Enhancing X-Ray Augmented Images for COVID-19 Disease Diagnosis Using Deep Learning Techniques

Abdelmoty M. Ahmed[*1], Belgacem Bouallegue [2], Amr Mohmed Soliman[3] ,Mahmoud M. Khattab[4]and Hammam M. Abdelaal[5]

[1] Faculty of Computer Science, Nahda University, Beni Suef, Egypt
[2]College of Computer Science, King Khalid University, Abha, Saudi Arabia
[3]Special Education Department, College of Education, King Khalid University, Abha, Saudi Arabia.
[4]Faculty of Information and Communication Technology, International Islamic University Malaysia, Kuala Lumpur, Malaysia
[5]Department of Information Technology, Faculty of Computers and information, Luxor University, Egypt

ABSTRACT
In most cases of diagnosing chest diseases, pneumonia, or even acute respiratory syndrome caused by the coronavirus (COVID-19), we rely on a complex set of data for clinical symptoms or x-rays of the chest or respiratory tract. Due to this complexity and the difficulty of interpreting data and feature extraction for x-rays, the importance of scientific research in this area increases. This importance is due to the urgent need for the effectiveness and accurate prediction and diagnosis of chest diseases and acute respiratory syndrome (COVID-19) in light of the circumstances of this epidemic around the world. Therefore, this paper aims to design and develop a model to deal with a dataset of clinical and diagnostic symptoms of patients with thoracic disease and pneumonia caused by the coronavirus to work on the accurate diagnosis of the disease. In this paper, we implement preprocessing of data and images of the chest and respiratory x-rays to obtain features that help us in the classification and diagnosis process. We conduct several experiments based on a set of algorithms. Firstly, we use the Very Deep Convolutional Networks model (VGG16) to extract and learn the features in addition to classify the data. Secondly, we use the Linear Discriminant Analysis (LDA) for dimensionality reduction. Finally, we use the Support Vector Machine (SVM) and Neural Network for classification; the experimental results indicate that the proposed models have enhanced efficiency compared to other models.

Keywords
COVID-19, Chest disease, pneumonia, Convolutional Neural Network, VGGNet-16, Machine learning, Deep Learning

1. INTRODUCTION

The outbreak of novel coronavirus-caused pneumonia (COVID-19) has attracted worldwide attention, spread across national and international borders leading to systemic complications and death. Since the first suspected case in Wuhan, China of COVID-19 on December 1st, 2019, the world totaled 47,230,786 cases and 1,209,766 deaths at the time of writing these words

The Chinese government declared that the disease was contained a new coronavirus (COVID-19). It spreads rapidly around the world, the danger of this new coronavirus not only in its massive spread but also in the severity of the damage that can cause to the respiratory system.. Therefore, early detection systems and predictive models to the effective planning of countries for the yet to come waves of the diseases are among the top urgent life-saving jobs at the present, many research teams across the world are focusing on.

Saudi Arabia found itself facing the same outbreak, generating considerable spreading among the Saudi population, since the authorities announced on Monday, March 2, 2020, the first case of coronavirus infection for a Saudi citizen coming from Iran via Bahrain.

In this paper, three models were designed to pre-treat the related medical images for the targeted cases, and then classify them in order to predict the pneumonia disease caused by the coronavirus. The three models have effectively used CNN Algorithms by using pre-prepared features, as well as the VGG16, as an incorporating method of pretreatment of the medical images or augmentation. The classification process was performed and also the comparison of the accuracy rate in each of the targeted cases.

A significant modification was made in this research, we pre-prepared the VGG16 to deal with a set of therapeutic images instead of normal image data to help the physicians to identify and diagnose the case as an initial diagnosis to preserving with that the physician's time and utilizing the resources with a proper diagnosis without delay.

This study seeks to create an accurate learning model for predicting one of the characteristics and its effect on the severity of coronavirus (COVID-19) based on the medical images for a targeted sample from Saudi Arabia hospitals. The construction of the models contains relevant and useful

Manuscript received April 5, 2026
Manuscript revised April 20, 2026
https://doi.org/10.22937/IJCSNS.2026.26.4.8

sections for selecting the best characteristics that have an effect on the chest radiation result of a patient's sample and how it affects patients with pneumonia caused through the new coronavirus.

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.

2. Related Work

The recommendation systems and medical data classification for optimal clinical disease analysis may be a challenging area of real-life research. Nonetheless, there have been numerous studies to investigate image preprocessing, medical data classification, and recommendation systems.

