A Review on COVID-19 Diagnosis Using Imaging and Artificial Intelligence

Sourabh Singh Verma, Santosh K. Vishwakarma, and Akhilesh Kumar Sharma

Abstract

The coronavirus epidemic is still on a surge and has harsh impacts on various factors across the globe including the economy and health. Though the recovery rate is also increasing, daily reporting cases are also increasing substantially. The best way till now is to take precautions and following the government guidelines. Till today, many different countries are line up to produce effective vaccination, but still, no such vaccine has completed its trial, and further, it will take a long time for the production and distribution among common citizens. We currently have a test process known as reverse transcription-polymerase chain reaction (RT-PCR) that is not reliable during the early stage of the disease. Also, a fast diagnosis is required as RT-PCR is time taking operation. Hence, imaging can be useful for the diagnosis as it can be quick and more reliable even in the early stage of the COVID-19 disease. Artificial techniques can be applied to radiological images such as CT scans and X-rays. In this article, we review the various research and responses in diagnosing the said disease using AI techniques on radiological images. Our findings suggest that using AI techniques like Convolution Neural Networks plays an important role in the diagnosing the COVID-19 by providing quick results and accuracy.

Keywords

COVID-19 • Diagnose • Survey • Review • Corona • Machine learning

1 Introduction

The coronavirus outbreak emerges initially in December 2019 (Wu et al., 2020; Huang et al., 2020), still, it is surging in various countries. To date around the globe, there are 1,090,734 infected case reported out of which 28,845,540 has recovered and 976,038 deaths are reported.[1] It was declared as a pandemic by the World Health Organization in March 2020 (World Health Organization, 2019). As per numbers, the mortality rate is quite low 3.07%, and the recovery rate is 73.6%. However, the mortality rate is quite high for the critical patient (Rothan & Byrareddy, 2020), or the patient who is already suffering from some issues.

There are varying levels of symptoms related to the COVID-19, and typically, it includes distress in respiration apart from its symptoms may also include normal flu symptoms like headache, fever, cough, fatigue, muscular stress, etc. Unlike SARS, it not only has a bad impact on the respiratory system but also affects other vital organs such as kidney and liver (McIntosh, 2019). The current potential test procedure reverse transcription-polymerase chain reaction (RT-PCR) required to be done repeatedly to confirm the status of the patient, and also, it is not accurate in asymptotic or initial stage. The accuracy and efficiency issues of RT-PCR lead to innovate a new way to effectively and quickly diagnose. From experience, radiology images are used for the diagnosis of various diseases. These images can be used as a supplement or follow-up process of PCR. Particularly, radiological chest images such as X-rays and compound tomography (CT) can be used in the early stages of the disease (Zu et al., 2019).

The main objective of this research article is to survey various quality articles published in the field of COVID-19 diagnosis with the help of artificial intelligence techniques especially machine learning. Their extensive experiments are compared considering evaluated parameters and metrics.

S. S. Verma · S. K. Vishwakarma (✉) · A. K. Sharma
SCIT Manipal University Jaipur, Jaipur, Rajasthan, India
e-mail: santoshscholar@gmail.com

S. S. Verma
e-mail: ssverma80@gmail.com

A. K. Sharma
e-mail: akhileshshm@gmail.com

[1] https://www.worldometers.info/coronavirus/ last accessed 2020/10/08.

P. K. Singh et al. (eds.), *Innovations in Information and Communication Technologies (IICT-2020)*,
Advances in Science, Technology & Innovation,
https://doi.org/10.1007/978-3-030-66218-9_34

This article will help researchers to compare various published researches add will also get comprehensive information about Covid-19 to add it's a dataset available across the research community. The remaining content of this paper includes Sect. 2, it will introduce important features of machine learning algorithms, and it will also highlight the different matrices that are used to measure results. Section 3 will include various comparisons done in this survey to analyze potential models to diagnose COVID-19.

2 Basic Taxonomy for Machine Learning Diagnosis COVID-19

In most of the recent research on COVID-19 diagnosis, it has been observed that most researchers are using available convolution neural networks models CNN or proposing their own CNN models. As it shows promising results with high accuracy of detection of the disease. Unlike ANN models that have only fully connected nodes, CNN has multiple layers with different functions such as feature extraction using the convolution matrix as shown in Fig. 1. It also uses an activation function to introduce non linearity such as sigmoid and ReLu. It also uses Max pool layers to minimize the spatial dimensions of the input. CNN also uses dropouts for thining the network during the training phase, and to prevent overfitting, thus it will improve the effectiveness of the whole model. An overall CNN model is shown in Fig. 1 with multiple layers and including Max pool and fully connected layer.

