7], ResNet [8] and DenseNet [9] highly aid in procedure of significant feature extraction. In addition, the classification used with high-rich extracted features exhibit improved performance in classifying images [10, 23, 25].

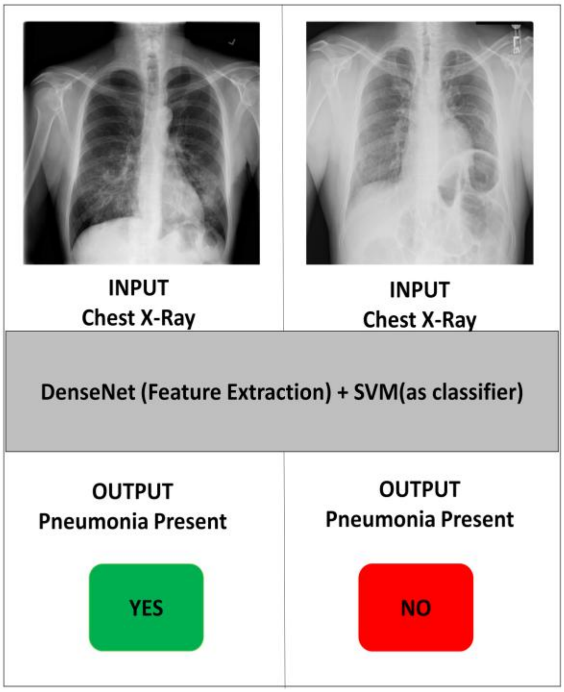

Fig. 1. An example of Normal CXR (right) and an example of a Pneumonia CXR (left) from ChestX-ray14 dataset. The pathology in the left CXR cannot be easily distinguished from the right CXR.

Chest screening subroutines which are mainly used for sensing lung nodules can also be used to diagnose other illnesses such as pneumonia, effusion, cardiomegaly etc. Among these, pneumonia is an infectious and deadly disease which strikes over millions of people, majorly those who are aged above 65 and suffering from chronic diseases like asthma or diabetes [11]. In the procedure of diagnosing pneumonia, chest XRays are considered as the most effective method to determine the extent and location of the septic region in the lungs. However, examining chest radio-graphs is not a leisurely task for radiotherapists. In chest X-ray images, appearance of pneumonia can be hazy and can be misapprehended with other diagnoses. The evaluation of chest X-Ray specifically in case of Pneumonia can be misleading because many other problems like congestive heart failure, lung scarring etc. can mimic a Pneumonia. This is the main reason behind the misclassification of the X-ray images in the dataset. Thus, the task is challenging and the development of an algorithm for detecting thoracic diseases like Pneumonia would increase the accessibility of clinical settings in remote areas as well. In this study, we evaluated the performance of different variants of pre-trained CNN models followed by different classifiers for classifying abnormal and normal chest X-Rays. The crucial contributions of this study are as follows: (a) comparative analytical study of different pre-trained CNN models as feature-extractors for analyzing chest X-Rays, (b) presentation of these models with different classifiers to propose ideal classifier in the same field of classification, (c) evaluation of optimal pre-trained CNN model with hyperparameter tuning of the best analyzed classifier to further meliorate the performance. The structure of this paper is described as follows: In Section 2, there is a description of the related research done in the same field. In Section 3, there is a description of all the details relevant to dataset used. In Section 4, the description of the applied methodology has been provided which has been divided into multiple stages. In Section 5, we present the experimental setup for the experiments carried out on different variants of pre-trained CNN models along with the results obtained on employing different classifiers. Section 6 consists of results and discussions about the final AUC-scores obtained.

II. Related Work

In recent time, exploration of Machine learning (ML) algorithms in detecting thoracic diseases has gained attention in research area of medical image classification. Lakhani and Sundaram (2017) [12] proposed a method of detecting pulmonary tuberculosis following the architecture of two different DCNNs AlexNet and GoogleNet. Lung nodule classification mainly for diagnosing lung cancer proposed by Huang et al. [13] also adopted deep learning techniques. Performance of different variants of Convolutional Neural Networks (CNNs) for abnormality detection in chest X-Rays was proposed by Islam et al. [14] using the publicly available OpenI dataset [15]. For the better exploration of machine learning in chest screening, Wang et al. (2017) [16] released a larger dataset of frontal chest X-Rays.

