Using X-ray Image Processing Techniques to Improve Pneumonia Diagnosis based on Machine Learning Algorithms

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***Abstract*—the diagnosis of chest disease depends in most cases on the complex grouping of clinical data and images. According to this complexity, the debate is increased between researchers and doctors about the efficient and accurate method for chest disease prediction. The purpose of this research is to enhance the first handling of the patient data to get a prior diagnosis of the disease. The main problem in such diagnosis is the quality and quantity of the images.In this paper such problem is solved by utilizing some methods of preprocessing such as augmentation and segmentation. In addition are experimenting different machine learning techniques for feature selection and classification.The experiments have been conducted on three different data sets. As the results showed, the recognition accuracy using SVM algorithm in the classification stage, the VGG16 model for feature extraction, and LDA for dimension reduction is 67% without using image pre-processing techniques, by applying pre-processing the accuracy increased to 89%. Using a two-layer NN the recognition accuracy is 69.3%. For the same model, the accuracy has increased with the addition of image pre-processing techniques to reach 96%.**

Keywords—Chest disease, machine learning, VGGNet-16, Deep Learning, LDA, PCA, KNN, Random forest

I. INTRODUCTION

The first diagnosis (initial screening) of a disease takes a lot of physician time and resources to reach the right diagnosis [3]. Physicians depend on x-ray images in their diagnosis; however, reading them by normal sight takes time, experience and effort. Our motivation is to enhance the initial diagnoses of a patient to help doctors to get a good insight of their patients without consuming a lot of time. Machine learning algorithms automate this process and relive the burden on physicians to experience reading such x-ray images. However, to develop a machine learning model for a good diagnosis requires a number of previously diagnosed x-ray images to create an accurate diagnostic model. Surprising advancement has been made in picture acknowledgment, essentially due to the accessibility of big scale clarified datasets (for example ImageNet) and the restoration of CNN [1]. CNN's empowers information-driven learning, exceptionally delegate picture highlights from sufficient information. There are three significant systems that effectively utilize CNNs to medical picture grouping: preparing the CNN with no preparation, utilizing off-the-rack pre-prepared CNN highlights, and leading unaided CNN pre-prepared with managed adjustments. Another successful strategy may be a move to tweaking CNN models (directed) pre-prepared from normal picture dataset to therapeutic picture errands (even though space move between two restorative picture datasets is likewise conceivable) [2]. Our motivation is to form the primary diagnosis of the patient to assist doctors to possess a decent insight into their patients without delay. On the other hand, to develop machine learning models a good scaled dataset with the quality of the images need to be present. This experiment solves those two problems using two different techniques which are augmentation and segmentation. Augmentation [4] is to expand the number of images and segmentation [9] is to increase the accuracy of the algorithms.
To test such hypothesis, we are experimented different classification algorithms to classify the chest images between deep learning algorithms and machine learning algorithms. In the first phase, the feature extraction phase, VGG16 algorithm was used. In the second phase, the classification phase, different algorithms are tested a support vector machines (SVM), K-Nearest Neighbor (KNN) and Random Forest. Feature selection is done using linear discriminate analysis (LDA) to reduce dimensions compared with Principal Component Analysis (PCA).

The rest of this paper is organized as follows: Section 2 explains the related work. The proposed methodology is illustrated in Section 3. Section 4 demonstrates experimental results and discussion. Finally, the conclusion is offered in Section 5.

II. RELATEDWORK

The recommendation systems and classification of medical data for perfect analysis of clinical disease may be a very changeling area of research in real-life. During this section, a brief discussion on some recent developments in image preprocessing, and medical data classification are presented.

Shorten et.al. in [4] presented a survey that discusses the existing methods for Data Augmentation, promising developments, and meta-level decisions for implementing Data Augmentation. Readers will understand how Data Augmentation can improve the performance of their models and expand limited datasets to take advantage of the capabilities of big data.

