COVIHunt: An Intelligent CNN-Based COVID-19 Detection Using CXR Imaging

Abhinandan Roul, Abhilash Pati, and Manoranjan Parhi

Abstract Recently, the individuals are under lockdown and limited mobility due to the random spreading of the COVID-19, i.e., coronavirus disease - 2019, worldwide as well as pandemic declared by the World Health Organization (WHO). RT-PCR, i.e., reverse transcriptase-polymerase chain reaction, tests that can detect the RNA from nasopharyngeal swabs have become the norm to allow people to travel within the nation and also to international destinations. This test is people-intensive, i.e., it involves a person collecting the sample, needs transportation with strict precautionary measures, and a lab technician to perform the test which may take up to 2 days to get the results. There is a lot of inconvenience to the people due to this process. Alternatively, X-Ray images have been used primarily by physicians to detect COVID-19 and its severity. Detection of COVID-19 through X-Ray can act as a safe, faster, and alternative method to RT-PCR tests. This method uses a Convolutional Neural Network (CNN) to classify the X-Ray scans into two categories, i.e., COVID-19 positive and negative. In this paper, a novel method named COVIHunt: an intelligent CNN-based COVID-19 detection technique using CXR imaging, is proposed for binary classification. From experiments, it is observed that the proposed work outperforms in comparison with other existing techniques.

Keywords Deep learning (DL) · Convolution neural network (CNN) · COVID-19 · Binary classification · CXR imaging

1 Introduction

COVID-19 originated from Wuhan, PRC, in November 2019 is a highly contagious disease caused by SARS-CoV-2. It spreads so quickly that it had to be declared a pandemic by WHO. The fatal disease is characterized by fever, cough, breathing issues, and loss of taste and smell [1, 2]. The pandemic has impacted the lives of all people across the earth. Now, social distancing, face masks, and having a hand

A. Roul · A. Pati · M. Parhi (✉)
Department of Computer Science and Engineering, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India
e-mail: manoranjanparhi@soa.ac.in

P. K. Mallick et al. (eds.), *Electronic Systems and Intelligent Computing*, Lecture Notes in Electrical Engineering 860, https://doi.org/10.1007/978-981-16-9488-2_28

sanitizer is recommended by all government organizations. Although these act as a temporary preventive measure, still people get infected by COVID-19.

Being a novel coronavirus, most citizens aren't immune to it. The vaccination drive is at its peak to help develop immunity against this deadly disease. As of March 2021, the COVID-19 infection rate is on a constant rise in India. The government has made the RT-PCR test mandatory to enter into certain states and educational institutions are shut down once again. Keeping the current situation in mind, new ways to trace COVID-19 patients must be developed for better management. It is proposed to use CXR imaging (Chest X-Rays) to detect infected patients and quarantine them [3]. Here, it is focused on PA (Posteroanterior) view of the lungs in X-Ray scans CXR imaging is cheap, readily available, and easy to administer. Furthermore, CXR images expose the patient to very low radiation of 0.1 mSv making it a safer alternative to CT scans or MRI. As an already available method in various regions, it can act as an effective method to collect data for detection. To diagnose patients on CXR images requires professionals with years of experience. As there's a shortage of such specialists and the patients are increasing exponentially, it is proposed to automate the detection system using machine learning and image processing technique [4–6].

In this paper, a novel method named COVIHunt: an intelligent CNN-based COVID-19 detection technique using CXR imaging, is proposed for binary classification. This method would reduce the workload on doctors and would enable them to focus on more critical aspects such as patient treatment and care. X-Rays being fast and scan being readily available, can act as an effective method for detection.

The **key contributions** of this research work can be stated as follows:

- A unique model is developed which can help to detect COVID-19 disease with the aid of CXR imaging.
- It has a significant improvement in accuracy for COVID-19 category detection.
- The application of various image augmentation techniques on the dataset helps to improve diversity in the training set which results in better generalization.

The remaining of this work can be organized as Sect. 2 for the works done related to this study. This study employed materials and methods are discussed in Sect. 3. Section 4 is for the discussion of the introduced model. The results obtained from various experiments along with a comparison study of existing related works are discussed under Sect. 5. Section 6 discusses the conclusions and future aspects of the research.