Recently, Pranav Rajpurkar, Jeremy Irvin, et al. (2017) [17] explored this dataset for detecting pneumonia at a level better than radiologists, they referred their model as ChexNet which uses DenseNet-121 layer architecture for detecting all the 14 diseases from a lot of 112,200 images available in the dataset. After the CheXNet[17] model, Benjamin Antin et al.(2017) [18] worked on the same dataset and proposed a logistic regression model for detecting pneumonia. Pulkit Kumar, Monika Grewal (2017) [19] using the cascading convolutional networks contributed their research for multilabel classification of thoracic diseases. Zhe Li (2018) [20] recently proposed a convolutional network model for disease identification and localization.

III. Dataset Description

The dataset used is ChestX-ray14 released by Wang et al. (2017) [16] also publicly available on the Kaggle [21] platform which consists of 112,120 frontal chest X-ray images from 30,085 patients. Each radiographic image in the dataset is labeled with one or more out of different 14 thoracic diseases. These labels were concluded through Natural Language Processing (NLP) by text-mining disease-classification from the associated radiological reports and are expected to be more than 90% accurate. For the sake of this work, following the approaches from the past [17], we treat the labels as ground truth for the purpose of pneumonia detection. Prior to the release of this dataset, the largest publicly available dataset of chest radio-graphs was Openi [15] which consisted of roughly 4,143 X-ray images.

All the radio-graph images in the dataset are of 1024 by 1024 resolution. Out of these 112,120 images, 1431 images are found to be labeled with pneumonia. In order to balance the dataset for binary classification, 1431 normal X-ray images (labeled with 'No Findings') have been selected from the dataset. Altogether, the final dataset used for the classification task is the subset of the original dataset which consists of 1431 positive image samples (images labeled with 'Pneumonia') and 1431 negative image samples (images labeled with 'No Findings'). After that, the dataset was divided into two parts out of which for the testing, 573 images were randomly selected from the whole final dataset. The images were downscaled from 1024 by 1024 resolution to 224 by 224 resolution before they were given input to the network.

IV. Methodology of Proposed Model

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) is described in Figure 2. The architecture of the proposed model has been divided into three different stages - the preprocessing stage, the feature-extraction stage and the classification stage.

A. 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 original 3-channel images were resized from 1024×1024 into 224×224 pixels to reduce the heavy computation and for faster processing. All of the further techniques has been applied over these downsized images.

B. 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.

1) Architecture of DenseNet-169: Deep Convolutional Networks (DCNNs) have become the most productive frameworks for image recognition because of the presence of peculiar types of the convolutional and pooling layers. But as the network gets deeper the input information or gradient passing through most of the layers gets vanished by the time the last layer of the network is reached. DenseNets overcome this problem of gradient vanishing by connecting all the layers with equal featutre-sizes directly with each other. The chief motive of using DenseNet architecture as a feature extractor is that deeper the network more generic features can be obtained. The pre-trained Densely Connected Convolutional Neural Network of 169 layers

