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Review

A Review Study of the Deep Learning Techniques used for the Classification of Chest Radiological Images for COVID-19 Diagnosis

Yu Wang, Carol Anne Hargreaves*

Department of Statistics and Data Science, National University of Singapore



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ABSTRACT

In the fight against COVID-19, the immediate and accurate screening of infected patients is of great significance. Chest X-Ray (CXR) and Computed Tomography (CT) screening play an important role in the diagnosis of COVID-19. Studies showed that changes occur in Chest Radiological images before the beginning of COVID-19 symptoms for some patients, and the symptoms of COVID-19 and other lung diseases can be similar in their very early stages. Further, it is crucial to effectively distinguish COVID-19 patients from healthy people, and patients with other lung diseases as soon as possible, otherwise inaccurate diagnosis may expose more people to the coronavirus. Many researchers have developed end-to-end deep learning techniques for the classification of COVID-19 patients without manual feature engineering. In this paper, we review the different deep learning techniques that have been used to analyze Chest X-Ray and Computed Tomography scans to classify patients with Covid-19. In addition, we also summarize the common public datasets, challenges, limitations, and possible future work. This review paper is extremely valuable as it confirms that (1) Deep Learning models are effective in classifying chest X-Ray images provided the training dataset is sufficiently large. (2) Data augmentation and generative adversarial networks (GANs) solve the small training dataset problem. (3) Transfer learning methods greatly enhanced the extraction and selection of features that were important for chest image classification. (4) Hyperparameter tuning was valuable for increasing the deep learning model accuracies to generally more than 97%. Our review study helps new researchers identify the gaps and opportunities for further or new research.

1. Introduction

The contagious disease, Coronavirus disease 2019 (COVID-19) was first identified in Wuhan, China, in December 2019 and soon spread worldwide (Page et al., 2021). The Coronavirus disease 2019 was caused by a severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which transmits when people breathe or are splashed or are sprayed with contaminated fluids via contaminated surfaces (CDC 2020). Therefore, to effectively control the spread of the infection, diagnosing patients as quickly as conceivable and applying preventative measures was necessary. The study of the coronavirus disease has become a research hotspot that has attracted worldwide scientists to study the topic further.

Possible symptoms of COVID-19 including fever, cough, and headaches (Islam, 2021) may appear one to fourteen days after exposure to the virus. But given sometimes that the symptoms are not clear and noticeable, medical test methodologies have been adopted to diagnose the disease. The standard method, real-time reverse transcriptase-polymerase Chain Reaction (RT-PCR) (Ai et al., 2020), has been used for routine screening and was found to be efficient and reliable. However, these tests detect ribonucleic acid (RNA) but not infectious viruses.

Serological tests, which detect antibodies produced by the body in response to infection was also developed and approved for use in some countries (NHS staff will 2020). Furthermore, chest radiological imaging such as computed tomography (CT) and X-rays are helpful for the diagnosis of COVID-19. Researchers in China found that the analysis of X-ray images was less specific for the infection, and that chest CT scan results were faster and more sensitive than PCR tests (Ai et al., 2020). Given that the radiology images' had high accuracy and efficiency, researchers paid more attention to classifying COVID-19 patients with CT scans and radiographs.

To better identify and diagnose cases, researchers in the field of medical biology, biostatistics, and computer science proposed various methods on chest image classification for the identification of Covid-19. The application of artificial intelligence for automation, especially deep-learning, is becoming more and more popular for researchers these days in the field of medical image classification, stock price prediction, etc. (Al-Sulaiman, 2022; Chand & Zhang, 2022; Verma et al., 2021). In this paper, we focused on academic papers that applied Deep Learning methods to classify COVID-19 patients based on chest radiological images. Our literature review provides the following major contributions:

* Corresponding author.

E-mail address: carol.hargreaves@nus.edu.sg (C.A. Hargreaves).

- 1 Provides a wide overview of COVID-19 detection, where deep learning methods and algorithms were applied to Chest X-Ray images or Chest CT scans, from 2020 to 2021. In these few years, we evaluate the evolution of methods that were applied to Chest X-Rays or Chest CT scans to detect Covid-19.
- 2 Further, we provide a summary of the common public datasets that have been used to identify Covid-19 from Chest X-rays or Chest CT scans.
- 3 We also identify the challenges and limitations that exist in detecting COVID-19 from chest images.
- 4 Further, we provide possible future directions for the application of deep learning techniques.

