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Early Detection of Coronavirus Cases Using Chest X-ray Images Employing Machine Learning and Deep Learning Approaches

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Abstract This study aims to investigate if applying machine learning and deep learning approaches on chest X-ray images can detect cases of coronavirus. The chest X-ray datasets were obtained from Kaggle and Github and pre-processed into a single dataset using random sampling. We applied several machine learning and deep learning methods including Convolutional Neural Networks (CNN) along with classical machine learners. In deep learning procedure, several pre-trained models were also employed transfer learning in this dataset. Our proposed CNN model showed the highest accuracy (94.03%), AUC (95.52%), f-measure (94.03%), sensitivity (94.03%) and specificity (97.01%) as well as the lowest fall out (4.48%) and miss rate (2.98%) respectively. We also evaluated specificity and fall out rate along with accuracy to identify non-COVID-19 individuals more accurately. As a result, our new models might help to early detect COVID-19 patients and prevent community transmission compared to traditional methods.

Keywords COVID-19 · Chest-Xray Images · Machine Learning · Deep Learning · CNN

1 Introduction

Novel coronavirus disease (COVID-19) is an ongoing pandemic caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [24]. It was first discovered at Wuhan, China on December 2019 and has maintained a phylogenetic similarity with Severe Acute Respiratory Syndrome (SARS-CoV) [27]. Coronaviruses were first discovered in 1960s from the nasal pits of patients [16].

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It is a massive infectious group that generally enveloped RNA viruses caused by respiratory, hepatic and neurologic disease among humans and other mammals [27, 10]. Coronaviruses come from a large family of viruses that cause diseases such as the Middle East Respiratory Syndrome (MERS-CoV) and SARS-CoV. The SARS-CoV, MERS-CoV and SARS-CoV-2 originate from bats [18]. The SARS-CoV-2 is the third coronavirus emergent condition to the human beings in the past two decades, preceded by the SARS-CoV and MERS-CoV outbreak in 2002 and 2012 respectively. Likewise, COVID-19 is an infectious disease that is spreading with a hilarious speed throughout the world [6, 12]. The World Health Organization (WHO) announced this outbreak as a public health emergency of international concern on 30^{th} January and as an pandemic on 11^{th} March, 2020 [4]. To control these diseases, WHO was notified individuals to maintain different pre-caution steps like keep social distancing, wash hand with soap and sanitizer, avoid touching noise, mouth, eye, etc. However, most of the affected countries are locked down their regions to prevent the spreading of this disease.

Coronavirus patients can be identified primarily with common symptoms such as fever, cough, fatigue, loss of appetite, muscle pain etc. The total number of infected patients is approximately 4,885,738 at May 19, 2020 where the percentage of total recovered, deaths, mild and critical condition patients are specified as 86%, 14%, 98% and 2% respectively [9]. To flatten the epidemic curve, it requires to identify COVID-19 positive patients, isolate and ensure treatment policy them in early stages. There are existing two types of testing procedures namely i) Molecular diagnostic tests, and ii) Serologic tests [23]. The molecular diagnostic test can recognize those people who are infected at the time of the test. The Reverse Transcription Polymerase Chain Reaction (RT-PCR) test is a molecular diagnostic test which is currently considered as the gold standard in the diagnosis of COVID-19 [5] that detects the viral RNA from sputum or nasopharyngeal swab. It is relatively associated with low true positive rate and requires specific equipment [5]. Another technique is currently under development that can discover proteins of the virus and detect COVID-19 called viral antigen detection. Instead, when a patient has been recovered, the molecular tests can no longer detect that this person has been previously infected. The growth of an antibody may be shown its reaction some time and depended on host. Serologic tests can detect antibodies in blood that are primary tools to identify patients of COVID-19. However, these tests are time consuming and unavailable for many people especially in low-and-middle income countries due to lack of laboratory and human resources. Nevertheless, we need to take some other procedures for detecting patients as fast as possible.