Mikołajczyk et.al. in [5] introduced multiple methods of data augmentation in the task of image classification. Starting from classical image transformations like rotating, cropping, zooming, histogram based methods and finishing at Style Transfer and Generative Adversarial Networks along with the representative examples. Also, presented a method of data augmentation based on image style transfer. The method allows generating the new images of high perceptual quality that combine the content of a base image with the appearance of another one. The newly created images can be used to pre-train the given neural network in order to improve the training process efficiency. Proposed method is validated on the three medical case studies: skin melanomas diagnosis, histopathological images and breast magnetic resonance imaging (MRI) scans analysis, utilizing the image classification in order to provide a diagnose. In such kind of problems, the data deficiency is one of the most relevant issues. Finally, the advantages and disadvantages of the methods being analyzed are discussed.

Wang er.al. in [6] provided a comparison between multiple solutions to the problem of data augmentation in image classification. Previous work has demonstrated the effectiveness of data augmentation through simple techniques, such as cropping, rotating, and flipping input images. They artificially compared each data augmentation technique in turn. One of the more successful data augmentations strategies is the traditional transformations mentioned above.

Makris et.al. [7] presented a comparison of recent Deep Convolutional Neural Network (DCNN) architectures for automatic binary classification of pneumonia images based fined tuned versions of (VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, Resnet50, MobileNet_V2 and Xception). The proposed work has been tested using chest X-Ray and CT dataset which contains 5856 images (4273 pneumonia and 1583 normal). They concluded that fine-tuned version of Resnet50, MobileNet_V2 and Inception_Resnet_V2 showed highly satisfactory performance with rate of increase in training and validation accuracy (more than 96% of accuracy). Unlike CNN, Xception, VGG16, VGG19, Inception_V3 and DenseNet201 displayed low performance (more than 84% accuracy).

Wanget.al.[8]used one amongst the pre-trained models, VGG-16 with Deep Convolutional Neural Network to classify images. The author worked on a picture classification problem with the restriction of getting a tiny low number of coaching samples per category. The information archive consists of images of dogs and cats and therefore the objective of the task is to make a heuristic and robust model that may categorize images into bins of cats and dogs separately.

Dar in [9], presented some segmentation methods with an explanation of the necessary points that need to be taken care of while doing segmentation. Also, they reviewed some papers and analyzed which method is best for image segmentation.

Buslaev et.al.[10], introduced rivalry winning profound neural systems with pre-prepared loads that were utilized for picture-based gender acknowledgment and age estimation. Move learning was investigated utilizing both VGG19 and VGG Face pre-prepared models by testing the impacts of changes in several structure plans and preparing parameters to boost expectation exactness. Preparing strategies, for instance, input institutionalization, information increase, and mark conveyance age encoding are considered. At last, a progression of profound CNNs was tried that originally characterized subjects by sexual orientation and afterward utilized separate male and feminine age models to anticipate age. A sexual orientation acknowledgment precision of 98.7% and a MAE of 4.1 years were accomplished. With appropriate preparation systems, great outcomes might be acquired by re-entrusting existing convolutional channels towards one more reason.

This work introduces two main ways to increase the accuracy of the classification process. Augmentation, which is an image processing technique to increase the number of the data set to overtake the problem of low number of images in the data set. The second technique is segmentation which is used to improve the quality of the images.

III. PROPOSED METHODOLOGY

The new proposed model is developed and implemented to form a diagnostic system. A number of different algorithms are used to classify patients in order to obtain the accuracy of the disease diagnosis process and help the doctors to provide a number of recommendations to patients about the pattern healthy protocols that help them without the need to visit a doctor. The overall procedure flow of the proposed methodology can be implemented via the following steps:
The primary one is image preprocessing which has also two steps: image augmentation and segmentation. First, augmentation is a technique to extend the dataset size by creating a modified version of the image. According to our experiment some augmentation methods only used to augment the x-ray image like zoom and some other ways. Some augmentation methods are not suitable for x-ray images as the

output is not reasonable when capturing the patient x-ray, like 90^o flipping. Second, area segmentation of the images utilizes a local threshold to segment images to many parts according to the difference in pixel values. Segmentation is good in this experiment because it is simple in its calculationand fast. Specifically, when applied on x-ray images where the region contrast is high, thus this method performance is very high. On the other hand, when using edge detection segmentation, instance segmentation, semantic segmentation, image segmentation based on clustering, or mask R-CNN the classification results is not so good for patient diagnosis classification.