The remainder of this paper is organized as follows: [Section 2](#) demonstrates our search criteria, which include the search protocol, the searched databases, and the inclusion and exclusion criteria. [Section 3](#) summarizes the deep learning algorithms used to identify COVID-19 across the different periods since the epidemic outbreak. [Section 4](#) briefly introduces the standard datasets used by researchers globally. [Section 5](#) discusses the challenges, limitations, and possible future directions. [Section 6](#) presents the conclusion.

2. Research methodology

In order to find the papers which are suitable for our topic more efficiently, we adopted a systematic literature review (SLR) ([Kumar et al., 2021](#); [Votto et al., 2021](#)). First, we used a search protocol with a combination of related keywords. Next, we defined the inclusion and exclusion criteria to filter the papers based on the title, keywords, and abstract. Most of the research papers used in our study were from the Web of Science and IEEE Xplore databases.

2.1. Search protocol construction

First of all, we chose many search terms “COVID-19”, “Radiological image”, “image classification”, “deep learning”, “neural network,” and “CNN” By restricting the article publishing date to the last two years, we tried different permutations and combinations of the keywords and searched in the database. For those articles which contained our search terms in the article title and keywords, we downloaded these articles for further analysis.

2.2. Inclusion and exclusion rules

After collecting a wide range of papers, including the search terms, applying inclusion and exclusion criteria to screen out is highly significant. We adopted only articles presenting innovative approaches to COVID-19 image classification and techniques related to deep learning. To analyze the development of COVID-19 radiological image classification worldwide, we tended to choose articles from various countries, but the research papers published in non-English were excluded.

2.3. Exclusion based on content

Furthermore, it is necessary to filter the papers by content – title, keywords, and abstract. Only papers with a detailed theoretical background and complete experimental procedures was selected. We also excluded the papers that deviated from our topic. We selected a total of thirty papers, all appropriate for studying COVID-19 radiological image classification in the artificial intelligence field.

3. Background information

Faced with the increasing number of infected people and high infection rates of COVID-19, researchers in many different fields proposed various Deep Learning methods on chest image classification based on

Chest X-rays or CT scans, or both to better identify and diagnose cases. To find studies that use deep learning methods to diagnose COVID-19 positive patients, we searched the papers according to the keywords involving the definition of “Image Classification”, “Deep Learning”, “COVID-19”, and “chest CT /X-Ray”. We next categorized the research papers into Phase 1 (February 2020 – April 2020), Phase 2 (May 2020 – December 2020) and Phase 3 (January 2021 – December 2021) based on their submission date.

3.1. Phase 1: the beginning of COVID-19 (February 2020 – April 2020)

COVID-19 emerged in late 2019, and by early 2020 had spread globally. In this phase, February 2020 – April 202, many attempts were made to analyze classical chest X-Ray images and CT scans using different processing architectures with different optimization methods to more accurately identify COVID-19 patients. We identified three main focus areas that researchers strived to introduce and develop, for the analysis of medical images to detect Covid-19. The three focus areas identified are listed below:

3.1.1. Feature selection

Many primary studies paid attention to feature extraction to determine the disease characteristic directly. For instance, Greece researchers ([Apostolopoulos et al., 2020](#)) employed a computer-aided diagnostic system, the Convolutional Neural Network (CNN) architecture called MobileNet (v2), which aimed to investigate the effectiveness of the Deep Learning methods and feature extraction, as well as to distinguish the Covid-19. They first performed an experiment utilizing six of the most common pulmonary diseases to evaluate the methodology of Deep Learning, then designed three different experiments altering the mining methods to inspect the variance of the extracted features of the COVID-19 Chest X-Ray images. The maximum accuracy achieved by their experiments was 99.18%, which proved that their strategy was worth adopting.