Recently, medical images such as chest X-ray and computed tomography (CT) scan images have been used to determine COVID-19 positive patients [22, 17]. But, CT scan imaging is a costly procedure and not available in every hospitals or medical centers. Alternatively, chest X-ray machines are available in almost all the nearest clinic, medical lab or hospitals rather than biomolecular laboratory test. It is cheaper, faster and wider spread to generate 2D images of the patients [14]. Moreover, the radiologists can use this kind of images to identify chest pathology and confirm COVID-19. Most of the existing works were implemented machine learning algorithms over chest-X-Ray images for detecting COVID-19 patients and focused on how classifiers can identify positive cases, but failed to detect false negative cases which causes more community transmission of COVID-19. Hence, the current work focuses on specificity and fall rate along with other detection matrices. In this study, we propose a new mechanism applying machine learning approaches on chest X-ray images for identifying COVID-19 positive patients in early stage. These findings may help to reduce the community spread of COVID-19.

2 Literature Review

Recently, several studies investigated COVID-19 medical images using various deep learning-based methods. Wang et al. [25] introduced an open source deep learning model and realized a large benchmark dataset called COVIDx with 13,975 patient's chest X-ray images to explore COVID-19. This model was not only ensured greater insights of COVID-19 critical factors but also extracted relevant information from the experimented images. Their study generated accuracy 93.3% over COVIDx dataset. Maghdid et al. [3] applied deep convolutional neural network (CNN) and transfer learning using AlexNet into X-ray and CT scan image datasets. They identified 94% accuracy (specificity 88%) for CNN and 98% for AlexNet (specificity 96%). Then, Ali Narin et al. [21] analyzed chest X-Ray images using three CNN models such as ResNet50, InceptionV3 and InceptionResNetV2 for COVID-19 automatic detection. Their study showed the highest 98% accuracy using 5-fold cross validation. Abbas et al. [1] proposed DeTraC deep CNN model that aimed to give solution by transferring knowledge from generic object recognition to domain-specific tasks. Their algorithm showed 95.55% accuracy (specificity of 91.87%, and a precision of 93.36%). Apostolopoulos and Mpesiana [3] implemented transfer learning using CNNs into a small medical image dataset. Their dataset contained 1427 X-ray images including 224 confirmed COVID-19 images. They showed the best accuracy 96.78%, sensitivity 98.66%, and specificity 96.46% respectively. Hemdan, Shouman and Karar [11] proposed COVIDX-Net including seven different deep CNN architectures that investigated 50 chest X-ray images with 25 COVID-19 cases. Their algorithm generated 90% accuracy and 91% F-score. After that, Khobahi, Agarwal and Soltanalian [13] proposed a semi-supervised learning methodology based on autoencoder that ensured average 93.5% accuracy. Li et al. [15] offered a light weighted deep neural network (DNN) based mobile app named COVID-MobileXpert. It could be used noisy snapshots of chest X-ray for the COVID-19 screening. Hence, both ShuffleNetV2 and MobileNetV2 were generated high AUROC values 94% and 94.30% respectively. Minaee et al. [20] proposed a deep learning framework based on 5000 images named COVID-Xray-5k where they applied ResNet18, ResNet50, SqueezeNet and Densenet-121, and claimed the sensitivity 97.5% and specificity 90% on average. Alom et al. [2] employed multitask deep learning methods to identify COVID-19 patients using X-ray and CT scan images. Their algorithm detected end-to-end COVID-19 and localized infected regions using deep learning methods. They also applied Inception Residual Recurrent CNN with Transfer Learning and obtained 84.67% of testing accuracy from X-ray images and 98.78% accuracy in CT-images. Lastly, Zhang et al. [26] pointed to build a deep anomaly detection model that applies into chest X-ray images dataset. Their classifier achieved the sensitivity 96% for detecting COVID-19 positive cases and specificity 70.65% for COVID-19 negative cases.