Convolution layer in CNN is used to apply a convolution filter/kernel to the image to produce the required resulting feature where each convolution filter represents some feature of interest, as shown in Fig. 2. Not like fully connected layers, the convolution layer helps to reduce the number of input pixels. Various filters are used to extract different features from images. For an input image I and filter F, the convolution step is shown in Eq. (1) as follows:

$$(I * F)(i,j) = \sum_a \sum_b F(a,b)I((i-a)(j-b)) \quad (1)$$

where a, b are index in filter matrix and i, j are index in the image.

In Fig. 2, we have moved the kernel by one step, and this is known as a stride. The stride may be large if you do not want to override the pixels of the input image. After going through the convolution process, the dimensionality can be further reduced by using pooling. The most used pooling is known as Max pooling which considers the maximum value in the pool window and ignores others. Mostly, authors reviewed in this article have used Max pooling to reduce the dimension. The whole process in CNN includes training of the model and testing of the model, and for this, the whole input is divided into two sets of test data and train data randomly.

3 Review on Proposed Models and Evaluation Comparisons

3.1 Evaluation Metrics and Confusion Metrics

To understand the various survey conducted, it is important to know the evaluation parameters and metrics used to verify

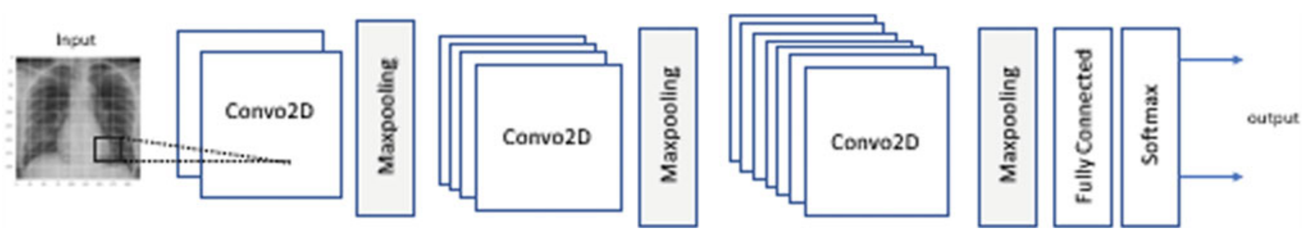
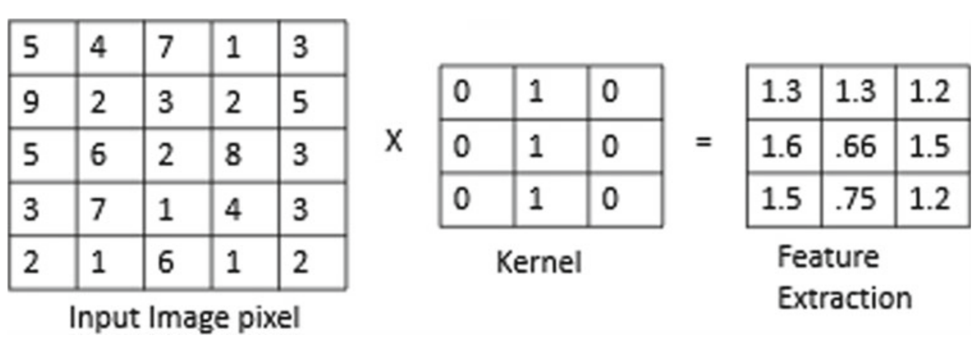


Fig. 1 Convolution neural network

Fig. 2 Convolution process for feature extraction using kernel



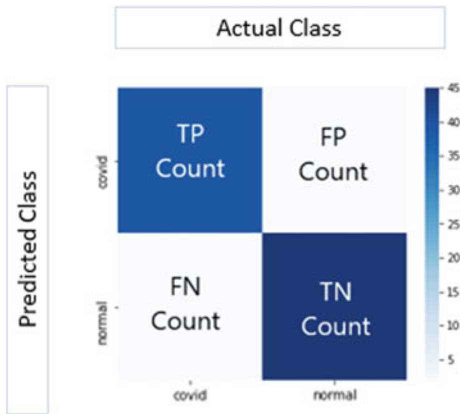


Fig. 3 Convolution metrics

the results of any proposed CNN models. All the evaluation parameters are derived from the confusion metrics. The confusion matrix has four quadrants that can be seen in Fig. 3.

