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A Novel Machine Learning Technique for Classification of COVID-19 and Pneumonia

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Abstract- **In order to control the spread of coronavirus and pneumonia, there is an increasing interest in the utilization of machine and deep learning frameworks for identification of the said diseases from x-ray images of patients. The main reason for this increasing interest is because the clinicians indicate that coronavirus and viral pneumonia must be diagnosed in the earliest stages. The research work presented in this paper is mainly based on machine learning and Artificial Neural Network (ANN) techniques to identify the occurrence of coronavirus and pneumonia diseases from a dataset, which was established manually, comprising of x-ray images of patients. In this paper, machine learning and ANN algorithm have been employed along with different feature extraction techniques for k-nearest neighbors (KNN), support vector machine (SVM), and naïve Bayesian (NB) such as shape matching using Hu Moments, edge orientation, Haralick texture features. Subsequently augmentation technique was applied for data enhancement. To justify the effectiveness of the proposed method, a comparative analysis was performed with other established methods. The results exhibited that the proposed method has accuracy, precision, sensitivity, and F1 score of 94%, 0.94, 0.96 and 0.95 respectively.**

Index Terms-- **Covid-19, Computed Tomography, Machine Learning, Artificial Neural Network.**

I. INTRODUCTION

Nowadays, the novel coronavirus (COVID-19) has turned into a global pandemic, and has affected the whole world with rapidly increasing number of positive cases. The lives of billions of people around the world, from health, economic and social perspectives have been affected. This disease results in Severe Acute Respiratory Syndrome Coronavirus 2 (SARS CoV-2). The identification of the first outbreak was held in Wuhan, China in the first week of December 2019 [1]. Till date, more than ten million cases have been reported and approximately 0.5 million death in different countries [2]. COVID-19 symptoms cough, fever and in some severe cases difficulty in breathing and muscle aches. during imaging frequently reveals bilateral pneumonia [3]. The screening and diagnosing process of different diseases is generally achieved by examining computerized tomography (CT) scan and x-rays images with the assistance of a radiologist. There is a high chance of misclassification error if a clinician examines the images with naked eye, and therefore the doctor cannot get the correct details of the patient. Therefore, the patient goes in more critical condition if the lesion cavities are not identified at the earliest stage. The nucleic acid identification technique and detection kits to identify the infection have come into large production. Considering the complexities in earlier detection, CT scanning is the most accurate and efficient method for evaluating and identifying the pneumonia severity [4]. Next to the breakout of a novel coronavirus hundreds and thousands of patients are in line for examination of CT scan in hospitals. The number of suspected and confirmed cases in Pakistan are increasing day by day however, there are not enough CT scan facilities available. Moreover, globally, the number of expertise in radiology/radiologists are limited, therefore disease investigation at an early stage. Once the patient is infected, the lung infection foci is too small, at the initial stage of COVID-19 infection the layers are 2.5mm, 1.25mm or even 0.625mm thinner. Scanning is usually required to replace CT scan i.e., 5mm for diagnosis and it could be time-consuming. Currently, radiological imaging is a key tool for COVID-19 detection. The CT images of infected or suspected patients have almost similar features comprising the initial stage of ground- glass opacities and the final phase of pulmonary consolidation [5]. However, the CT images have been used for early diagnosing of these cases. Therefore, pneumonia images are similar and cause overlapping with other inflammatory lung disease. With the advancement in AI technique specially machine and deep learning method, various tools have been developed to assist radiologist and categorization, computation analysis and evaluation of different type of data. Therefore, intelligence system could be developed for in-depth non-invasive machine vision-based technique for the early detection of various disease. In case of x-ray imaging Computer aided diagnostic (CAD) technique are employed for various chest disease identifications such as tuberculosis and pneumonia. A study presented in [6] demonstrate that a Chex net algorithm was built and data was distributed randomly for training and testing. Their study was able to detect pneumonia and achieved accuracy of 76% having F1 score of 95%. In [7] the authors proposed a technique to remove the graphical features to facilitate clinical screening. They established a method which was followed by internal and external validation and obtained specificity and sensitivity of 0.88 and 0.87, respectively. In order to fulfil these drawbacks and shortcomings, the developed method employs ANN technique which is quite accurate and efficient than the aforementioned methods.

