Detecting COVID-19 from chest X-ray images using machine learning and deep convolutional neural networks

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Article Info

ABSTRACT

The world was affected by a novel coronavirus in December 2019 that changed human life. Several types of research have been done, substantial scientific advances have been made, and millions of dollars have been spent on bringing scholars and scientists to one platform to end this critical pandemic. Ascertaining COVID-19 diagnoses in the initial stage of the pandemic was critical, specifically for patients with no manifestations. In this case, artificial intelligence-based systems were proposed to identify the virus at an earlier phase. Thus, the present study suggests a machine vision scheme to identify COVID-19 from chest X-ray images. Three machine learning approaches, such as logistic regression (LR), decision tree (DT), and random forest (RF), were implemented with more than 95% accuracy. The deep convolutional neural network (CNN) architecture was also proposed and implemented with a 99.99% detection rate. Therefore, the present work can effectively detect COVID-19 cases in the early stages.

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1. INTRODUCTION

In December 2019, the coronavirus hit the globe as the COVID-19 variant. The COVID-19 virus was harmful to humans and severely impacted worldwide, starting from the Wuhan province of China. It is highly infectious and contagious [1], [2]. The COVID-19 was formerly recognized as the SARS-CoV-2 variant of the coronavirus family. The virus was known to spread by being in close contact with the infected person [3]. In this case, significant methods of detecting COVID-19 cases were used, such as reverse transcription-polymerase chain reaction (RT-PCR) or gene decoding for respiratory or blood samples [4]. However, scientists have developed vaccines worldwide to help the body pick a fight against the variant virus. However, no adequate medication or vaccine is still available for the COVID-19 disease that protects humans 100% against the virus [5], [6]. COVID-19 has been known to attack the lungs and tissues of the infected person, like Pneumonia [7]–[9]. The research shows that the manifestations of Pneumonia and the COVID-19 variant are highly related, including cough with phlegm or pus, fever, colds, body pains, a headache, and hardship breathing, which can be noticeable with chest X-ray or computed tomography (CT) imaging [10], [11]. However, differentiation between the cause being COVID-19 or Pneumonia bacteria/virus needs to be identified early as the chances for the COVID-19 virus to spread are severely high, which may lead to several deaths as well [12]–[14]. Thus, chest X-ray images are essential to the verdict of the earlier control used globally as a first-line analytical

mechanism [15]. The situation of the lungs can be noticed using radioscopy scans together with the various phases of infection or retrieval [16]. Radiotherapists have documented anomalies seen in the chest scans of COVID-19 patients.

In this regard, several studies have been conducted on detecting COVID-19 patients using chest X-rays and lung CT scan image data with a machine or deep learning models with some limits. For instance, Santosh [2] proposed artificial intelligence-driven tools to help identify COVID-19 outbreaks and diagnoses. Therefore, Mukherjee *et al.* [1] used a deep neural network model that collectively utilizes CT scans and chest X-ray images to interpret COVID-19 cases with a precision of 96.28%. Das *et al.* [3] reported that X-ray imaging is more affordable than CT scan methods for detecting various diseases, including COVID-19. Similarly, the study [17] used the CNN-enabled InceptionV3 model on chest X-ray images to detect COVID-19 cases with 96% accuracy. In addition, the research on COVID-19 classification has been done by Saeed and Alwawi [18] using CNN modelling and chest X-ray images with only 92.29% testing accuracy. In the study, Cahyani *et al.* [19] combined the Resnet50 and BiLSTM models in classifying COVID-19 cases using chest X-ray images with 98.48% accuracy.

