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A Comparative Study of the Deep Learning Approaches used for Pneumonia Detection

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Abstract: Pneumonia is a disease that affects approximately 10 Lakh people every year, the timely detection of which is the key to saving multiple lives. There have been various approaches, the primary goal of which has been to detect pneumonia from frontal chest X-Rays. If researchers can propose definite and reliable solutions to this problem, then the model can be used for various diagnostic problems. This study aims to give a brief introduction of the previous work done on pneumonia detection from the frontal thoracic X-Rays using machine learning. A comparative study between the different approaches that have been used so far is presented here. The results and approaches have been compared considering the classification model, hyper-parameters, architecture, source of training dataset and performance metrics of the models.
Keywords: pneumonia, convolutional neural networks, computer vision, disease

I. INTRODUCTION

Pneumonia is a form of acute respiratory infection that affects the lungs. It is the single largest infectious cause of death in children worldwide [1]. Pneumonia affects children and families everywhere but is most prevalentin South Asia and sub-Saharan Africa. Children can be protected from pneumonia, it can be prevented with simple interventions, and treated with low-cost, low-tech medication and care. Pneumonia is caused by several infectious agents, including viruses, bacteria and fungi.

Under most cases, pneumonia evades detection at an earlystage because the symptoms of a common flu are the same as that of pneumonia. Hence, an approach wherepneumonia can be detected by the frontal thoracic X-Rayof an individual has been under study. If such a model is developed successfully, an early diagnosis of pneumoniacan be done in developing and under-developed countriesat a minimal cost, thus saving a lot of lives by allowing timely intervention. Neural networks have been applied in various fields of medicine[2]. Neural networks are ideal in recognizing diseases using scans due to the ability of learning by example, hence the details of how to identify the diseasesis required. Some notable examples of such algorithms are AlexNet[3], ResNet [4], LeNet-5[5] or VGG[6]. When it comes to analyzing image inputs, deep convolutional neural networks are preferred. Theprimarypurpose of 'convolution' in convolutional neural networks is to extract features from the input image. Convolution preserves the spatial relationship between pixels by learning image features using smaller segments of input data. The convolutional neural networks follow ahierarchical model which works on building a network, which resembles a funnel, and it finally gives out a fully connected layer where all the neurons are connected to each other and the output is processed. The reason that a deep neural network is used is that the algorithm can scandata to search for features that correlate and combine themto enable faster learning without being explicitly told to do so. The study in this paper focused on comparing the previousreports of detecting pneumonia from the frontal thoracic X-Rays. There have been various approaches and each approach has been beneficial in some aspect of the model design for further research. This comparison is presentedsince no current literature compares the methods, while highlighting the unique strengths of each algorithm.

II. COMPARATIVE STUDY

A. *Comparative Performance Analysis of Machine Learning Classifiers in Detection of Childhood Pneumonia Using Chest Radiographs [7]*

The approach proposed in this paper used the features anddataset employed in studies for the construction of a full Computer-aided Design system (CAD) for pneumonia detection called PneumoCAD[8], which has been appliedto assist in diagnostics, as well as to train and improve radiologists' expertise in childhood pneumonia detectionusing chest radiographs. The image dataset consists of 156 8-bit grayscale images obtained with a digital camerathat captured the chest X-rays images at a resolution of 1024 × 768 pixels. Out of these images, 78 are scans of pneumonia patients. The following texture-based features were tested, implemented, and selected: coefficient of variation, contrast, correlation, energy, average energy, entropy, average deviation, difference variance, differenceentropy, inverse difference moment, residual mean, sum average, sum entropy, sum variance, suavity, variance, standard deviation. All features have been extracted in nine subspaces of the Haar wavelet [9].

The first method incorporated in this study includes eachfeature being tested with three classifiers, K-nearest neighbors (KNN)[10] (the k-parameter was set to 9),Support Vector Machines (SVM)[11] (standard Gaussiankernel parameters were used, C = 1, σ = 1) and Naïve Bayes[12]. The efficiency that was recorded with just themethods was 82% with KNN, 80% with SVM and 60% with Naive Bayes.

The second method was incorporated in order to test the robustness of each classifier applied in pneumonia detection and to avoid overfitting. Outliers which are out of the interval $\bar{x}-\sigma \leq x \leq \bar{x}+\sigma$, where x is a sample, $\bar{x}$ the feature mean and σ the standard deviation, were removed. Post which a 10-fold cross-validation test with each classifier using every feature in 9 subspaces of wavelet was performed. The result concluded that severalfeatures showed overall good results, namely: entropy, difference variance, sum entropy, and suavity. In SVM tests the best values for the parameters were: [C = 1.2; σ = 1] for entropy [C = 5.7; σ = 0.5] for difference varianceand [C = 0.6; σ = 0.6] for sum entropy. For KNN thebestcalibration led to k=11 for suavity, k=7 for sum entropy and k=9 for entropy.