Hence, the main aim of the study is to evaluate the classification performance by employing the ANN technique using a self-developed dataset. After implementation of the entire process and testing, the proposed technique exhibits higher classification accuracy i.e. 94% and extract the radiological features for timely and accurate than the methods described in [6] and [7]. This research study has three main objectives:

1) To established CT images database
2) To extract various attributes as feature for training
3) Employing traditional and deep learning-based machine learning methods for classification

This paper is organized as follows. Section II shows the literature review followed by Methodology in section III. Experimentation is presented in section IV followed by results and discussion in section V, finally, section VI concludes this paper.

II. LITERATURE REVIEW

Although many techniques have been utilized to detect complications in lungs [8], and chests [9] using x-rays. Most of the researchers classify the detection of pneumonia using normal and abnormal x-rays using texture features. The work in [10] discusses an accurate course to fine dual scale technique to identify cavity in chest x-rays. First, a Gaussian matching method was utilized, and subsequently the texture information was encoded using local binary pattern and finally coarse-scale fine gradient orientations features were utilized. In another study [11] the authors employed machine learning techniques for detection of coronavirus. The study used a set of images which were examined from CT tools. The proposed study employed five features extraction techniques to know about the set of features which differentiate the normal and lesion patches with high accuracy. The accuracy claimed on manually dataset was 97% using performance metrics. With the development of deep learning and computer vision very small features during an analysis of an image can be extracted. In [12], a technique was developed for detection of the lesion and gastrointestinal endoscopy to assist the clinicians in real-time. Currently, the field of medical imaging is very hot and various vision algorithms are being used to enhance the quality of images, image segmentation and image analysis to facilitate the clinicians in the process of diagnosing and screening [13]. The work in [14] proposed to diagnose the pulmonary nodules, classification of the malignant and benign lesion, and analysis of chest x-ray and tuberculosis prediction [15].

During the prediction of COVID-19 hallmarks [16], the opacity of ground glass and patchy shadows are bilateral distribution therefore according to hallmarks that convolutional neural network (CNN) could assist to determine and specify the uniqueness of the features for recognition. A method for standard screening was employed in [17] to identify the viral nucleotides between the specimens and microorganism which were obtained through tracheal aspirate, nasopharyngeal swab and oropharyngeal swab respectively. However, the recent studies [18] have identified that the real-time polymerase chain reaction (RT-PCR) has low sensitivity and specificity as (60-71) % for COVID-19 detection. By contrasting the demonstration of CT chest to identify the novel coronavirus at the initial stages, the sensitivity was about (56-97) % and aiding the rectification of false-negative (FN) which was obtained from (RT-PCR) at the development of initial phases of viral infection.

According to Fang et al. in [19], the real-time polymerase chain reaction (RT-PCR) was compared with the sensitivity of CT chest, this study showed the COVID-19 and nucleic acid viral detection. History of 50 patients were looked at who travelled or were inhabitants of affected areas, and had complications of fever and respiratory tract infections. Therefore, the patients were kept under observations and the screening process RT- PCR was repeated again and again and eventually they were confirmed to be affected by novel coronavirus. In the proposed study the sensitivity of chest CT non-contrast for identification of COVID-19 was 98% as compared to the initial testing of (RT-PCR) which was 71%. So, this is quite interesting and high recall and accuracy rate as recent trend of finding a novel corona virus classification and detection. Bernheim et al. in [20-23], proposed a method in which 121 CT chest images were examined in three different stages i.e. initial, intermediate and last phases of viral infections, and the opacities of ground glass were considered as a characteristics of disease which included consolidative opacities of pulmonary and bilateral ground glass. It was observed in the proposed study that the severity of infection increased time by time and later it was also determined that the recognition of disease which involved the sign of lung, crazy-paving, and sign of reverse halo. The study showed that among the patients who were examined 28% were at the earliest stage, intermediate patients were 76%, and 88% were of the last stages. Andrew et al. in [6] proposed a Chex Net algorithm and applied the technique on a publicly available dataset. The data was randomly distributed i.e., 9.8k images for training, 6k images for validation and 430 images for testing. The system detected pneumonia, and the performance was good as compared to an expert radiologist and the F1 score were 95% which was more efficient and accurate. Wang et al. in [7] developed a deep learning framework to extract the features of a novel coronavirus from CT images. The proposed study collected samples of 1119 CT scan, and modified the technique to develop the algorithm for the external and internal validation. This study achieved an accuracy of 89.5%.