3 Materials and Methods

The working methodology has been detected COVID-19 patients from the publicly available datasets. Figure 1 illustrates the working steps of our methodology. This process has been split into data collecting, pre-processing, classification and evaluation respectively. In this work, this approach is described more elaborately in the following section:

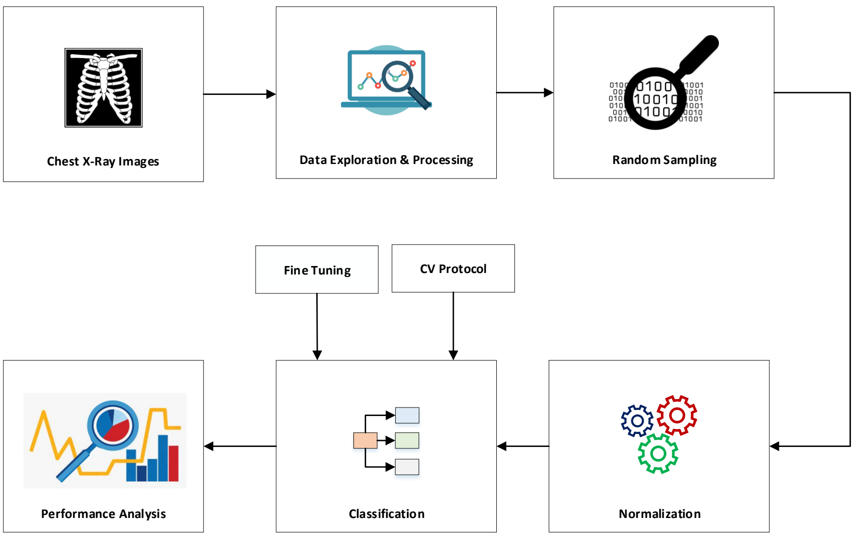


Fig. 1: Working Procedure

3.1 Data Collection

The chest X-ray images were obtained from the COVID-19 Radiography Database [7] which was considered as primary dataset in this work. This dataset contained 1341 normal, 1345 viral pneumonia, and 219 COVID-19 patient's images. It is noticed that the distribution of different types of images were not same. To balance this dataset, we collected 66 images from Cohen et al. [8] and added them to the 219 COVID-19 images of primary dataset. For other classes, we applied random under-sampling to generate a balanced dataset. Finally, an experimental dataset had been generated that contained 285 normal, viral pneumonia and COVID-19 images respectively. Figure 2 illustrates the three types of chest X-ray images as follows.

(a) (b) (c)

Fig. 2: Chest X-ray images of (a) COVID-19 (b) normal and (c) viral pneumonia patients

3.2 Data pre-processing

In the data pre-processing step, we applied normalization method into images to generate binary values. Then, this images were transformed into grayscale images. However, pre-trained CNN models such as VGG16, ResNet50, InceptionV3 cannot support grayscale images where RGB images have been considered to detect COVID-19 patients. We resized the files into 100×100 pixels. Then, these images were normalized to divide it by 255 because there are were 256 color values (0-255) and mapped between 0 to 1 corresponding to probability theory. Hence, it was more convenient to map the data into this interval. In few cases, it improved the performance of the model depending on what activation function was getting used.

3.3 Baseline classifiers

This study applied, as the baseline classifiers, classical machine learning algorithms and deep learning approaches. several classical machine learning classifiers had been used such as support vector machine (SVM), random forest (RF), k-nearest neighbor (k-NN), logistic regression (LR), Gaussian naive Bayes (GNB), Bernoulli naïve Bayes (BNB), decision tree (DT), Xgboost (XGB), multilayer perceptron (MLP), nearest centroid (NC) and perceptron. When we trained the dataset, several associated parameters of the machine leaning models were changed and optimized more accurate results. This process is called fine tuning. The fine-tuned parameters of classical classifiers are represented at Table 1. Moreover, several deep learning classifiers were also employed such as convolutional neural network (CNN), deep neural network (DNN) and several pre-trained CNNs such as Residual Neural Network (ResNet50), Visual Geometry Group Network 16 (VGG16), and Inception network V3 (InceptionV3) for transfer learning. The details of proposed CNN is given at section 3.4. For DNN, we considered batch size 32, number of epochs 50, adam optimizer, and learning rate 0.0001 with weight decay. Again, some regularization terms were considered for reducing overfitting in the deep learning models. When pre-trained models had been loaded, it was downloaded required weights and confirmed that it was correctly loaded. Then, Flatten layer was added into these pre-trained models which flats the input to one dimension. Then, we were employed a dense layer with 64 neurons, 'relu' activation function and regularizer 0.001 respectively. Before and after employing the dense layer, dropout layer had been used to reduce the overfitting issues. Finally, 3 classes had been assigned with 'softmax' activation function. To compile the model, categorical_crossentopy loss function and adam optimizer is considered with 0.00001 learning rate. Therefore, we used last 1 layers trainable for ResNet50 and considered the last 62 layers to be trainable for InceptionV3.

