A Short Survey on Deep Learning Models for Covid-19 Detection Based on Chest CT and X-ray Images

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Abstract. The continued and rapid global spread of COVID-19 is taking a heavy toll on the global economy and human health, which has attracted the attention of professionals in various fields. Controlling the spread of this disease and reducing the threat to human life is of paramount importance. There are no clinically effective drugs for this disease. However, research on deep learning-based diagnostic systems for COVID-19 has yielded significant results and is expected to be an essential weapon in the fight against COVID-19 in the future. This paper provides a brief summary and evaluation of 15 studies on deep learning-based COVID-19 diagnostics, covering a total of 13 common pre-trained models and nine custom deep learning models in the COVID-19 dataset, and discusses the current challenges and future trends in this category of research. This paper aims to help healthcare professionals and researchers understand the advances in deep learning techniques for COVID-19 diagnosis to assist them in conducting relevant research to stop the further spread of COVID-19.

Keywords: COVID-19 · Coronavirus · Deep learning · Machine learning · Epidemic

1 Introduction

COVID-19 is an acute atypical respiratory disease caused by a novel coronavirus (SARS-CoV-2) infection. The main symptoms of COVID-19 are persistent cough, fever and breathlessness, which can be life-threatening in severe cases [1]. Furthermore, COVID-19 is highly infectious and mutable and can be transmitted by droplets from human respiration, making it extremely difficult to control [2]. Therefore, rapid diagnosis and isolation are essential to interrupt the spread of COVID-19.

The currently accepted standard for confirming the diagnosis of COVID-19 is the reverse transcription-polymerase chain reaction (RT-PCR) [3]. This test is cumbersome and time-consuming, and the yield of reagents easily influences the speed of detection. Most importantly, RT-PCR has a high rate of false negatives and often requires multiple tests to obtain accurate results [4]. Fortunately, with the rapid development of modern

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technology, numerous solutions based on new medical facilities and intelligent tools are available to assist in diagnosing this type of disease, such as CT and X-ray, to obtain accurate images of human organs. By analysing the effects of these, specialist doctors can diagnose the subject accurately. However, due to the large number of COVID-19 infections, it is not enough to rely on manual diagnosis by specialist doctors.

Deep learning is a statistically based artificial intelligence technique widely used in healthcare and industry as a reliable image recognition technology [5]. Diagnostic systems based on deep learning techniques can automate the recognition and identification of CT and X-ray images. These systems could be fall into two main categories, pre-trained models based on migration learning and customised deep learning models for specific domains.

This paper provides a brief review of research on COVID-19 diagnostic systems based on deep learning techniques and provides statistics and evaluation of some of the currently available systems and frameworks. The second part of the paper presents statistics on COVID-19 diagnostic systems based on pre-trained models. The third section presents statistics on custom deep learning models for COVID-19 diagnosis. The fourth and fifth sections briefly discussed all models covered in the paper and the limitations of this work.

2 Pre-trained Models

A pre-trained model is one in which the parameters of an already trained model are migrated to a new model to help train the new model. Typically, training a new model from scratch requires a large number of computational resources and time costs based on a large-scale dataset. Since most of the data or tasks are correlated, transfer learning allows the model parameters already learned to be shared with the new model, thus speeding up the convergence of the new model and optimising the learning efficiency of the new model. Most of the standard pre-training models available for transfer learning are based on convolutional neural networks, such as ResNet, SqueezeNet, DenseNet, VGG, Inception, AlexNet, GoogleNet.

Minaee, Kafieh [6] trained ResNet18, ResNet50, SqueezeNet and DenseNet-121 based on transfer learning. They used 2000 chest X-ray images of normal people and 84 chest X-ray images of COVID-19 patients from publicly available datasets and performed data augmentation on COVID-19 patient data samples (420 samples after augmentation). Their experiments sampled the input images as 224*224 and were trained using a cross-entropy loss function and an ADAM optimiser with a learning rate of 0.0001. The pre-trained model with the highest accuracy obtained was SqueezeNet, which achieved 99.2%. Narin, Kaya [7] trained more pre-trained models based on transfer learning and tested models including ResNet50, ResNet101, ResNet152, InceptionV3, and InceptionResNetV2. They used a more balanced dataset of 100 chest X-ray images, including 50 COVID-19 patients and 50 healthy people's chest X-ray images. Due to the small size of the dataset, a 5-fold cross-validation method was used to reduce the negative impact of the dataset size limitation. In this experiment, the pre-trained model with the highest accuracy was ResNet101 with 96.1 ± 2.6.