2 Related Work

Ismael and Sengur [7] have proposed a method to detect COVID-19 based on chest X-rays using deep learning techniques. CNN models such as VGG16, ResNet101, and ResNet50, and for classification, SVM classifiers with diverse kernel functions such as Linear, Cubic, and Gaussian were used for feature extraction, concerning the accuracy, sensitivity, specificity, F1-score, and AUC as evaluative measures on the open-source dataset with 180 COVID-19 samples and 200 Normal cases. The authors claimed to have achieved an accuracy of 95.79% using ResNet50 features+SVM with a sensitivity of 94%, specificity of 97.78%, F1-score of 95.92%, and AUC of 0.9987.

Wang et al. [3] suggested COVID-Net a deep-CNN (DCNN) method to detect COVID-19 from CXR images using projection–expansion–projection–extension (PEPX) design which decreases computational complexity, concerning accuracy and sensitivity as evaluative measures on the COVIDx dataset with 13,975 CXR images and thereby claiming to have an overall accuracy of 93.3% with a 91% sensitivity on COVID-19 class and 94% sensitivity on non-COVID-19 class.

Rahaman et al. [8] have proposed a methodology for COVID-19 diagnosis by automatic CAD system utilizing deep transfer learning with application of VGG, Xception, ResNetV1, ResNetV2, MobileNet, DenseNet, and Inception networks as pre-trained base layers concerning the accuracy, precision, recall, and F1-score as evaluation metrics on the dataset by J. P. Cohen. The authors have achieved an accuracy of 89.3% using VGG19 with an average precision of 90%, recall of 89%, and F1-score of 90%.

Heidari et al. [9] have proposed a technique to detect COVID-19 using image pre-processing techniques which includes histogram equalization algorithm (HE), bilateral low pass filter coupled with a CNN model concerning the accuracy, sensitivity, specificity as evaluative measures on a dataset acquired from various public repositories having 8474 CXR images. The authors have claimed to have received an accuracy of 94.5%, sensitivity of 98.4%, and specificity of 98%.

Jain et al. [10] have proposed a methodology to classify COVID-19 infections through the use of DL methods such as InceptionV3, Xception, and ResNeXt models concerning the precision, recall, and F1-score as evaluation metrics on the dataset by Prashant Patel on Kaggle thereby claiming accuracy of 93% with a precision, recall and F1-score of 91%, 89%, and 90% on normal class and 97%, 78%, and 95%, respectively, on COVID-19 class.

3 Materials and Methods

3.1 Dataset Used

Open-source data has been used in this research [11]. The collected dataset was then processed to clear irrelevant images and keep only PA views of the X-Ray. The PA view of COVID-19-infected and normal lungs are depicted in Figs. 1 and 2, respectively. Furthermore, a dataset containing healthy lungs was also collected for our model to recognize healthy lungs. Then the data was segregated into two classes, one containing an equal number of images for X-rays of COVID-19-positive patients and the other containing the healthy patients' images. In the pre-processed dataset, there are 466 COVID-19 samples and 474 healthy lung samples in training data. In the validation set, 39 samples of infected patients' X-Ray images and 40 samples of

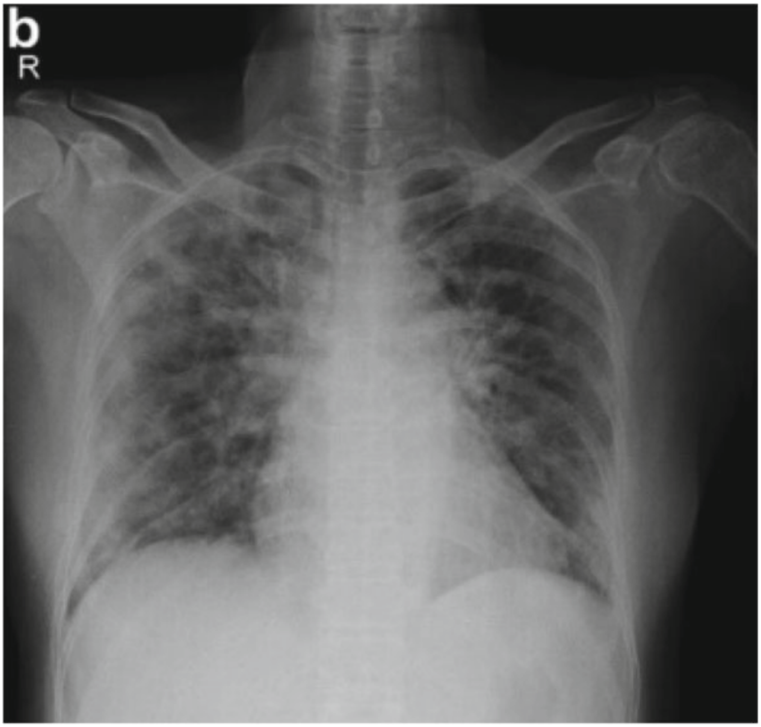

Fig. 1 PA view of COVID-19-infected lungs

healthy patients of the normal image are kept. Finally, the test set has 20 samples of each class.