Similarly, the study [20] focused on hybrid CNN and RNN modelling with chest X-ray images with 97.8% accuracy in diagnosing COVID-19 cases. The earlier studies have used similar approaches like deep or machine learning models on chest X-ray images with limited detection rates. Hamlili *et al.* [21] used Resnet-50 and transfer learning on chest X-ray images to detect COVID-19 cases and obtained 97.3% multiclass accuracy. However, the study [21] also classified Pneumonia with COVID-19 as a regular class, which could be the reason for the limited precision. Alwawi and Abood [22] have followed the histogram equalization method with CNN for COVID-19 diagnosis on chest X-ray images. However, the results achieved in [22] are limited, i.e. 92.1%, due to limited training samples. Furthermore, Masadeh *et al.* [23] applied the CNN model to the COVID-19 chest X-ray dataset and achieved 97.44% accuracy in identifying COVID-19 cases. CT scan images were also used with the CNN model to detect COVID-19 [24]. However, various activation functions were used to activate the CNN model, and the focus was on the wavelet activation function due to its high accuracy in detecting COVID-19 [24].

However, earlier studies have focused on various machine and deep learning methods with either chest X-ray or lung CT scan images for detecting COVID-19 cases. Some studies also reported using chest X-ray and CT scan images to notice COVID-19 and various other diseases with some limits. However, the earlier results were limited to advanced machine or deep learning models and chest X-ray imageries. The detection rate of machine learning models was also lower in prior investigations than in deep learning models. Moreover, earlier proposed deep learning models could have improved the accuracy of detecting COVID-19 cases. Thus, an accurate, effective, and lightweight system is needed to see the COVID-19 cases in the early stages with the highest recognition rate.

Therefore, the present study focuses on chest X-ray images and cutting-edge machine and deep learning methods to accurately determine and categorize COVID-19 patients with the highest results. In the present study, we applied three machine learning models, such as logistic regression (LR), decision tree (DT), and random forest (RF), with a deep convolutional neural network (CNN) model to distinguish COVID-19 diagnosis automatically. The machine learning methods were compared with a deep learning-based CNN model. The proposed models require simple chest X-ray scans to replace the diagnosis and have an end-to-end design. The present significant study focuses on the automatic analysis of COVID-19 by chest X-rays. The significant contributions of the present study are to develop an efficient, lightweight, and automatic system using chest X-ray and machine-deep learning-enabled models that detect COVID-19 cases at early stages. The primary objectives are: i) to use chest X-ray scans to detect normal and COVID-19 patients; ii) to renovate the raw image to extract the efficient features; iii) to develop and implement machine and deep learning models; and iv) to evaluate and validate the obtained accuracy.

The paper is divided into four sections. This section outlines the problem with a detailed literature study for finding the shortcomings in earlier studies. This section also focuses on the significant contributions and objectives of the present study. Section two proposes a clear framework for data collection, pre-processing, machine learning and deep learning-enabled model development, classification of COVID-19 cases, and its evaluations. Results are examined in section three, comparing the outcome of the present study with standard literature. The final section concludes the present study.

2. MATERIALS AND METHODS

The offered framework is displayed in Figure 1. The framework as shown in Figure 1 focuses on collection datasets, its pre-processing, dividing training and testing sets, resizing the image into appropriate sizes, offering deep learning architecture and implementing the models for classifying the normal and COVID-19 cases, calculating, validating, and evaluating the results achieved via proposed approach. The details of our proposed framework are discussed in the next section.
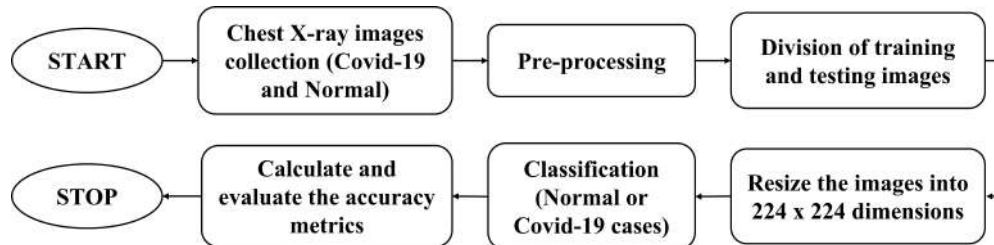
Figure 1. The workflow of the offered framework used in the present study