The third method incorporated feature selection, which took the full feature vector, with all 17 texture features, and used a Sequential Forward Elimination (SFE) [13] test, which is a simple greedy search algorithm, to find the best feature set for each classifier. The results showed that with SVM the selected features were correlation, average deviation, difference variance and standard deviation, onewavelet subspace from each. With KNN the selected features were energy and suavity, with one subspace each.Naive Bayes best result was with entropy, difference variance and sum average, one subspace each. The efficiency of the third method is listed in table 1:

Medical Results (By Radiologists)	PneumoCAD – KNN without SFE	PneumoCAD – SVM withSFE
66%	66%	77%

Table 1: Diagnosis by KNN (K-nearest neighbors), SVM (Support Vector Machine) and SFE (Sequential Forward Elimination)

In conclusion, the SVM classifier produced the mostaccurate results and has shown to be more stable with training data variation.

B. CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning [14]

An algorithm called CheXNet is reported in this publication. CheXNet is a 121-layer convolutional neural network trained on ChestX-ray14 [15], which was the largest publicly available chest X-Ray dataset at that time.The dataset contained 112,120 frontal view X-Ray images with 14 diseases. Four practicing academic radiologists annotated a test set, on which the performance of CheXNet was compared to that of radiologists. It was found that CheXNet exceeded the average radiologist performance. CheXNet was then extended to detect all 14 diseases in ChestX-ray14. Before inputting the images into the network, the images were downscaled to 224×224and normalized based on the mean and standard deviation of images in the ImageNet training set[16]. The training data was also augmented with random horizontal flipping. Bootstrap was used to construct 95% bootstrap confidence intervals (CIs)[17], to calculate the average F1score for both the radiologists and CheXNet on 10,000 bootstrap samples, sampled with replacement from the test set. The 2.5th and 97.5th percentiles of the F1 scoreswere considered as the 95% bootstrap CI. It was found that CheXNet achieves an F1 score of 0.435 (95% CI 0.387, 0.481), higher than the radiologist average of 0.387 (95% CI 0.330, 0.442). Table 2 summarizes the performance of each radiologist and of CheXNet. To determine whether CheXNet's performance is statistically significantly higher than radiologist performance, the difference between the average F1 score of CheXNet and the average F1 score of the radiologists was also calculated on the same samples.

	F1 Score (95% CLI)
Radiologist 1	0.383 (0.309, 0.453)
Radiologist 2	0.356 (0.282, 0.428)
Radiologist 3	0.365 (0.291, 0.435)
Radiologist 4	0.442 (0.390, 0.492)
Radiologist Average	0.387 (0.330, 0.442)
CheXNet	0.435 (0.387, 0.481)

Table 2: Radiologists' vs CheXNet F1 Score (95% CLI); where CLIisbootstrap confidence interval and F1 score is a performance metric

The results obtained in terms of efficiency for this approach are stated in Table 3.

Pathology	Wang et al. (2017)	Yao et al. (2017)	CheXNet
Atelectasis	0.716	0.772	0.8094
Cardiomegaly	0.807	0.904	0.9248
Effusion	0.784	0.859	0.8638
Infiltration	0.609	0.695	0.7345
Mass	0.706	0.792	0.8676
Nodule	0.671	0.717	0.7802
Pneumonia	*0.633*	*0.713*	*0.7680*
Pneumothorax	0.806	0.841	0.8887
Consolidation	0.708	0.788	0.7901
Edema	0.835	0.882	0.8878
Emphysema	0.815	0.829	0.9371
Fibrosis	0.769	0.767	0.8047
Pleural Thickening	0.708	0.765	0.8062
Hernia	0.767	0.914	0.9164

Table 3: CheXNet performance in comparison with published results.The first column indicates the pathological disease, first and second column mentions the accuracy of the papers published previously andthe last column states the accuracy of this paper.

The following limitations of the study were identified. First, only frontal radiographs were presented to the radiologists and model during diagnosis, but it has been shown that up to 15% of accurate diagnoses require the lateral view; it was expected that this setup provides a conservative estimate of performance. Second, neither themodel nor the radiologists were permitted to use patient history, which has been shown to decrease radiologist diagnostic performance in interpreting chest radiographs.

C. An Efficient Deep Learning Approach to PneumoniaClassification in Healthcare[18]

A convolutional neural network model trained from scratch was proposed to classify and detect the presence of pneumonia from a collection of chest X-Ray image samples. Several data augmentation methods[19] were employed to artificially increase the size and quality of thedataset as listed in Table 4.