Surprising advancement has been made in picture acknowledgment, essentially due to the accessibility of big-scale clarified datasets (for example ImageNet) and also the restoration of CNN. CNN's empower learning information-driven, exceptionally delegate, layered progressive picture highlights from adequate preparing information. Be that because it may, get datasets as extensively clarified as Image Net within the restorative imaging area stays a test. There are at once three significant systems that effectively utilize CNNs to medicinal picture grouping: preparing the CNN with none preparation, utilizing off-the-rack pre-prepared CNN highlights, and leading unaided CNN pre-preparing with managed adjusting. Another successful strategy may be a move to be told, i.e., 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) [1, 2]. Disease first diagnosis takes plenty of doctor time and resources to succeed in the proper diagnosis[3] . Our motivation is to form the primary diagnosis of the patient to assist doctors to possess a decent insight into their patients without delay.

Fari Muhammad Abu-Bakr [4] used the chest radiography dataset to be able to teach COVID-Net to classify COVID patients. It consists of 16,756 chest radiography images with 13,645 patient cases from a couple of open access databases. Furthermore, the author looks into how COVID-Net can make estimations using the ability explanation method to attain much deeper visions into the essential aspects of COVID situations that can enable clinicians to enhance screening. The proposed technique in [5] is utilized to portion the number of chose districts (N) within the first image. This may begin with picking a subjective seed point inside each chose area, set power esteem to appreciate 10% of the (Max-Min) force estimation of the primary image. At that time, the area developing calculation accustomed test, the full pixels neighbor to the seed point whether or not they fulfill the force go motioned above or not.

Linda Wang et al. [6] used one of the pre-trained VGG16 models using a deep convolutional neural network (CNN) to classify the images. The image classification problem with the restriction of getting a tiny low number of coaching samples per category has been tackled. The information archive consists of images for dogs and cats; therefore, the objective of the task is to make a heuristic and robust model that may categorize the images into bins of cats and dogs separately.

Qahtan M. Yaset al. [9] also presented Augmentations, which is an open-source Python library for rapid and versatile image acceleration. Augmentation efficiently applies an elegant kind associated with image transform operations that are optimized for overall performance, and it did so when offering a concise, however powerful image augmentation user interface for various computer perspective tasks, including object category, segmentation, and detection. Typically, they illustrate that Augmentations is quicker than some of the other popular image augmentation resources for all ordinarily applied image transformations, without reducing the range of procedures or the capability to compose them into a lot more complex pre-processing pipeline.

Alexander Buslaev et al. [10] introduced a rivalry-winning profound neural system with pre-prepare loads that are utilized to recognize the image-based gender and to estimate the age. Movement learning is investigated by utilizing VGG19 and VGG Face pre-prepared models through examining 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 is tried that originally characterizes subjects by sexual orientation, and afterward utilizes different models of male and female age to anticipate age. A recognition precision of sexual orientation is accomplished at 98.7% and a MAE of 4.1 years. This paper explains that, with appropriate preparation systems, great outcomes can be acquired by re-entrusting existing convolutional channels towards one more reason.

The main contribution of our work is to pre-prepared the VGG16 to deal with a set of therapeutic images instead of normal image data to help the physicians to identify and diagnose COVID patients.

3. Proposed Methodology

As we mentioned earlier, the primary goal of this research is to create an accurate learning model for predicting one of the characteristics and its effect on the severity of coronavirus (COVID-19) based on the medical data of a sample of patients with pneumonia in a hospital in the Kingdom. Therefore, we contribute to the development of a pre-trained VGG16 model to represent an accurate diagnostic system for patients with the pneumonia of coronavirus (COVID-19). The new proposed model is developed and implemented in three basic stages to form a diagnostic system and can provide recommendations. Several different algorithms are applied to classify patients to obtain the accuracy of the disease diagnosis process and assist the physicians to provide an appropriate recommendation for patients about their health 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:

Firstly, the primary method is the use of image pre-processing, which includes two fundamental steps; image augmentation to extend the set of information, and image segmentation to divide the image into smaller parts. Applying both augmentation and segmentation at the pre-processing phase would necessarily improve the accuracy of the algorithms.