Second step is using different algorithms to make feature extraction, dimension reduction, and classification. VGG16 is employed to form feature extraction. SVM, KNN, random forest, and naive Bayes are accustomed for feature classification. Another model with another point of view is employed which has VGG16 for feature extraction and a pair of layers neural network for classification.

Our contribution during this paper is to form a way to enhance patients' data to give more accurate models for classification. Although machine learning (ML) and deep neural networks (DNN) have a great achievements and perspectives, they have some relevant challenges to tackle. That is the lack of sufficient amount of the training data or uneven class balance within the datasets. One of the ways of dealing with this problem is called data augmentation. Also, the quality of the medical images can mislead the classification process. In this paper we will discuss augmentation methods to increase the data set number of images and segmentation to increase the image quality. Different algorithms are used to make patient classification to decrease the time of patient diagnosis

A.Data Set

Our dataset is extracted from the clinical database within the National Institutes of Physical fitness Clinical Center and consists of ~60% of all informed chest x-rays in the particular hospital. Therefore, this dataset can be considered more associated along with the actual patient human population distributions plus realistic. This particular dataset contains several images from healthy and non-healthy volunteers

TABLEI. DATASETS SPECIFICATION

	Dataset name	Size	size after augmentation	size after segmentation
1	Small dataset	256	2600	2600
2	Big dataset	2600	No augmentation	2600
3	COVID-19	200	2000	2000

As shown in tableI this research has three different data sets the first one is the small one which has 256 images with noise. Thus, image augmentation has been applied to increase the dataset size to enhance the accuracy. Segmentation has been done for extra enhancement of the classification accuracy. Thesecond dataset is the big dataset which contains 2600 image and was used to compare the effect associated with image preprocessing on classification results. The third dataset is the COVID-19 dataset and contains 200 x-ray images.

B. Proposed model

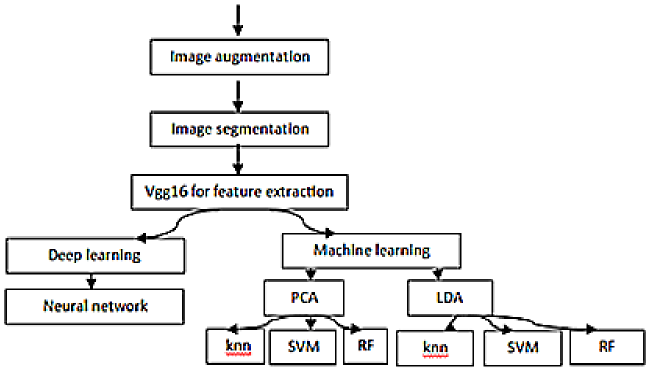

Fig.1.The proposed methods and algorithms compared for higher accuracy

Figure1 shows the flow of the system which contains two steps. The first step is image preprocessing which have two main stages the first is **image augmentation** to increase the number of images in the dataset. The second stage is region segmentation to increase the accuracy of the algorithm by concentrating on the area of interest. After image preprocessing, VGG16 algorithm is applied to extract features. Afterwards, different Deep Learning (DL) and Machine learning (ML) algorithms are experimented to get higher accuracy. DL is applied using two layers neural network. ML algorithms are PCA or LDA for dimension reduction after dimension reduction one of k-NN, SVM and RF algorithms are used for classification.

C. Data preprocessing

In this section, two main methods are used to enhance the accuracy of the algorithm by increasing the number of the images.