Method	Setting
Rescale	1/255
Rotation Range	40
Width Shift	0.2
Height Shift	0.2
Shear Range	0.2
Zoom Range	0.2
Horizontal Flip	True

Table 4: Setting for image augmentation. The method lists the variousmethods implemented for augmenting the dataset.

The architecture consisted of the convolution, max- pooling, and classification layers combined. The feature extractors comprised conv3×3, 32; conv3×3, 64; conv3×3, 128; conv3×3, 128, max-pooling layer of size 2×2, and a Rectified Linear Activation Unit (RELU) activator between them [20]. The output of the convolution and max-pooling operations were assembled into 2D planes called feature maps [21]. The feature maps of 198×198×32, 97×97×62, 46×64×128, and 21×21×128 were obtained, from the convolution operations and 99×99×32, 48×48×64, 23×23×128, and 10×10×128 sizes of feature maps from the pooling operations, respectively,with an input of image of size 200×200×3. Each plane ofa layer in the network was obtained by combining one ormore planes of previous layers.

The classifier was placed at the end of the convolutional neural network (CNN) model. It was an artificial neural network (ANN) often referred to as a dense layer. The output of the feature extractor (CNN part) was converted into a 1D feature vector for the classifiers. The classification layer contained a flattened layer, a dropout of size 0.5, two dense layers of size 512 and 1, respectively, a RELU between the two dense layers andasigmoid activation function that performed the classification tasks [22].

The results which were recorded for different sizes of datasets are mentioned in Table 5.

Data Size	Training Accuracy	Validation Accuracy
100	0.9375	0.9226
150	0.9422	0.9343
200	0.9531	0.9373
250	0.9513	0.9297
300	0.9566	0.9267
Average	0.94818	0.93012

Table 5: Performance of model on different data sizes of the dataset.The training and validation accuracy are listed.

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.

For pre-trained CNN models including Xception[27], VGG16[28], VGG-19, ResNet-50, DenseNet-121 and DenseNet-169, the performance was evaluated followed by different classifiers including Random Forest, K-

D. Pneumonia Detection Using CNN based Feature Extraction[23]

A pneumonia detection system using the ’Densely Connected Convolutional Neural Network’ (DenseNet- 169)[24] was reported. The original 3-channel images were resized from 1024×1024 into 224×224 pixels to reduce the heavy computation and for faster processing.

The DenseNet169 architecture consisted of oneconvolution and pooling layer at the beginning, 3 transition layers, 4 dense blocks. After these layers, the final layer i.e. the classification layer was present. The first convolutional layer performed 7×7 convolutions withstride 2 followed by a max pooling of 3×3 used with stride 2. Then the network consisted of a dense block followed by 3 sets each of which consisted of a transition layer followed by a dense block. The last layer in the network received the feature-maps of all the preceding layers thusameliorating the flow of gradient throughout the entire network. This required the concatenation of the feature- maps of the preceding layers which could not be done unless all the feature-maps were of the same sizes but as the Convolutional Neural Networks primarily intended towards the down sampling of size of feature-maps, the DenseNet architecture was divided into multiple densely connected dense blocks mentioned above. The layersbetween these dense blocks were referred to as transition layers. Each transition layer in the network consisted of a batch normalization layer and a 1×1 convolutional layer followed by a 2×2 average pooling layer that used a strideof 2. Next to this was the final classification layer which performed global average pooling of 7×7 followed by a final fully connected layer which used ’softmax’ as the activation[25].

The final feature representation obtained were interpretedas a 50176×1-dimension vector which then supplied as input to different classifiers. After feature extraction, different classifiers such as Random Forest[26], Support nearest neighbors, Naive Bayes and Support Vector Machine(SVM). The results are stated in Table 6.

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
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

Table 6: The AUC (Area under Curve); which is a performance metric,is listed which was obtained by various pre-trained models withdifferent classifiers

Statistical results demonstrated the use of ResNet-50 and DenseNets (DenseNet-121 and DenseNet169) as the optimal pre-trained CNN models for the feature extraction stage and use of SVM (with rbf kernel[29]) as the classifier for the classification stage.

The gamma and C parameters of RBF kernel highlyaffected the performance of SVM as proposed by the authors. Intuitively, the gamma parameter was used to define the amount of influence that a single training example should go to in which lesser value implied ’far’ and larger value implied ’close’.

The C parameter compensated the misclassification of training samples. The results of the ResNet-50, DenseNet-121 and DenseNet-169 with the SVM classifier, under different parameters of gamma and C are listed in Table 7.