The experimental results of Shamsi, Asgharnezhad [8] showed that CT images have richer features than X-ray images for better prediction results in AI-based COVID-19 diagnosis. Their experiments used 100 chest X-ray images (25 COVID-19 patient images and 75 healthy human images) and 746 chest CT images (349 COVID-19 patient images and 397 healthy human images) to predict the results of ResNet50, DenseNet-121, InceptionResNetV2, and VGG16 pre-trained models were trained based on transfer learning. It is worth mentioning that eight classifiers were tested separately for each model to ensure the fairness of the results. In the end, the highest accuracy was 98.6% (ResNet50 + Linear SVM) based on X-rays and 87.9% (ResNet50 + Linear SVM) based on CT images. Loey, Manogaran [9]'s research used 345 CT images from COVID-19 patients and 397 from healthy individuals, in a total of 742 chest CT images, to train five pre-trained models (ResNet50, AlexNet, VGG16, VGG19 and GoogleNet) based on transfer learning. They used data augmentation techniques to prevent possible overfitting problem and the Conditional Generative Adversarial Network (CGAN) to improve the classification performance. Also using CT images as a training dataset was a study by Ahuja, Panigrahi [10], who used 746 chest CT images (349 from COVID-19 patients and 397 from healthy individuals) for ResNet18, ResNet50, ResNet51 and Squeeze. ResNet101 and SqueezeNet, four pre-trained models were trained based on transfer learning. The experiments also used data augmentation techniques and ultimately achieved excellent performance, with 99.4% accuracy from the ResNet18 model. Table 1 and Table 2 shows the detail performance comparison of pre-trained models in above studies.

Table 1. Summary of pre-trained models on COVID-19 diagnosis based on chest X-ray datasets

Authors	Data size	Models	Acc (%)	Sen (%)	Spc (%)
Minaee, Kafieh [6]	Total = 2420 (Covid-19 = 420 Non-Covid = 2000)	SqueezeNet	99.2	98 ± 2.7	92.9 ± 0.9
		ResNet50	99	98 ± 2.7	89.6 ± 1.1
		ResNet18	98.9	98 ± 2.7	90.7 ± 1.1
		DenseNet-121	97.6	98 ± 2.7	75.1 ± 1.5
Shamsi, Asgharnezhad [8]	Total = 100 (Covid-19 = 25 Non-Covid = 75)	ResNet50	98.6 ± 2.1	99.9 ± 1.2	98.2 ± 2.8
		InceptionResNetV2	98 ± 3.2	96.3 ± 7.8	98.5 ± 3.5
		VGG16	96.6 ± 3.4	98.8 ± 9.9	98.3 ± 3.1
		DenseNet-121	96.4 ± 3.1	93.9 ± 9.3	97.2 ± 3.7
Narin, Kaya [7]	Total = 100 (Covid-19 = 50 Non-Covid = 50)	ResNet101	96.1 ± 2.6	74.3 ± 25.7	98.2 ± 1.6
		InceptionV3	95.9 ± 3.7	90.5 ± 6.7	96.4 ± 3.6
		ResNet50	95.1 ± 3.4	92.7 ± 5.9	95.3 ± 4
		ResNet152	93.4 ± 3.9	57.45 ± 35.4	96.8 ± 2.5
		InceptionResNetV2	93.5 ± 3.7	81.7 ± 11.1	95.5 ± 3.4

(Acc = Accuracy; Sen = Sensitivity; Spc = Specificity).

