Biomedical Signal Processing and Control 69 (2021) 102920

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

X-ray and CT-scan-based automated detection and classification of covid-19 using convolutional neural networks (CNN)

Samritika Thakur *, Aman Kumar

Department of Electronics and Communication, National Institute of Technology, Hamirpur, India

ARTICLE INFO

Keywords:
Deep learning
CNN
Accuracy
Recall
Precision
ROC

ABSTRACT

Covid-19 (Coronavirus Disease-2019) is the most recent coronavirus-related disease that has been announced as a pandemic by the World Health Organization (WHO). Furthermore, it has brought the whole planet to a halt as a result of the worldwide introduction of lockdown and killed millions of people. While this virus has a low fatality rate, the problem is that it is highly infectious, and as a result, it has infected a large number of people, putting a strain on the healthcare system, hence, Covid-19 identification in patients has become critical. The goal of this research is to use X-rays images and computed tomography (CT) images to introduce a deep learning strategy based on the Convolutional Neural Network (CNN) to automatically detect and identify the Covid-19 disease. We have implemented two different classifications using CNN, i.e., binary and multiclass classification. A total of 3,877 images dataset of CT and X-ray images has been utilised to train the model in binary classification, out of which the 1,917 images are of Covid-19 infected individuals . An overall accuracy of 99.64%, recall (or sensitivity) of 99.58%, the precision of 99.56%, F1-score of 99.59%, and ROC of 100% has been observed for the binary classification. For multiple classifications, the model has been trained using a total of 6,077 images, out of which 1,917 images are of Covid-19 infected people, 1,960 images are of normal healthy people, and 2,200 images are of pneumonia infected people. An accuracy of 98.28%, recall (or sensitivity) of 98.25%, the precision of 98.22%, F1-score of 98.23%, and ROC of 99.87% has been achieved for the multiclass classification using the proposed method. On the currently available dataset, the our proposed model produced the desired results, and it can assist healthcare workers in quickly detecting Covid-19 positive patients.

1. Introduction

Coronaviruses are a family of viruses that can infect both animals and humans. These viruses are surrounded by protein spikes which gives it an illusion of a crown and crown in Latin means “corona” [1]. Hence, these viruses are named Coronaviruses. It can cause common colds, flu, fever, and other illnesses in humans, as well as more severe diseases like SARS-Cov (Severe Acute Respiratory Syndrome-Coronavirus) and MERS (Middle East Respiratory Syndrome) [2]. MERS was discovered in Saudi Arabia in 2012, and SARS-Cov was first found in China in 2003. Corona virus outbreak-2019 is the current coronavirus-caused disease. In December 2019, health institutions of Wuhan city in the Hubei province of China reported several unknown pneumonia cases [3]. Institutions in China confirmed on January 7, 2020, that the viral pneumonia cases were caused by a novel coronavirus, which then spread around the world. The outbreak was classified as a pandemic on March 11, 2020 by World Health Organisation(WHO) [4,5]. Up till now the SARS-Cov-2 has globally infected 16,18,46,189 people and caused 33,59,004 deaths. Behind heart disease and cancer, the age-adjusted death rate rose by 15.9% in 2020, making Covid-19 the third leading cause of death in the U.S and not only that, in just eight weeks, the new Covid-19 epidemic has become India’s second-principal cause of mortality, claiming the lives of 2,600 people a day, or 18,271 per week. Covid-19 has spread all over the world, killing a plenty of people. The confirmed cases have been continuously escalating, however the real magnitude of the initial outbreak in 2020 is not known because the testing was normally not available at that time [6].

In 2019, the most prevalent method for assessing coronavirus disease is real-time reverse transcription-polymerase chain reaction (RT-PCR), however it is insensitive and can occasionally result in false negatives. Due to which detecting Covid-19 in the early stage becomes difficult. Also, as this disease is highly contagious, it has overburdened the healthcare systems all over the world. Hence, radiological imaging of patients can be very helpful in examining the patients. Radiological

* Corresponding author.
E-mail addresses: 19m437@nith.ac.in (S. Thakur), akumar@nith.ac.in (A. Kumar).

https://doi.org/10.1016/j.bspc.2021.102920
Received 26 March 2021; Received in revised form 20 June 2021; Accepted 24 June 2021
Available online 30 June 2021

imaging of the chest, such as CT and X-ray, is important in the early identification and cure of Covid-19 [7]. The most common findings in X-rays are ground glass opacities, strides or lines etc, and the most common findings in CTs are ground glass opacities, solid white consolidations, crazy paving patterns etc [8,9]. These image findings in combination with laboratory examinations can be very helpful in detecting Covid-19 [10].

The use of Artificial Intelligence (AI) is growing rapidly. It is already used in cybersecurity, manufacturing, education, and logistics. Now, it is also being used in the healthcare sector for the prediction, detection, and classification of diseases with the help of radiological imaging. The significant trend of AI in medical and healthcare is using deep learning. Radiologists and scientists are concentrating on deep learning techniques to discover imaging characteristics from CTs and X-rays of the disease. Deep learning has transformed automated disease detection and management by correctly examining, recognizing, categorizing patterns in medical images [11].

Detection and classification of Covid-19 can be achieved with either by **manual detection** or by **automatic detection**. Manual detection majorly includes taking RT-PCR, isothermal amplification test, rapid serological test, etc. but the problem with manual detection is.

- Sparse availability of testing kits.
- It is a costly detection method, i.e., not everyone can afford it.
- Most of the manual detection tests take about 5–6 hours to generate the results and those which give results within minutes are not reliable as they are insensitive and sometimes can yield false negatives.
- The most important thing to remember is that Covid-19 is extremely infectious and can infect healthcare workers while manually diagnosing the patients. The lives of healthcare workers are also in jeopardy, and the system is overburdened [12].