III. METHODOLOGY

As discussed in objectives of this research, this paper first uses traditional machine learning algorithms, and then Artificial Neural Networks for classification of Covid-19 and pneumonia from x-rays and CT Scans. Both methods are explained one by one in this section. Machine learning (ML) is the widest field of study in image recognition. As the occurrence of human cleverness, ML allows identifying the pattern which is seen in earlier cases and experiments. Different imaging modalities have various features for every disease therefore to identify these complications in images it requires frameworks of machine learning. To establish an algorithm of ML, a model is trained on a given dataset, and a logical inference is then made. In medical imaging categories like for clinical outcomes or diagnosis, the framework should be pre-built for the final decision and the training process would be supervised. However, the case could be unsupervised, if there are no defined classes. Traditional Machine Learning Approach includes a classifier which classifies three different images i.e., normal, pneumonia and corona affected. Figure 1 shows the entire workflow of the system.

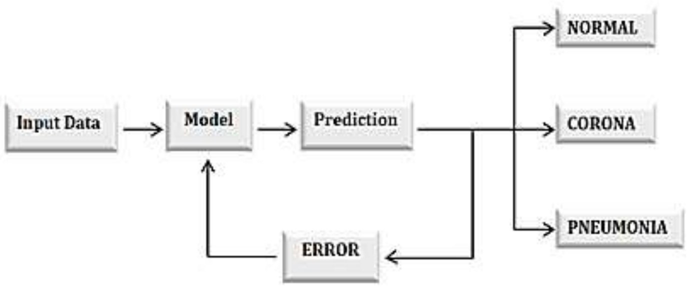

FIGURE 1: SCHEMATIC BLOCK DIAGRAM

This method includes the following subsections. In the study of Covid-19 classifications, researchers have used different datasets. In this approach, three different classes of data is used which includes x-rays and CT scans of normal patients, corona patients, and pneumonia patients. The data was collected from different areas. The normal and pneumonia patient's data was acquired from Kaggle.

The total number of images for normal and pneumonia is 3995 per each class, which include 3000 x-ray images and 995 CT scan images per class, as shown in Fig. 2.

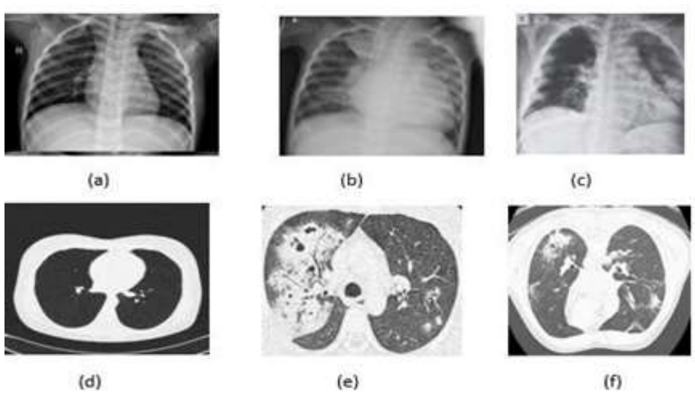

FIGURE 2: (A) NORMAL, (B) PNEUMONIA, (C) CORONA, (D) NORMAL CT SCAN, (E) PNEUMONIA CT SCAN, (F) CORONA CT SCAN

The steps involved before training and testing phases for image classification are the data augmentation, pre-processing, feature extraction. A brief explanation of these steps is given as follows:

A. DATA AUGMENTATION

Data augmentation is a strategy that enables practitioners to significantly increase the diversity of data available for training models, without actually collecting new data. Data augmentation techniques such as cropping and horizontal flipping are commonly used to train large neural networks. In this paper flipping method used for augmentation of corona patient images which increased data up to 3965 from 120 images of x-rays and CT scans.

B. PRE-PROCESSING

In pre-processing of images, the data was taped through a sensor mostly related to geometry and values of the pixel brightness errors. Therefore, these errors were corrected by employing a suitable mathematical model. In this study, morphological features were employed to remove the blurriness effect from the CT scan images. Another enhancement technique was used for the brightness of the image pixel in order to modify enhancement quality and also to improve the image appearance visualization which is better and suited for human interpretation.