3.2 Convolution Neural Network (CNN)

A CNN is a DL method is employed in general while image-related researches carried out. In short, known as ConvNets, they are primarily used for image classification problems [12]. The convolutional layer takes an input image extracts some features and passes them to the next layer. The filters in the CNNs can detect patterns. They learn the local patterns such as edges, lines, textures, shapes, etc. The deeper they go, the more intricate patterns, they observe. In ConvNets, the neurons are arranged in three dimensions, i.e., width, height, and depth.

The convolutional layer performs the most computational task. The parameters consist of specific learnable filters, image matrix, kernel size, padding, and strides. Each filter is small and convolves over the whole image to detect features. With each passage through a layer, the image becomes abstracted to a feature map. The hyperparameters that control the output volume are depth, stride, and zero-padding.

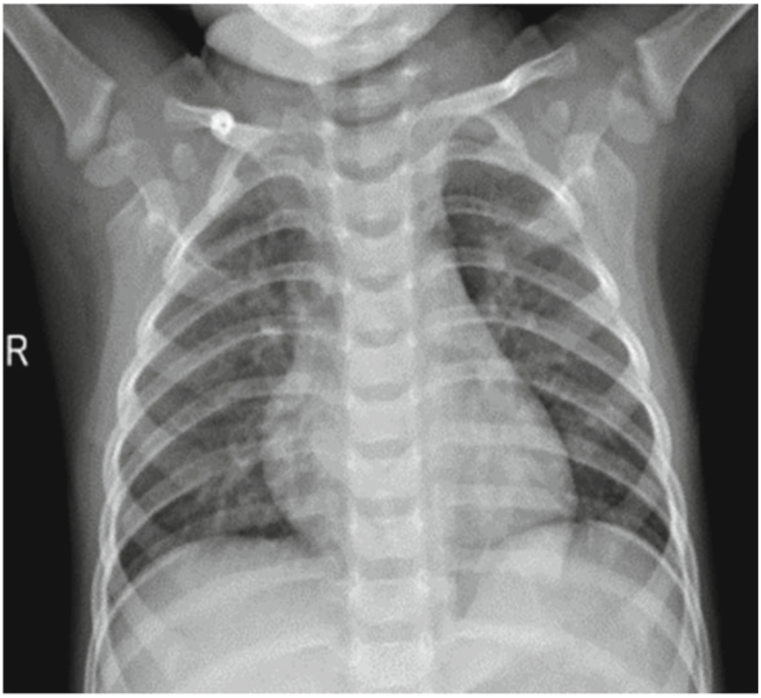

Fig. 2 PA view of COVID-19 normal lungs

3.3 *Max Pooling*

Max Pooling operation is generally added to the CNNs after each convolutional layer. It helps to decrease the dimensions of the images with each successive iteration. It generally preserves the information in a large image file but with reduced data storage. The Max Pooling technique employed in this research work is depicted in Fig. 3. Strides determine the number of pixels required by the filter to move as it slides across the image.

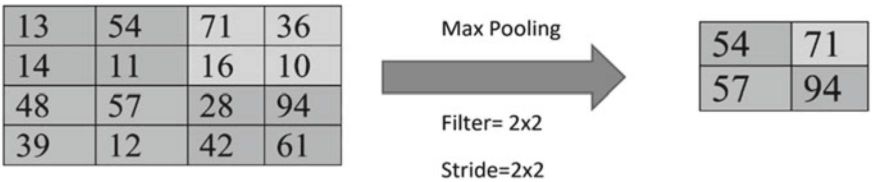

Fig. 3 The max pooling technique

3.4 Activation Function

In this research, for all the inner layers ReLU (Rectified Linear Technique) is used as the activation function, which can be defined as:

$$y = max(0, x) \tag{1}$$

It is a linear function that will produce the output directly if it is greater than zero else, it outputs zero. In other words, it preserves the output values of positive inputs and maximizes the negative input values to zero. The benefits of ReLU are that it prevents the problem of vanishing gradient, enables the model to train faster, computationally inexpensive, and produces accurate results. The sigmoid function is a very popular activation function having a sigmoid curve. The output is always scaled to a value between 0 and 1 and can be defined as:

$$S(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

3.5 Regularization Technique

This technique makes slight modifications to the learning algorithm such that the model performs well in real-life data. A problem of overfitting arises if the model is not generalized. In this work, dropout layers are used to deactivate neurons in several layers to avert the network from learning the training data too well [13]. The sensitivity to specific weights of neurons is reduced, which enhances the capability of the network to generalize well.