2.1. Dataset and its pre-processing

The X-ray image dataset utilized for this analysis is downloaded from an open-source Kaggle and GitHub repository [25]. We used 1,986 chest X-ray images for normal (1,056) and COVID-19 (930) cases. The entire image dataset has been validated and clarified, and judgements on the X-ray images are included. We employ two categories of publicly available datasets in the experimental analysis. These open-source images are of different extents, though they are not flexible. The downloaded images are of various sizes and qualities. In addition, these images had multiple orientations and were skewed and noisy. Therefore, we pre-processed the images and reformatted each image to a similar size of 224×224 pixels. The final input to the implemented techniques was a $224 \times 224 \times 3$ image, and RGB reversion was required. The sample of chest X-ray images is demonstrated in Figure 2, which contains normal cases as shown in Figures 2(a) and 2(b) and COVID-19 cases as shown in Figures 2(c) and 2(d), respectively.
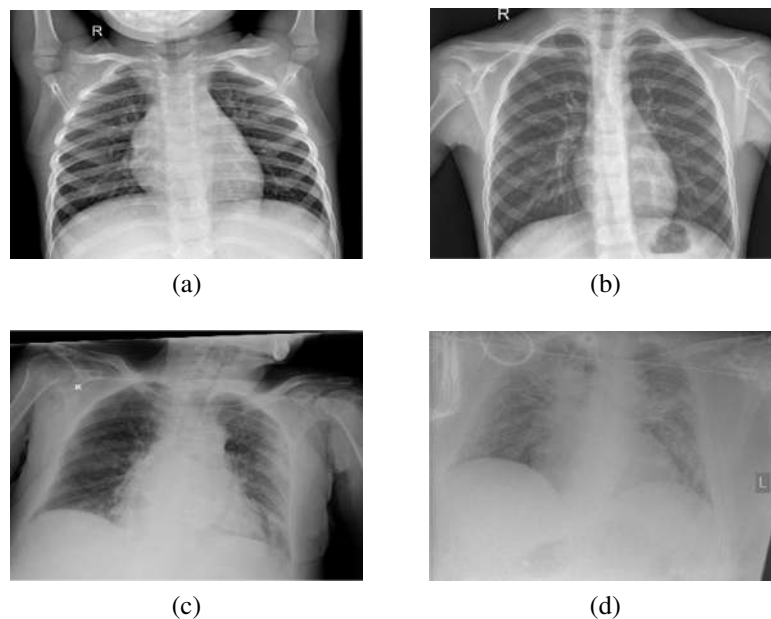

(a)

(b)

(c)

(d)

Figure 2. Samples of (a) normal, (b) normal, (c) COVID-19 images, (d) COVID-19 images

2.2. Proposed implemented models
2.2.1. Convolutional neural network

A deep learning-based CNN approach is used in the present research to determine the relevance of various image components. CNN has recognized COVID-19 patients in X-ray scans using multiple layers in our instance. These different layers derive essential elements from the provided input data, which are later given to the classification phase. We used three main steps in CNN: convolution, pooling, and dense (output) layers. However, the convolution and pooling layers are multiple and are arranged in various ways. Different features were detected from input data using several kernels [10]–[13] in the convolution layer. In the present study, three convolution and pooling layers were operated. The convolution layers were 32, 64, and 128, with a 3×3 filter size. We have used the rectified linear unit (ReLU) activation function in the convolution layers. The pooling window size was 2×2 with a max pooling function as shown in Figure 3. The outcome of the dropout layer was passed via two dense layers, including the ReLU activation function. The outcome layer consists of two-dimensional layers with SoftMax activation function. The implemented CNN model with its layers is depicted in Figure 3.
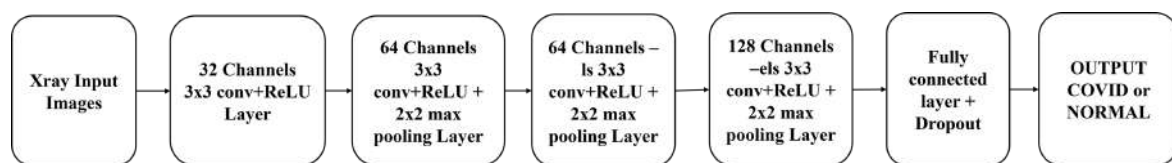