C. FEATURES SELECTION

The process of feature selection is an important stage in ML algorithms. A wide spectrum of features could be extracted from an image. Some features are irrelevant in most cases for a given examination or due to data redundancy noise occur in the feature vector. The relevant features i.e. textures and shape-based features could be used for identification of CT scan images. However, the above features are not sufficient to distinguish a CT scan image. Therefore, in order to achieve better performance this study employed a set of features like Hu Moments, Haralick Textures and Histogram of Oriented Gradients.

D. FEATURES EXTRACTION

The next step in Covid-19 identification is features extraction which comprises of calculating values numerically by employing a descriptor that shows visual content of the image. The process would be obtained by execution of techniques called feature extractors. This technique performs the process of quantitative imaging which includes histogram analysis, shape and texture classification. As the features could be extracted by this technique, therefore the numerical values are noticed in the feature vector. The features are categorized into three classes: (i)grey level, (ii) texture, and (iii) shape. Generally, in the process of features extraction the grey-level features method is used, and construction of histogram is performed directly. A histogram is an explanation of the values which are presented in the grey level image and the computation covers counting of pixels only with the intensities of grey-level.

While employing the description of grey level, histogram analysis would not give the entire information of the spatial distribution of an image which could be analyzed by determination of texture features. Particularly texture features. would become more important because it could be followed by the information of lesion which leads to image identification. Shape features offer edge detail in an image and also guide about the features of geometry which are extracted from the object segmentation like its contour, curves and junction's region. Extracting shape features of an object is a difficult task and therefore its dependency would be based on the efficiency of the segmentation technique. Lesions are seen in CT images of chest and lung in the form of adjacent opacities and structures like vessels could be seen, and therefore using only shape features, could lead to poor segmentation. However, to observe the x-rays and CT images it could be seen that the images have minute contrast in shapes, edges and textures. Therefore, these features would be employed for classification as discussed in the following subsections.

TABLE I:
HU MOMENTS VALUES FOR CT IMAGES

Images	H0	H1	H2	H3	H4	H5	H6
	1.02479994e-03	3.47737713e-10	6.34685204e-12	1.04005874e-11	8.22900211e-23	1.73964420e-16	-1.92069680e-23
	1.0481938e-03	7.89544051e-08	3.39069824e-13	1.36621522e-11	2.51000935e-23	3.15440745e-15	-1.53182101e-23
	1.30675042e-03	1.01611359e-08	3.27679271e-11	2.50193470e-11	-2.97406688e-22	-2.40135416e-15	-6.51719050e-22

a) HU MOMENTS

Hu moments are used for shape analysis, and their feature vectors are shown in Table 1. CT images of pneumonia and corona infected are in different shapes and sizes, as discussed in features extraction domain. The moments in the image are a weighted average and amplitude of image pixels as shown in equation (1).

$$M = \sum x \sum y \, I\,(x, y) \qquad (1)$$

Where I is the image and (x, y) shows the pixel values.

b) EDGE ORIENTATION FEATURE

In the proposed study, by examining the CT images of chest i.e., normal, pneumonia and corona affected from the top view, i.e., spatially, it was observed that all images have different edge distribution. The shapes of these images could be utilized to calculate the characteristics of edge orientation. Therefore, from the CT images, the edge of the histogram orientation feature was extracted. Canny filters were employed for detecting edges in various orientations. The Gaussian filter was applied to transform the image before implementing a Canny filter, which smoothened the image slightly and eliminated noise from the image, and then the edge detector was used. The histogram was computed after completing the feature of edge orientation.

c) HARALICK TEXTURE FEATURE

Different CT images of the chest have varying textures. The surface of the object should be investigated to identify lesions in an image based on textures. Therefore, texture characteristics are employed to classify infected and normal images of CT scan. Haralick textures were placed into service for identification based on texture. Gray Level Co-occurrence Matrix (GLCM) was calculated for computation of the Haralick feature. It uses the principle of adjutancy in images and tries to locate the pairs of pixel changes in various directions