Table 1: Different associated parameters of classical machine learning classifiers

Classifier	Parameters
SVM	Linear kernel, gamma = 0.0001
KNN	K= 5, euclidean distance
GNB	Priors = None, var_smoothing = 1eˆ-09
BNB	Alpha = 1.0, binarize = 0.0
DT	gini criterion, best splitter
LR	Liblinear solver, max_iter = 1000
RT	Max_depth = None, random_state = 0
GB	Max_features = 2, max_depth = 2, random_state = 0
XGB	Learning_rate =0.1, max_depth = 3
MLP	Adam solver, alpha = 1eˆ-5, random_state = 1
NC	Manhattan metric
Perceptron	Tol = 1eˆ-3, random_state = 0

3.4 Proposed Convolutional Neural Networks

Convolutional Neural Networks (CNN) is a special class of artificial neural networks (ANN) which can take images as input and investigate it as well (see Figure 3). In CNN architecture, there is sparse connection between layers and weights that are shared between output neurons in the hidden layers. It gives extremely good performance in computer vision and image analysis sector such as image recognition, object detection, semantic segmentation and medical image analysis etc. It considers an input layer by maintaining the sequence of hidden and output layers. Like regular ANN, CNN consists of sequence of hidden layers and they are basically denoted as convolutional and polling layer. Therefore, the operations of these layers are called as convolutional and polling operation respectively. Alternatively, they are stacked to lead a series of fully connected layers followed by an output layer.

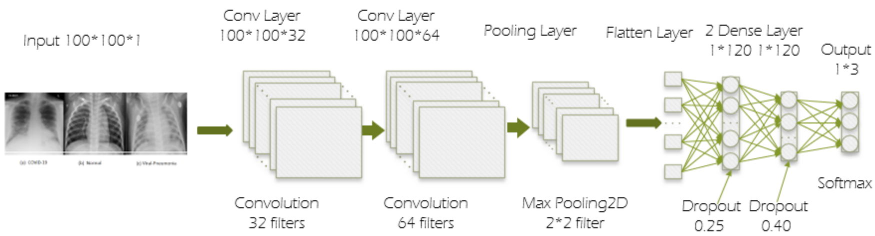


Fig. 3: Proposed Convolution Neural Network

There were considered two convolutional layers in our proposed CNN structure. The input images were referred to the first convolutional layer, and the data size was $100 \times 100 \times N$ where N was the number of channels for hyper spectral images in addition to consider gray-scale images as input $N = 1$. For the number of input, we generated multiple channels to produce output in every layer. The findings of any hidden layer that means every output neuron was connected with a small neighborhood in the input through a weight matrix which is called filter or kernel. Then, we defined multiple kernels for every convolution layer in each giving rise to an output. The weight matrix or filter or kernel moved around the every region or possession of the image and proceeded it to the multiple with the underline pixel values, add them up and it's a sum of products can generate the corresponding output volume. Each filter is moved around the input giving rise to one 2D output. The output is staked giving rise to an output volume corresponding to the filter.