Secondly, several algorithms are used to make feature extraction, dimension reduction, and classification. VGG16 is employed to form feature extraction with Support Vector Machine (SVM), k-nearest neighbor's algorithm (k-NN) random forest, and naive Bayes which are accustomed to making feature classification. Furthermore, another model uses VGG16 to make feature extraction and also to make the classification. Besides, another model with another point of view is employed to contain VGG16 for the process of feature extraction and a pair of neural network layers is used for classification.

Finally, after the patient's classification process, a life-style recommendation system is created. For both care providers and patients, Lifestyle recommendation systems are also proven to enhance the decision-making process and quality. Without leaving your house, the medical advisory system makes it easy to require any medical advice with high precision. This paper utilizes systematic logic to form unique recommendations for patients.

In this section, we formulate the learning model for the prediction of one of the characteristics and their effect on coronavirus (COVID-19) severity. Accordingly, this formulation has been classified into data set, the proposed model, data preprocessing, feature extraction using VGG16, and other algorithms for classification that were described in the following subsections. Also, the schematic diagram of the whole procedure flow for the proposed methodology is shown in Figure 1.

Table 1: Different data sets

dataset No.	Number of images	Number of images after augmentation	Number of images after segmentation
1	256	2600	2600
2	2600	No augmentation	2600
3	200	2000	2000

3.1 Data Set

Our dataset is derived from the picture archiving and communication systems (PACS) clinical database inside the National Institutes of Physical fitness Clinical Center that contains approximately 60% of all up-to-date chest x-rays of the particular hospital. Accordingly, this data set is assumed to be considerably more associated along with the actual patient human population distributions plus realistic. This particular data set contains several images from healthy and non-healthy

This analysis, as shown in Table 1, contains three separate sets of data. 256 images are used in the first data set, which gives the algorithm low accuracy as per Shorten [11], augmentation improves classification performance. Therefore, we perform the image augmentation process to increase the amount of data set and enhance the accuracy. Furthermore, the segmentation process is performed for more enhancement of the classification accuracy, which is achieved afterwards. The second data set contains 2600 images. All classification algorithms are performed again for this dataset to know the associated effect of image preprocessing on a particular data set. In the same manner that the COVID-19 data set is used, we perform a classification of patients which usually contains 200 x-ray images to become the third data set.

3.1.Proposed Model

Figure 1 shows the flow of the system which contains three steps. The first step is to perform the image preprocessing through image augmentation and image segmentation. Initially, image augmentation process aims to increase the particular number of images for the data set while, image segmentation process aims to increase the accuracy of the algorithm. Then, VGG16 is applied to extract the features by applying deep learning using two layers of neural network or other machine learning algorithms such as PCA and LDA for dimension reduction.

Finally, KNN, SVM, and RF algorithms are used to perform classification.

3.2 Data Preprocessing

Image augmentation and image segmentation are used for the image preprocessing methods to enhance the accuracy of the algorithm as shown in Figure 2.

3.2.1 Image augmentation

The quality of the training set has a significant impact on the outcome of deep learning-based clinical image tasks. Collecting adequate samples and classifying them with high quality and balanced distributions is a daunting task. Transforming the original image data set is an essential task that increases the accuracy of the overall performance of the proposed model for medical "x-ray" data. The transformations take into account the different combinations of x-rays and the nature of the medical image. Some of the most popular image augmentation widely used in deep learning. Generally, data augmentation techniques can be divided into two categories; Geometric and Photometric, several of these techniques have been applied in our present paper:

Geometric transformations: Geometric transformation alters the geometry by transferring image pixels to new positions, can also called "Position augmentation" This includes flipping, cropping, rotation, translation, scaling, etc. [11]. [12].