All the research papers we reviewed have discussed and used the confusion metrics for processing the research. The confusion matrix consists of four quadrants, and these are True Positive TP, False Positive FP, False Negative FN and True Negative TN. TP is the number of positive cases correctly identified in the model, and FP is the number of positive cases wrongly identified as negative cases. FN is the count of negative cases wrongly identified as positive cases, and TN is the count of total negative cases correctly identified as negative. To be an ideal classification, it is required that FN and FP should be zero.

Based on four quadrants of confusion matrix, Table 1 shows different metrics that can be evaluated.

For a detailed review, we will compare and review a limited set of quality published articles such as (Rahimzadeh & Attar, 2020; Mohammed, 2020; Ucar & Korkmaz, 2020; Mahmud et al., 2020).

These all articles have proposed some new models or modified the existing models to improve the results, i.e., efficiency and effectiveness of the updated model for giving better results. To review these articles, we have considered the following important facts:

a. Datasets and image distribution
b. Experimental setup and review on performance metrics of proposed machine learning models.

Based on the above facts, these models were reviewed and compared.

3.2 Datasets

There are various free datasets are available which consist of X-ray images of COVID-19, pneumonia, SARS and normal persons. As per the present scenario, availability of COVID-19 X-ray images is much less than what is available for the other disease and normal ones. The dataset and images used by the proposed articles are represented in Table 2 as follows.

The augmentation can be used to increase the number of COVID images, as only 66 images (Ucar & Korkmaz, 2020) are available in the given dataset, and a large number of normal and pneumonia images are available. This may be efficient to predict the cases which are COVID negative, but as the task is to diagnose COVID cases using X-ray, it was required that number of positive images must be increased, so various types of image augmentation are applied to outcome 1229 COVID images.

3.3 Result Discussion and Review on Performance Metrics of Compared Machine Learning Models

Before starting with the result comparison, let us get a brief on the methodology used in these models. Model (Rahimzadeh & Attar, 2020) manages to use an unbalanced dataset to train efficiently. They also propose a model, that is a concatenation of Xception and ResNetV20 model. The overall accuracy obtained for all the cases is 91.4% (Mohammed, 2020) uses the DarkNet model (Redmon et al., 2017) as the basis for classification, and it is using seventeen layers of convolution layers followed by flattening. It uses

Table 1 Performance metrics

Metrics	Equations	Desire value	
		Most	Least
Accuracy (ACC)	$(N_{TP}+N_{TN})/(N_{TP}+N_{TN}+N_{FN}+N_{FP})$	1	0
Sensitivity	$N_{TP}/(N_{TP}+N_{FN})$	1	0
Specivity	$N_{TN}/(N_{TN}+N_{FP})$	1	0
Precision	$N_{TP}/(N_{TP}+N_{FP})$	1	0
False positive rate	$N_{FP}/(N_{TN}+N_{FP})$	0	1
F-Score	$(2\times \text{Precision}\times \text{sensitivity}/(\text{precision}+\text{sensitivity})$	1	0

Table 2 Dataset and image distribution

Article	Dataset	Input images		Distibution (others)	Augmentation
		Covid-19	Others		
Rahimzadeha and Attar (2020)	Chestxray dataset (https://github.com/ieee8023/covid-chestxray-dataset and (https://www.kaggle.com/c/rsna-pneumonia-detection-challenge	149	484	250 normal 234 pneumonia	Yes
Mohammed (2020)	Xu (2020), Wang et al. (2017)	127	1000	500 normal 500 pneumonia	No
Ucara and Korkmaz (2020)	Chest X-ray dataset (Cohen, 2020) and Kaggle chest X-ray pneumonia dataset (Kermany et al., 2018)	66	5245	1349 normal 2896 pneumonia	Yes {after augmentation 1229 each case of Covid19, pneumonia and Normal}
Mahmud et al. (2020)	X-Ray images collected in Guangzhou Medical Center, China	305	915	305 normal 305 bacterial pneumonia 305 viral pneumonia	No