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
DenseNet-121 + SVM	1.5	1.9e-05	0.7296
DenseNet-121 + SVM	2	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 + SVM	1.5	1.9e-05	0.7791
DenseNet-169 + SVM	2	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

Table 7: Results obtained by parameter tuning, C and gamma are parameters of the rbf kernel of the SVM (Support Vector Machine)

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.
The limitations mentioned by the authors are, first, there was no history of the associated patient considered in theevaluation model proposed by the authors. Second, only frontal chest X-rays were used but it has been proved thatlateral view chest X-rays were also helpful in diagnosis. Third, since the model exercised a lot of convolutional layers, the model needed very high computational power.

E. Deep-learning Framework to Detect lung Abnormality– A Study with Chest X-Ray and Lung CT Scan Image[30]

Two different Deep Learning (DL) techniques were proposed to assess the considered problem: the initial DL method, named a modified AlexNet (MAN)[31], was proposed to classify chest X-Ray images into normal and pneumonia class. In the MAN, the classification wasimplemented using Support Vector Machine (SVM), andthe performance was compared against Softmax. Further, the performance was validated with other pre-trained DLtechniques, such as AlexNet, VGG16, VGG19 and ResNet50. The second DL work implemented a fusion ofhandcrafted and learned features [32] in the MAN to improve classification accuracy during lung cancer assessment. This work employed serial fusion and Principal Component Analysis (PCA)[33] based features selection to enhance the feature vector.
The structure of the modified AlexNet consisted of traditional initial layers (Block 1 to Block 5), a flattened layer to lessen the feature vector (FVx1) and two fully connected layers to select the essential amount of the deeplearning features to train and test the classifier. In this work, every initial block consisted of convolution, ReLU, normalization, and max pooling layers to improve the feature extraction capability. Finally, the existing SoftMax layer was replaced by a Support Vector Machinewith a linear kernel.

The dataset which was used consisted of the Chest X-Raydataset and clinical-grade lung CT images with various nodule sizes [8, 27, 43]. The dataset contained 1,018 slices of 1,010 cases of lung CT. The images were converted to a grayscale version and then resized into 227x 227 x 1 pixels.
The features were then extracted with the Haralick [34] and Hu approach[35]. The Haralick method helped to extract the essential information, which formed afeature-vector with 18 vital features. The Hu moments then helped to achieve 9 related nodule features.
A pre-trained AlexNet was used to analyze the chest X- Ray images, and the performance was compared against VGG16, VGG19 and ResNet50. The experimentaloutcome of AlexNet was poor as compared to VGG16, VGG19 and ResNet50. Hence a modified AlexNet was used. The results of this paper are listed in Table 8.

Database	Features	Approach	Accuracy
Chest X-Ray	learned features	AlexNet	0.8695
		VGG16	0.8465
		VGG19	0.8725
		ResNet50	0.8725
		MAN-SoftMax	0.9525
		MAN- SVM	0.9680
LIDC-IDRI	learned features	AlexNet	0.8327
		VGG16	0.8400
		VGG19	0.8520
		ResNet50	0.8607
		MAN-SVM	0.8647
	handcrafted + learned features	AlexNet	0.8667
		MAN-SVM	0.9227
		MAN-KNN	0.9573
		MAN-RF	0.9590

Table 8: Overall results of the work done by considering learned features and handcrafted features on the Chest X-Ray dataset (which contains over 112,00 images) and the LIDC-IRDI dataset (which contains 224,617 images)

F. A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images[36]

The methodology adopted in this work included the following steps: chest X-ray image preprocessing, data only 12 filters with a small set of new feature maps. The third model was the ResNet18. The architecture was based on the reformulation of network layers as learning residual functions with respect to the layer inputs. The depth of the residual network was eight times deeper than VGG nets, but its complexity was lower. The fourthmodel used was Inception V3. It allowed increased depthand width of the deep learning network but maintaining the computational cost constant at the same time. It worked as a multi-level feature generator by computing 1×1, 3×3 and 5×5 convolutions. The last model used wasGoogLeNet. This model used global average pooling. It also contained inception modules, which can output convolutions of different types using different kernels on the same input; all outputs were then stacked as the final output of that layer.
In order to combine the products of the 5 architectures used, the authors used the ensemble classificationapproach with the usage of the adam optimizer [40]and the cross-entropy loss function.
For evaluation, the dataset from the Guangzhou Women and Children's Medical Center was used. This dataset contained a total of 5232 images, where 1346 images belonged to the Normal category, 3883 images depicted Pneumonia, out of which 2538 images belonged to augmentation, transfer learning using AlexNet,DenseNet121, InceptionV3[37], resNet18 and GoogLeNet[38] neural networks, feature extraction and ensemble classification[39].
The data augmentation involved resizing the images to 224× 224×3, then applying Random Horizontal Flip (to deal with the pneumonia symptoms on either side of the chest), Random Resized Crop (to get deeper relation among pixels), and finally augmenting images with a varying intensity of images.