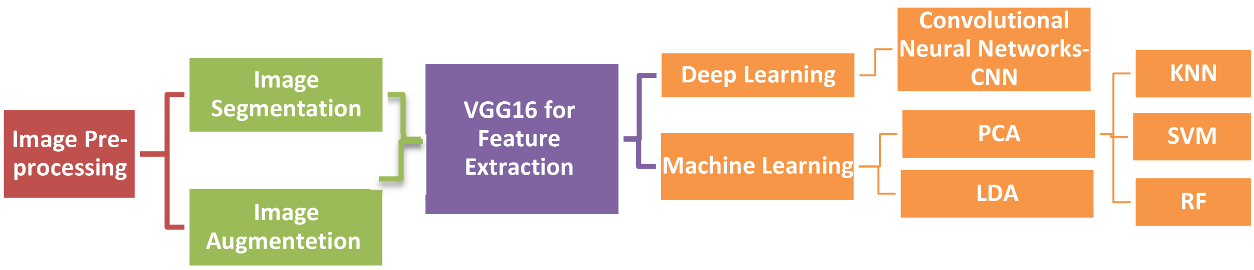

Figure 1: The schematic diagram of the proposed model

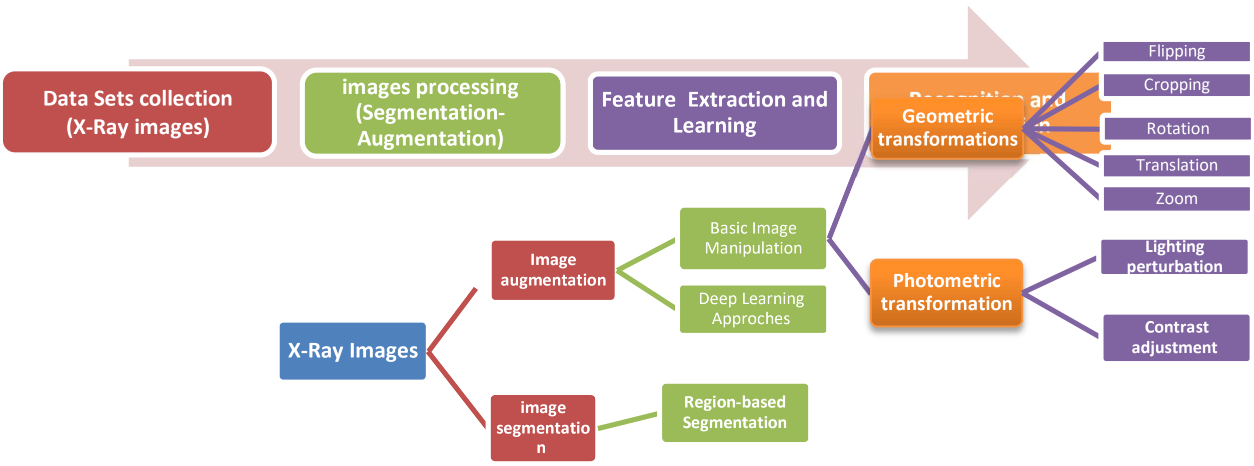

Figure 2: The Image Augmentation and processing Techniques and Implementation in our models

Flipping: flipping operation for the horizontal axis and the vertical axis.

Cropping: Cropping images is a realistic processing stage for image augmentation using both the mixed dimensions of width and height through cropping a centralized area for every image [13] Rotation: Rotation of images are performed by rotating them either left or right along an axis among 1° and 359°. Also, the rotational degree parameter is highly specified to protect the rotational augmentations, or the image is rotated randomly in rotation. [14], in this work the rotation degree 40.

Padding: In padding, the image is padded with a given value on all sides.

Translation: The operation of shifting images to the left, right, up, or down directions is a really helpful transforming to prevent positional bias within the data. For instance, centering all images in a data set is very popular in the methods of face recognition. Therefore, this requires testing of the model on fully centralized images. Often the remaining space is either filled with a fixed value of 0s or 255s or is filled in random or Gaussian noise because the original image is translated during the direction operation. The post augmented image dimensions are preserved using this padding [15], where the width shift direct of this work is [-50,50].

Random Zoom Augmentation: It is randomly made zoom of the image in and new pixel values can be applied around the image or maybe interpolated pixel values respectively. The proportion of the zoom can be chosen either as an array or tuple. The range for the zoom is [1-value, 1+value] if a float is assigned. If you specify 0.3 as an example, the range is [0.7, 1.3], or among 70% (zoom in) and 130% (zoom out).

We can use both dimensions of image to make zooming. It is appearing that 0.5 zooming can zoom image in or out by 50%. This work uses a 0.2 zoom range to make image augmentation [12].

Photometric transformation:

Photometric transformation alters the RGB channels by shifting pixel colors to new values also called "Color augmentation" or color jittering deals with altering the color properties of an image by changing its pixel values in our work we use

Lighting perturbation: changing environment lighting or Random Brightness Augmentation: One way to augment is to change the brightness of the image. The resultant image becomes darker or lighter compared to the original one. We can change the image brightness by darkening images or brightening 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 parameter to Image Data Generator() function which defines a minimum and maximum range to be a float that represents a percentage for choosing the amount of brightness. Values of 1.0 make the image dark, e.g. [0.5, 1.0], the values greater than 1.0 make the image brighter, e.g. [1.0, 1.5], and 1.0 do not effect on brightness [16]. The brightness value that use in this work is from 0.2 to 1.0.