3.6 Fully Connected Layer

All outputs from the previous layer are linked to each neuron in the following layer in this layer. Each setting in this layer has a significant influence on class prediction. The activation function uses the output of the final completely connected layer to calculate the prediction score for each class.

3.7 Image Augmentation Techniques

Due to the limited availability of COVID-19 X-ray scans, image augmentation is used to generate more data during training to increase diversity in the training set.

This method helps to replicate some real-world features which happen naturally while data collection. The images are subjected to shearing, rotation, and zooming [14]. Shearing means to transform the image along a horizontal or vertical axis with a magnitude rate. Rotation is the process by which the image is rotated by certain degrees along its axes. Zoom augmentation means focusing on specific parts of the image particularly and add pixels to the image data. Horizontal and vertical flip augmentation help to change the orientation of the image by reversing complete rows and columns of pixels of the image.

4 Proposed Model

The proposed model is a shallow-CNN with three Convolutional layers. The input image is rescaled to size 300 × 300 to allow for faster processing and better GPU memory management. The first convolutional layer uses ReLU to activate 32 filters with a kernel size of 3 × 3. After that, another convolutional layer with 64 filters and ReLU as an activation function is added. To decrease the dimensionality of pictures from the preceding output layer, we use the Max Pooling layer. A dropout layer follows the third convolutional layer, which consists of 128 filters with a kernel size of 3 × 3. To make it a 1D array, the model is flattened. After flattening, a completely linked layer of 64 units is followed by a dense layer of 128 units, which is triggered by the sigmoid function and precedes a 1-unit output layer. A binary cross-entropy loss method is employed to build the model, defined as

$$L = \frac{1}{Os} + \sum_{i=1}^{Os} \left(y_i . \log \hat{\boldsymbol{y}}_i + (1 - \hat{\boldsymbol{y}}_i) . \log(1 - \hat{\boldsymbol{y}}_i) \right) \quad (3)$$

where “L” is for Loss and “Os” is for Output Size.

The intention of selecting the BCE function is since our model has two output classes. This model uses Adam optimizer due to the unparalleled benefits of ADAM (Adaptive Moment Estimation). Adam has the benefits of AdaGrad and RMSProp to handle noisy and sparse gradients [15]. Being computationally efficient and requiring less memory space, it is easy to implement. The model has 18,976,129 trainable parameters. The model was trained over 15 epochs with 24 steps per epoch. In the experimental run, the training is stopped at the seventh epoch as the desired training accuracy was achieved, any further training might result in overfitting. The block diagram of the proposed work, COVIHunt is shown in Fig. 4. Table 1 represents the architecture of the network.

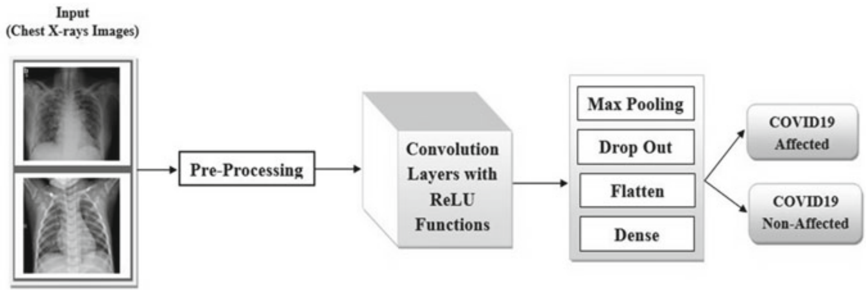

Fig. 4 Block diagram of the proposed model

Table 1 The architecture of the network

Layer type	Output shape	Param#
Conv2d	(298, 298, 32)	896
Activation	(298, 298, 32)	0
Conv2d	(296, 296, 64)	18,496
Activation	(296, 296, 64)	0
Max pooling	(148, 148, 64)	0
Dropout	(148, 148, 64)	0
Conv2d	(146, 146, 128)	73,856
Activation	(146, 146, 128)	0
Max pooling	(48, 48, 128)	0
Dropout	(48, 48, 128)	0
Flatten	(294,912)	0
Dense	(64)	18,874,432
Dense	(128)	8320
Dense	(1)	129
Activation	(1)	0
Total params: 18,976,129 Trainable params: 18,976,129 Non-trainable params: 0		

5 Results and Discussion

The CNN architecture which was created from scratch performed well on the given dataset. The training accuracy is found to be 97.4% with a loss of 0.091. Figures 5 and 6 illustrate the model accuracy as a function of the number of epochs, as well as the reduction in loss as the number of epochs increases for both training and validation data.