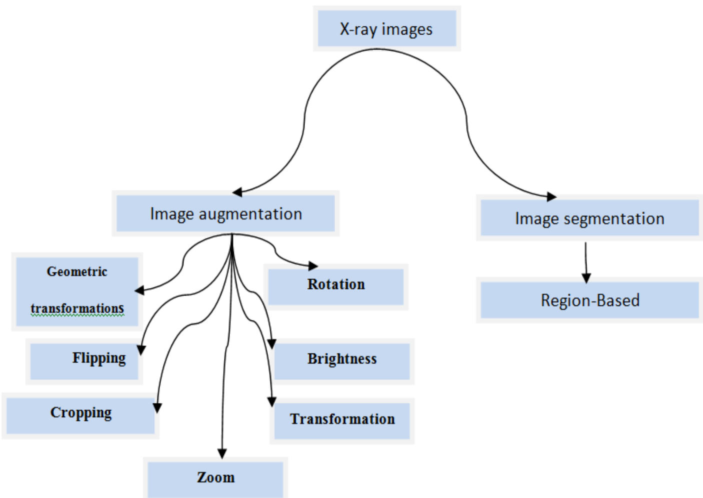

Fig.2. The image processing methods

Figure 2 shows the image preprocessing stage which contains of image augmentation that appears in the right side of the figure that shows the different types of augmentation and image segmentation which appears in the left side of the figure

1) Data augmentation

Image augmentation is used to increase the number of images within the dataset. Geometric transformations mechanisms such as rotation, flipping. Typically, the safety related to a good information augmentation technique relates to its post-transformation good appearance according to content of the image that means the typical kind of images gives a good augmentation results with some ways of augmentation but not good with others. For instance, *rotations* plus *flips* are usually safe upon ImageNet challenges, like cat versus dog, but certainly not safe for digital acknowledgment tasks, like 6 compared to 9[11].

Flipping: Horizontal axis flipping is definitely common than vertical flipping on the axis. This enhancement is one of the particular simplest to implement and even has good prove upon datasets like CIFAR-10 in addition to ImageNet. On datasets including text recognition like MNIST or SVHN, this is usually often not just a label-preserving alteration[12].

Cropping: Cropping images are a practical processing step for image augmentation with mixed height and width dimensions by cropping a central patch of each image [13]. Random cropping may reduce the dimensions. Cropping removes columns/rows of pixels at the sides of images. The images in this work are cropped by 20%.

Rotation: Rotation images are done by rotating it right or left on an axis between 1° and 359°. To protect the augmentation, rotation degree parameter, called *rotation target*, has to be determined based on the image content. Simple rotations just like between 1 and 20 or − 1 to − 20 may be useful on digit recognition tasks like MNIST. Even when the objects in the image are rotated, the information is preserved in the post-transformation[14]. The **rotation target** of this work is 40°.

Translation: is shifting images left, right, up, or down, as a useful transformation to avoid positional bias within the data. As an example, if all the images in a dataset are centered, which is common in face recognition datasets, may require the model to be tested on perfectly centered images likewise. The original image is translated in a certain direction, the remaining space is often crammed with either a relentless value like 0s or 255s, or it may be stuffed with random or Gaussian noise. The post augmented image dimensions are preserved using this padding height shift can be used as a hyper parameter for translation method to go up and down. The width shift also a hyper parameter used when using left and right translation. The **width shift** direction in this work is [-50, 50].

Random Brightness Augmentation: is changing the image brightness by darkening or brightening the image or even both. It is useful for our model to be trained with several image lighting. We can achieve that by assigning the *brightness_range* argument to *ImageDataGenerator()* function that specifies min and max ranges as a float number representing percentage for choosing a brightening amount. Values as 1.0 darken the image, e.g. [0.5 : 1.0], the values larger than 1.0 make the image brighter, e.g. [1.0 : 1.5], and 1.0 does not affect on brightness. The brightness values used in this work is from 0.2 to 1.0 [16].