Figure 3. The proposed convolutional neural network architecture

2.2.2. Logistic regression

The statistical LR method is used for binary classification, which aims to indicate the probability that an input belongs to a particular class. The process is based on a logistic function, which transforms a linear combination of input features into a value between 0 and 1, representing the likelihood of the input related to a specific type. In LR, the input elements are multiplied by their related weights, and the resultant values are summed to construct a linear predictor. This predictor is given via the logistic function to create the calculation. The sigmoid function having an S-shaped curve is used in the LR method. This function calculates any real-time digit to a likelihood value between 0 and 1 [26]. Notably, the sigmoid function is defined using (1).

$$\sigma(z) \quad = \quad 1 + e\text{-}_z 1 \tag{1}$$

where z provides the linear predictor, and $\sigma(z)$ gives the predicted probability.

Our study uses an X-ray dataset with regular and COVID-19 labelled samples and optimizes the model's weights to reduce the discrepancy between the expected likelihoods and the actual class. This is usually done via maximum likelihood computation, which concerns discovering the weights that maximize the probability of the experimental cases provided by the input elements [26]. This analysis used the LR model to discriminate between the standard and COVID-19 patients.

2.2.3. Decision tree classifier

The DT is a supervised method used in the present study for classification that deals with multiple rules. This widespread machine-learning technique builds a tree-like model of decisions and their probable consequences based on the training data. The tree consists of nodes describing a decision or a component, branches defining possible results, and leaves illustrating the output or the class label [27].

2.2.4. Random forest classifier

The RF is the most well-known supervised machine learning method. The RF is made on "learning together", which combines several variables to determine a complex case and improve a model's performance. That means a RF is, as the name implies, "a subset that contains several DTs in the different subsets of a given database and carries actions to enhance the accuracy of that database". High accuracy can be acquired, and congestion is avoided in forests with many trees [28].

2.3. Accuracy assessments

The correctness of the models was assessed through a 10-fold cross-validation method with evaluation methods like correctness, precision, recall (sensitivity), and F1 score via (2) to (5) [1].

$$Accuracy \quad = \quad \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision \quad = \quad \frac{TP}{TP + FP} \tag{3}$$

$$Recall(Sensitivity) \quad = \quad \frac{TP}{TP + FN} \tag{4}$$

$$F1 - Sccore \quad = \quad 2 * \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

Where TP, FP, TN, and FN state to a true positive, false positive, true negative, and false negative, correspondingly [1]. The class-specific results were best for RF and CNN models compared to LR and DTs.

3. RESULTS AND DISCUSSION

In the current research, we used LR [26], DTs [27], RFs [28], and deep CNN [10], [11] for detecting COVID-19 via X-ray images. The experimentations were executed using Python programming language on the Google Collaboratory platform through a GPU processor. The COVID-19 and normal images were trained and tested with 1,612 and 374 images, respectively. However, among 374 tested X-ray scans, 140 were of COVID-19 patients, and the remaining 234 were of normal patients. The nearest neighbour interpolation method [29] was used to resize the dimensions of chest X-ray images with $224 \times 224 \times 3$. Subsequently, these processed images were given as input to the models. The best hyperparameters for the LR method were 'C' -0.0001 and 'penalty' 12.

Similarly, the best hyperparameters for the DT were full leaf nodes and minimum sample spilt with five and two, respectively. In contrast, the best parameters for the RF methods were maximum depth (five), maximum features (auto), estimators (500) and Gini criterion. The best hyperparameters were chosen for each model through the grid search method and the ten-fold cross-validation method on the trained images. In the case of CNN, the DenseNet-169 architecture was used with 46 epochs and 32 batch sizes. The resized images were provided to the Dense Net architecture. Thus, the model automatically learned the features through the input chest X-ray images. The model utilized 5,668,097 parameters for training purposes with 46 epochs. The ten-fold cross-validation method [1], [29] was also operated to evaluate and produce more accurate and realistic results. Lastly, the models were tested using the test images, confusion matrices as shown in Figures 4 and 5 were generated, and the results for all methods were validated. Figures 4(a) and 4(b) illustrate the confusion matrices derived using LR and DT models, respectively. Figures 5(a) and 5(b) depict the confusion matrices generated using the RF and CNN models. The overall accuracy was 81%, 82%, 86%, and 99% for the DT, LR, RF, and CNN, respectively.