Contrast adjustment: applying color fixations as layers. The contrast is defined as the degree of separation between the darkest and brightest areas of an image, the contrast of the image can also be changed.

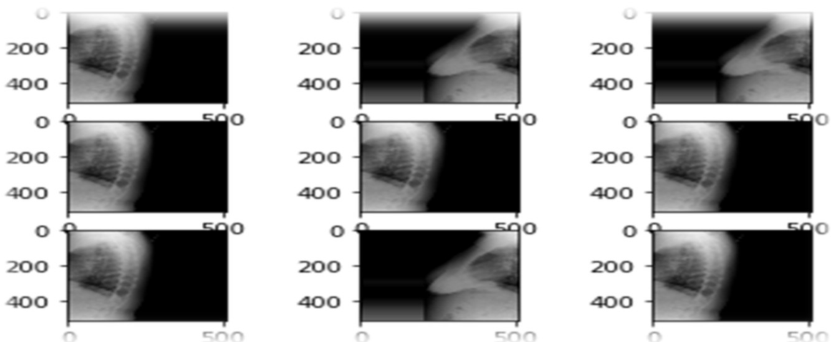

Figure 3: Samples for Image augmentation

Figure 3 shows image augmentation using different image augmentation techniques. Cropping, width shift, brightness, zooming, rotation, and shearing are all used to apply augmentation process to increase the dataset and getting better accuracy.

3.2.2 Region-based Segmentation

Data segmentation to improve the accuracy of the machine learning algorithms have been used as follows: A simple virtue of segmenting various objects may be to use their pixel values. One important thing to note, if there is a pointy contrast between the pixel values of the objects and the background of the image, they are different, in such case, the threshold value can be defined (as an object or typically the background). The below or over pixel values can be classified accordingly as the resulting threshold. This approach is understood as threshold segmentation.

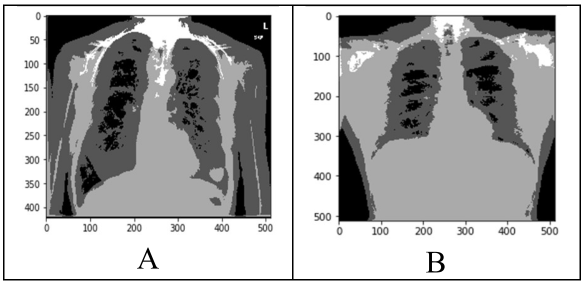

Figure 4: samples for Image segmentation

In Figure 4 the image A mentions nodular patient and image B is 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 particular region-based segmentation is definitely used to enhance the particular image color variety concerning improving classification accuracy.

VGG16 is used for feature extraction and also for classification after data processing. VGG16 is used to employ a pre-trained model to obtain the goal of the particular transfer learning of how to reduce typically the time of training.

3.3 Feature extraction using VGG16

VGG16 is employed to extract the features of the x-ray images altogether the models introduced during this paper. The input for the cov1 layer is a hard and fast of size 224 x 224 RGB image. The image is felt like a stack of convolutional layers, in which filters are used with 3×3 of a very tiny receptive field. This receptive field is the lowest size to obtain the left/right, up/down, and center notion. Looking at one of the settings, it also has 1×1 convolution filter. This can be a linear transformation of input channels that do not have linearity afterwards. The convolution step is the same as 1 pixel. The process of padding the inputs of convolutional layer is considered to preserve the spatial resolution after convolution step. Five layers of max pooling after convolutional (it's not like all the convolutional layers are accompanied by max pooling). Max pooling is performed over a window of 2×2 pixels, with step 2 [17].

It has architecture consists of a special number of convolutional layers. After these layers, there are three fully connected layers, where the final layer is the soft-max layer. Typically, the configuration of the totally connected layers is usually exactly the same altogether networks, where all the hidden layers possess the rectification nonlinearity (ReLU) function. Also, it is definitely noticeable that no a single of the networks (except one) includes Nearby Response Normalization (LRN). This particular normalization does not promote the particular performance assign to the ILSVRC dataset; however, it results within an increase in both memory usage and computation time. VGG 's total style is Visual Geometry Group, where VGG network generally includes VGG16 and VGG19. Through this network, the massive size kernels are exchanged by several numbers of 3x3 filters. As a result, we obtain complex features at a low cost.