It's now clear that the Covid-19 outbreak has placed a strain on our already stretched healthcare services and there is an exponential growth in the number of infected people around the world. The articles discussed in Section 2 provides sound advice on how to use AI and technology to combat the pandemic. The objectives of this research are:

- To accurately detect and classify Covid-19 disease from normal (healthy) and pneumonia patients.
- For checking the generalizability of the method, developing a larger dataset which includes both X-rays and CTs.
- To achieve a higher value of performance measures for both binary as well as multiclass problems.
- To calculate all the performance measures and compare the different parameters of the proposed technique to those of current techniques.

2. Literature survey

The need for automated identification of Covid-19 is urgent, and it can be accomplished using AI-based solutions. The accomplishments of deep learning based techniques in automated detection of the disease in the healthcare sector and quick enhancement in the Covid-19 cases have demanded the need for deep learning-based detection systems. Recently, many scientists have utilized images for the diagnosis of Covid-19 [13].

In [14], Narin et al. utilized transfer learning to consolidate three binary classification with four classes. This investigation looked at five pre-trained convolutional neural networks based models (InceptionV3, ResNet50, ResNet152, Inception-ResNetV2, and ResNet101) for distinguishing Covid-19 and pneumonia tainted patients utilizing chest X-ray radiographs. Among the five models tested, the pre-trained Resnet-50 model delivers the best classification results.

Maghdid et al. built a simple ConvNet and tweaked an AlexNet model that had already been trained using a dataset that included both X-rays and CTs, the authors utilised both deep learning and transfer learning techniques. This study indicated that using transfer learning, the used model can provide accuracy of up to 98% and 94.1% using the modified CNN [15].

Apostolopoulos et al., used two datasets on transfer learning, one containing 224 images of Covid-19 and another contaning 224 images of Covid-19 disease. The best specificity, accuracy, and sensitivity scores obtained were 96.46%, 98.66%, and 96.78%, respectively [16]. Ozturk et al. recommended a binary (Covid-19 vs. no-disease) and multi-classification (Covid-19 vs. No-Disease vs. Pneumonia) model. DarkCovidNet is the name of the model, and it gave a classification accuracy of 98.8% for binary classes and 87.2% for multi-class categories [17]. Panwar et al. used the transfer learning method of nCOVnet and VGG16 was used to detect patients of Covid-19 using X-ray [18]. Vaid et al. suggested a method with a 96.3% accuracy based on transfer learning and patient's chest X-rays [19].

In [20], Majeed et al. proposed simple 4 layer CNN, which was compared to 12 pretrained CNNs for classification and detection of Covid-19 (Vgg19, ResNet101, GoogleNet, InceptionResNetV2, ResNet50, SqueezeNet, Vgg16, Densenet201, Xception, ResNet18, Alexnet, InceptionV3). The authors justified the results with the help of CAM (Class Activation Mapping). This paper was based on binary classification and multiclass classification having 4 categories – normal or no-infection, Covid-19, viral pneumonia, and bacterial pneumonia. For the first type of classification (normal vs Covid-19) their model achieved a sensitivity of 93.15% and specificity of 97.86%, for the second type of classification (Normal vs Covid-19 vs Viral) their model achieved a sensitivity of 91.78% and 99.05% (for Covid-19 cases only) and for the third classification (Covid-19 vs Viral vs Bacterial pneumonia), the model gave a sensitivity of 94.52% and specificity of 99.35% (for Covid-19 cases only).

In [21], Shibly et al. developed a VGG-16 Network based Faster Region Framework for the diagnosis of Covid-19 with the aid of X-ray images from Convolutional Neural Networks (Faster R-CNN). The authors produced a personalised data set that included 5,450 images from 2,500 patients. The data was used for training and evaluation. In order to create the custom experiment dataset, the authors fuse and update two publicly available data sets. The authors performed a binary classification with 97.36% accuracy, 97.65% sensitivity and 99.28% accuracy.

In [22], CoroNet is a model of the Deep Convolutional Neural Network introduced by Khan et al. to detect infection in the chest by X-ray imagery automatically. The model proposed is centred on the Xception architecture pretrained with the ImageNet data set before finally being trained on a Covid-19 dataset and additional chest-pneumonia X-ray images of two publicly available sources. According to the experimental data, the suggested model has an overall recall rate of 93% for Covid-19 cases and accuracy of 89.6%, and a rate of 98.2% for 4-class instances. The categories for classification are Covid-19, pneumonia(viral and bacterial) and normal patients.

In [23], Hassantabar et al. created two disease diagnosis algorithms: deep neural network (DNN) methods based on image fractal features and CNN methods based on lung X-rays. In this study, the authors used a database of computed tomography images. The images were divided into two categories: Covid-19 patients and non-Covid-19 patients or images of ordinary people. With higher sensitivity (96.1%) and accuracy (93.2%), the presented CNN architecture outperforms the DNN process, which has an accuracy of 83.4% and sensitivity of 86%.

In [24], a deep learning methodology based on a mix of a CNN and long short-term memory(LSTM) was created by Islam et al. to automatically categorise Covid-19. In this technique, CNN is utilised to extract deep features, while LSTM is utilised to detect the extracted features. The Long Short Term Memory (LSTN) is a feedback-connected artificial recurrent neural network with memory. In this paper, the classification and detection performances of CNN and CNN-LSTN were also compared. With an accuracy of 99.4%, an F1-score of 98.9%, precision of 99.2%, an AUC of 99.9%, and sensitivity of 99.3%, CNN-LSTN produced the best results.

In [25], Kumar et al. used chest X-ray to classify individuals infected with Covid-19 by deep learning. For feature extraction, the system used nine pre-trained models and for classification SVM was used. A total of 158 X-ray images of patients without Covid-19 and Covid-19 were included in the two datasets. With 95.52% F1-score and 95.38% accuracy, the combined ResNet-50 and SVM model outperformed other models.