The performance scores for all evaluation methods shown in Figures 6 and 7 for COVID-19 and regular patients were computed. The experiment outcomes indicate that the accuracy was 99.99%, 98.28%, and 97.16% for both classes using CNN and RF methods, respectively. The DT and LR methods have produced 94.28% and 72.85% accuracy for the COVID-19 class. In contrast, 93.5% and 79.05% accuracy was achieved for the normal course with the DT and LR methods, respectively. The average precision for the CNN and the RF was 99% and 98% for both classes. However, the LR method produced an average 83% precision score, which is also satisfactory. We obtained the highest recall and F1 score as shown in Figures 6 and 7 for CNN (99%), RF (98%), and DT (95%). The results demonstrate that the chest X-ray images are appropriately classified and predicted as COVID-19 and regular patients.
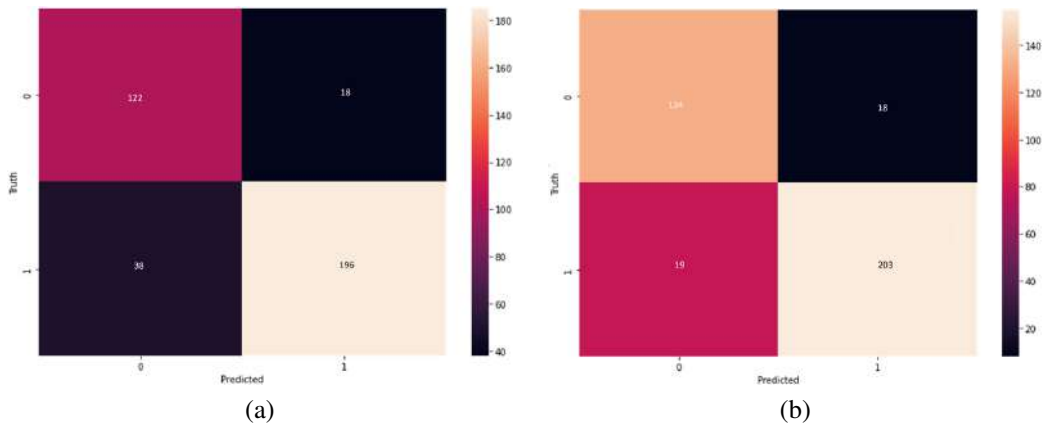
Figure 4. Confusion matrix generated using (a) logistic regression and (b) decision tree
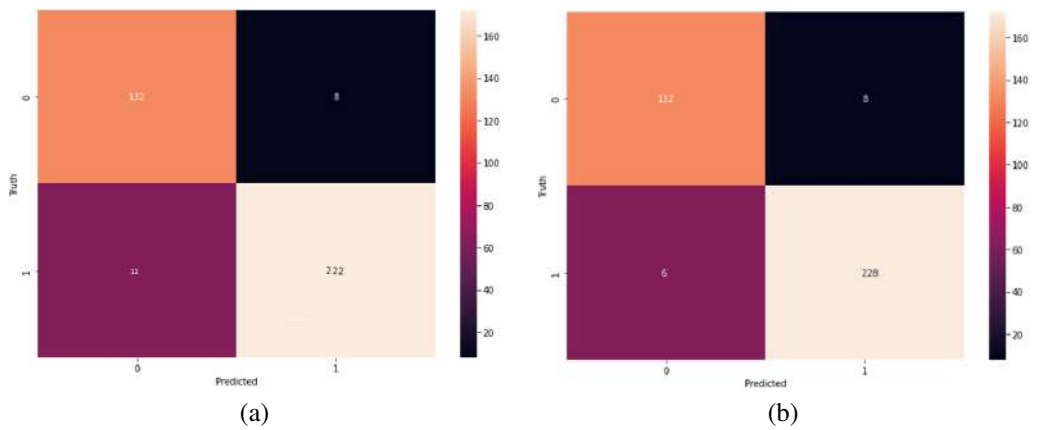