On the basis of 4356 chest CT collected collected from their hospital, Chinese scientists’ ([Li et al., 2020](#)) developed a three-dimensional Deep Learning framework to extract both 2D local and 3D global representative features named COVNet based on a ResNet50 architecture. It had a reliable ability to detect COVID-19 patients from pneumonia patients and normal people. Further, [Ozturk et al. \(2020\)](#) offered a slightly different idea by introducing an end-to-end architecture called DarkCovidNet inspired by the DarkNet architecture. Two different scenarios, classification of three categories (COVID-19, No-Findings, and Pneumonia) and two categories (COVID-19 and No-Findings) were used and the accuracies were 87.02% and 98.08% respectively. The model managed to overcome the radiography’s inability to detect the subtle details and mild symptoms in the early stage without using any feature extraction methods.

3.1.2. Limited data

Available dataset that is large enough for training the model is considered vital for the degree of exactitude and model evaluation in Deep Learning. Between February 2020 and April 2020, many research groups (e.g., ([Ucar & Korkmaz, 2020](#); [Apostolopoulos et al., 2020](#); [Waheed et al., 2020](#); [Wang et al., 2020](#))) realized that the problem of incomplete data and limited data size for the detection of COVID-19 was critical. Hence, Ucar & Korkmaz ([Ucar & Korkmaz, 2020](#)) utilized a multiscale offline augmentation as the first stage of their model to alleviate the uneven sample distribution of the public dataset. Further, [Apostolopoulos et al. \(2020\)](#) applied data augmentation by rotating their images. They also stated in their paper that some data limitations should be mentioned, i.e., the relatively small sample of COVID-19-infected cases, older recorded pneumonia incident samples, and unavailability of further data related to demographic characteristics.

[Waheed et al. \(2020\)](#) pointed out that the CNNs can readily overfit on a small dataset, while the medical image collection was expen-

Table 1
Comparison of Deep Learning Models published between February 200 - April 2020

Author	Countries and Regions	Submit Time	Image Type	Main Model	Class Label and Sample Size	Accuracy (%)
Li et al. (2020)	China	Feb-20	Chest CT	COVNet (Based on ResNet50)	1296 COVID-19 1735 Pneumonia 1325 Normal	96.00
Wang et al. (2020)	Canada	Mar-20	Chest X-Ray	COVID-Net	13975 CXR images across 13870 patient cases in three classes: positive COVID-19 images non-COVID-19 pneumonia patient cases Normal patient cases	93.30
Ozturk et al. (2020)	Turkey, UK, Singapore, China Taiwan, Japan	Apr-20	Chest X-Ray	DarkCovidNet (Based on DarkNet)	125 COVID-19 500 Pneumonia 500 No-findings	93.00
Ucar & Korkmaz (2020)	Turkey	Apr-20	Chest X-Ray	COVIDiagnosis-Net (Based on Deep Bayes-SqueezeNet)	76 COVID-19 4290 Pneumonia 1583 Normal	97.93
Apostolopoulos et al. (2020)	Greece	Apr-20	Chest X-Ray	MobileNet v2	224 COVID-19 714 Pneumonia 504 Normal	2-class: 99.18 7-class: 87.66
Waheed et al. (2020)	India, Turkey, Brazil	Apr-20	Chest X-Ray	CovidGAN (Based on Auxiliary Classifier Generative Adversarial Network)	72 COVID-19 120 Normal	95.00

sive and hard to gather. So, to alleviate the drawbacks, they presented an Auxiliary Classifier Generative Adversarial Network (ACGAN) based model called CovidGAN to generate synthetic images and designed a CNN-based model to detect COVID-19. They also claimed in this paper that to the best of their knowledge, they were the first to present a GAN architecture for improvement in COVID-19 detection.

In addition, Wang et al. (2020) built a public open access benchmark dataset called COVIDx based on four other public datasets. At first the CXR images of COVID-19 positive patient was scarce but it was updated constantly. And the COVIDx dataset, later, updated on 11/28/2021, already contained 16,490 positive COVID-19 images.

Apart from the dataset, Wang et al. (2020) also proposed an open-source deep convolutional neural network architecture called COVID-Net, with a lightweight residual projection-expansion projection-extension (PEPX) design pattern, which had a selective long-range connectivity at various areas, and considerable architectural diversity. Beyond that, they also leveraged an explainability-driven audit, GSInquire, to make the detection process more interpretable and transparent.