Hemdan et al. developed a deep learning algorithm for detecting Covid-19 in X-ray pictures. Seven pre-trained models and 50 X-ray images were employed in the framework. VGG-19 and DenseNet-201 were the most accurate and precise of the classifiers tested, with 90% accuracy and 83% precision [26].

Wang et al. [27] created Covid-Net, an open-source deep neural network specifically designed for Covid-19 patient detection with a binary classification accuracy of 92.4% (Covid-19 vs Non-Covid).

Most of the studies discussed perform binary classification and multiclass classification based on either X-rays or CTs but not both. Also, the dataset used does not contain enough images of Covid-19 positive patients and the performance of the methods discussed is high for binary classification but not for multiclass problems. The suggested model's architecture is depicted in Fig. 2. It may not be a substitute for existing detection methods, but it will assist doctors in better identifying and understanding the disease in this time of need, as it is a new disease about which we know very little. The followings are the key contribution of our study:

- We created a dataset of 11,095 images, including 6,354 CT scans and 4,741 X-ray images of Covid-19, pneumonia, and healthy people.
- To classify the X-ray and CT-scan images of healthy persons, pneumonia patients, and COVID-19 patients, the suggested method contain a two-class and a three-class problem. The two-class problem involves distinguishing Covid-19 patients from normal or healthy people, while the three-class problem involves distinguishing Covid-19 patients from healthy people and pneumonia patients.
- We tested the models to see how well our model performed in terms of accuracy, precision, sensitivity, F1-score, and AUC/ROC.
- Finally, we conduct a comparison of the results obtained with our techniques and existing methods.

3. Material and methods

3.1. Proposed method

For binary and multiclass classification, we have created two convolutional neural networks. For Covid-19 and normal or healthy people, binary classification has been used. Covid-19, pneumonia, and normal or healthy individuals are the three classes that have been multi classified.

The proposed approach is broken into three primary sections:

- **Collection of Dataset and Preprocessing:** During this stage, photos of Covid-19 positive individuals, pneumonia patients, and normal or disease-free patients have been collected. The photos comprise both CT and X-rays of all the categories, allowing for the creation of a huge dataset. Detailed information about the dataset is given in Section 3.2. After collection of Datasets, preprocessing of images has been done. Pre-processing has been performed because:
  1. Medical images have letters, symbols made on them.
  2. The images are taken from different online sources due to which their sizes may vary from source to source.
  3. Medical images usually include noises like salt and pepper which hamper the quality of the image.
- **Development of CNN:** Using CT and X-rays together, two CNNs for binary and multiclass classification have been developed to reliably identify and categorise Covid-19. We have used the data prepared in the previous stage to train these models (both binary and multiclass) so that they could recognise the patterns involved. The CNN models have been created using Python and the Keras package in conjunction with TensorFlow2 on the Kaggle notebook, which offers free NVIDIA TESLA P100 GPUs [28]. Because our device lacked the power to train and test such a large number of photos, all of the model testing and training has been performed online. Both models have been implemented in Keras and Tensorflow using SGD (Stochastic Gradient Descent) optimizer having a learning rate of 0.02, epoch value of 200 for binary classification model and 300 for a multiclass model with a batch size of 10. Detailed information about development of CNN is given in Section 3.3

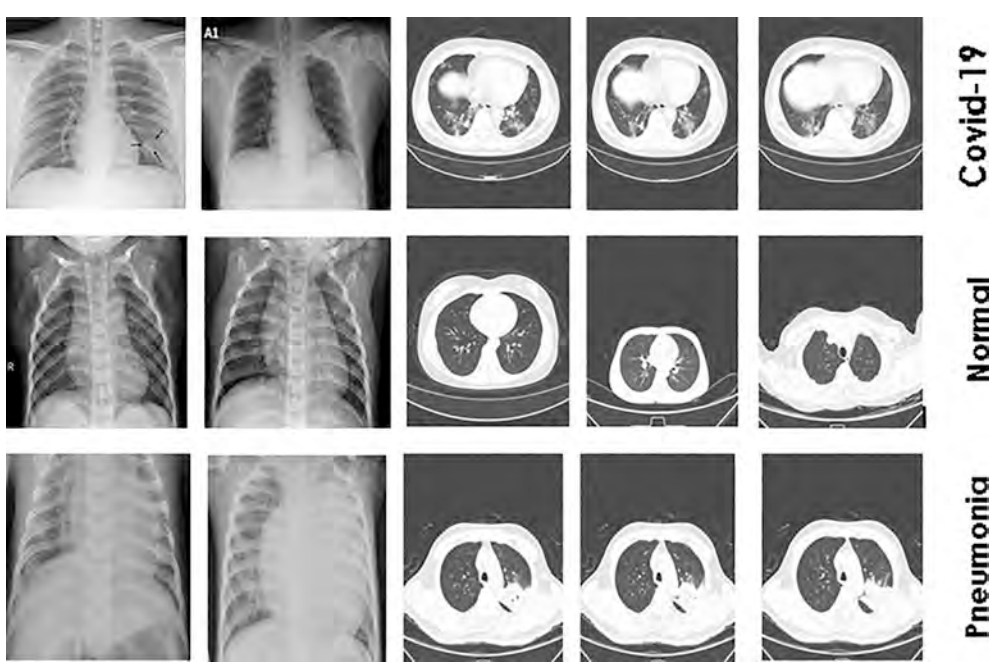

Fig. 1. Images of Covid-19, Normal, Pneumonia Parients.