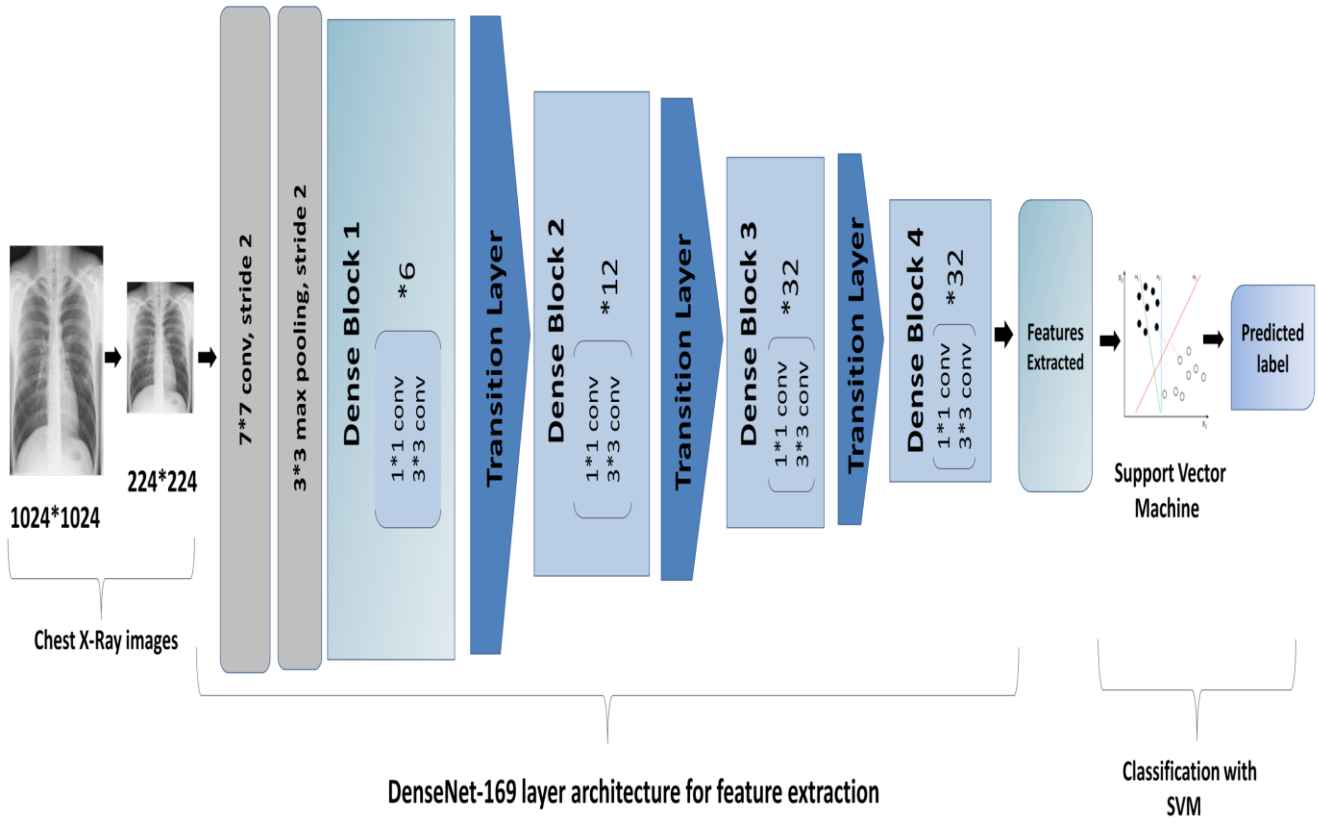

Fig. 2. Represents a flow diagram of our methodology applied.

(DenseNet-169) has been used for the feature extraction process. This model was proposed by Huang et al. (2016) [9] and the variant used in our study is trained on the large-scale publicly available ImageNet dataset. The DenseNet-169 architecture comprises of one convolution and pooling layer at the beginning, 3 transition layers, 4 dense blocks. After these layers, the final layer i.e the classification layer is present. The first convolutional layer performs 7×7 convolutions with stride 2 followed by a max pooling of 3×3 used with stride 2. Then the network consists of a dense block followed by 3 sets each of which consist a transition layer followed by a dense block. The dense connectivity as proposed by Huang et.al [9] in DenseNets are received by bringing in direct connections from any layer to any other layer in the network. The lth layer in the network receives the feature-maps of all the preceding layers thus ameliorating the flow of gradient throughout the entire network. This requires the concatenation of the feature-maps of the preceding layers which cannot be done unless all the feature-maps are of the same sizes but as the Convolutional Neural Networks primarily intend towards the down sampling of size of feature-maps, the DenseNets architecture is divided into multiple densely connected dense blocks mentioned above.The layers between these dense blocks are referred to as transition layers. Each transition layer in the network consists of a batch normalization layer and an 1×1 convolutional layer followedbya 2×2 average pooling layer that uses a stride of 2. As mentioned above there are 4 dense blocks , each of which contains 2 convolution layers first is of size 1 × 1 followed by 3×3. The size of all the four dense blocks in DenseNet169 architecture pretrained on ImageNet is 6, 12, 32 and 32. Next to this is the final layer that is the classification layer which performs the global average pooling of 7×7 followed by a final fully-connected layer which uses 'softmax' as the activation.