In the convolutional layers, 3×3 sized kernels were employed. In the first convolutional layer, there were 32 filters, therefore the output of the first con-

Table 2: Evaluation Metrics

Metrics	Definition	Formula
Accuracy	Accuracy is the summation of TP and TN divided by the total instance values of the confusion matrix.	$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}}$
AUC	It measures the capability of the model to distinguish between classes is called AUC.	$\text{AUC} = \int_{x=0}^{1} TPR\left(FPR^{-1}(x)\right) dx$
F-Measure	The harmonic mean of precision and recall is called F-Measure / F1-score.	$\text{F-Measure} = \frac{\text{2TP}}{\text{2TP+FP+FN}}$
Sensitivity	The ratio of true negatives that are correctly identified is called as sensitivity.	$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}}$
Specificity	The ratio of true negatives that are correctly identified is called as specificity.	$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}}$
Fall Out	The ratio of TP and the summation of FP and TN is called false positive rate / fall out.	$\text{Fall Out} = \frac{\text{FP}}{\text{FP+TN}}$
Miss Rate	The ratio of FN and the summation of FN and TP is called false negative rate / miss rate.	$\text{Miss Rate} = \frac{\text{FN}}{\text{FN+TP}}$

volutional layer was $100 \times 100 \times 32$. Subsequently, the data was forwarded to the second convolutional layer and there were 3×3 size kernel and 64 filters, hence the output of the second convolutional layer was $100 \times 100 \times 64$. Then, we employed maxpooling2D layer with pooling size 2×2. In this situation, a flatten layer could be used to flat the input. A couple of dense layers had been implemented with 120 and 60 neurons respectively. After each of the dense layers, a dropout layer was provided to reduce overfitting issues. The size of the output volume or 2D map was determined and each slice had been split that called feature or activation map. Finally, an output dense layer had been employed with C neurons where C was the number of classes. To deal with multi-level classification, we used softmax activation function and in compiling the loss function categorical cross entropy and adam optimizer was considered in this model.

3.5 Evaluation

The performance of individual classifiers was assessed by different evaluation metrics such as accuracy, AUC, F-measure, sensitivity, specificity, fall out and miss rate respectively. The brief description of them is given in Table 2.

4 Experiment Results

Several machine and deep learning classifiers (N=17) were used to investigate chest X-ray images of normal, pneumonia and COVID-19 patients. There were used scikit learn library to implement machine learning classifiers in chest x-ray images. Then, deep learning model such as DNN, CNN and pre-trained models of CNN (VGG16, MobileNet, ResNet50) were implemented by using keras library in python. Therefore, all of these classifiers were employed 10 fold cross validation in these work. All application had been implemented on a laptop withAsus VivoBook S, Core i5-8250U Processor 8th gen - (8 GB/1 TB HDD/Windows 10 Home/) Intel UHD Graphics 620.

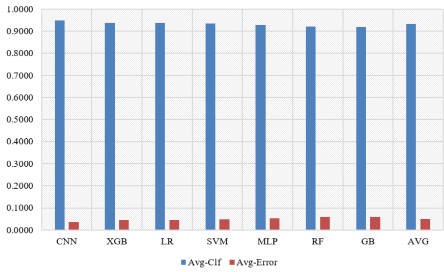
The performance was assessed by different evaluation metrics: accuracy, AUC, F-measure, sensitivity, specificity, fall out and miss rate respectively. Thus, most of the classifiers generate excellent results to classify chest X-ray images in this experiment. Among of these different classifiers, seven of them show the results greater than 90%, six classifiers represent their performance greater than 70% and less than 90% (see Table 3). Consequently, the rest of the classifiers are represented their results less than 70% which is not much good to investigate accurate results. The average results of different classifiers have been represented at Figure 4. Among all of these classifiers, proposed CNN shows the highest accuracy (94.03%), AUROC (95.53%), F-measure (94.03%), sensitivity (94.03%), specificity (97.01%), fall out (4.48%) and miss rate (2.98%) where it classifies into 272 instances as COVID-19 from 285 instances accurately (see Table 4). Besides, XGB shows the second maximum accuracy and minimum error rate along with other metrics. Then, LR, SVM, MLP, RF and GB demonstrate better results than other algorithms except CNN and XGB. Moreover, the average performance of all classifiers is satisfactory for all evaluation metrics. In this circumstance, the average results of this seven classifier is greater than 90% (see Figure 4a).