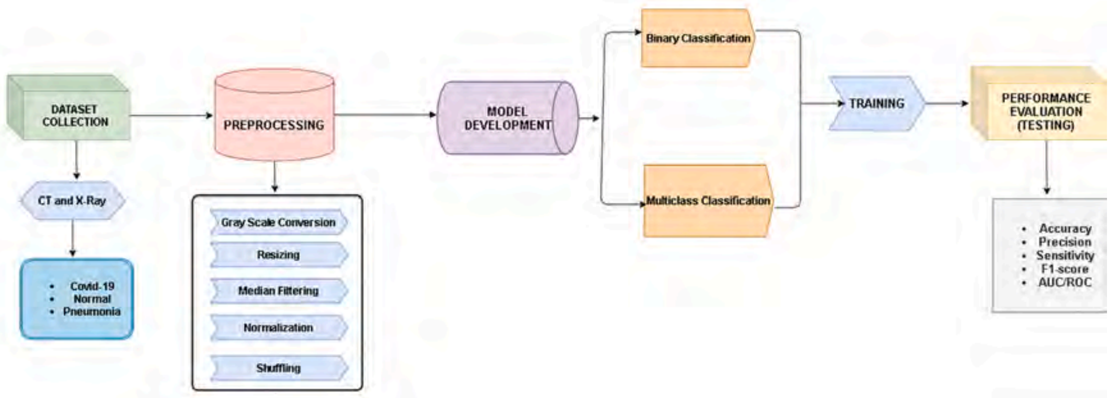

Fig. 2. Architecture of Proposed Model.

- **Calculation of Performance Measures:** A full experimental study of accuracy, sensitivity, precision, F1 score and AUC/ROC has been presented in order to test the performance of the proposed system. As shown in Fig. 3, testing results have been presented using a confusion matrix. A Confusion matrix is a type of comparison table which compares the actual results and the results predicted by the CNN models. The performance measures calculated are accuracy, precision, recall(or sensitivity), specificity, F1-score, and ROC or AUC. The performance measures are defined in Eqs. (1)–(4) as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

where
TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative.

The results of the testing of both CNNs have been shown in Section 4.1. Also, the results of the proposed method have been compared with the existing methods in Table 3.

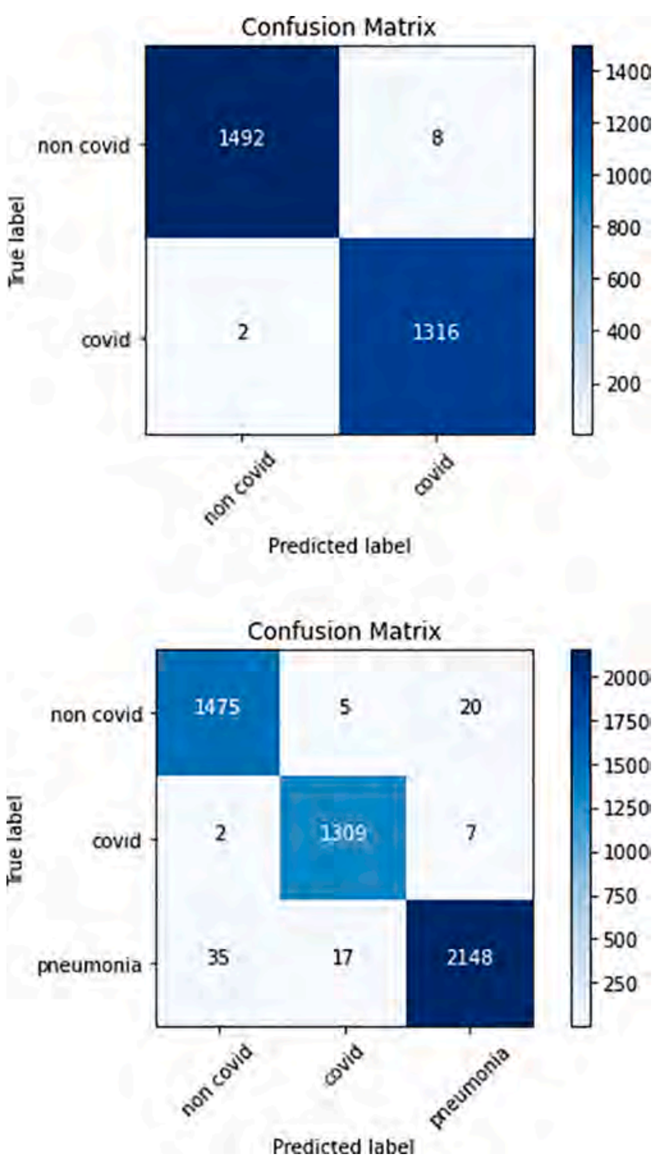

Fig. 3. Confusion Matrixs of a) Binary Classification b) Multiclass Classification.

3.2. Datasets

The occurrence of Covid-19 is very recent, due to this the labeled data on Covid-19 is not readily available. Hence, we have to count on variable online sources of images of normal, pneumonia, and Coronavirus Disease-2019. The dataset, which is a mixture of numerous datasets, has been downloaded from Kaggle. The dataset contain X-ray and CT images of all the three classes [29–32]. Kaggle is an online community of data scientists [28]. We have a dataset of 11,095 images taken from Kaggle. The dataset is split into two sections: training and testing. Out of a total of 11,095 pictures, 6,077 have been used for training and 5,018 have been used to test the models. A total of 3,877 image datasets from CTs and X-rays were utilised to train the model in binary classification, with 1,917 images from Covid-19 infected individuals among them. For multiple classifications, the model has been trained using a total of 6,077 images, with 1,917 images of Covid-19 infected people, 1,960 images of normal healthy people, and 2,200 images of pneumonia infected people. For binary classification 2,818 (Covid-19 v/s normal) images and for multiclass classification all the 5,018 (Covid-19 v/s normal v/s pneumonia) images have been used for testing purpose. This dataset can be used in further studies and can also help in enabling more coherent detection of Covid-19 patients. Table 1 shows the division of X-ray and CT images into each category. Fig. 1 depicts the visualization of X-ray and CT images for each category.