The algorithm of KNN is based on clustering things of the same nature. This classifier is computationally fast and easy to employ on a supervised learning model and could be utilized for classification problems. The classifier was trained on the above-mentioned features and the information in various required categories was identified. Through a majority poll of its neighbors, an image was classified with those images which were assigned to the group by a distance function. If the value of k=1 so that case would be assigned to its nearest neighbor. The KNN classifier could be employed by the following equations. Initially, nearest neighbor method was employed for training test data i.e., x and K against data training employing the first equation to compute the distance. In k dimensional space with two points i.e., x and y have distance function as shown in equation (2).

$$\text{Euclidean Distance} = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^{2}} \qquad (2)$$

To calculate the Manhattan distance, two data points are required as shown in equation (3).

$$\text{Manhattan} = \sum_{i=1}^{k} |x_i - y_i| \qquad (3)$$

Minkowski distance is a generalized distance metric it employs the following equation for distance calculation between the data points. The following equation (4) presents the Minkowski distance formula.

$$\text{Minkowski} = \left(\sum_{i=1}^{k}(|x_i - y_i)^{q}\right)^{1/q} \qquad (4)$$

IV. EXPERIMENTATION

The developed neural network architecture was designed in python. This architecture consisted of one input layer, two hidden layers, and one output layer. The input layer and first hidden layer are defined having an input shape of 3072, as there are 32x32x3=3072 pixels in a flattened input image. The developed neural network architecture was designed in python. This architecture consisted of one input layer, two hidden layers, and one output layer. The input layer and first hidden layer are defined having an input shape of 3072, as there are 32x32x3=3072 pixels in a flattened input image. The first hidden layer had 1024 nodes. The second hidden layer had 512 nodes. Finally, the number of nodes in the final output layer were the number of possible class labels — in this case, the output layer had three nodes, one for each of our class labels (normal, corona and pneumonia). The architecture is shown in Fig. 3.

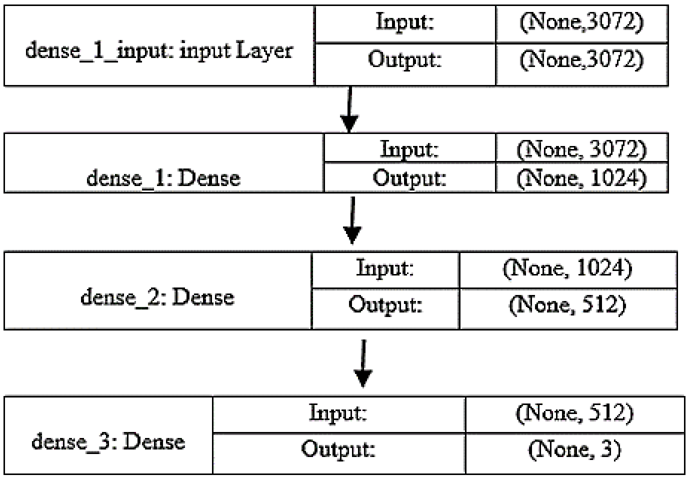

FIGURE 3: ARTIFICIAL NEURAL NETWORK ARCHITECTURE

In the traditional machine learning and proposed method, the training process of the dataset could be the next step to train the algorithm. This process of training is supervised learning in which three different types of data (corona, pneumonia and normal patients) were fed to the algorithms. However, the main work was to process the entire framework therefore to efficiently identify the three cases of CT images in the presence of artifacts, black region and blurriness. From Scikit-learn, several learning techniques were employed in traditional machine learning approaches such as K-Nearest Neighbour (KNN), Logistic Regression, and Support Vector Machine (SVM). So, for the training purpose in traditional learning approach, 200 images of three different classes i.e. normal, pneumonia and COVID-19 affected, were employed. Whereas in case of the proposed method once a network has been structured for a particular application, the network is then ready for training. To start the process, the initial weights were chosen randomly, subsequently training process was initiated. In order to check the performance a well-established Kaggle dataset was employed. The network was trained on various x-rays and CT scans images. During training, 70% dataset was allocated, and the remaining 30% was kept for testing. The actual output was compared with the desired output and the error generated was feedback to the network overcoming error. The simulations were performed for 20,000 epochs. A steady state response was observed between 19,000 and 20,000 epochs.

V. RESULTS AND DISCUSSION

This study deals with COVID-19 identification in two phases. In phase one images were classified based on machine learning, and in stage two the images were identified on the basis of an artificial neural network. Data was randomly distributed for training and testing purposes. After training, experiments were conducted on unseen data i.e. unknown x-rays and CT scans. The results for traditional machine learning classifiers are shown in Fig. 4.