Zoom Augmentation: is a randomly made zoom of the image. It can zoom in and add new pixel values around the image or an interpolated pixel value respectively. The proportion of the zooming is done using a float percentage. A chosen floating value, f, is assigned, then two post-augmentation zoomed images are generated. One to zoom in by(1+f) and another to zoom out by (1-f).As an example, if f = 0.3 specified, then the image is transformed to two images with size of 70% (zoom in) and 130% (zoom out) of the original image. Actually, using 0.5 zooming changes the image in or out by 50%, however, in x-ray images main details are lost. Hence, in this experiments not more than 0.2 zoom range is used for image augmentation to preserve the intrinsic information[12].

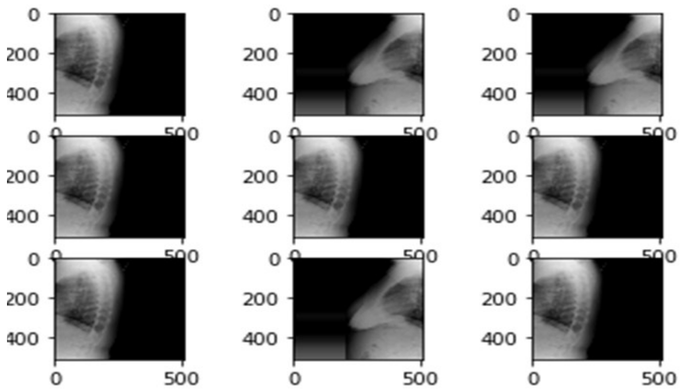

Fig.3. Samples for Image augmentation

Figure3 shows image augmentation using different image augmentation techniques. The augmentation methods utilized in this research are chosen to be suitable in for x-ray diagnosis and often improve the number of images for effective training and testing. Cropping, translation, brightness, zooming, and rotation are all ways for augmentation. Image augmentation is very useful in this case because the data set is very small so the training accuracy and the testing accuracy are very bad so the augmentation is needed to increase the dataset and getting better results.

2) Region-based Segmentation

Data segmentation is done to enhance the accuracy of the machine learning algorithms in the classification step which utilized as follows:

To segment different objects in the image you have be to use their pixel values. A very important point to notice – the pixel values are different for the objects and therefore the image's background if there's a contrast between them. In this case, we can set a threshold value. (As an object or typically the background)The below or over pixel values will become classified accordingly as the resulting threshold. This approach is known as Threshold Segmentation.

The segmentation process consists of the following stages:
• Initial segmentation into N regions based on color and size,
• Merging pixels based on color homogeneity.
• Reduction of shape complexity based on the mean of the gray image.
• Removal of small regions that have weak color criterion.
• Merging very complex regions with weak color criterions' but not small.
• Merging regions with very similar color, weak geometric criterion.
• Creation of simple regions, weak color criterion based on condition
If R_i>image mean then R_i =3, else if R_i>0.5 then R_i=2, else if R_i>0.25 then R_i=1,elseR_i=0

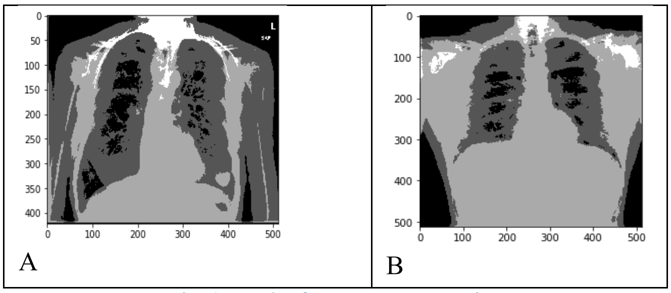

Fig. 4.samples for Image segmentation

In figure4, the image A mentions a nodular patient and image B mentions a normal patient. Within the x-ray, the area associated with nodular is not very clear because of the weak variant of colors within the image so the region based segmentation is definitely used to enhance the image color variety to improve the classification accuracy.

D. Feature extraction using VGG16

VGG16 is employed to extract features of the x-ray images. . The VGG16 model consists of several layers. The first later is a convolutional layer. The input to the first convolutional layer is an image with 224 x 224 sizes. The image is going through a stack of convolutional (conv.) layers where the filters were used as follows: A convolution layers along with the non-linear activation function which is a rectified linear unit (or ReLU). There are 13 convolution layers, 5 max-pooling layers and 3 fully connected layers. So, the total number of layers is 16 of which 13 is for convolution layers and 3 for fully connected layers, thus the name is given as VGG-16. At the output, we have a *softmax* layer [17] [18]. VGG16 is a pre-trained model that applies transfer learning that reducing the time of the training phase.