Table 2. Summary of pre-trained models on COVID-19 diagnosis based on chest CT datasets

Authors	Data size	Models	Acc (%)	Sen (%)	Spc (%)
Ahuja, Panigrahi [10]	Total = 746 Covid-19 = 349 Non-Covid = 397	ResNet18	99.4	100	98.6
		ResNet50	98.8	100	97.2
		ResNet101	97	97.9	95.8
		SqueezeNet	95.2	95.8	94.4
Shamsi, Asgharnezhad [8]	Total = 746 (Covid-19 = 349 Non-Covid = 397)	ResNet50	87.9 ± 5.8	86.5 ± 7.1	89.1 ± 5.4
		VGG16	86.5 ± 5.8	84.8 ± 8.2	88.1 ± 5.9
		DenseNet-121	85.9 ± 5.9	84.9 ± 8.4	86.8 ± 6.3
		InceptionResNetV2	84.3 ± 7.3	83.2 ± 9	91.9 ± 7.4
Loey, Manogaran [9]	Total = 742 (Covid-19 = 345 Non-Covid = 397)	ResNet50	82.64	80.85	91.4
		VGG16	78.05	75.53	93.3
		GoogleNet	77.07	75.53	82.9
		VGG19	76.54	88.3	91.4
		AlexNet	75.73	88.3	87.6

(Acc = Accuracy; Sen = Sensitivity; Spc = Specificity).

3 Custom Deep Learning Models

A custom deep learning model is a deep learning model specifically tailored to a particular application domain, often based on the evolution or adaptation of a deep learning model, the fusion of multiple deep learning models, or the combination of deep learning techniques with other artificial intelligence techniques. Because they are specifically designed for a particular domain, custom deep learning models can often achieve more specialised functionality and more accurate performance. However, without parameters inherited from pre-trained models, custom deep learning models must be trained from scratch, which implies higher computational and time costs than migration learning. This paper summarised and evaluated several custom deep learning models for Covid-19, which is as below.

Islam, Islam [11] proposed a CNN and Long Short-Term Memory (LSTM) 20-layer hybrid network (CNN-LSTM) for COVID-19 diagnosis. The network consists of 12 two-dimensional convolutional layers with a maximum pooling layer after every two or three convolutional layers, a fully connected layer connecting an LSTM network layer to the output layer at the end of the network to sort and classify the X-ray images after the analysed temporal features. The CNN-LSTM model was trained using a balanced dataset (1525 chest X-ray images from COVID-19 patients, 1525 chest X-ray images from pneumonia patients and 1525 chest X-ray images of the healthy population) and achieved reasonably good results (accuracy of 99.2%). The model proposed by Li, Zhang [12], COVID-GATNet, combined DenseNet and Graph Attention Networks (GAT). The experiment used a large dataset (containing 399 chest X-ray images from COVID-19 patients, 7399 chest X-ray images from pneumonia patients, and 10,192 chest X-ray images from the healthy population) to train and test the model. Due to the small number of chest X-ray images from COVID-19 patients in the dataset, the COVID-19 class of the dataset was expanded using geometric transformation operations, and the expanded COVID-19 class consisted of 1197 X-ray images. The experiment achieved relatively good results, with an accuracy of 94.3%. Toraman, Alakus [13] presents a Convolutional CapsNet (Conv-CapsNet) for binary classification tasks and multiclassification tasks of COVID-19 chest X-ray images. The experiment also used data augmentation techniques to expand the dataset with 231 images from COVID-19 patients, resulting in 1050 images. The model achieved an accuracy of 97.23% ± 0.97%. Hussain, Hasan [14] used 2100 chest X-ray images (500 from COVID-19 patients, 800 from pneumonia patients and 800 from the healthy population) for a 22-layer CNN consisting of convolutional, pooling, dense, flatten and Leaky ReLU layers. A final accuracy of 99.1% ± 0.5% was achieved in the binary classification task of COVID-19 (COVID-19, Normal). Mukherjee, Ghosh [15] proposed a shallow CNN for COVID-19 diagnosis, which is only a 6-layer network consisting of the input layer, convolution layer, max-pooling layer, two dense layers, and output layer. After training with 321 chest X-ray images from COVID-19 patients and 321 chest X-ray images from people not infected with COVID-19, an accuracy of 99.69 was achieved in the binary classification task.