Figures 7, 8, 9, and 10 depict the channels in intermediate activation. The initial layer acts as an edge detector collection. All information in the image is retained by

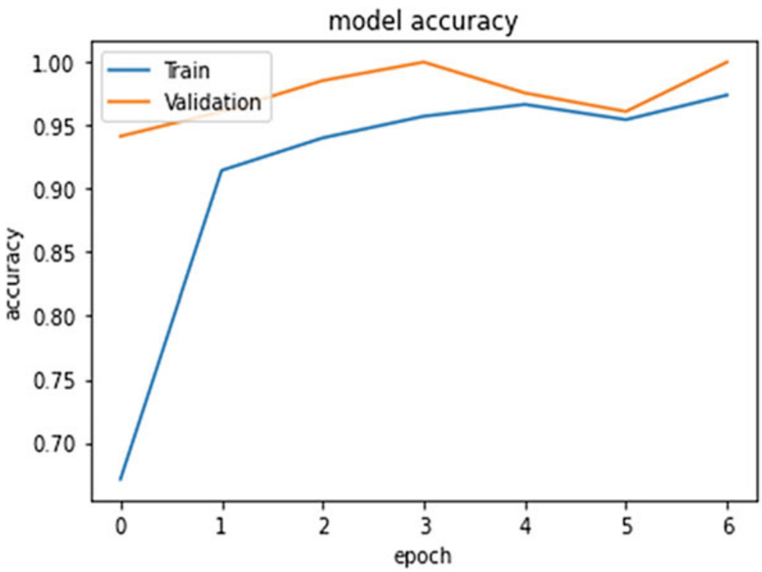

Fig. 5 Accuracy of training and validation data

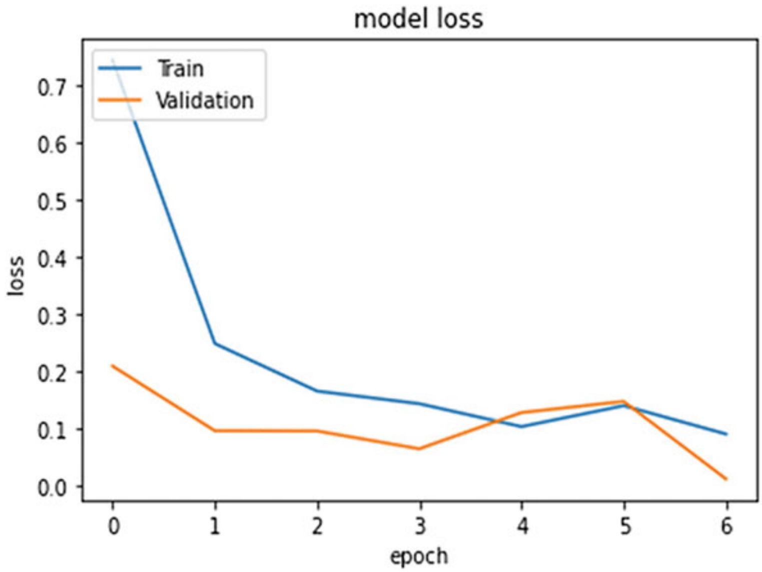

Fig. 6 Loss of training and validation data

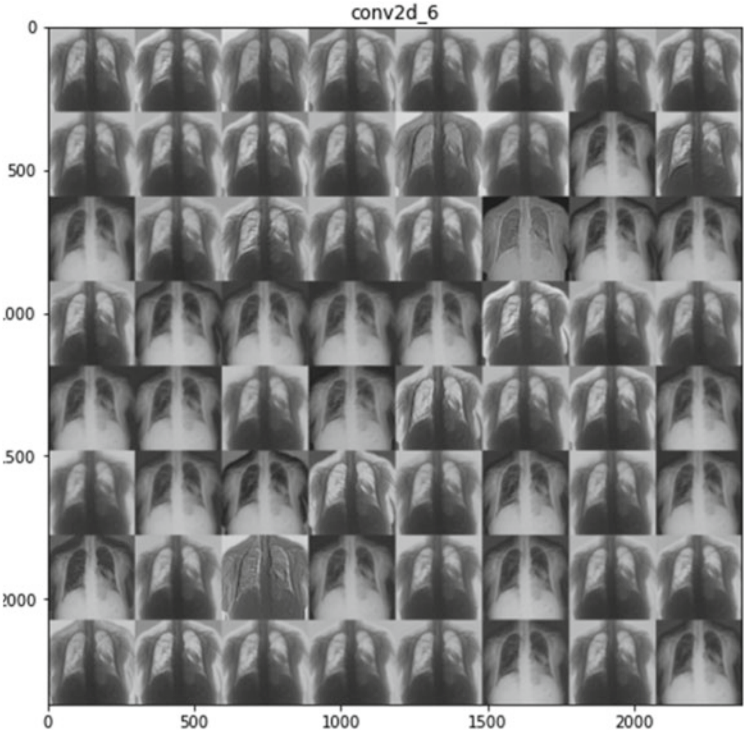

Fig. 7 Convo2D layer

the CNN layers. As the network goes deeper the activations become less visually interpretable. The information about the image's visual components diminishes as the layer depth increases, but more information about the image's class is stored. With an increase in depth layers, the sparsity of activation increases, i.e., in the prior layers, all filters become activated by input image, but in later layers, more filters are left blank.

It is found the precision is 95% for the COVID-19 class which shows that the predictions of the model are accurate and reliable, which is depicted in Table 2. It never predicts a non-infected patient as having COVID-19 which can be known from the 100% precision of normal class. A higher precision helps us to know that the number of false negatives is low. The recall is a measurement