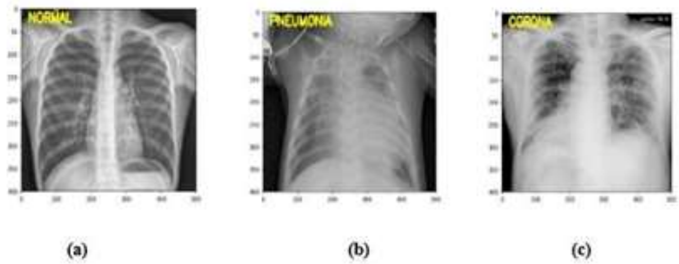

FIGURE 4: X-RAY BASED DISEASE DETECTION

It is clearly shown in Fig. 5 that the accuracy of KNN classifier is higher than the other two techniques.

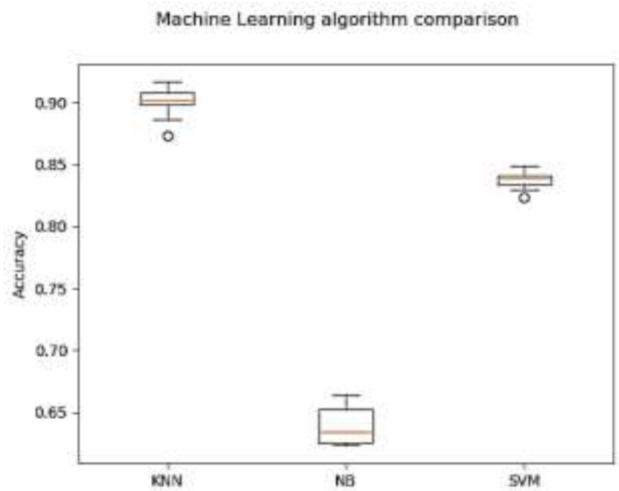

FIGURE 5: COMPARISON OF MACHINE LEARNING FRAMEWORK

Performance of the proposed system using the ANN technique is shown in Fig. 6. It is evident that 99.73% pneumonia was detected as indicated in Fig. 6 (c), while 97.84% corona was diagnosed as shown in Fig. 6 (f).

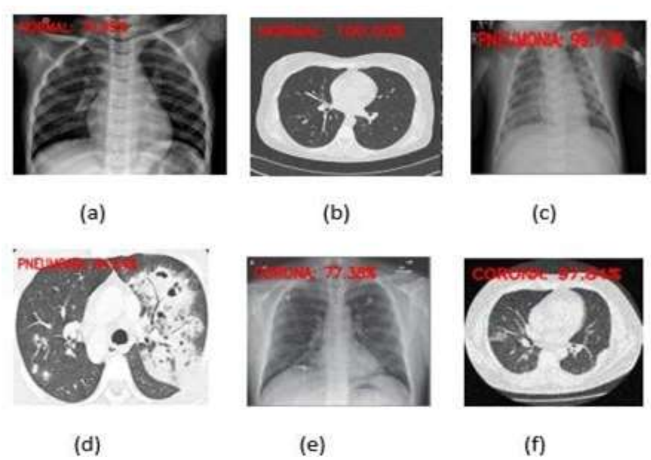

FIGURE 6: (A) NORMAL X-RAY, (B) CT (NORMAL), (C) PNEUMONIA, (D) PNEUMONIA DETECTION IN CT, (E) COVID IN X-RAY, (F) COVID IN CT

Four performance metrics were generated for evaluation. These parameters are precision, recall, F1 score, and accuracy. The values of these metrics are shown in the TABLE II.

TABLE II:
PERFORMANCE METRICS

Classes	Precision	Recall	F1 Score	Accuracy
Corona	0.94	0.96	0.95	
Normal	0.95	0.94	0.95	0.94
Pneumonia	0.93	0.93	0.93	

The collection of datasets for Covid-19 classification comprised of learning curves, and widely used diagnostic tool in machine learning for algorithms that learn from a training dataset incrementally. The model can be evaluated on the training dataset and a holdout validation dataset after each update during training and plots of the measured performance can be created to show learning curves. It is more common to use a score that is minimizing, such as loss or error whereby better scores (smaller numbers) indicate more learning and a value of 0.0 indicates that the training dataset was learned perfectly and no mistakes were made. Figure 7 shows the training and validation curve, where train loss is training loss, train_acc is training accuracy, val_loss is validation loss, val_acc is validation accuracy.