Many researchers have also proposed custom deep learning models for COVID-19 chest CT images classification. The method proposed by ELGhamrawy [16] uses a whale optimisation algorithm on top of CNN to select the most relevant features and tests three different classifiers, SVM, Naïve Bayes and Discriminant Analysis. After training with a dataset containing 583 chest CT images (432 from COVID-19 patients and 151 from viral pneumonia patients), an accuracy of 97.14% (SVM) was achieved. Amyar, Modzelewski [17] proposed an automatic classification segmentation method for classifying COVID-19 chest CT images. The framework consists of an encoder, two decoders and a multilayer perceptron (MLP), where the encoder is for reconstruction, the decoder for segmentation and the MLP for classification. The model was trained and tested using a dataset of 449 chest CT images from COVID-19 and 920 chest CT images from people without COVID-19 and achieved an accuracy of 94.67%. Yao and Han [18] presents a model using wavelet entropy for feature extraction, Feedforward Neural Network as the classification model and Biogeography-Based Optimisation as the optimisation algorithm. A balanced dataset consisting of 66 data from COVID-19 patients and 66 data from an uninfected COVID-19 population was used for training and testing. A final accuracy of 73.95 ± 0.98 was achieved. Chen [19] proposed a method with histogram equalisation (HE), grey scale co-occurrence matrix (GLCM), and SVM algorithm to identify COVID-19 chest CT images, and achieved 75.03% ± 1.12% accuracy on dataset that includes 296 chest CT images (148 from healthy people, 148 from COVID-19 patients). The Table 3 shows the detail performance comparison of all above models.

Table 3. Summary of custom deep learning methods for COVID-19 diagnosis

Model	Data type	Data size	Acc	Sen	Spc	Pre
Shallow CNN [15]	Chest X-ray Images	Total = 642 (Covid-19 = 321 Non-Covid = 321)	99.69	1.00	99.38	99.38
CNN_LSTM [11]	Chest X-ray Images	Total = 4575 (Covid-19 = 1525 Pneumonia = 1525 Non-Covid = 1525)	99.20	99.30	99.20	–
CoroDet (22-layer CNN) [14]	Chest X-ray Images	Total = 1300 (Covid-19 = 500 Normal = 800)	99.10 ± 0.5	94.20 ± 3.00	95.90 ± 3.70	97.70 ± 1.50
Conv-Capsnet [13]	Chest X-ray Images	Total = 2331 (Covid-19 = 231 Pneumonia = 1050 Normal = 1050)	97.23 ± 0.97	97.42 ± 1.81	97.04 ± 1.50	97.08 ± 1.42
WOA-CNN [16]	Chest CT Images	Total = 583 (Covid-19 = 432 Pneumonias = 151)	97.14	96.27	97.60	95.47
Encoder-Decoder with MLP [17]	Chest CT Images	Total = 1369 (Covid-19 = 449 Non-Covid = 920)	94.67	96.00	92.00	–
COVID-GATNet [12]	Chest X-ray Images	Total = 17990 (Covid-19 = 399 Pneumonia = 7399 Normal = 10192)	94.30	91.90	–	98.90
GLCM-SVM [19]	Chest CT Images	Total = 296 (Covid-19 = 148 Normal = 148)	75.03 ± 1.12	72.03 ± 2.94	78.04 ± 1.72	76.66 ± 1.07
WE-BBO [18]	Chest CT Images	Total = 132 (Covid-19 = 66 Non-Covid = 66)	73.95 ± 0.98	72.97 ± 2.96	74.93 ± 2.39	74.48 ± 1.34

(Acc = Accuracy; Sen = Sensitivity; Spc = Specificity; Pre = Precision).