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This work employed five pre-trained models which weretrained on the ImageNet dataset and then used them for the Chest X-Ray dataset. The first model used was the AlexNet model. This network used a Rectified Linear Unit (ReLU) to add non-linearity. It used dropout layers instead of regularization to deal with overfitting. Overlapping pooling was also used to reduce the size of the network. The second model used was the DenseNet121. The DenseNet architecture required fewer parameters than a traditional CNN. DenseNet layers used Bacterial Pneumonia and 1345 images depicted Virus
Pneumonia. The results obtained experimentally are stated in Table 9.

Model	Epoch	AUC	Accuracy
AlexNet	200	0.9783	0.9286
DenseNet121	100	0.9878	0.9262
InceptionV3	100	0.9733	0.9201
GoogLeNet	50	0.9829	0.9312
ResNet18	200	0.9936	0.9423
Ensemble model	-	0.9934	0.9639

Table 9: Comparative results for each model on the test set where theAUC and accuracy is measured. Both AUC and Accuracy are metricsfor performace

The performance could be further improved by increasingthe dataset size, using a data augmentation approach, andby using hand-crafted features as proposed by the authors.

G. Pneumonia Classification using Deep Learning in Healthcare[41]:

A CNN algorithm was used along with different data augmentation techniques for improving the classificationaccuracies which had been discussed to increase the performance which would help in improving the validation and training accuracies and characterization ofexactness of the CNN model and accomplished various results.

The dataset used in this paper was the Chest X-Raydataset. The data augmentation techniques used for this paper are mentioned in Table 10.

Operations	Values
Zoom Range	0.2
Rotation	45
Width-shift	0.2
Height-shift	0.2
Flip-horizontal	True
Flip-vertical	True
Re-scale	1/255
Range-shear	0.2

Table 10: Setting for Image Augmentation. The method lists the various methods implemented for augmenting the dataset.

The convolutional neural network in this paper included the following: The layers for feature extractors were of the specifications conv3×3, 32, conv3×3, 32, conv3×3, 64, conv3×3, 128, conv3×3, 128, conv3×3, 128 and RELU activators in between them. Then, the output obtained from the convolutional layers and max pooling layers were being converted into 2D planes which were called as feature maps for the convolution operations andpooling operations. The size of the input image was 200 × 200 × 3. Further, the Sigmoid Activation Function wasused as the classifier.

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The results obtained in this paper are stated in Table 11.

Size	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
100	0.9432	0.9227	0.1423	0.1990
150	0.9512	0.9333	0.1324	0.2010
200	0.9488	0.9236	0.1336	0.1992
250	0.9325	0.9111	0.1411	0.1889
300	0.9412	0.9233	0.1317	0.1909
Avg.	0.9436	0.9289	0.1378	0.1988

Table 11: Performances of Accuracy and Loss on different size of theChest X-Ray dataset

H. Pneumonia Detection Using Convolutional Neural Network[42]

Several models were reported to determine the best possible model in detecting pneumonia with the most accurate results. This study had trained five different models of CNN, namely AlexNet, LeNet, GoogleNet, ResNet and VGGNet using 1024 x 1024 resolution of 26,684 dataset images. The study utilized the Radiological Society of North America (RSNA) dataset through the Kaggle RSNA Pneumonia Detection Challenge which contained 26,684 image data. The models were then set for proper setting to the needed task.The Fine-Tuning method could extract new featuresfrompneumonia and could reduce the original dimensionality to prevent any waste of computing resources. Every single block used in the architecture was followed by wholly inter-connected layers and a softmax activation. Feature extraction was composed of an input image, convolution, max pooling while classification involved fully interconnected layers and output.

The results obtained by the pre-trained models in this paper are listed in Table 12.

Model	Criteria	Normal	Pneumonia
AlexNet	Image Size	224 x 224 x 3	
	Precision	0.68	1.00
	Recall	1.00	0.84
	F1 Score	0.81	0.91
GoogleNet	Image Size	224 x 224 x 3	
	Precision	0.99	1.00
	Recall	1.00	0.99
	F1 Score	0.99	0.98
LeNet	Image Size	224 x 224 x 3	
	Precision	0.91	0.99
	Recall	0.97	0.97
	F1 Score	0.96	0.98
ResNet	Image Size	224 x 224 x 3	
	Precision	0.85	0.89
	Recall	0.90	0.89
	F1 Score	0.83	0.78
VGGNet	Image Size	224 x 224 x 3	
	Precision	0.94	0.97
	Recall	0.92	0.98
	F1 Score	0.93	0.98

Table 12: Review of Models used in the (by Sammy V. Militante, Brandon G. Sibbaluca, in the year 2020) study

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I. Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using ChestX-ray[43]

In this paper, four different pre-trained deep Convolutional Neural Network (CNN): AlexNet, ResNet18, DenseNet201 and SqueezeNet[44] 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, andnormal, bacterial, and viral pneumonia.