2) Extraction of Features: The process of feature extraction from the model explained in this section 4.2.1 εapplies all the layers of the network except the final classification layer. The final feature representation obtained were interpreted as a 50176×1 dimension vector which then supplied as input to different classifiers.

C. 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) [13] . The gamma and C parameters of RBF kernel highly affects the performance of SVM. Intuitively, the gamma parameter is used to define amount of influence that a single training example should goto in which lesser value implies 'far' and larger value implies 'close'. So the gamma parameter shows the inverse of radius of the influence of samples that were selected as support vectors by the model. On the other hand the C parameter compensates the misclassification of training samples. A low C provides a smooth surface where as a high C tries to classify all training samples correctly by providing the model exemption to select more samples as support vectors.

V. Experimental Setup

This section deals with the description of several experiments performed in order to propose the optimal model toward the Pneumonia detection problem.

A. *Feature-Extractor and Classifier*

For pre-trained CNN models including Xception [7], VGG16 [6], VGG-19 [6], ResNet-50 [8], DenseNet-121 [9] and DenseNet-169 [9], we evaluated their performance followed by different classifiers including Random Forest, K-nearest neighbors, Naive Bayes and Support Vector Machine(SVM). Table-1 lists the performance of all these models in the procedure of classifying abnormal and normal chest X-Rays. It was observed that ResNet-50 CNN model of depth 168 followed by SVM classifier outperformed all the other prerained CNN models attaining an AUC score of 0.7749. We observed that DenseNets also accomplished results near ResNet50 achieving an AUC of 0.75(approx). Table-2 shows the results obtained by DenseNet-121 and DenseNet-169. Statistical results demonstrated the use of ResNet-50 and DenseNets (DenseNet-121 and DenseNet-169) as the optimal pre-trained CNN models for the feature-extraction stage and use of SVM (with rbf kernel) as the classifier for the classification stage. Figure 3 shows the performance of ResNet50 and DenseNets (DenseNet-121 and DenseNet-169) along with different classifiers and demonstrates SVM classifier as the optimal one to accomplish higher AUC scores along with all three pretrained CNN models. In the process of evaluating the optimal CNN model, it was also noted that VGGNets (VGG16 and VGG19) accomplishes the lowest scores among all the pretrained models employed.

B. *Optimal Hyperparameters Optimization*

To further improve the performance of models, we performed hyper-parameter tuning with SVM classifier (rbf kernel in each case). We observed that the process highly affected the statistical results with an accomplishment of most prominent AUC score till now. We performed around 350 combinations of C and gamma individually with each preferred CNN model to achieve better results. But a majority of tuned hyper-parameter values showed no substantial improvement in the performance. Table-3, Table-4 and Table-5 lists only the important combinations of C and gamma in case of all the three models: (a) ResNet-50 followed by SVM, (b) DenseNet-121 followed by SVM (c) DenseNet-169 followed by SVM. The process of searching optimal hyper-parameters of SVM classifier demonstrated a significant improvement in case of DenseNet-121 as well as in DenseNet-169 but no statistical significant improvement was observed while performing hyper-parameter tuning in case of features-extracted from ResNet-50. Figure 4 shows the variation of AUC scores with respect to different combinations of C and gamma in case of DenseNet-121 and