In this paper, the final layer is removed to extract features from other layers in the .csv file except in one model (that used the VGG16 also for classification). The classification step is done using different machine learning algorithms also with 2-layer deep neural network with SGD optimizer and Batch Normalizations. VGG16 is used for feature extraction also for classification after data processing in another model.

E. A few different algorithms for classification

Machine learning, deep learning algorithms are used after feature extraction using VGG16 in this manner:

1. In the first method VGG16 is used for feature extraction, PCA for dimension reduction after that apply SVM, KNN or RF on the resulted features to examine the accuracy.
2. In the second method VGG16 used for feature extraction also for image classification.
3. In the third method VGG16 used for feature extraction after that two layers neural network (figure5) is utilized for image classification with this structure.

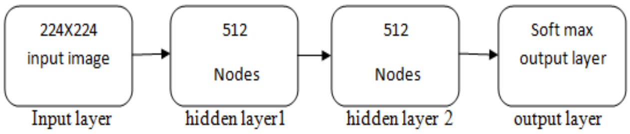

Fig .5. Neural network architecture used for classification

IVRESULTS AND DISCUSSION

The data set of COVID-19 [19] has 200 images which are not efficient in classification using deep learning algorithms (the accuracy is 52%) so it is needed to be augmented [20][21]for two times to examine the accuracy of the algorithm.

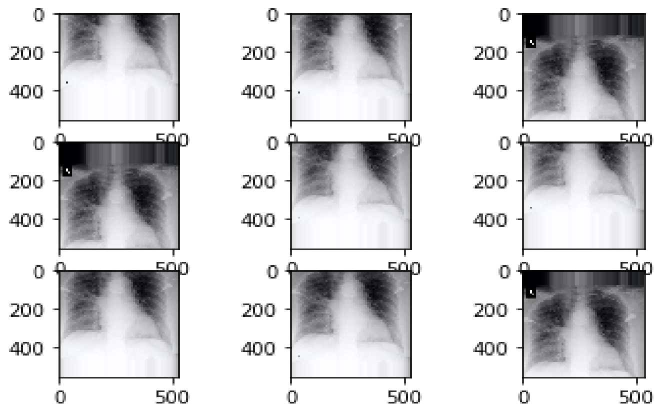
Fig. 6. Corona virus image augmentation

In the first augmentation time (figure 6), the data set become 1000 images and get 62% accuracy. In the second time of augmentation, the data set become 2000 image then Applying image segmentation to get 93% accuracy when using two layer neural network algorithm.

TABLE II. COVID-19 DATA SET BEFORE AND AFTER AUGMENTATION AND APPLYING FOR NEURAL NETWORK

No. of images	200 image	1000 image	2000 image +segmentation
Accuracy	52%	62%	**93%**

TableII shows the number of images in the COVID-19 data set and the accuracy of using a neural network for classification. In the third columns, we increase the number of images to 1000 images which increase the accuracy of the algorithm to 62% after making another augmentation and increase the number of images to 2000 images the accuracy of the algorithm reached 93%.

TABLE III. NEURAL NETWORK ALGORITHM WITH THE ACCURACY OF EACH ALGORITHM FOR THE FIRST DATASET (SMALL DATASET)

Algorithm	Accuracy
Neural network classification without segmentation or augmentation	69.3 %
Neural network classification after augmentation without segmentation	75%
Neural network classification after segmentation without augmentation	70%
Neural network classification after augmentation and segmentation	**96%**
VGG16 classification	49%
VGG16 classification After augmentation without segmentation	59%
VGG16 classification after segmentation without augmentation	53%
VGG16classification after augmentation and segmentation	65%

In tableIII the first line represents the using of VGG16 for feature extraction then uses two layers neural network for classification, the achieved accuracy is 69.3%. The second line represents the using of VGG16 for feature extraction while applying augmentation on the data set to increase the data set images number to become 2600 that is 256 before and achieved 75% accuracy. We achieved 96% when using neural network for classification and augmentation and segmentation as image preprocessing.