The final layer has been removed just to save features extracted from other layers in the .csv file except in one model. Classification is done using different machine learning algorithms as well as two layers of deep neural network. In the exception model, the classification using VGG16 not only uses it for feature extraction as it is in the other models.

3.4 A few different algorithms for classification

Both machine and deep learning algorithms are used on the extracted feature immediately after feature extraction in this particular manner:

1. In the first method, VGG16 and PCA are used for feature extraction and dimension reduction respectively, after that, SVM with kernel RBF or KNN or RF is applied on the resulted features to reach the maximum accuracy.
2. In the second method, VGG16 and LDA are used for feature extraction and dimension reduction respectively, after that, SVM with kernel RBF or KNN or RF is applied on the resulted features to reach the maximum accuracy.
3. In the third method, VGG16 is used for feature extraction and image classification.
4. In the fourth method, VGG16 is used for feature extraction, after that, two layers of neural network are used for image classification.

4. Results and Discussion

The classification process is done using COVID-19 patient's data set. The data set has 200 images which are not efficient in using deep learning algorithms (the accuracy is 52%). Therefore, image augmentation has been applied for two times to get higher accuracy of the algorithm.

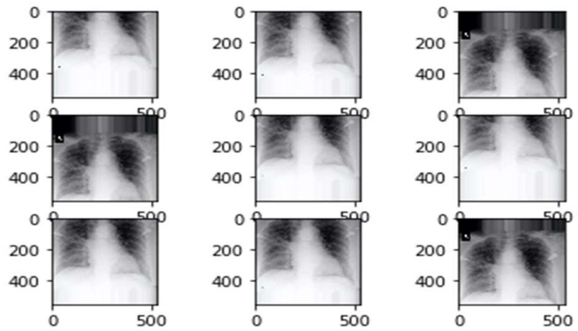

Figure 5: Coronavirus image augmentation

In the first augmentation step, the data set becomes 1000 images and gets 62% accuracy. In the second time of augmentation, the data set becomes 2000 image and the applied image segmentation also achieves 93% accuracy.

Table 2: COVID-19 data set before and after augmentation and applying for neural network

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

Table 2 shows the number of images in the COVID-19 data set and the accuracy of using a neural network for classification. In the third column, we increase the number of images to 1000 images which increase the accuracy of the algorithm to 62%. After making another augmentation and increases the number of images to 2000 images, the accuracy of the algorithm reaches 93%.

Table 3: Neural network algorithm with the accuracy of each algorithm

Algorithm	**Accuracy**
Neural network classification	69.3 %
Neural network classification after augmentation	95%
Neural network classification after augmentation and segmentation	96%
Vgg classification	49%
Vgg classification After augmentation	59%

In table 3, the first line represents the use of VGG16 for feature extraction and then uses two layers of neural network for classification; the achieved accuracy is 69%. While the second line represents the use of VGG16 for feature extraction whereas applying augmentation on the data set to increase the data set images number to become 2600 after being 256 which achieved 95% accuracy. We achieve 96% using neural network for classification and augmentation also segmentation as image preprocessing.

Table 4: Neural network algorithm with the accuracy of each algorithm using another data set.

Algorithm	**Accuracy**
Neural network classification	65%
VGG16 classification	65%

In table 4, we use different data set which has 2600 x-ray image without augmentation. The first line represents the use of VGG16 for feature extraction and then uses two layers of neural network for classification; the achieved accuracy is 65%. The second line represents the use of VGG16 for feature extraction while applying area segmentation on the data set which achieves 68% accuracy. The third line uses VGG16 for feature extraction and also for classification that has 65% accuracy. We get 69% of accuracy after segmentation. It is clear that segmentation increases the accuracy of the model.

In table 5, we use the 2600 x-ray image without augmentation which is the third data set. The first line represents the use of VGG16 for feature extraction and then uses PCA for dimension reduction and KNN for classification, the achieved accuracy is 62%. The second line represents the use of VGG16 for feature extraction and also PACA then random forest for classification which achieves 73% accuracy.