Table 3 Comparison chart for performance metrics

Article	Model	Experimental setup	Compared with	Performance metrics in %				
				Accuracy	Sensitivity	Specificity	Precision	F1-Score
Rahimzadeh and Attar (2020)	Xception and ResNet50V2 concatenation	GPU: Tesla P100 RAM:25 GB At Google collaborator (using Keras)	Xception, ResNet50V2	99.50	80.53	99.56	35.27	48.9
Mohammed (2020)	DarkCovidNet	Not specified	Ioannis (2020), Wang and Wong (2020), Sethy and Behra (2020), Hemdan et al. (2020), Narin et al. (2020), Song et al. (2020), Wang et al. (2020), Zheng et al. (2020), Xu et al. (2020)	98.08	95.13	95.3	98.03	96.51
Ferhat Ucara et al. (Ucar and Korkmaz 2020)	COVIDiagnosis-Net	GPU: Quadro M4000 RAM:32 GB using Matlab	Li and Zhu (2020), Wang and Wong (2020), Afshar et al. (2020), Farooq and Hafeez (2020), Chowdhury et al. (2020)	98.3	98.3	99.1	98.3	98.3
Mahmud et al. (2020)	CovXNet	GPU: NVIDIA RTX 2080 Ti with 4608 CUDA cores RAM: 24 GB	Residual, Inception, VGG16	97.4	97.8	94.7	96.3	97.1

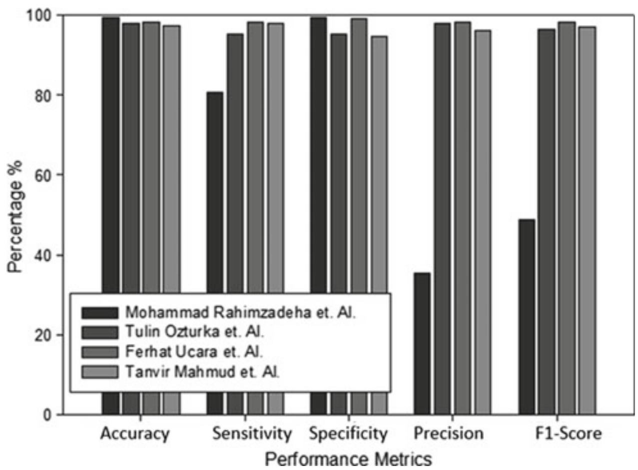


Fig. 4 Visualization depicting comparison of performance metrics

LeakyRelU operations for nonlinearity, in classification, it was successful to mark accuracy of 98% for binary classification that is much higher comparing with multiclass classification. Squeezenet with Baysen optimization is used (Ucar & Korkmaz, 2020) to design a model for COVID-19 cases. Different convolution stride sizes and paddings are used for model configuration, and to increase the number of infected images, it uses image augmentation with different parameters such as sheer, flip, brightness, and noise. It is classifying the images into three categories COVID, pneumonia and normal, overall accuracy is 98.26%, while overall specificity is 99.13%. In CovXNet (Mahmud et al., 2020), the metalerner is introduced to process on different shapes of input images, and it uses Relu as an activation function. In binary classification, its accuracy is up to 97.4%.

To elaborate the comparison, in Table 3, we have shown different performance metrics, models, and data on which these articles are analyzed. The accuracy for COVID-19 image detection ranges from 97.44 to 99.50, the sensitivity ranges from 80.53 to 98.3, precision ranges from 35.27 to 98.3, the minimum value of specificity is 94.7, while the maximum is 99.56 and range 48.9–98.3 in terms of F1-score. The plot in Fig. 4 visualizes comparisons using the given proposed models with different performance metrices. The result in the plot is itself illustrative for instance, and it shows (Wu et al., 2020) is having highest accuracy. In this visualization, all metrics are shown in percentage

4 Conclusion

From literature and previous experiments, it is found that the deep learning method is a rapid and accurate way to classify the images into binary or multiclass images. During the COVID period, various researchers contributed their work using deep learning models to examine the radiological images. Researchers and contributors are still adding CT and X-ray images in the open datasets. In this paper, we surveyed on proposed models for COVID-19 diagnosing using radiological images. For comparisons, we have considered various metrics such as accuracy, sensitivity, specificity, and F1 score. It is found that deep learning models are very promising for COVID-19 detection, and the accuracy of these models ranges from 97.4 to 99.50%. For the urgent need, in the future, computer vision will be contributing farther to investigate such viral infections.

References

Afshar, P., Heidarian, S., Naderkhani, F., Oikonomou, A., Plataniotis, K. N., Mohammadi, A., et al. (2020). Covid-Caps: A capsule network-based framework for Identification of Covid19 cases from X-Ray images. https://arxiv.org/abs/2004.02696.

Chowdhury, M. E. H., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M. A., Mahbub, Z. B., et al. (2020). Can AI help in screening Viral and COVID-19 pneumonia? https://arxiv.org/abs/2003.13145.

Cohen, J. P., Morrison, P., Dao, L. (2020). *COVID-19 image data collection*. https://arxiv.org/abs/2003.11597.