4 Discussion

4.1 Open Discussion

This paper summarises 15 studies on building and testing artificial intelligence-based COVID-19 diagnostic systems. Five of these studies tested the performance of pre-trained models in COVID-19 diagnostics, and these studies covered 13 commonly used pre-trained models. The other nine studies discussed in this paper constructed and tested different custom deep learning models. The performance of the different models included in all studies is presented in Table 1, Table 2, and Table 3 with the selected performance metrics being accuracy, sensitivity, specificity, and precision (the section of pre-trained models does not include precision.). Due to the differences in the datasets used in the different studies, it is impossible to make a valid comparison between the different models. However, in the pre-trained model section, ResNet50 was tested in all five studies about pre-trained models so that it is possible to compare its performance with other pre-trained models. ResNet50 has achieved the highest accuracy in [8, 9], second accuracy in [6, 10] also achieved the third accuracy of all five models tested in [7]. It shows that ResNet50 has stable performance in the diagnostic task of COVID-19. Due to the different number of datasets used in the different studies, it is not possible to provide a valid comparison regarding the performance of the chest CT image dataset and the chest X-ray image dataset in the COVID-19 task. However, in [8], both datasets were used to test different pre-trained models, and as seen in the results of that study, despite the fact that the amount of chest X-ray image dataset used in the study was much smaller than the chest CT image dataset, the results based on the chest X-ray image dataset still generally outperformed the chest CT image dataset.

4.2 Challenges and Future Trends

Although deep learning techniques based on chest CT images and chest X-ray images have achieved promising performance in detecting COVID-19, there are still many challenges before the technology can be widely used in the medical field. (i) Data shortage. Deep learning techniques often rely on a large number of data to achieve robust performance. However, as COVID-19 is an emerging disease, there is still a shortage of standard data. Almost all studies of COVID-19 diagnostic systems based on deep learning techniques have used multi-source patchwork datasets from the Internet, which lack a uniform standard for quality assurance and pose a significant challenge for different performance comparisons. Researchers need to design and develop more optimised algorithms to address the negative impact of performance from smaller datasets to overcome this challenge. Also, establishing a unified high-quality dataset is extremely important for the research of deep learning-based COVID-19 diagnostic systems. (ii) Insufficient computational resources. In addition, medical imaging technologies often result in images with high resolution, and analysis of such images requires extremely high computational costs. Most researchers resize image data before training the model, which causes some data loss and image model performance. As technology has evolved, corresponding solutions have emerged, such as cloud computing technologies that can provide higher computational power. Also, more new technologies are emerging, and hardware devices are upgrading quickly. The negative images caused by the lack of computing resources will slowly decrease. Researchers can experiment with newer technologies and hardware to analyse high-resolution medical images to achieve higher performance. (ii) Lower social awareness. RT-PCR as a PCR-based method is recognised and accepted worldwide as a well-established technique. In contrast, most people in the world are not aware of deep learning-based automated detection systems and find it difficult to build sufficient trust in them. Educational outreach about deep learning technology is critical before popularising the COVID-19 automated diagnostic system based on deep learning technology.

5 Limitations of the Study

The purpose of this paper is to provide a brief summary of the currently available AI-based diagnostic systems for COVID-19. Although the different techniques used and the resulting performance of several studies are presented, several shortcomings need to be addressed in future work. Firstly, the number of studies covered in this paper is too small to provide a simple comparison and does not allow valid conclusions to be drawn. Secondly, this work has not been replicated for all models, and it is not possible to compare the performance of individual models on the same dataset. Therefore, the model performance discussed in the paper is only informative and does not give an accurate picture of the performance strengths and weaknesses of the different models. Third, to unify the performance metrics of different studies, only accuracy, sensitivity, specificity, and precision are used to compare model performance, but this cannot provide a comprehensive assessment of model performance. Fourthly, only a brief description of the models is summarised, but not an in-depth and detailed description of the techniques used in the models. For more details on the different models, the reader should consult the relevant references.

6 Conclusions

COVID-19 continues to spread rapidly worldwide, setting new records for the cumulative number of diagnoses and deaths, posing a vital threat to the global economy and human lives. Deep learning-based COVID-19 diagnostic systems can automate the analysis of chest CT images and chest X-ray images and have achieved excellent performance, promising to be an essential weapon in the fight against COVID-19. However, no current studies indicate that COVID-19 diagnostic systems based on deep learning techniques can be used as authoritative COVID-19 diagnostic tools. This paper provides a brief summary and evaluation of COVID-19 diagnostic systems using different deep learning techniques and discusses current challenges and future trends. It is hoped that soon, with the concerted efforts of the community, medical professionals and researchers, accurate and efficient COVID-19 diagnostic systems based on deep learning techniques that are recognised in various fields will be available to control the spread of COVID-19 and reduce its threat.

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