The AlexNet network was made up of five convolutionallayers (CLs) with 145 three pooling layers, two fully connected layers (FLCs), and a Softmax layer. The dimension of 146 input images for the AlexNet was 227× 227 × 3 and the first CL converted input image with 96147 kernels sized at 11×11×3 with a stride of four pixels.

ResNet18 was used by the authors for detection. The image size used was 224 x 224 pixels. Typically, deep neural network layers learn low- or high-level features during training, while ResNet learns residuals instead of features. DenseNet201 has also been used for pneumonia detection. The input image size used was 224 x 224. Eachlayer in DenseNet had direct access to the original input image and gradients from the loss function. Therefore, thecomputational cost was reduced significantly. The SqueezeNet was trained with more than 1 million imagesand it had 50 times fewer parameters than AlexNet. The foundation of this network was a fire module, whichconsisted of the squeeze layer and 174 expand layer. Thesqueeze layer had only 1 × 1 filters, which were fed to an expanded layer that had 175 convolution filters.

The training parameters of the above-mentioned models are listed in Table 13, where momentum is denoted by ρ,mini-batch size is denoted by κ and learning rate is denoted by α.

CNN Model	Optimization	ρ	K	
AlexNet	Gradient Descent	0.9	16	0.0003
ResNet18				
DenseNet201				
SqueezeNet				

Table 13: Training parameters for different pre-trained models, whereρ is the momentum, κ is the mini-batch size and α is the learning rate

The input image was applied to different networks, and the output activations of the first convolution layer were examined. The activation map could take a different rangeof values and was therefore normalized between 0 and 1.The strongest activation channels were observed and compared with the original image. It was noticed that thischannel activates on edges. Three different forms of performance evaluations and comparisons were carried out in this study: two classes (normal and pneumonia), three classes (normal, bacterial pneumonia, and viral pneumonia), and two classes (bacterial pneumonia and viral pneumonia) classification using four different deep learning algorithms through transfer learning.

The comparative performances of the datasets on the different pre-trained models is mentioned in Table 14.

Task	Models	Accuracy	AUC
Normal and Pneumonia	AlexNet	0.945	0.942
	ResNet18	0.964	0.963
	DenseNet201	0.98	0.98
	SqueezeNet	0.961	0.96
Normal, Bacterial Pneumonia and Viral Pneumonia	AlexNet	0.884	0.911
	ResNet18	0.877	0.91
	DenseNet201	0.933	0.95
	SqueezeNet	0.861	0.895
Bacterial and Viral Pneumonia	AlexNet	0.90	0.89
	ResNet18	0.87	0.87
	DenseNet201	0.95	0.952
	SqueezeNet	0.83	0.83

Table 14: Performance metrics (accuracy and AUC) for different models on 3 sets of different classification tasks.

J. Deep Learning for Automatic Pneumonia Detection[45]:

The solution of the Radiological Society of North America (RSNA) Pneumonia Detection Challenge hostedon Kaggle platform is presented by the authors. This approach used a single-shot detector (SSD[46]), squeeze-and-excitation deep convolutional neural networks (CNNs)[47], augmentations and multi-task learning[48]. The algorithm automatically located lung opacities on chest radiographs and demonstrated one of the best performances in the challenge. The labelled dataset of thechest X-ray images, and patients' metadata was publicly provided for the challenge by the US National Institutes of Health Clinical center. This database comprised frontal-view X-ray images from 26684 unique patients. The model proposed in this paper was based on the RetinaNet[49] implementation on Pytorch[50] with the following modifications: i) Images with empty boxes were added to the model and contributed to the losscalculation/optimization. ii) The extra output for small anchors was added to the CNN to handle smaller boxes.

iii) An extra output for global image classification with one of the classes was added to the model. This output was not used directly to classify the images, however, making the model predict the other related function improved the result. iv) dropout was also added to the global classification output to reduce overfitting.

For the learning rate scheduler, ReduceLROnPlateau[51] with the patience of 4 and learning rate decrease facto rof 0.2 was used. Then a few different encoder architectures were tested: Xception, NASNet-A-Mobile[52], ResNet- 34, -50, -101, SE-ResNext-50, -101, and DualPathNet92[53], Inception-ResNet-v2 and PNASNet- 5-Large. The SE-ResNext architectures demonstrated optimal performance on this dataset. The dataaugmentations included resizing, mild rotations, shift,scale, shear, horizontal flip and a limited amount of gamma augmentations.

Table 15 lists the results obtained in this paper.