Table 3: Performance Analysis of Classification Methods

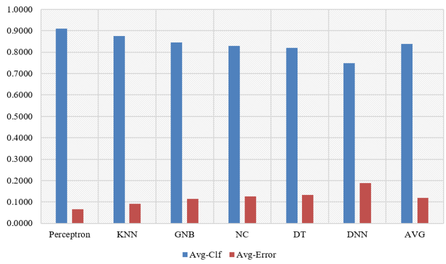
Classifier	Accuracy	AUC	F-Measure	Sensitivity	Specificity	Fall-Out	Miss Rate
CNN	0.9403	0.9552	0.9403	0.9403	0.9701	0.0448	0.0298
XGB	0.9274	0.9456	0.9274	0.9274	0.9637	0.0545	0.0362
LR	0.9251	0.9438	0.9253	0.9251	0.9625	0.0563	0.0374
SVM	0.9228	0.9421	0.923	0.9228	0.9614	0.0580	0.0385
MLP	0.9157	0.9368	0.9163	0.9157	0.9578	0.0633	0.0421
RF	0.9064	0.9298	0.906	0.9064	0.9532	0.0704	0.0467
GB	0.9052	0.9289	0.9049	0.9052	0.9526	0.0713	0.0473
Perceptron	0.8935	0.9201	0.8938	0.8935	0.9467	0.0802	0.0532
KNN	0.8538	0.8903	0.8558	0.8538	0.9269	0.1103	0.073
GNB	0.8187	0.864	0.8155	0.8187	0.9093	0.1371	0.0906
NC	0.7988	0.8491	0.8009	0.7988	0.8994	0.1523	0.1005
DT	0.7883	0.8412	0.7889	0.7883	0.8941	0.1604	0.1058
DNN	0.7029	0.7772	0.7035	0.7029	0.8514	0.2263	0.1485
ResNet50	0.6070	0.7052	0.5948	0.6070	0.8035	0.3016	0.1964
VGG16	0.6035	0.7026	0.5816	0.6035	0.8017	0.3043	0.1982
BNB	0.5625	0.6719	0.5180	0.5625	0.7812	0.3370	0.2187
InceptionV3	0.5298	0.6473	0.5314	0.5298	0.7649	0.3633	0.2350
AVG	**0.8001**	**0.8501**	**0.7957**	**0.8001**	**0.9000**	**0.1524**	**0.0999**

Table 4: Confusion Matrix of CNN

		Actual Class		
		Covid-19	Normal	Viral Pneumonia
Predicted Class	Covid-19	272	5	8
	Normal	4	269	12
	Viral Pneumonia	8	14	263



(a)



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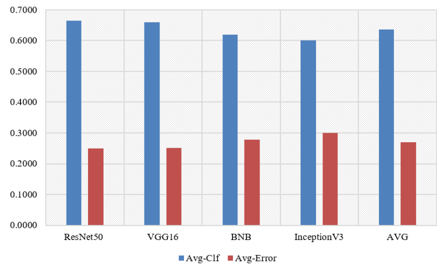

(c)

Fig. 4: Average experimental results and error rates of classifiers whose (a) average results greater than 90% (b) average results greater than 80% (c) average results greater than 70%

In the proposed CNN, the accuracy, f-measure and sensitivity represent as the indicator of how COVID-19 positive (target) cases can be determined by more appropriate way. The highest result of accuracy, f-measure and sensitivity is 94.03% and AUC is 95.52% correspondingly. All of this metrics is effective to explore and identify the target cases in this work. Instead, AUC shows better result than accuracy, f-measure and sensitivity. Therefore, specificity is one of the most important metrics because it represents how COVID-19 negative patients can be explored more accurately. The incremental result of specificity is indicated as the more appropriate identification of the COVID-19 negative patients. It causes the reduction of the community transmission that have been increased by the infectious persons whose don't identified as positive cases.

Therefore, the shrinking of false negative rate also represents the reduction of community transmission. Our proposed CNN is represented highest specificity (97.01%) and lowest miss rate / false negative rates (2.98%) respectively. In addition, the average specificity and miss rate is also found the maximum and minimum values than any other metrics respectively (Figure 4a). Hence, it can handle these kinds of risk more accurately than existing works. Therefore, proposed CNN is manipulated and detected COVID-19 positive cases more accurately by avoiding fall out/false positive rates.