TABLE 1

RESULTS OBTAINED BY VARIOUS PRE-TRAINED MODELS WITH DIFFERENT CLASSIFIERS

Feature Extractor	Classifier	AUC
XCeption	SVM(rbf kernel)	0.7034
XCeption	Naïve Bayes	0.6362
XCeption	k-nearest neighbors	0.6867
XCeption	Random Forest	0.6406
VGG-16	SVM(rbf kernel)	0.5
VGG-16	Naïve Bayes	0.6193
VGG-16	k-nearest neighbors	0.6847
VGG-16	Random Forest	0.6563
VGG-19	SVM(rbf kernel)	0.5
VGG-19	Naïve Bayes	0.5952
VGG-19	k-nearest neighbors	0.68502
VGG-19	Random Forest	0.6481
ResNet-50	**SVM(rbf kernel)**	**0.7749**
ResNet-50	Naïve Bayes	0.6891
ResNet-50	k-nearest neighbors	0.7298
ResNet-50	Random Forest	0.5793

TABLE 2

RESULTS OBTAINED BY DENSENET-121 AND DENSENET-169

PRE-TRAINED MODELS WITH DIFFERENT CLASSIFIERS

Feature Extractor	Classifier	AUC
DenseNet-121	SVM(rbf kernel)	0.7577
DenseNet-121	Naïve Bayes	0.6691
DenseNet-121	k-nearest neighbors	0.6981
DenseNet-121	Random Forest	0.6771
DenseNet-169	SVM(rbf kernel)	0.7476
DenseNet-169	Naïve Bayes	0.6758
DenseNet-169	k-nearest neighbors	0.6835
DenseNet-169	Random Forest	0.6733

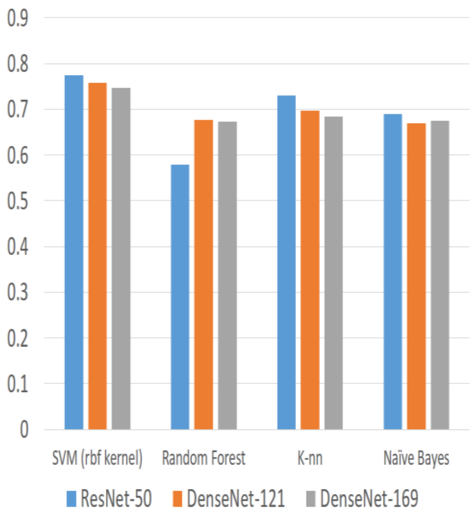

Fig. 3. Represents a bar graph of AUC scores obtained using pre-trained CNN models with different classifiers.

TABLE 3

RESULTS OBTAINED BY PARAMETER TUNING WHEN PRE-TRAINED RESNET-50 MODEL IS USED AS FEATURE EXTRACTOR

Technique	C	gamma	AUC
ResNet-50 + SVM	1.5	1.9e-05	0.7859
ResNet-50 + SVM	1.5	0.9e-05	0.7841
ResNet-50 + SVM	1.5	2.5e-05	0.7840
ResNet-50 + SVM	2	1.9e-05	0.7842
ResNet-50 + SVM	3	1.9e-05	0.7841

TABLE 4

RESULTS OBTAINED BY PARAMETER TUNING WHEN PRE-TRAINED DENSENET-121 MODEL IS USED AS FEATURE EXTRACTOR

Technique	C	gamma	AUC
DenseNet-121 + SVM	1.5	1.9e-05	0.7296
DenseNet-121 + SVM	2.0	1.9e-05	0.7634
DenseNet-121 + SVM	3	1.9e-05	0.7669
DenseNet-121 + SVM	3	0.9e-05	0.7699
DenseNet-121 + SVM	**3**	**0.85e-05**	**0.7717**
DenseNet-121 + SVM	3	0.8e-05	0.7681
DenseNet-121 + SVM	3.5	1.9e-05	0.7652

DenseNet-169. Experimental results demonstrated DenseNet-169 (as feature-extractor) + SVM (as classifier with rbf kernel at C=3.5 and gamma=1.9e-05) as the ideal model for analyzing chest X-Rays for Pneumonia detection task and thus is the proposed customized model in our work.