TABLEIV. VGG16 ALGORITHM (FEATURE EXTRACTION) WITH DIFFERENT MACHINE LEARNING ALGORITHMS AND ACCURACY OF EACH ALGORITHMFOR THE FIRST DATASET (SMALL DATASET)

	Accuracy	**Precision**	**Recall**	**F1**
VGG16feature extraction +PCA+KNN	67%	.63	.66	.63
VGG16feature extraction +PCA+R F	71%	.73	.72	.70
VGG16feature extraction +PCA+SVM	65%	.63	.62	.61
VGG16feature extraction +LDA +SVM	67%	.66	.62	.64
VGG16feature extraction +LDA+KNN	79%	.75	.76	.75
VGG16feature extraction +PCA+SVM + augmentation	78%	.73	.77	.78
VGG16feature extraction +PCA+ R F + augmentation	81%	.84	.83	.84
VGG16feature extraction +PCA+ KNN + augmentation	70%	.70	.70	.68
VGG16feature extraction +LDA+ KNN+ augmentation	82%	.83	.82	.83
VGG16feature extraction +LDA+ SVM+ augmentation	83%	.84	.83	.84
VGG16 feature extraction +LDA+ SVM+ augmentation + segmentation	**89%**	**.88**	**.89**	**.88**

Table IV shows the VGG16 algorithm used for feature extraction then PCA or LDA are used for dimension reduction then some kind of machine learning algorithms are used like KNN, SVM, or RF on the small data set. VGG16, LDA and KNN give the best result before augmentation with accuracy 79%. After augmentation VGG16 combined with LDA and SVM got accuracy 83%. Using VGG16for feature extraction, LDA for dimension reduction, augmentation, and segmentation has the best accuracy 89%.

TABLE V. NEURAL NETWORK ALGORITHM WITH THE ACCURACY OF EACH ALGORITHM FOT THE SECOND DATASET(THE BIG DATASET)

Algorithm	Accuracy
Neural network classification	90%
Neural network classification after segmentation	**94%**
VGG16 classification	65%
VGG16 classification after segmentation	70%

In table V the big dataset which has 2600 x-ray image without augmentation has been used. The first line represents using VGG16 for feature extraction then uses a two-layer neural network for classification, the accuracy is 90%. The second line represents using VGG16 for feature extraction while applying area segmentation on the data set which achieved 94% accuracy. The third line uses VGG16 for feature extraction also for classification that got 65% accuracy. We got 70% of accuracy after segmentation. It is clear that segmentation increases the accuracy of the model.

TABLE VI. VGG16 ALGORITHM (FEATURE EXTRACTION WITH DIFFERENT MACHINE LEARNING ALGORITHMS AND ACCURACY OF EACH ALGORITHMFOT THE SECOND DATASET(THE BIG DATASET)

	Accuracy	**Precision**	**Recall**	**F1-Measure**
VGG16 feature extraction +PCA+KNN	79%	.78	.77	.78
VGG16 feature extraction +PCA+R F	77%	.75	.73	.74
VGG16 feature extraction+ PCA + SVM	81%	.80	.80	.81
VGG16 feature extraction +LDA	**82%**	.79	.80	.80

+SVM				
VGG16 feature extraction +LDA+KNN	80%	.80	.80	.79

In tableVI we use the 2600 x-ray image (big data set) without augmentation which is the second data set. The first line represents using VGG16 for feature extraction then uses PCA for dimension reduction and KNN for classification, the accuracy is 79%. The second line represents the using of VGG16 for feature extraction and also PCA then random forest for classification which achieved 77% accuracy. SVM combined with LDA AND VGG16 reached the best accuracy 82%