Besides, perceptron, KNN, GNB, NC, DT and DNN generate their results which are less than 90% but gather than 70% on average (see Figure 4b) and shows good accuracy along with other metrics (see Table 3). The characteristics of these classifiers are realistic with these COVID-19 dataset like neural network/regression based models. Like previous step, the average accuracy and sensitivity of these classifiers are represented 80.93% and the average AUC, F-measure and specificity are found as 85.70%, 80.97% and 90.46% respectively (see Figure 5a). However, the specificity of these classifiers is better than accuracy, sensitivity, AUC and F-measure in turn. Again, the average results of BNB and pre-trained CNNs such as ResNet50, VGG16, InceptionV3 are generated less than 70% and greater than 50% to investigate COVID-19 cases (see Figure 4c). The classification results of these classifiers are shown in Table 3. Due to investigate a small amount of COVID-19 cases, these advanced classifiers cannot show more accurate results like CNN and other classifiers. The average accuracy and sensitivity of these classifiers are shown 57.57% and the average AUC, F-measure and specificity are generated 68.18%, 55.65% and 78.78% respectively (see Figure 5a).

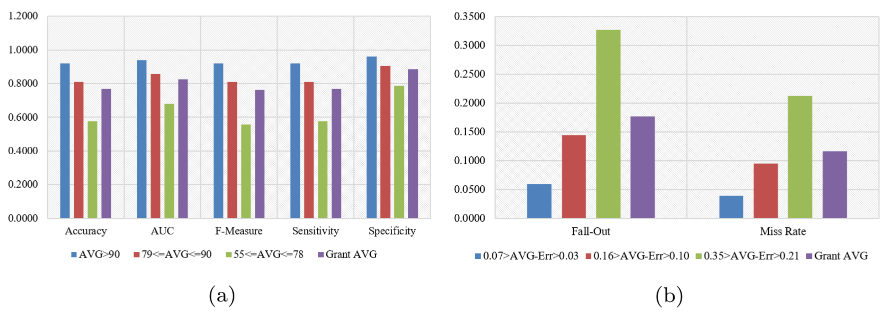

Fig. 5: Average Result of (a) Evaluation Metrics (b) Residuals.

However, this work is represented using many classifiers which can detect COVID-19 cases as well. In this work, proposed CNN model is found the best classifier to organize this task with high performance and can assist physician and policy maker to identify them quickly and take necessary steps against COVID-19.

5 Discussions

5.1 Comparison with Existing Works

In this work, several classical machine leaning and deep learning classifiers were used to investigate chest X-ray images to detect COVID-19 positive cases rapidly. Most of the classifiers were identified exploring previous works where these kinds of algorithms have been shown the best results. There were happened several works related to COVID-19 chest x-ray image analysis where some limitation has been found in previous work and those efforts has been investigated. Numerous works focused on how classifiers can identify COVID-19 positive cases frequently [25, 11, 13, 15, 2]. But, nowadays the community transmission is a great issue to prevent spread of COVID-19 among people. The growth of false negative rates can accelerate the man to man transfer of COVID-19. So, we specially focus on the results of specificity and fall rate along with other metrics. Our proposed CNN model shows better specificity (97.01%) and lower miss rate (2.98%) than existing works that can prevent community transmission of COVID-19 as well [19, 1, 3, 20, 26]. Nevertheless, some works had been implemented just splitting their dataset into training and testing approaches based on holdout method [1]. So, all of the training data were not justified as validation set in their experiment. In this work, we also justified these results using various evaluation metrics like accuracy, AUC, F-measure, sensitivity, specificity, fall out and miss rate respectively. But, there were not utilized more evaluation metrics to verify their works with existing models [25, 15, 13]. Several works had been analyzed a few number of COVID-19 samples along with other cases [11, 26, 21]. As a result, the experimental dataset was remained imbalanced and the miss rate had been increased that is responsible for community transmission of COVID-19. In this work, we balanced the target classes named normal and viral pneumonia using random under sampling techniques in view of COVID-19 samples. Some works were conducted their work with separate dataset where there were lackage of COVID-19 samples in the both of these datasets [13, 3]. But, we integrated COVID-19 samples of another related datasets and increased the value of current output in this experiment. Therefore, some works were improved their results specially their accuracy by merging non-COVID classes (e.g., class 3 to 2) [3]. It is realized that normal and viral pneumonia are hardly associated with COVID-19. In current work, we considered these conditions along with COVID-19 and analyze this conditions to justify the current situation of COVID-19 epidemic. There are also proposed many states of arts of CNNs with transfer learning that are used to analyze chest X-ray images and find good results [3, 1, 19]. When they employed their pre-trained transferred learning, it represented good results to classify COVID-19 in this analysis. Likewise, we implemented pre-trained CNN models to observe the situation of their performance. But, it was not shown better results for only 855 results. If we increased the image files of another conditions, then it raised the risk of decreasing false positive rate. Therefore, this model had been trained with various machine learning models to detect COVID-19 cases at early stages. In recent work, no one justify their work with machine learning based classifier along with deep learning [3, 21, 11]. This model can be represented the solution for small and a large number of chest X-images to detect COVID-19. If the number of COVID-19 images are found small quantity, then proposed CNN also show the best results.