Figure 5. Confusion matrix generated using (a) random forest and (b) CNN
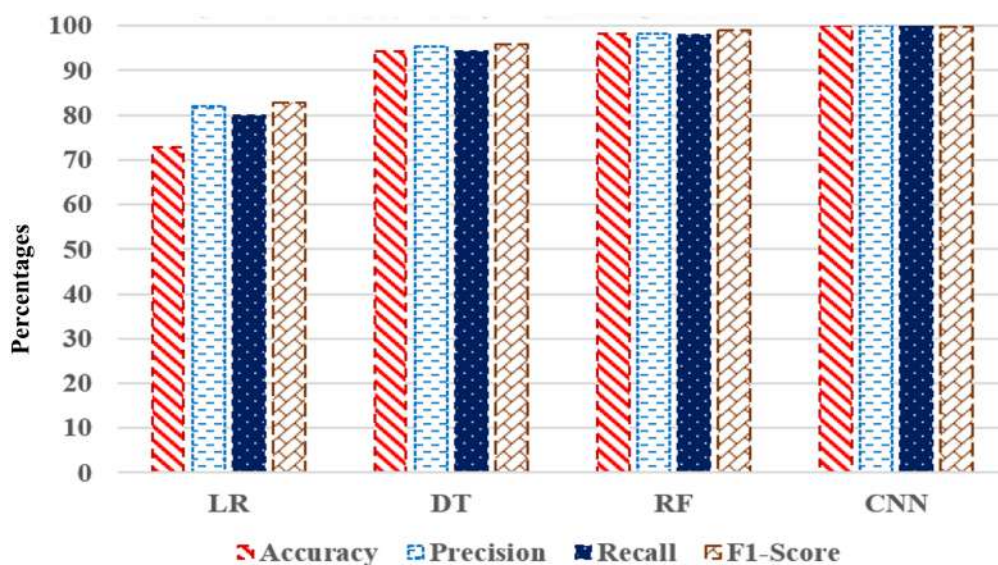

Figure 6. Performance metrics for LR, decision tree, random forest, and CNN methods for COVID-19 class
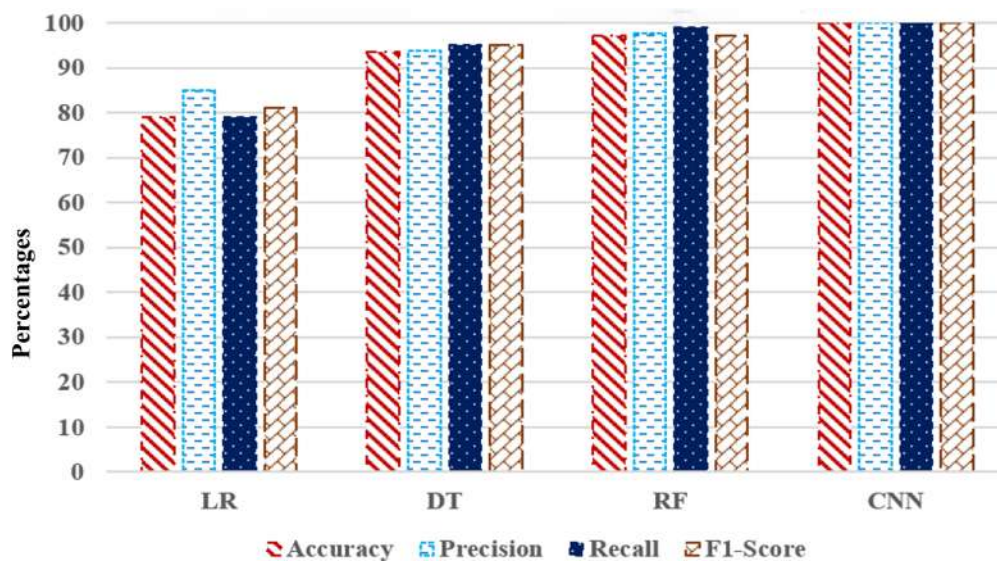
Figure 7. Performance metrics for LR, decision tree, random forest, and CNN methods for normal class