3.1.3. Hyperparameter tuning

Hyperparameter selection was always a crucial problem in the field of Deep Learning. In order to enhance hyperparameter optimization, Ucar & Korkmaz (2020) created a novel model called COVIDiagnosis-Net for the rapid diagnostic of the COVID-19 by using a deep SqueezeNet combined with Bayes optimization. In other words, Bayes optimization, worked by dealing with a global optimization or minimization problem for the objective function using the prior knowledge from the learned data, when tuning the hyperparameters.

The research articles published in early 2020 about COVID-19 chest image classification analysis, revealed the research focus for scientists and opened the doors for more interest in this field. A summary of the key research papers that were published between February 2020 – April 2020 is shown in Table 1 below. Although the model accuracies appear to be good, we can see that these research papers either lack data or are short of categories and undoubtedly, their efficiency still needs time and more experiments to test.

In Table 2 we summarize the main challenges outlined by researchers, from the perspective of data limitations to feature selection to hyperparameter tuning. As for the problems of optimizing generative adversarial networks (GANs) for the synthesis of chest images and the application of the image deep learning algorithms in clinical medicine,

Table 2
Main challenges for Chest Image Classification for Covid-19 between February 2020-April 2020

Challenges Domain	Challenges	List of references
Hyperparameters	Hyperparameters optimization are limited	Ucar & Korkmaz (2020)
Data	Imbalance/Incomplete/Limited data	Apostolopoulos et al. (2020); Ucar & Korkmaz (2020); Waheed et al. (2020) Li et al. (2020)
Feature	Single data source (come from same hospital) Hard to classify subtle details Hard to classify the overlapping in lung responds to various insults	Ozturk et al. (2020) Li et al. (2020)
Methods	Classical data augmentations are limited, GANs can be better Deep Learning methods lack transparency and interpretability	Waheed et al. (2020) Apostolopoulos et al. (2020); Li et al. (2020)
Clinic	Lack of clinical testing/laboratory confirmation	Li et al. (2020); Waheed et al. (2020)

no effective solutions had been proposed by scholars in the papers published between February 2020 – April 2020.

3.2. Phase 2: middle period of COVID-19 (May 2020 – December 2020)

During this phase (May 2020 – December 2020), COVID-19 has been preliminarily controlled in many regions of the world, but the emergence of the Delta variant in October 2020 made the situation serious. The amount of research on the coronavirus increased exponentially and more deep learning architectures were proposed to better handle the problems of feature selection, limited data and hyperparameter tuning that were mentioned in phase 1.

3.2.1. Feature selection

There were many researchers devoted to improving the feature extraction and getting more accurate results. For example, Wang et al. (2021)'s architecture included three main parts, preprocessing, feature extraction, and classification by using the well-known GoogleNet Inception v3 CNN. From the feature extraction they processed Region of Interest (ROI) images, and the lung contour was precisely delineated to en-

sure the practicality of the model. Further, [Perumal et al. \(2021\)](#) used a Haralick Texture Feature Extraction, which provides information about a particular pixel's intensity with a position related to the neighboring pixels in three classical architectures, ResNet 50, Inception V3, and VGG 16. Their results showed that the prediction made by the transfer learning model based on VGG-16 gained a better accuracy.

In addition, [Ismael & Şengür \(2021\)](#) showed that the Deep Learning approach, especially deep features and the Support Vector Machine (SVM) classifier outperformed others. [Ismael & Şengür \(2021\)](#) applied five pre-trained CNN models and four SVM kernels, and finally the deep features extracted from the ResNet50 model and SVM classifier with the Linear kernel function produced the highest accuracy score, 94.7%.

Further, [Tuncer et al. \(2021\)](#) presented a novel exemplar chest image classification method including a lightweight multileveled feature extraction method built by using Fourier-transform and a fuzzy tree. Sixteen classifiers were used in the classification stage and the Cubic SVM model achieved the highest accuracy.