Table 5: VGG16 algorithm with different machine learning algorithms and accuracy of each algorithm

	Accuracy	Precision	Recall	F1-Measure
VGG16 feature exe_pca+knn	62%	.42	.60	.67
VGG16 feature exe_pca+R F	73%	.70	.73	**.44**
VGG16 feature exe_pca+svm	68%	.55	.65	.58
VGG16 feature exe+lda +svm	76%	.80	.62	**.60**
VGG16 feature exe_lda+knn	75%	.71	.70	.75

Table 6: VGG16 algorithm with different machine learning algorithms and accuracy of each algorithm

	Accuracy	Precision	Recall	F1-Measure
VGG16 feature exe_pca+knn	67%	.44	.66	.53
VGG16 feature exe_pca+R F	71%	.73	.72	**.64**
VGG16 feature exe_pca+svm	**78%**	**.53**	**.72**	.61
VGG16 feature exe+lda +svm	67%	.79	.62	**.64**
VGG16 feature exe_lda+knn	**79%**	**.75**	**.76**	.75
VGG16 feature exe_pca+svm+ augmentation	65%	.73	.65	**.58**
VGG16 feature exe_pca+ R F+ augmentation	**83%**	**.84**	**.83**	.84
VGG16 feature exe_pca+ knn+ augmentation	68%	.68	.68	**.68**
VGG16 feature exe_lda+ knn+ augmentation	**82%**	**.83**	**.82**	.83
VGG16 feature exe_lda+ svm+ augmentation	83%	.84	.83	**.84**

Table 6 shows (on the 256 images without augmentation) the VGG16 algorithm which is used for feature extraction and then PCA or LDA are used for dimension reduction, then some kind of machine learning algorithms are used like CNN, SVM, or random forest. VGG16 and LDA give the best accuracy before augmentation with accuracy 79%. After augmentation, VGG16 plus PCA plus random forest have the best accuracy and also VGG16 plus LDA and SVM with accuracy 83%. The use of VGG16 for feature extraction, LDA for dimension reduction, augmentation, and segmentation have the best accuracy.

Table 7: Shows different data run time for different algorithm

Process Model Phase	Time
Run Time for one image augmentation	17 sec
Run Time for one image segmentation	90 sec
VGG16 feature extraction for 256 images	280 sec
VGG16 feature extraction for 2600 image	2080 sec
Neural network for 256 images	3140 sec
Neural network for 2600 images	8540 sec

Figure 6 shows (on the data set of 256 images without augmentation) the 3D linear curve for different combinations of algorithms (number two indicates after augmentation).

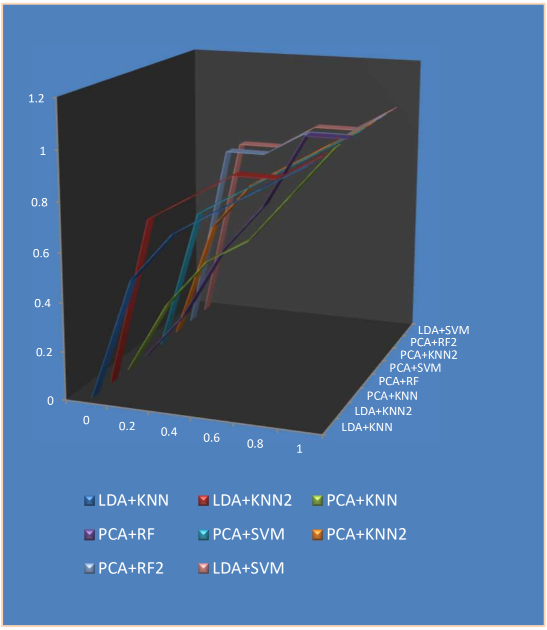

Figure 6: 3D linear curve for VGG16 and different machine learning algorithms

Figure 7 shows different combinations of vgg16 algorithms used for feature extraction and LDA or PCA for dimension reduction uses more than one algorithm for classification and shows the roc curve for each one which applied on 2600 images without augmentation.

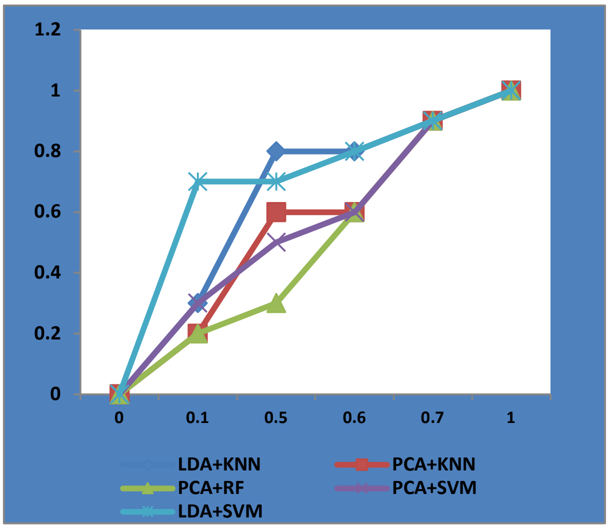

Figure 7: Roc curve for VGG16 algorithm with different machine learning algorithms on 2600 image.