TABLE VII. SHOWS DIFFERENT DATA RUN TIME FOR DIFFERENT ALGORITHMS

Run Time for one image augmentation	17 sec
Run Time for one image segmentation	90 sec
VGG16feature extraction for 256 image	280 sec
VGG16feature extraction for 2600 image	2080 sec
Neural network for 256 image	3140 sec
Neural network for 2600 image	8540 sec

Table VII shows the run time for different algorithms used for classification in this work

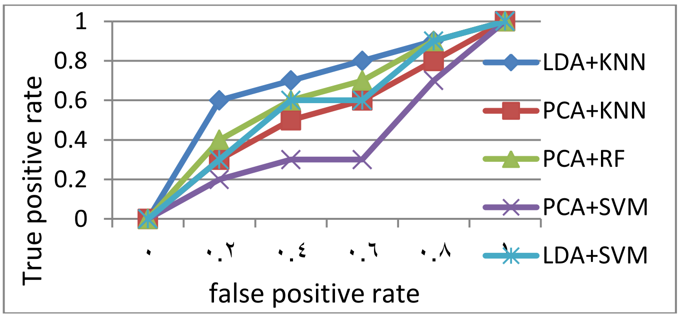

Fig.7. ROC curve for vgg16 and different machine learning algorithms(small dataset before augmentation)

Figure7 shows the ROC curve after applying different dimension reduction algorithms also different machine learning algorithms for classification on the data set of 256 images without augmentation (small dataset).

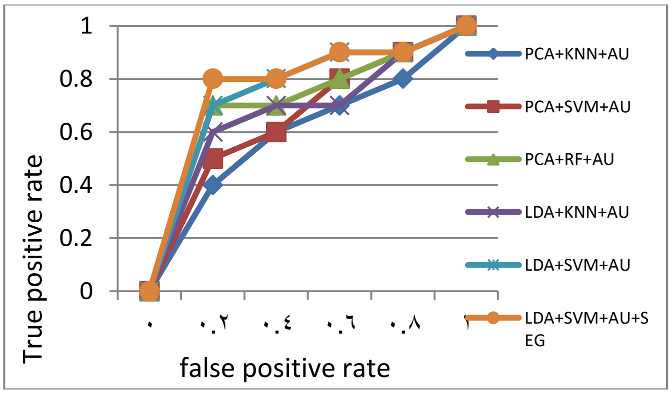

Fig.8. ROC curve for vgg16 and different machine learning algorithms(small dataset after augmentation)

Figure8 shows the ROC curve after applying different dimension reduction algorithms also different machine learning algorithms for classification on the small dataset after augmentation.

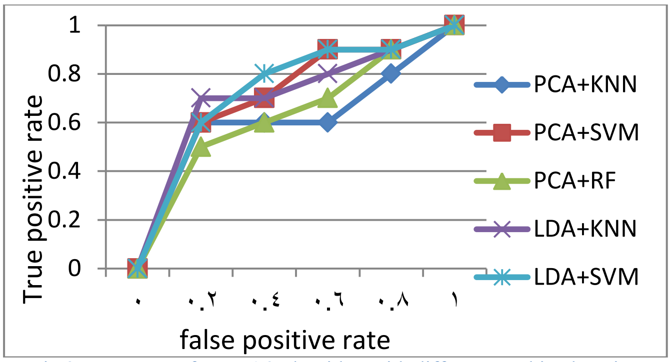

Fig.9. ROC curve for vgg16 algorithm with different machine learning algorithms on 2600 image (big daaset)

Figure9 shows different combinations of VGG16 algorithms used for feature extraction and LDA or PCA for dimension reduction also uses more than one algorithm for classification and shows the ROC curve for each one which applied on 2600 images without augmentation (big dataset).

V. CONCLUSION

In this, we have provided some deep learning, machine learning, and network architectures. We have gone through the various state-of-the-art deep learning architectures. We explained about the pre-trained models, by applying transfer learning and VGG16. Moreover, we discussed some of the hit data set with a large volume of data. From this work, we concluded that the size of data may affect the accuracy and the number of epochs also.

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