of false negatives against true positives. This means there are lesser chances of having a negative report on the prediction of a person having COVID-19. The F1-score is a metric that is used to balance Precision and recall. In our experiment, it is found that the F1-score for the COVID-19 positive class is 98% and for the negative class (not infected) is 97%. The support metric of COVID-19 and normal patients shows that the class is balanced with 20 samples of COVID-19 and 20 samples of normal patients' data. A

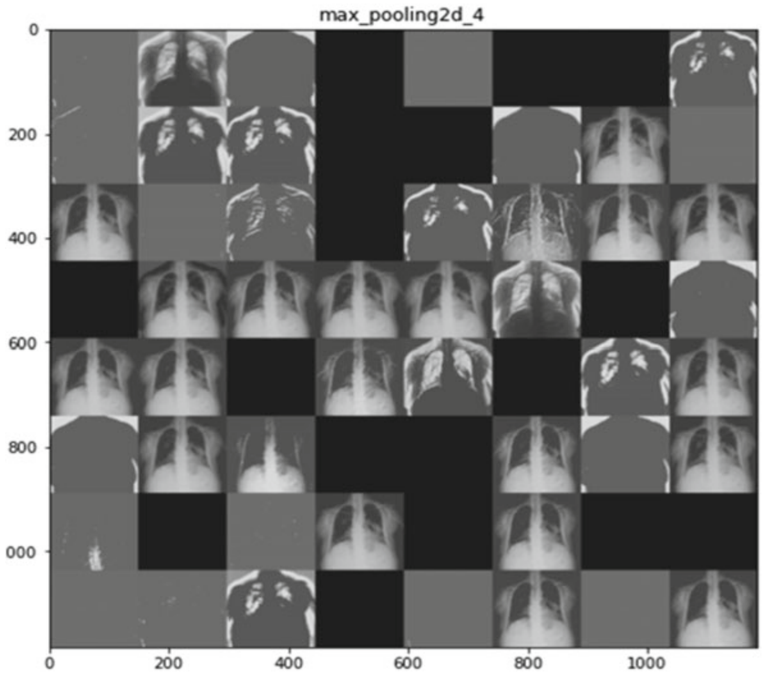

Fig. 8 Max pooling layer

comparison of this proposed work, COVIHunt, with some related existing works is stated in Table 3.

The proposed model, COVIHunt, has some advantages as well as disadvantages, can be stated as:

Advantages:

- The model will help to classify and get instant results of people being infected.
- It is faster, cheap, and efficient.
- It will act as an alternative method to conduct tests where rapid testing kits or the RT-PCR method is infeasible.

Disadvantages:

- The model might result in false negatives due to improper imaging.
- Early stage infections might not get detected.
- It is required to get more data to guarantee clinical accuracy.