3.3. Development of CNN

Deep learning is an area of machine learning which reproduce the operation of the human mind for processing facts in fields together with speech identification, herbal language processing, audio identification, social community filtering, system translation, bioinformatics, computer vision, clinical photo analysis, cloth inspection and lots of more [11]. CNN is the most established deep learning algorithm, with excellent potential in a variety of applications such as image categorization, object recognition, and medical image examination. CNNs are used to process large amounts of data. After all, they do not require manual feature extraction or segmentation because they learn on their own from the data they are fed [33,34]. CNN's architecture is split into two sections: feature learning and classification. CNNs are made up of three layers: a convolution layer, a pooling layer, and a fully connected layer. Convolution and pooling layers are used to extract features, and fully connected layers are used to classify them [35]. To detect Covid-19 we have developed two CNNs, each for binary and multiclass classification.

Input Layer: It is the initial layer and is responsible to read the image dataset. The X-ray and CT scan images are first represented in matrix form, and then a pre-processing step is applied. The images are firstly converted to grayscale and then resized to 224-by-224. A median filter is also applied to the dataset to keep salt and pepper noise in check. Before feeding into the next layer the images are normalized as well and data shuffling is also done in the training process.

Convolution Layer: It is the most significant layer of CNN because it is utilised for feature extraction from images as well as learning features for image categorization. **Filters (also known as kernels)** are used to extract characteristics from a matrix of values (called weights). To detect the features, a convolution operation is carried out between the filter and the image. For an input matrix f (image) and filter k, the two-dimensional discrete convolution operation is given in Eq. (5) as:

$$F(i,j) = (f * k)(i,j) = \sum_{m}\sum_{n} k(m,n) f(i-m, j-n) \tag{5}$$

When a feature is found in a specific part of an image, the value of the convolution operation performed on that part of the image is greater. When the feature is absent, the convolution produced is minimal [36]. In this study, three convolution layers having 64, 32, 16 filters respectively are used for binary classification and four convolution layers having 16, 32, 64, 128 filters respectively are used for multiple classification. Both classifications have used a filter size of 3*3. This layer is mainly used for the generation of feature maps.

Leaky ReLU: Each layer's output is fed into the non-linear Activation function. It's done to add non-linearity to the equation. A variety of nonlinear functions, such as sigmoid, Rectified linear unit(ReLU), hyperbolic tangent (tanh) function, and others, can be used as activation functions, but we chose Leaky ReLU as the best fit for our model. The equation of Leaky ReLU is given in Eq. (6) as:

$$\begin{aligned} f(x) &= 0.01x \quad for\ x < 0 \\ x & \quad\quad\quad for\ x \geqslant 0 \end{aligned} \tag{6}$$

Pooling Layer: The next layer is Pooling. The motive of this layer is to minimize the size of the feature maps that are created. Spatial pooling, down-sampling, and sub-sampling are other terms for it. It comes in a variety of forms, including average pooling, maximum pooling, and sum pooling. We used max-pooling in this study, which results in the output being the largest element of the feature map.

Fully Connected Layer: This layer is responsible for the classification part. The features generated in the feature extraction process have to be converted into a one-dimensional vector before feeding it to the fully connected layer. This layer is made up of several neurons or nodes, and each neuron in one layer is connected to every other neuron in the following layer. Each fully connected layer has a non-linear activation function such as ReLU, leaky ReLU, and so on. The classifier used for binary classification is sigmoid and for multiple classification softmax is used. The mathematical expressions for sigmoid and softmax classifier are given in Eq. 7 and Eq. 8 respectively as:

$$Sigmoid(x) = \frac{1}{1+e^{-x}} \tag{7}$$

$$Softmax(x_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_i}} \tag{8}$$

CNNs are created by putting all of the layers discussed above together. We also used a dropout layer, which is used to avoid overfitting and divergence.

4. Results and discussions

4.1. Results

A confusion matrix is used to display the results of both classifications. The confusion matrix is used to generate all of the performance metrics. Our binary classification model could not recognize 10 out of 2,818 images, according to the confusion matrix in Fig. 3(a). Eight of the ten misclassified photos were non-Covid, whereas the other two were of Covid-19 positive patients. This demonstrates that our approach is able to accurately identify Covid-19 patients, resulting in high true positive and true negative rates. Our model misclassified 86 images out of 5018 for multiclass classification as shown in Fig. 3(b). The proportion of negative instances wrongly classified as positive cases in the data is referred to as "fall-out" (i.e the likelihood of false alarms being raised). For two class problem it is 0.533% and for three class problem we have achieved an average of 0.86% which is less than 1%. Our binary classification model performed better in case of false-positive rate as compared to three class problem.

Covid-19 is represented by 9 of the 86 shown in Fig. 3(b). Our multiclass model is unable to correctly identify the pneumonia photos. This demonstrates that the binary classification model outperformed the multiclass approach. The ROC curve for a binary classification model is shown in Fig. 4(a). For binary classification, the ROC is 100%. It's a graph that shows how the true positive rate (TPR) and the false positive rate (FPR) are related. This demonstrates that the binary classification model correctly distinguished between positive and negative class points. Fig. 4(b) shows the ROC for multiclass model. The ROC for multiclass model is 99.87%. The binary class model performed better than the multiclass model.

From the study, the binary classification model accomplished an

Table 1
The division of used dataset.