3.2.2. Limited data

To mitigate the consequences of insufficient data, some researchers were working to expand the data set with more comprehensive and effective images ([Misztal et al., 2020](#); [Wang et al., 2021](#)), and some used data augmentation methods to add simulated or processed images to mimic the real images ([Elzeki et al., 2021](#); [Ismael & Şengür, 2021](#); [Liang et al., 2020](#); [Menon et al., 2020](#)). Generative Adversarial Networks (GANs) is popular for data augmentation and in this phase, some GAN optimization ideas were successfully achieved. [Liang et al. \(2020\)](#) applied conditional generative adversarial networks (cGAN) that involved the conditional generation of images. In this architecture the U-net was used for both the Generator (G) network and the Decoder (D) network to make the architecture simpler. Further, [Menon et al. \(2020\)](#) extended the basic GAN by incorporating the Mean Teacher method (MTT-GAN), which included two separate models, a generator network and a discriminator network and Transfer Learning was used to train both of these two networks. What's more, [Das et al. \(2020\)](#) proposed a truncated Inception Net V3 model to reduce model complexity to avoid possible overfitting.

3.2.3. Hyperparameter tuning

In this phase, hyperparameter tuning was no longer the focus, instead, transfer learning became popular and transfer learning became the common tool for researchers to boost their model accuracy results. Many methods involving transfer learning was developed to optimize the proposed networks ([Elzeki et al., 2021](#); [Wang et al., 2021](#); [Ismael & Şengür, 2021](#); [Perumal et al., 2021](#); [Menon et al., 2020](#)). In addition, transfer learning alleviated the problem of the lack of COVID-19 positive data to some extent.

3.2.4. Discussion

However, not much research had made progress in the clinical area. [Wang et al. \(2021\)](#) realized this problem and managed to enroll some patients with COVID or viral pneumonia for assessing the value of the algorithm, but the number for clinical testing was still too small. We still had a long way to go before it could be applied to the real-life and clinical domains.

Most of challenges addressed before April 2020 had new innovative solutions. However, there were always new challenges to be found and enhanced. [Lee et al. \(2020\)](#) argued that previous studies on transfer learning strategy had focused only on the efficacy of the proposed network through comparison between different Deep Convolutional Neural Network (DCNN) models, and the effect of the hidden layer depth and the degree of the fine-tuning of transfer learning for the same CNN architecture had not been comparatively studied. Hence, [Lee et al. \(2020\)](#) designed an experiment consisting of two main groups, one used VGG-16 as the backbone network and the other one applied VGG-19 to evaluate the effects of the hidden layer depths. Then each group was divided into 6 subgroups according to the degree of fine-tuning. At last,

the fine-tuned model with two blocks of the VGG-16 model performed best among the 12 sub-experiments. Discussion about the limitation of CT scans was put forward by [Das et al. \(2020\)](#) and left to be optimized by future researchers.

During May 2020 – December 2020, some researchers proposed novel models to classify COVID-19 Chest images. [Elzeki et al. \(2021\)](#) presented a novel Deep Learning architecture called Chest X-Ray COVID Network (CXRVN), which had four convolution layers, three pooling layers, and one fully connected layer. The GAN data augmentation method and transfer learning were also employed in different experiments and the effects to improve the overall accuracy were proven successfully.

A summary of key findings on chest image classification for COVID-19 in this time period is provided in [Table 3](#).

[Table 4](#) below shows the challenges proposed by papers submitted between May 2020 to December 2020.

3.3. Phase 3: recent COVID-19 period (January 2021 – December 2021)

When it comes to January 2021 – December 2021, with the invention and marketing of vaccines, people finally saw the dawn of victory over the epidemic. Scientists had come up with more sophisticated and complex answers to these challenges with bigger datasets and more comprehensive considerations.

3.3.1. Feature selection

[El-Kenawy et al. \(2021\)](#) presented an innovative thought, and proposed an Advanced Squirrel Search Optimization Algorithm (ASSOA) for feature extraction, which was established and inspired by the Squirrel Search (SS) basic optimization algorithm to select features. In the first step, CNN-model ResNet-50 with data augmentation, dropout, and transfer learning was used to learn features. The ASSOA algorithm was then applied for the feature selection process. Multilayer Perceptron Neural Network (MLP), which was optimized by the proposed ASSOA algorithm, would classify inputs in the final stage.