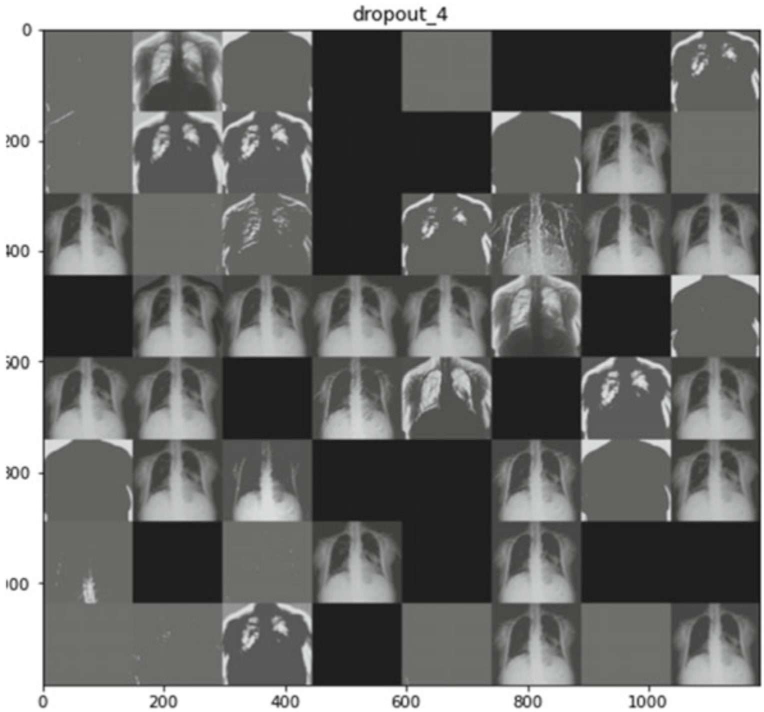

Fig. 9 First dropout layer

6 Conclusion and Future Scope

In this research, a deep learning-based image classification technique termed as COVIHunt has been proposed to identify COVID-19-infected patients. The accuracy of the dataset is found to be 97.5% which is reliable. Keeping in mind the current situation of the pandemic, this method will help in faster diagnosis and quick quarantine decisions. Being a novel method, it needs further fine-tuning to get better at real-life data and act as a tool with clinical accuracy. Deployment of this tool will help to collect data from numerous patients which will act as a database for future work related to lungs ailment. In the future, it is planned to take the age, gender, and demographic information of a person to get better classification results.

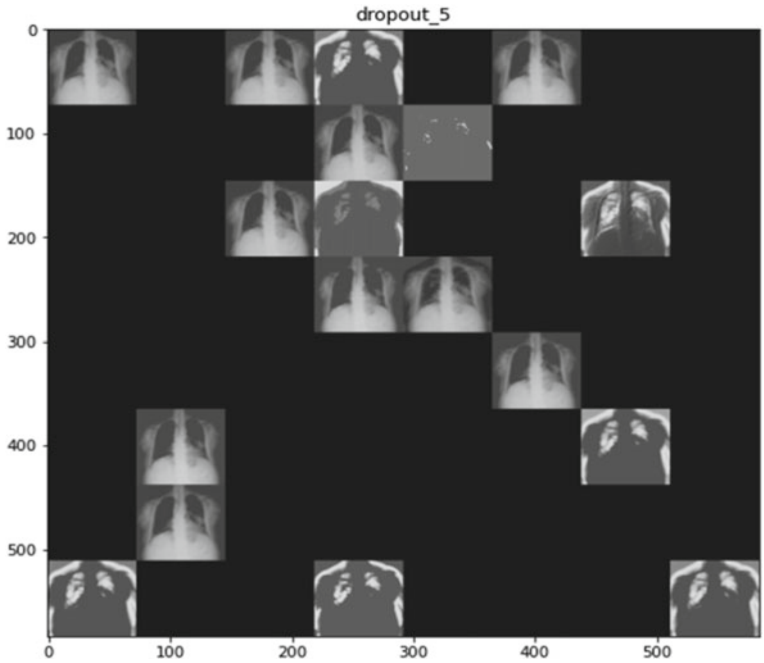

Fig. 10 Second dropout layer

Table 2 The results obtained using COVIHunt

	Accuracy	Precision	Recall	F1-score	Support
COVID-19	0.99	0.95	0.99	0.98	20
Normal	0.95	0.99	0.95	0.97	20
Weighted avg	0.975	0.98	0.97	0.975	40