Augmentations	Best mAP
No augmentations	0.246127
No augmentations	0.246127
Light augmentations	0.254429
Heavy augmentations	0.250230
Heavy augmentations, custom rotations	0.255617
Heavy augmentations, no rotations	0.260971

Table 15: Pneumonia detection mAP (mean average precision results)achieved with various augmentations sets on validation

There was a difference in the train and test labelling process of the dataset provided. The train set was labelledby a single expert, while the test set was labelled bythree independent radiologists. The optimal threshold for the non-maximum suppression (NMS) algorithm[54] was also different for the train and test sets due to different labelling processes.

The results of detection models can change significantly between epochs and depend largely on thresholds. Therefore, it was beneficial to ensemble models from different checkpoints to achieve a more stable and reliablesolution.

III. CONCLUSION

Here, the prominent work done in the field of applying CNNs to pneumonia detection is summarized and compared in order to understand the primary approach towards the pneumonia detection problem. Some approaches use transfer learning while the others build theconvolutional neural network model from scratch. It is found that using transfer learning requires a lot of computational power. The same accuracy can be achievedby both the methods provided sufficient parameters and dataset size is considered.

We can also conclude that the ReLU activation function performs the best in the neural network architecture. Several classifiers can be used but the Support Vector Machine (SVM) and the Softmax classifier perform the best in medical diagnosis.

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IV. TABULAR SUMMARY OF STUDIES COMPARED

Paper	Dataset	Input Image size	Pre-processing	Model(s)Used	Classifier(s) used	Parameters	Validation method	Distinctive features	Results
Rafael T. Sousa et al., 2013	156 8-bit grayscale images obtaine d with a digital camera	1024 × 768	None	PneumoCAD	K-Nearest Neighbors, Support Vector Machines, Naïve Bayes	k- parameter= 9, standard Gaussian kernel parameters were used, C = 1, σ =1	Cross-validation	It used a Sequential Forward Elimination (SFE) test	0.77 accuracy
Pranav Rajpurkaret al., 2017	ChestX-ray14	224 x 224	Data Augmentation	CheXNet (which is a 121-layer CNN) specially designed for pneumonia detection.			Cross-validation	They used the bootstrapto construct 95% bootstrapCI to test the efficiency	0.77 accuracy
Okeke Stephen et al., 2019	Chest X-Ray dataset	200 x 200 x 3	Data Augmentation	A CNN of shape: conv3×3, 32; conv3×3, 64; conv3×3, 128; conv3×3, 128, max- pooling layerof size 2×2 with a ReLU activator.	A flattened layer, a dropout of size 0.5, two dense layersof size 512 and 1	ReLU and sigmoid activation	Cross-validation	The model was built from scratch	0.93 accuracy
Dimpy Varshni et al., 2019	6 pre-trained models with 4 classifiers	224 x 224	None	Xception, VGG16, VGG-19, ResNet-50, DenseNet- 121 and DenseNet-169	Support Vector Machines (rbf kernel)	Different values of gamma andC	External dataset of ImageNet used	Use transfer learning and used various models and parameters	0.80 AUC
Abhir Bhandaryet al., 2019	Chest X-Ray dataset and clinical-grade lung CTimages	227 x 227 x 1	Converting into grayscale	Modified AlexNet for training, and AlexNet, VGG-16 andVGG-19 for extracting features	Support Vector Machines (linear kernel)	ReLU activation function	External dataset of clinical grade lungCT imagesused	This work employs serial fusionand PCA based features selection to enhance the feature vector whichare extractedby Haralick and Hu method.	0.96 accuracy

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Vikash Chouhanet al., 2020	Chest X-Ray and ImageNet dataset	224 x 224 x 3	Data Augmentation	Transfer learning using AlexNet, DenseNet121 InceptionV3, ResNet18 and GoogLeNet	Ensemble classification	Adam optimizer	External dataset of ImageNet dataset used	5 pre-trained models are used for feature extraction	0.96 accuracy
Garima Verma etal., 2020	Chest X-Ray dataset	200 x 200 x 3	Heavy Data Augmentation	A CNN of shape: conv3×3, 32, conv3×3, 32, conv3×3, 64, conv3×3, 128, conv3×3,128, conv3×3, 128 with a ReLU activator	Sigmoid activation function as Classifier		Cross-Validation	This work mainly focuses on different data augmentation techniquesto improve accuracy	0.94 accuracy
Sammy V. Militante et al., 2020	RSNA dataset	224 x 224 x 3	None	Transfer learning using AlexNet, LeNet, GoogleNet, ResNet and VGGNet	Every single block used in the architecture is followedby wholly inter-connected layers and a softmax activation.		External datasets of each pre-trained model	The Fine-Tuning method is used which can extract new featuresand can reduce the original dimensions	F1, Precision and Recall are measured for all models*
Tawsifur Rahmanet al., 2020	5257 images of ChestX-Rays	227 x 227 x 3	None	Transfer learning using AlexNet, ResNet18, DenseNet201 and SqueezeNet	Standard AlexNet, ResNet18, DenseNet201 and SqeeuzeNet classifiersand parameters		Cross-validation	The strongest activation channels were observed and were compared with the originalimage.	DenseNet-201 showedbest results
Tatiana Gabrusevaet al., 2020	RSNA	224 x 224 x 3	Heavy Data Augmentation	Model was based on RetinaNet	Encoder architectures like Xception, NASNet-A-Mobile, ResNet-34, -50, -101, SE-ResNext-50, -101, and DualPathNet 92, Inception-ResNet-v2 and PNASNet-5-Large were studied	For learning rate scheduler, the authorsused ReduceLR OnPlateau with the patience of4 and learning rate decrease factor of 0.2	Cross-validation	This approach used SSD, squeeze- and-excitation, CNNs, and multi-task learning	SE-ResNet's perform the best and heavydata handling gives 0.26 mAP