	CT			X-RAY			
DATA	Covid-19	Normal	Pneumonia	Covid-19	Normal	Pneumonia	OVERALL
TRAINING	1017	1060	1100	900	900	1100	6077
TESTING	1018	1059	1100	300	441	1100	5018
OVERALL	2035	2119	2200	1200	1341	2200	11095

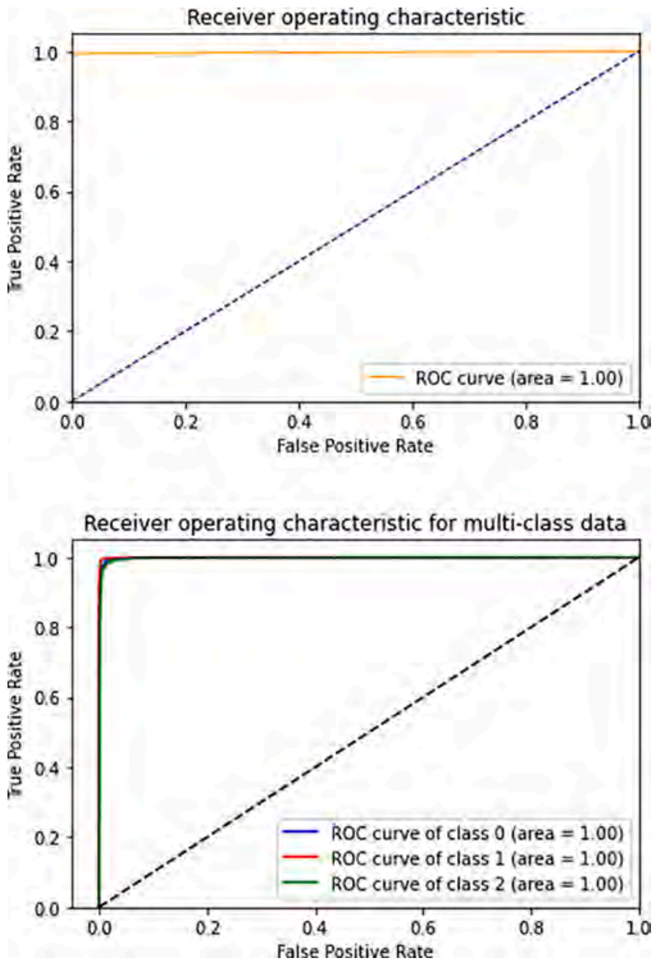

Fig. 4. ROC Curves a) Binary Classification b) Multiclass Classification.

overall accuracy of 99.64%, recall (or sensitivity) of 99.58%, the precision of 99.56%, F1-score of 99.59%, and ROC of 100% and multiclass model accomplished an overall accuracy of 98.28%, recall (or sensitivity) of 98.25%, the precision of 98.22%, F1-score of 98.23%, and ROC of 99.87% on the dataset used. Table 2 shows the overall performance of both models in terms of sensitivity, precision, accuracy, F1-score, and ROC. From the Table 2 it can be observed that the binary classification model outperformed the multiclass model.

4.2. Discussion

We have created two distinct binary and multiple classification models, performance of which has been evaluated using the performance metrics as discussed in the previous section. As shown in Table 3, We have achieved an accuracy of 99.61% for binary classification and 98.28% for multiclass classification. One can observe that the multiclass CNN model performed well for both binary as well as multiclass classification. The models could not identify only those images which were of poor quality or images which were not very clear. Also, the model for multiclass classification could not differentiate between some of the Covid-19 and Pneumonia images properly because both of these have almost the same symptoms and image findings. It also could not differentiate between some of the Normal and Pneumonia images properly because the symptoms of pneumonia are not very visible during the initial days and some of the images have poor quality. Our model has achieved the ROC of 100% for binary classification and 99.87% for multiclass classification as shown in Fig. 4. Hence, our proposed model has a very good ability to distinguish between the classes.

Our proposed model is performing better or comparable to most of the already available works in this field. It can be observed that all of the methods achieved an accuracy above 80% and most of the existing methods also checked their model's performance in terms of two or three performance measures except for [17,24,21]. The highest value of parameters in terms of existing methods is achieved by [24]. Their model has a 99.4% accuracy, a 98.9% F1-score, 99.3 % sensitivity, 99.2 % specificity and 99.9 % AUC. However, the lack of images of Covid-19 patients could explain the low accuracy of other approaches. Because CNN is the most extensively used method for pattern recognition and image classification, the majority of the approaches used it for their research. Most of the detection and classification work done on Covid-19 is:

- Mostly based on transfer learning.
- Have a smaller dataset or less number of Covid-19 images available.
- Mostly uses only one type of image i.e either X-rays or CT for detection and classification and not both.
- Have extracted features beforehand or manual extraction of features.
- For binary classification, the performance metrics have a larger value, but not for multiclass classification.

Our proposed CNN models have a larger dataset as compared to the existing methods, make use of both CT and X-rays, no manual extraction of features was done and our model also achieved higher values of performance measures for both binary as well as multiclass classification on the available dataset. It can assist the healthcare workers to perform better in this difficult time in case of an emergency.

Table 2
Overall performance of two CNN for binary and multiclass classification.