Table 3 Comparison of COVIHunt with other existing models

Work	Method(s) used	Dataset(s) used		Findings			
				Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Ismael and Sengur [7]	CNN models such as VGG16, ResNet101, and ResNet50, and for classification, SVM classifiers	An open-source dataset with 180 COVID-19 samples and 200 Normal samples		95.79	96	94	95.92
Wang et al. [3]	DCNN with PEPX design	COVIDx dataset with 13,975CXR images		93.3	98.9	91 (COVID-19) 94 (normal)	-
Rahaman et al. [8]	Image enhancement methods such as CLAHE, HE, BCET with CNNs	COVQU-20 dataset with 18,479 CXR images	Gamma correction	96.29	96.28	96.29	96.28
			Segmented Lungs	95.11	94.55	94.56	94.55
Heidari et al. [9]	Histogram equalization algorithm (HE), bilateral low pass filter coupled with a CNN model	Data was collected from public repositories having 8474 images with 416 confirmed COVID-19 cases		94.5	-	98.4	-
Jain et al. [10]	Deep learning models such as InceptionV3, Xception, and ResNeXt	Prashant Patel, Chest X-ray data on Kaggle	Normal	93	91	89	90
			COVID-19		97	78	95
Proposed work	CNN (3 Conv2d layers) for binary classification	940 CXR images with 466 COVID-19		97.5	98	97	97.5

References

1. Velavan TP, Meyer CG (2020) The COVID19 epidemic. Tropical medicine & international health: TM & IH 25(3). https://doi.org/10.1111/tmi.13383
2. Pati A, Parhi M, Pattanayak BK (2021) COVID19 pandemic analysis and prediction using machine learning approaches in India. In: Advances in intelligent computing and communication, pp 307–316. Springer, Singapore
3. Wang L, Lin ZQ, Wong A (2020) COVID-Net: a tailored deep convolutional neural network design for detection of COVID19 cases from chest X-ray images. Sci Rep 10:19549
4. Yasin R, Gouda W (2020) Chest X-ray findings monitoring COVID19 disease course and severity. Egypt J Radiol Nucl Med 51:193
5. Wang S, Nayak DR, Guttery DS, Zhang X, Zhang Y (2021) COVID-19 classification by CCSHNet with deep fusion using transfer learning and discriminant correlation analysis. Inf Fus 68:131–148
6. Nayak SR, Nayak DR, Sinha U, Arora V, Pachori R (2021) Application of deep learning techniques for detection of COVID-19 cases using chest X-ray images: a comprehensive study. Biomed Signal Process Control 64:1–12
7. Ismael AM, Şengür A (2021) Deep learning approaches for COVID19 detection based on chest X-ray images. Expert Syst Appl 164. https://doi.org/10.1016/j.eswa.2020.114054
8. Rahaman MM, Li C, Yao Y, Kulwa F, Rahman MA, Wang Q, Qi S, Kong F, Zhu X, Zhao X (2020) Identification of COVID19 samples from chest X-ray images using deep learning: a comparison of transfer learning approaches. J Xray Sci Technol 28:821–839. https://doi.org/10.3233/XST-200715
9. Heidari M, Mirniaharikandehei S, Khuzani AZ, Danala G, Qiu Y, Zheng B (2020) Improving the performance of CNN to predict the likelihood of COVID19 using chest X-ray images with preprocessing algorithms. Int J Med Informat 144. https://doi.org/10.1016/j.ijmedinf.2020.104284
10. Jain R, Gupta M, Taneja S, Hemanth DJ (2021) Deep learning-based detection and analysis of COVID19 on chest X-ray images. Appl Intell 51:1690–1700. https://doi.org/10.1007/s10489-020-01902-1
11. Chen N, Zhou M, Dong X, Qu J, Gong F, Han Y, Qiu Y, Wang J, Liu Y, Wei Y, Xia J, Yu T, Zhang X, Zhang L (2020) Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. Lancet 395:507–513. https://doi.org/10.1016/S0140-6736(20)30211-7
12. Albawi S, Mohammed TA, Al-Zawi S (2017) Understanding of a convolutional neural network. In: 2017 International conference on engineering and technology (ICET)
13. Khan SH, Hayat M, Porikli F (2018) Regularization of deep neural networks with spectral dropout. Neural Netw
14. Shorten C, Khoshgoftaar TM (2019) A survey on image data augmentation for deep learning. J Big Data 6:60
15. Zhang Z (2018) Improved Adam optimizer for deep neural networks. In: 2018 IEEE/ACM 26th International symposium on quality of service (IWQoS)