5.2 Impact on Heathcare Sector in Pandemic Situation

There are not found any testing tool that is 100% accurate to detect COVID-19 cases. To identify COVID-19 cases, many techniques are implemented such as RT-PCR test, viral antigen detection in this work. But, many times these experimental processes are costly, time-consuming and required specific instructions to implement them. Sometimes sample collection is not feasible from a large amount of people rapidly. As a result, a huge amount of people remains undetected. Instead, chest-X-ray images are available to detect COVID cases as well. Community transmission is one of the important issue when someone are affected it by infectious persons. Moreover, it is not only needed to identify just positive cases but also required to detect negative cases more appropriate way. If some positive cases have been detected as negatives, they spread it out throughout his community. Physicians and healthcare workers cannot take proper steps when many patients are admitted to the hospital and this situation may also hard to handle for the policy maker. If these cases are detected at early stage, they can isolate themselves from the community and give possible treatment rapidly that reduces the transmission rate of COVID-19 among community. Therefore, we needed a suitable tool/model to detect COVID-19 positive and negative cases more feasible way. Our proposed CNN model can automatically detect positive and negative cases using chest-X-ray images more accurately. This model can be manipulated COVID-19 cases in more appropriate way (see Section 5.1). In addition, we also focused to detect COVID-19 negative cases so that community transmission can be hampered as possible. In this pandemic situation, it is not possible to gather more COVID-19 chest-X-ray images to train machine learning model. But, proposed CNN model trained with a small amount of chest-X-ray images, hence physicians and heathcare workers can use this method in feasible way rather than existing processes.

5.3 Impact on Social life and Economical condition

The pandemic situation is happened severe day by day in recent times. Different sectors such as agriculture, business, finance are hampered rapidly during this period. Many people loses their jobs and cannot manage new things due to the lock-down situation. This situation arises because this disease can transmit human to human within a very short time. Undetected COVID-19 cases can spread out this disease throughout their community rapidly. Therefore, early detection is only solution to detect COVID-19 cases and take proper steps as possible. To do this task, there are needed a cost effective tools that can identify COVID-19 cases rapidly with more appropriate way from a mass amount of people. Our proposed CNN model can detect COVID-19 positive and negative cases more effectively and make trustworthy to the people. This model can help people to detect COVID cases at early stage. By using this model, COVID-19 cases can be detected and isolated rapidly and social and economical crisis can be handle as possible by following this process.

6 Conclusion and Future Work

The study is about to identify COVID-19 by investigating chest X-ray images of patients and lessen the spread rate of this disease in an early stage. We proposed both machine learning and deep learning-based approach by investigating open source normal, viral pneumonia and COVID-19 patient's images to predict COVID-19 automatically in a short period of time. Our results show that CNN yielded the highest score with 94.01% accuracy and specificity 97.01%, while most of the deep learning methods did not represent good results like general classifiers. Our approach may be helpful in clinical practices for early detection of COVID-19 cases and prevent future community transmission.

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