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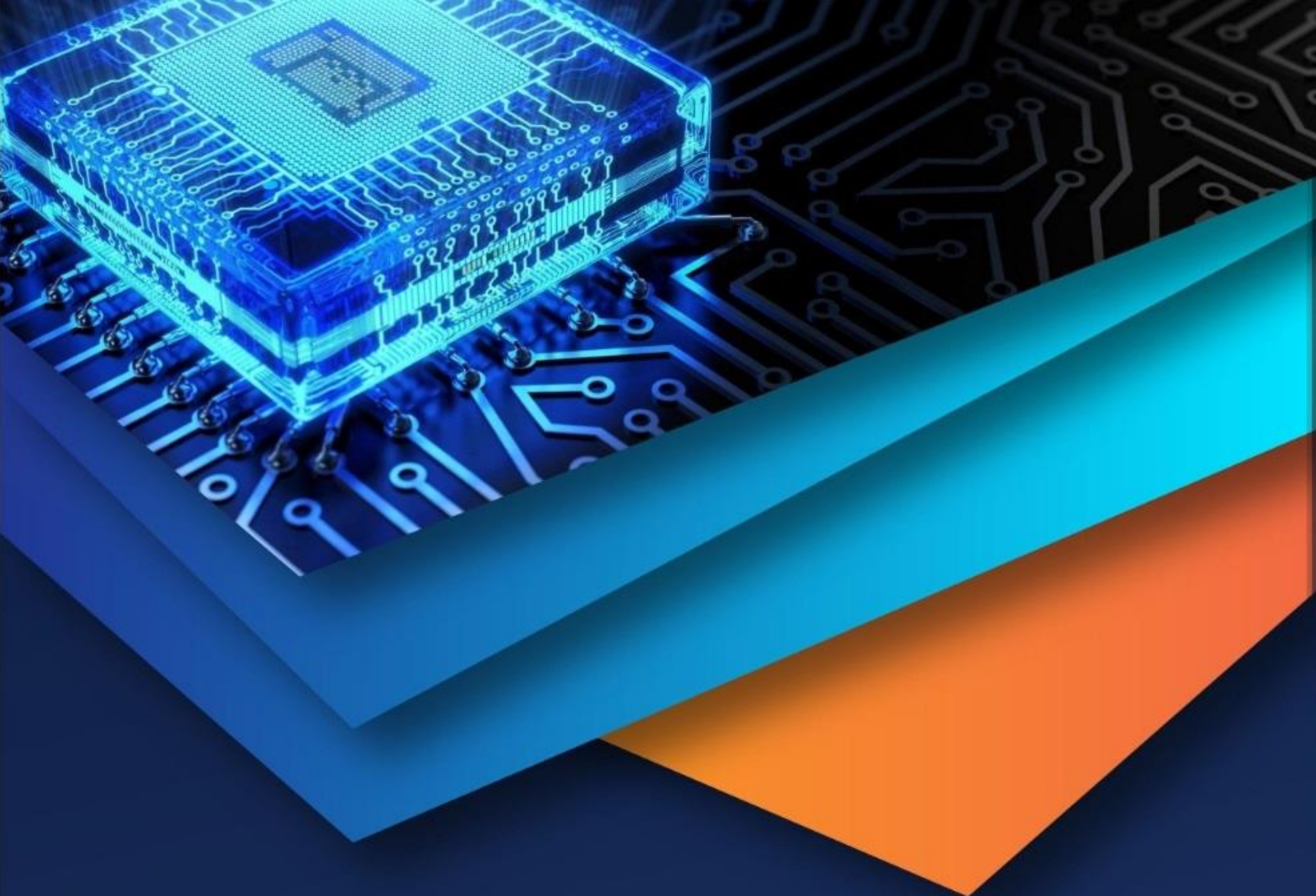

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