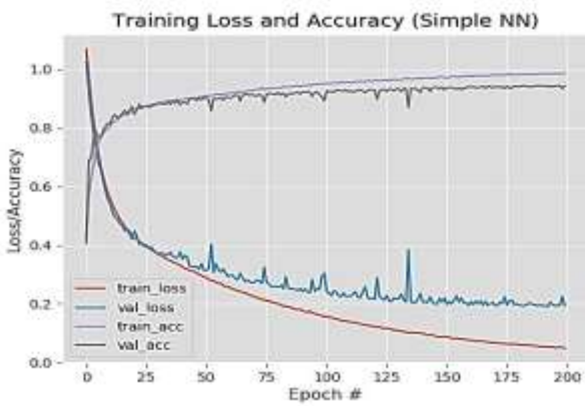

FIGURE 7: MODEL PERFORMANCE

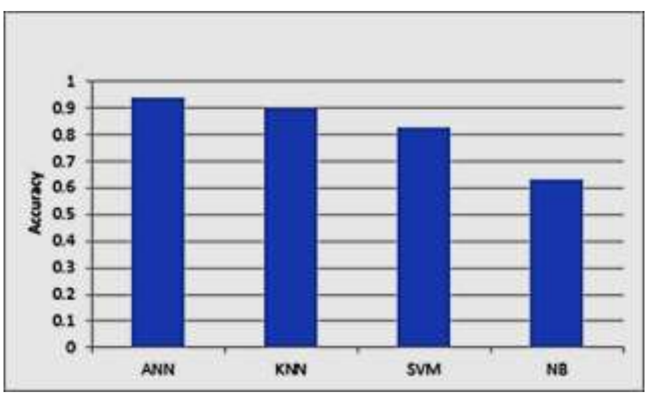

FIGURE 8: Accuracy on Basis of Different Models

Figure 8 shows the accuracy of the Machine Learning and ANN on the training and testing of the dataset. The accuracy of the other three model KNN, NB and SVM were 90, 83 and 63% respectively, while the accuracy of the proposed model on the basis of ANN was 94% on the dataset. Thus, the higher accuracy of the proposed method shows better performance against other various techniques as shown in Fig. 8.

It is clearly shown and perceptible from TABLE III that the accuracy of the proposed method is 94% and the other method, by Andrew et al. [6] is 76% in the case of chest x-rays. Thus, the proposed method is more accurate.

TABLE III
COMPARISON OF PERFORMANCE METRICS IN TERM OF X-RAYS

	[6]	Proposed Method
Accuracy (pneumonia)	0.76	0.94
F1 Score	0.95	0.95

On the basis of CT images, the proposed method was compared to the existing method presented in [7]. It can be noticed from TABLE IV that in case of CT images the proposed technique achieved higher accuracy than the method of [7]. Moreover, the proposed method is more efficient in case of f1 score, sensitivity, and precision respectively.

TABLE IV
COMPARISON OF PERFORMANCE METRICS IN TERMS OF CT IMAGES

	[7]	Proposed method
Accuracy	0.89	0.94
Precision	0.88	0.94
Sensitivity	0.87	0.96
F1 score	0.77	0.95

VI. CONCLUSION

The first case of Covid-19 was reported in Wuhan, China, and since then this epidemic has affected the public health, and world economy. Covid-19 infection is like the viral infection of the pneumonia. Therefore, the pandemic of these viral infections made the living activity more difficult and the situation out of control. Different imaging modalities have been used for clinical studies. This study involved utilization of machine learning as well as ANN based techniques for classification of Corona and pneumonia diseases from images of x-rays and CT scans. Form the results acquired, it is concluded that the proposed ANN method has higher accuracy than the traditional machine learning classifiers. The results exhibited that the proposed method has accuracy, precision, sensitivity, and F1 score of 94%, 0.94, 0.96 and 0.95 respectively.

In future experimentation of disease classification in x-ray images with reference to other disease such as Tuberculosis etc. is in progress.

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