Classification	Accuracy	Precision	Sensitivity	F1-score	ROC
Binary	99.64%	99.56%	99.58%	99.59%	100%
Multiclass	98.28%	98.22%	98.25%	98.23%	99.87%

5. Conclusion

Covid-19 has a median R_0 of 5.7, according to a new study published online in Emerging Infectious Diseases. The 5.7 indicates that one person infected with Covid-19 has the ability to infect 5 to 6 people, rather than the 2 to 3 expected by researchers. Not only that, but the virus is evolving, and different types of strains have been discovered in different parts of the world. These changes are making the virus stronger by the day, and thousands of people are dying every day. As a result, several countries have been affected, with several incidents of community spread. Due to this, various countries are running out of resources and healthcare workers require diagnostic tools to investigate cases of potential Covid-19. Hence, we have developed simple models based on X-rays and CTs to detect and classify the Covid-19 cases. Our models are deep learning-based, and we've done binary and multiclass classification. The experimental results for binary classification show an overall accuracy of 99.64%, recall(or sensitivity) of 99.58%, the precision of 99.56%, F1-score of 99.59%, and ROC of 100%. The experimental results for multiple classifications show an accuracy of 98.28%, recall(or sensitivity) of 98.25%, the precision of 98.22%, F1-score of 98.23%, and ROC of 99.87%. In terms of performance measurements as well as dataset, our models exceeded the majority of existing approaches. This method can prove to be very helpful in case of an emergency. Our models proved to be efficient on the current dataset. However, it still needs clinical study and testing.

Despite having a great performance, it has some drawbacks. It only looks at the posterior and anterior (PA) views of X-rays, therefore it can't tell the difference between other X-ray perspectives like anterior-posterior (AP), lateral, and so on. It also needs Grad-CAM (Class Activation Mapping) visualisation. Radiologists were not asked for assessing the performance of our suggested method. Finally, it must be tested on

Table 3
Comparison of proposed method with existing methods.

Existing methods	Dataset used (covid-19 positive)	Classification	Method used	Performance measures				
				Accuracy	Precision	Sensitivity	F1-score	ROC or AUC
[14]	X-Rays 192	Binary	Transfer Learning	97%	–	–	–	–
[24]	X-Rays 1525	Binary	CNN+LSTM	99.4%	–	99.3%	98.9%	99.9%
[22]	X-Rays 284	Multiclass	DCNN	89.6%	93%	98.2%	–	–
[17]	X-Rays 127	Binary & Multiclass	DCNN	Binary – 98.08 % Multiclass – 87.02%	Binary – 98.03% Multiclass – 89.96%	Binary – 95.13% Multiclass – 85.35%	Binary – 96.51% Multiclass – 87.3%	–
[21]	X-Rays 283	Binary	RCNN	97.36%	99.29%	97.65%	98.46%	–
[23]	CTs 200	Binary	DNN & CNN	DNN – 82.39% CNN – 93.20%	–	DNN – 68.96% CNN – 96.09%	–	–
[15]	CTs and X-Rays 431	Binary	Transfer learning (TL) and CNN	TL – 98% CNN – 94.1%	–	TL – 96%(X-rays), 72%(CT) CNN – 100%(X-rays), 90%(CT)	–	–
Proposed Method	**CTs and X-Rays 3,235**	**Binary and Multiclass**	**CNN**	**Binary – 99.64% Multiclass – 98.28%**	**Binary – 99.56% Multiclass – 98.22%**	**Binary – 99.58% Multiclass –98.25%**	**Binary – 99.59% Multiclass – 98.23%**	**Binary – 100% Multiclass – 99.87%**

various datasets to accurately forecast performance. Images having multiple disease signs along with Covid-19 cannot be classified properly. The future scope of the method would be to check the model's compatibility with larger and different datasets. It can also be Grad-CAM visualised and assessed by radiologists. If more information about the dataset is available, the suggested model could be used to investigate gender and age-based disparities in disease detection.