5. CONCLUSION

In this paper, 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. Based on this survey motivation we are going to implement a face recognition system with accurate performance in minimum time.

ACKNOWLEDGMENT

The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University.

CONFLICT OF INTEREST

No potential conflict of interest is reported by the author(s).

FUNDING

The funding is provided by the Deanship of Scientific Research at King Khalid University for funding this work through Large Groups [grant number RGP.2/253/44]

References

[1] SUBHA, R.; ANANDAKUMAR, K.; BHARATHI, "A. Study on cardiovascular disease classification using machine learning approaches". *International Journal of Applied Engineering Research*, 2016, 11.6: 4377-4380.
[2] Shin, H. C., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogues, I., ... & Summers, R. M.. "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning". *IEEE transactions on medical imaging*, (2016), 35(5), 1285-1298.
[3] Hussein, A. S., Omar, W. M., Li, X., & Ati, M. "Efficient chronic disease diagnosis prediction and recommendation system". *In: 2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences,(2012, December)*. (pp. 209-214). IEEE.
[4] Abubakar, F.M., "A study of region-based and contour-based image segmentation". *Signal & Image Processing,* 2012. 3(6): p. 15.
[5] Smith, P. and C. Chen. "Transfer learning with deep CNNs for gender recognition and age estimation". In: *2018 IEEE International Conference on Big Data (Big Data).* IEEE, 2018. p. 2564-2571.
[6] Saranyadevi, S., R. Murugeswari, and S. Bathrinath. "Fuzzy Logic based Recommendation System for Road Accident Data Analysis". *In: 2019 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS)*. IEEE, 2019. p. 1-6.
[7] Tammina, S., "Transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images". *International Journal of Scientific and Research Publications*, 2019. 9(10): p. 143-150.
[8] Wang, L. and A. Wong. "Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images". *Scientific Reports*, 2020, 10.1: 1-12.
[9] Yas, Q.M. and M. Khalaf. "A Trusted MANET Routing Algorithm Based on Fuzzy Logic". In: *International Conference on Applied Computing to Support Industry: Innovation and Technology. Springer, Cham*, 2019. p. 185-200.
[10] Buslaev, A., et al., "Albumentations: fast and flexible image augmentation". *Information*, 2020. 11(2): p. 125.
[11] Shorten, C. and T.M. Khoshgoftaar, "A survey on image data augmentation for deep learning". *Journal of Big Data,* 2019. 6(1): p. 60.
[12] Mikołajczyk, A. and M. Grochowski,"Data augmentation for improving deep learning in image classification problem". In: *2018 international interdisciplinary PhD workshop (IIPhDW)*. IEEE, 2018. p. 117-122.

[13] Takahashi, R., T. Matsubara, and K. Uehara. "Data augmentation using random image cropping and patching for deep cnns". *IEEE Transactions on Circuits and Systems for Video Technology*, 2019, 30.9: 2917-2931.
[14] Bloice, M.D., C. Stocker, and A. Holzinger. Augmentor: an image augmentation library for machine learning. *arXiv preprint arXiv*:1708.04680, 2017.
[15] Perez, L. and J. Wang, "The effectiveness of data augmentation in image classification using deep learning". *arXiv preprint arXiv*:1712.04621, 2017.
[16] Tellez, D., et al., "Quantifying the effects of data augmentation and stain color normalization in convolutional neural networks for computational pathology". *Medical image analysis*, 2019. 58: p. 101544.
[17] Zhang, X., et al., "Accelerating very deep convolutional networks for classification and detection". *IEEE transactions on pattern analysis and machine intelligence*, 2015. 38(10): p. 1943-1955.
[18] Jain, A. and C. Gupta, "Fuzzy logic in recommender systems, in Fuzzy Logic Augmentation of Neural and Optimization Algorithms", *Theoretical Aspects and Real Applications.* 2018, Springer. p. 255-273.