Farooq, M., & Hafeez, A. (2020). COVID-ResNet: A deep learning framework for screening of COVID19 from radiographs. http://arxiv.org/abs/2003.14395.

Hemdan, E. E. D., Shouman, M. A., & Karar, M. E. (2020). COVIDX-Net: A framework of deep learning classifiers to diagnose COVID-19 in X-Ray images. https://arxiv.org/abs/2003.11055.

Huang, C., Wang, Y., et al. (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *Lancet, 395*(10223), 497–506.

Ioannis D. A., & Bessiana, T. (2020). COVID-19: automatic detection from X-Ray images utilizing transfer learning with convolutional neural networks. https://arxiv.org/abs/2003.11617.

Kermany, D., Zhang, K., & Goldbaum, M. (2018). Labeled optical coherence tomography (OCT) and chest X-Ray images for Classification. Mendeley Data, V2. http://dx.doi.org/10.17632/rscbjbr9sj.2.

Li, X., & Zhu, D. (2020). COVID-Xpert: An AI powered population screening of COVID-19 cases using chest radiography images. https://arxiv.org/abs/2004.03042.

Mahmud, T., Rahman, M. A., & Fattah, S. A. (2020). CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization. *Computers in Biology and Medicine, 122*, 103869.

McIntosh, K. (2020). *Coronavirus disease 2019 (COVID-19): Epidemiology, virology, clinical features, diagnosis, and prevention*. 2020-04-10.

Mohammed, K. (2020). Automated detection of COVID-19 coronavirus cases using deep neural networks with X-ray images. *Al-Azhar University Journal of Virus Researches and Studies*.

Narin, A., Kaya, C., & Pamuk, Z. (2020). Automatic detection of coronavirus disease (COVID- 19) using X-Ray images and deep convolutional neural networks. https://arxiv.org/abs/2003.10849.

Rahimzadeh, M., & Attar, A. (2020). A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2. *Informatics in Medicine Unlocked, 19,* 100360.

Redmon, J., & Farhadi, A. (2017). Yolo9000: Better, faster, stronger. https://arxiv.org/abs/1612.08242.

Rothan, H. A., & Byrareddy, S. N. (2020). The epidemiology and pathogenesis of coronavirus disease(COVID-19) outbreak. *Journal of Autoimmune* 102433.

Sethy, P. K., & Behera, S. K. (2020) Detection of coronavirus disease (COVID-19) based on deep features. *Preprints* 2020, 2020030300 (https://doi.org/10.20944/preprints202003.0300.v1).

Song, Y., Zheng, S., Li, L., Zhang, X., Zhang, X., Huang, Z., & Chong, Y. (2020). Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images, medRxiv.

Ucar, F., & Korkmaz, D. (2020). COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images. *Medical Hypotheses, 140,* 109761.

Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., Summers, R. M. (2017). Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In *Conference 2017, Conference on Computer Vision and Pattern Recognition* (pp. 2097–2106). Honolulu: IEEE.

Wang, S., Kang, B., Ma, J., Zeng, Z., Xiao, M., Guo, J., & Xu, B. (2020). A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19), medRxiv.

Wang, L., & Wong, A. (2020). *COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest radiography images*. https://arxiv.org/abs/2003.09871.

World Health Organization. (2019). Novel Coronavirus(2019-nCoV) Situation Report-30. https://www.who.int/docs/defaultsource/coronaviruse/situationreports/20200219-sitrep-30-covid-19.pdf?sfvrsn=6e50645_2.

Wu, F., Zhao, S., Yu, B., et al. (2020). A new coronavirus associated with human respiratory disease in China. *Nature, 579*(7798), 265–269.

Xu, X., Jiang, X., Ma, C., Du, P., Li, X., Lv, S., et al. (2020). *Deep learning system to screen coronavirus disease 2019 pneumonia, engineering*, In Press. arXiv preprint arXiv:200209334.

Xu, X., Jiang, X., Ma, C., Du, P., Li, X., Lv, S., et al. (2020). Deep learning system to screen coronavirus disease 2019 pneumonia. arXiv preprint arXiv:200209334.

Zheng, C., Deng, X., Fu, Q., Zhou, Q., Feng, J., Ma, H., & Wang, X. (2020). Deep learning-based detection for COVID-19 from chest CT using weak label, medRxiv.

Zu, Z. Y., Jiang, M. D., Xu, P. P., Chen, W., Ni, Q. Q., Lu, G. M., & Zhang, L. J. (2020). Coronavirus disease 2019 (COVID-19): A perspective from China. *Radiology*. https://doi.org/10.1148/radiol.2020200490.