TABLE 5

RESULTS OBTAINED BY PARAMETER TUNING WHEN PRE-TRAINED DENSENET-169 MODEL IS USED AS FEATURE EXTRACTOR

Technique	C	gamma	AUC
DenseNet-169 + SVM	1.5	1.9e-05	0.7791
DenseNet-169 + SVM	2.0	1.9e-05	0.7901
DenseNet-169 + SVM	3	1.9e-05	0.7969
DenseNet-169 + SVM	3	0.9e-05	0.7966
DenseNet-169 + SVM	3.5	0.85e-05	0.7912
DenseNet-169 + SVM	**3.5**	**1.9e-05**	**0.8002**
DenseNet-169 + SVM	3.5	0.9e-05	0.7999
DenseNet-169 + SVM	3.5	2e-05	0.7904
DenseNet-169 + SVM	4	1.9e-05	0.7984

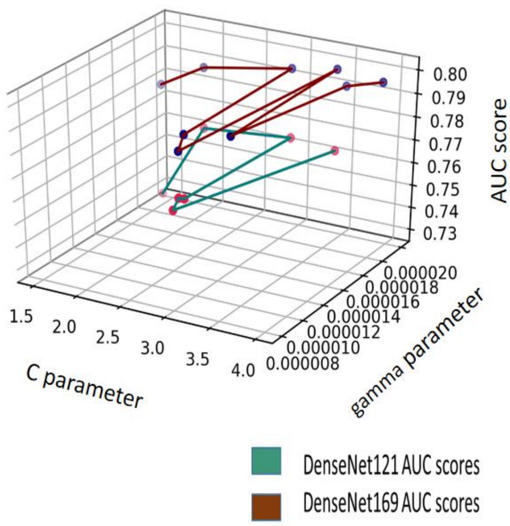

Fig. 4. Represents effect of different C and gamma parameter values with respect to AUC score in case of DenseNet121 and DenseNet169.

We performed the above experimental analysis to choose the best model for classifying Chest X-Rays. In the process of determining optimal feature extractor among all the accessible pre-trained CNN models, ResNet50 outperformed the results of all the other models followed by SVM classifier at default hyper-parameter values. But the process of optimal hyperparameters optimization suggested the use of DenseNet-169 for providing better feature representation.

VI. Results And Discussion

The customized model i.e a combination of CNN based feature-extraction and supervised classifier algorithm resulted in optimal solution for classifying abnormal (Pneumonia labeled) and normal Chest X-Ray images primarily due to the substantive features provided by DenseNets [9] followed by optimal hyper-parameter values of SVM classifier. Literature studies reveal the contribution

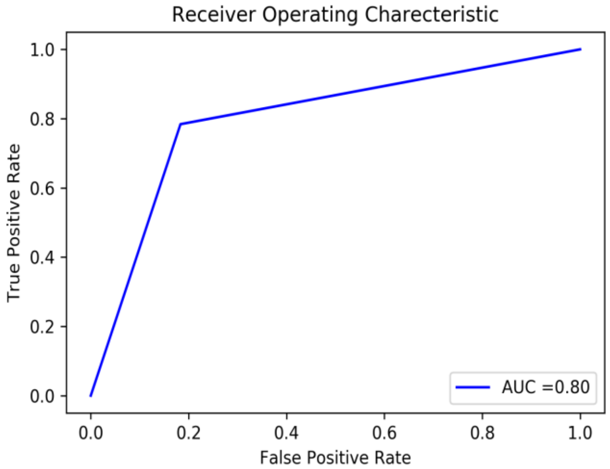

Fig. 5. Represents the test ROC curve for DenseNet-169.