3.1. Comparison of results

The outcomes obtained via the proposed techniques are compared with the earlier research to show the novelty of the present study. Several researchers used machine and deep learning approaches to detect COVID-19 cases with some limited accuracy. Table 1 compares the outcomes of the current studies with those of earlier studies. Earlier studies have primarily used machine and deep learning algorithms on chest X-ray datasets to diagnose COVID-19. However, there are still several challenges in detecting COVID-19 cases in early research, and the results could be better. Thus, the proposed study used a freely available dataset and achieved the highest accuracy using LR, DT, RF and deep CNNs. The results of the present study are pretty promising compared to the earlier reported results. For instance, the accuracies in previous studies [17]–[23] are lesser than the present study using the deep learning-enabled models on chest x-ray images. In addition, the results achieved using deep neural network, DenseNet-169 architecture, and VGG-19 in studies [1], [29], [30] have provided 96.28%, 96.37%, and 93.48% accuracies, respectively. Some studies [31] used deep and machine learning methods with 95.38% accuracy. In our case, we focused on three machines and the CNN method with more than 99% accuracy, which is better than earlier studies [1], [17]–[23], [29]–[33]. It was noticed from the earlier research that chest X-ray images are the key datasets in detecting COVID-19 cases with other diseases like Pneumonia. In addition, some studies revealed the use of non-freely available CT scan images with a limited success rate. Therefore, the present research is more accurate, effective, and significant than the previous studies using the freely available chest X-ray dataset and proposed models.

Table 1. Comparative results on chest X-ray by machine and deep learning algorithms

Images	Classification models	Accuracy (%)	References
Chest X-ray and CT scan	Deep neural network	96.28	[1]
Chest X-ray	InceptionV3	96	[17]
Chest X-ray	CNN	92.29	[18]
Chest X-ray	Resnet50 and BiLSTM	98.48	[19]
Chest X-ray	CNN and RNN	97.80	[20]
Chest X-ray	Resnet-50 and transfer learning	97.30	[21]
Chest X-ray	CNN	92.10	[22]
Chest X-ray	CNN	97.44	[23]
Chest X-Ray	DenseNet-169	96.37	[29]
Chest X-ray	VGG-19	93.48	[30]
Chest X-ray	ResNet-50 + SVM	95.38	[31]
Chest X-ray	COVID-Net	92.40	[32]
Chest X-ray	ResNet-50	98	[33]
Chest X-ray	**LR, DT, RF, and CNN**	**99.99**	**This study**

4. CONCLUSION

In the present paper, we implemented a methodology using machine and deep learning models to detect COVID-19 and regular patients through chest X-ray images. The raw chest X-ray images were pre-processed through the nearest neighbour interpolation method and then given training and testing to the models. We used LR, DTs, and RF models with satisfactory performances. However, the deep CNN model has provided the best accuracy, i.e., 99.99%. It is concluded that the proposed lightweight CNN-based DenseNet-169 model has achieved the highest detection rate in detecting COVID-19-positive and regular patients. Further, we obtained coherent results using machine learning models to identify and classify COVID-19 cases. The experimental results were confirmed and validated through accuracy, precision, recall and F1 score. In the future, we will use more datasets with explainable artificial intelligence-enabled models to detect COVID-19 cases early with 100% accuracy. The present work has several limitations, such as a limited dataset, imbalanced data, lack of interpretability, generalization of data, and ethical concerns of AI. Addressing these limitations requires dataset curation, healthcare expert feedback and validation of different datasets.

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