CRediT authorship contribution statement

Samritika Thakur: Conceptualization, Methodology, Software, Writing - original draft. **Aman Kumar:** Writing - original draft, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Marco Ciotti, Silvia Angeletti, Marilena Minieri, Marta Giovannetti, Domenico Benvenuto, Stefano Pascarella, Caterina Sagnelli, Martina Bianchi, Sergio Bernardini, Massimo Ciccozzi, Covid-19 outbreak: an overview, Chemotherapy 64 (5–6) (2019) 215–223.
[2] Chaolin Huang, Yeming Wang, Xingwang Li, Lili Ren, Jianping Zhao, Hu. Yi, Li Zhang, Guohui Fan, Xu. Jiuyang, Gu. Xiaoying, et al., Clinical features of patients infected with 2019 novel coronavirus in wuhan, China, Lancet 395 (10223) (2020) 497–506.
[3] Wu. Fan, Su. Zhao, Yu. Bin, Yan-Mei Chen, Wen Wang, Zhi-Gang Song, Hu. Yi, Zhao-Wu Tao, Jun-Hua Tian, Yuan-Yuan Pei, et al., A new coronavirus associated with human respiratory disease in china, Nature 579 (7798) (2020) 265–269.
[4] Coronavirus disease 19 (covid-19), WHO. URL: https://www.who.int/, February 2020.
[5] Muhammad Adnan Shereen, Suliman Khan, Abeer Kazmi, Nadia Bashir, Rabeea Siddique, Covid-19 infection: origin, transmission, and characteristics of human coronaviruses, J. Adv. Res. 24 (2020) 91–98.
[6] Covid-19 and the World.
[7] Yicheng Fang, Huangqi Zhang, Jicheng Xie, Minjie Lin, Lingjun Ying, Peipei Pang, Wenbin Ji, Sensitivity of chest ct for covid-19: comparison to rt-pcr, Radiology 296 (2) (2020) E115–E117.
[8] Chun Shuang Guan, Zhi Bin Lv, Shuo Yan, Yan Ni Du, Hui Chen, Lian Gui Wei, Ru Ming Xie, Bu Dong Chen, Imaging features of coronavirus disease 2019 (covid-19): evaluation on thin-section ct, Acad. Radiol. 27 (5) (2020) 609–613.
[9] Weifang Kong, Prachi P Agarwal, Chest imaging appearance of covid-19 infection, Radiol. Cardiothorac. Imaging 2 (1) (2020) e200028.
[10] Adam Bernheim, Xueyan Mei, Mingqian Huang, Yang Yang, Zahi A Fayad, Ning Zhang, Kaiyue Diao, Bin Lin, Xiqi Zhu, Kunwei Li, et al., Chest ct findings in coronavirus disease-19 (covid-19): relationship to duration of infection. Radiology, (2020) 200463.
[11] Mohammad Jamshidi, Ali Lalbakhsh, Jakub Talla, Zdeněk Peroutka, Farimah Hadjilooei, Pedram Lalbakhsh, Morteza Jamshidi, Luigi La Spada, Mirhamed Mirmozafari, Mojgan Dehghani, et al., Artificial intelligence and covid-19: deep learning approaches for diagnosis and treatment, IEEE Access 8 (2020) 109581–109595.
[12] Alireza Tahamtan, Abdollah Ardebili, Real-time rt-pcr in covid-19 detection: issues affecting the results, Expert review of molecular diagnostics 20 (5) (2020) 453–454.
[13] Talha Burak Alakus, Ibrahim Turkoglu, Comparison of deep learning approaches to predict covid-19 infection, Chaos Solitons Fractals 140 (2020), 110120.
[14] Ali Narin, Ceren Kaya, and Ziynet Pamuk, Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. arXiv preprint arXiv:2003.10849 (2020).
[15] Halgurd S Maghdid, Aras T Asaad, Kayhan Zrar Ghafoor, Ali Safaa Sadiq, and Muhammad Khurram Khan. Diagnosing covid-19 pneumonia from x-ray and ct images using deep learning and transfer learning algorithms. arXiv preprint arXiv: 2004.00038, (2020).
[16] Ioannis D Apostolopoulos, Tzani A Mpesiana, Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks, Phys. Eng. Sci. Med. 43 (2) (2020) 635–640.
[17] Tulin Ozturk, Muhammed Talo, Eylul Azra Yildirim, Ulas Baran Baloglu, Ozal Yildirim, and U Rajendra Acharya, Automated detection of covid-19 cases using deep neural networks with x-ray images. Comput. Biol. Med. 121(2020) 103792.
[18] P.K. Harsh Panwar, Muhammad Khubeb Gupta, Ruben Morales-Menendez Siddiqui, Vaishnavi Singh, Application of deep learning for fast detection of covid-19 in x-rays using ncovnet, Chaos Solitons Fractals 138 (2020), 109944.
[19] Shashank Vaid, Reza Kalantar, Mohit Bhandari, Deep learning covid-19 detection bias: accuracy through artificial intelligence, Int. Orthop. 44 (2020) 1539–1542.
[20] Taban Majeed, Rasber Rashid, Dashti Ali, and Aras Asaad. Covid-19 detection using cnn transfer learning from x-ray images. medRxiv, (2020).
[21] Kabid Hassan Shibly, Samrat Kumar Dey, Md Tahzib-Ul Islam, Md Mahbubur Rahman, Covid faster r–cnn: a novel framework to diagnose novel coronavirus disease (covid-19) in x-ray images, Inform. Med. Unlocked 20 (2020), 100405.
[22] Asif Iqbal Khan, Junaid Latief Shah, Mohammad Mudasir Bhat, Coronet: a deep neural network for detection and diagnosis of covid-19 from chest x-ray images, Comput. Methods Programs Biomed. 196 (2020), 105581.
[23] Shayan Hassantabar, Mohsen Ahmadi, Abbas Sharifi, Diagnosis and detection of infected tissue of covid-19 patients based on lung x-ray image using convolutional neural network approaches, Chaos Solitons Fractals 140 (2020), 110170.
[24] Md Zabirul Islam, Md Milon Islam, Amanullah Asraf, A combined deep cnn-lstm network for the detection of novel coronavirus (covid-19) using x-ray images, Inform. Med. Unlocked 20 (2020), 100412.
[25] Prabira Kumar Sethy, Santi Kumari Behera, Pradyumna Kumar Ratha, and Preesat Biswas. Detection of coronavirus disease (covid-19) based on deep features and support vector machine, (2020).

[26] Ezz El-Din Hemdan, Marwa A. Shouman, and Mohamed Esmail Karar. Covidx-net: a framework of deep learning classifiers to diagnose covid-19 in x-ray images (2020). arXiv preprint arXiv:2003.11055.
[27] Linda Wang, Zhong Qiu Lin, Alexander Wong, Covid-net: a tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images, Sci. Rep. 10 (1) (2020) 1–12.
[28] Kaggle, url:https://www.kaggle.com, February 2020.
[29] Ct images of covid-19 patients. url:https://www.kaggle.com/hgunraj/covidxct?select=2A_images, February 2020.
[30] X-ray images of covid-19, pneumonia and normal patients. url: https://www.kaggle.com/prashant268/chest-xray-covid19-pneumonia, February 2020.
[31] X-ray images of pneumonia and normal patients, year =.
[32] Ct scan images of covid-19, pneumonia and normal patients, February 2020.
[33] Rikiya Yamashita, Mizuho Nishio, Richard Kinh Gian Do, Kaori Togashi, Convolutional neural networks: an overview and application in radiology, Insights into Imaging 9 (4) (2018) 611–629.
[34] Le Lu, Yefeng Zheng, Gustavo Carneiro, Lin Yang. Deep learning, Deep learning and convolutional neural networks for medical image computing, Adv. Comput. Vision Pattern Recog. 10 (2018) 978–983.
[35] Sa.ad. Albawi, Tareq Abed Mohammed, Sa.ad. Al-Zawi, Understanding of a convolutional neural network, in: In 2017 International Conference on Engineering and Technology (ICET), IEEE, 2017, pp. 1–6.
[36] Keiron O'Shea and Ryan Nash, An introduction to convolutional neural networks, arXiv preprint arXiv:1511.08458, 2015.