of transfer learning methods including feature-extractions toward visual recognition tasks[4,23,25]. For this reason, we extracted features from various variants of pre-trained CNN models available such as VGGNets [6], Xception [7], ResNet-50 [8] and DenseNets [9]. Studies from the literature also reveal the use of classifiers in combination with CNN-based feature extraction majorly in medical image analysis [10] to meliorate the performance of models. Following the mentioned past approaches, we evaluated each of the pre-trained models with distinct classifiers to determine the ideal model for the purpose. We observed from the comparative experimental results presented in Table 1 and Table 2 that ResNet50 outperformed the results of all the other pre-trained CNN models when employed with default parameter values of SVM classifier. In addition, DenseNets were also observed to achieve results close to ResNet50. Literature studies reveal that DenseNets outperformed all the pre-trained CNNs in the ImageNet dataset (Huang et al., 2017 [9]). For this reason, we chose ResNet50, DenseNet-121 and DenseNet169 as the optimal CNN models for the feature-extraction stage and SVM as the optimal classifier for the classification stage for further experiments in the study. The selection of SVM classifier with rbf kernel based on the statistical results presented in Figure 3 further led to hunt of optimal hyperparameter values (C and gamma). In the process of tuning hyper-parameters, we performed close to 350 combinations of C and gamma, the crucial combinations among these are presented in Table 3,4 and 5. We observed in this process that DenseNet-169 outperformed all the other customized models and hence chosen as the best feature-extractor for the final customized model followed by optimal hyper-parameter values of SVM rbf kernel. The best results achieved with DenseNet169 architecture as feature extractors can be explained due to its capability of accessing feature-maps from all of its preceding layers. Literature studies [9] of DenseNets mentions the information flow from the beginning layer to the end layers and removal of redundant features by transition layers as the primary reasons for the high-features representations. To our knowledge, no literature was found to perform the studies on the combination of CNN based feature extractions and supervised classifier algorithms for the underlying task. In the process of meliorating the model performance, we found that our customized model outperforms the results documented in the recently released work of Benjamin Antin et al. [18] for the same problem of pneumonia detection.

TABLE 6

RESULTS OF THE PROPOSED MODEL

Feature Extractor	Classifier	C	gamma	AUC
DenseNet-169	SVM(rbf kernel)	3.5	2e-05	0.7904
DenseNet-169	**SVM(rbf kernel)**	**3.5**	**1..9e-05**	**0.8002**
DenseNet-169	SVM(rbf kernel)	3.5	0.9e-05	0.7999

TABLE 7

RESULTS OBTAINED BY BENJAMIN ANTIN ET AL. (2017) [18] IN PNEUMONIA DETECTION PROBLEM.

Author Name	Technique Used	AUC
Benjamin Antin [18]	Logistic Regression	0.60
Benjamin Antin [18]	DenseNet-121	0.609

Table 6 and Table 7 shows the statistical results of our customized model and model proposed by Benjamin et al. respectively. The proposed model in our work achieves AUC of 0.8002 and the associated ROC curve is presented in Figure 5.

VII. LIMITATIONS

Although the results were overwhelming, there were still some limitations in our model which we believe are vital to keep in consideration. The first biggest limitation is that there is no history of the associated patient considered in our evaluation model. Secondly, only frontal chest X-rays were used but it has been shown that lateral view chest X-rays are also helpful in diagnosis [22]. Thirdly, since the model exercises a lot of convolutional layers, the model need very high computational power otherwise it'll eat up a lot of time in computations.

VIII. CONCLUSION

Presence of expert radiologists is the topmost necessity to properly diagnose any kind of thoracic disease. This paper primarily aims to improve the medical adeptness in areas where the availability of radiotherapists is still limited. Our study facilitate the early diagnosis of Pneumonia to prevent adverse consequences (including death) in such remote areas. So far, not much work has been contributed to specifically to detect Pneumonia from the mentioned dataset. The development of algorithms in this domain can be highly beneficial for providing better health-care services. In this regard, we have proposed a model architecture for detecting Pneumonia from frontal chest X-ray images with the utilization of Densenet as feature-extractors and SVM as classifier. We observed the performance of various pretrained CNN models along with distinct classifiers and then on the basis of statistical results selected DenseNet-169 for the feature extraction stage and SVM for the classification stage. We also showed that performing hyper-parameter optimization in the classification stage ameliorated the model performance. With the series of experiments conducted, we aim to provide the dominating pre-trained CNN model and classifier for the future work in the similar research domain. Our study will likely lead to the development of better algorithms for detecting Pneumonia in the foreseeable future.

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