[Zhu et al. \(2021\)](#) proposed a method based on GANs that generates handcrafted features by radiomic counterparts of CT images, called generative adversarial feature completion and diagnosis network (GACDN). Their framework focuses on the problem of single-view diagnostic frameworks ignoring basic information in handcrafted features for a particular location. Experiments showed that not only could the model achieve better classification performance and quality of generated features, but also it would reduce technical and time cost compared with the state-of-the-art methods.

3.3.2. Limited data

[Bashar et al. \(2021\)](#) managed to train their model on bigger public datasets. Their research team optimized the Deep Learning approach for automatic classification and diagnosis, using what appears to be the largest open-source dataset on Kaggle in their range of knowledge. The dataset consisted of four categories: COVID-19 positive images, normal images, lung opacity images, and viral pneumonia images. Data augmentation techniques, image enhancement, and transfer learning of VGG19, VGG16, DenseNet, AlexNet, and GoogleNet were required and achieved the highest average accuracy of 95.63%.

Furthermore, to operate potential huge data volumes, [Chakraborty et al. \(2021\)](#) applied MongoDB with GridFS interface as a data storage in their system which mainly used the transfer learning method to classify CXR data into COVID-19, Pneumonia, and Normal. In addition, a new challenge about data biased was raised by [Li et al. \(2021\)](#). They pointed out that the CT scans in a dataset might come from a single source and were likely to have implicit image characteristics representing the origin, since the different sources were equipped with different CT scanners, scanning protocols, and post-processing procedures. This raised the problem that the classification results might have a relationship with the source rather than images

Table 3
Comparison of proposed models and methodologies of papers in May 2020-December 2020

Author	Countries and Regions	Submit Time	Image Type	Main Model	Class Label and Sample Size	Accuracy (%)
Das et al. (2020)	Australia	May-20	Chest X-Ray	Truncated Inception Network (Based on Inception Net V3)	162 COVID-19 4280 Pneumonia 342 TB(China) 58 TB(USA)	99.96
Ismael & Şengür (2021)	Iraq, Turkey	May-20	Chest X-Ray	Resnet-50+SVM	95 End-to-end training	94.70
Wang et al. (2021)	China	Jun-20	Chest CT	GoogleNet Inception v3 CNN	180 Viral pneumonia 79 Confirmed nucleic acid testing 15 COVID but first two nucleic acid test were negative	82.90
Perumal et al. (2021)	India	Jul-20	Chest CT & X-Ray	Haralick + VGG16, Resnet50 and Inception V3	2538 Bacterial Pneumonia 1345 Viral pneumonia 1349 Normal	93.00
Misztal et al. (2020)	Poland	Aug-20	Chest CT & X-Ray	COVID-19 CT & Radiograph Image Data Stock	6000 Self-contained Dataset	92.00
Tuncer et al. (2021)	Turkey, Finland, Saudi Arabia	Oct-20	Chest X-Ray	A Novel Exemplar Chest Image Classification Method	135 COVID-19 150 Pneumonia 150 Normal	97.01
Elzeki et al. (2021)	Egypt	Oct-20	Chest X-Ray	Chest X-Ray COVID Network (CXRVN)	Dataset 1: 25 COVID-19, 25 Normal Dataset 2: 221 COVID-19, 234 Normal Dataset 3: 221 COVID-19,234 Normal,148 Pneumonia	94.50
Lee et al. (2020)	Korea	Oct-20	Chest X-Ray	VGG-16, VGG-19	607 Normal 607 Pneumonia 607 COVID-19	95.90
Liang et al. (2020)	China, Canada	Dec-20	Chest X-Ray	cGAN,ResNet	219 COVID-19 1341 Normal 1345 viral pneumonia	97.80
Menon et al. (2020)	USA	Dec-20	Chest X-Ray	MTT-GAN, VGG-19,AlexNet	Binary-class: 1400 COVID-19, 1400 Normal Multi-class: 1400 COVID-19, 1400 Normal, 1400 Bacterial pneumonia, 1400 Viral pneumonia	92.45

Table 4
Challenges faced for Chest Image Classification for Covid-19 in May 2020 to December 2020

Challenges Domain	Challenges	List of references
Hyperparameters Data	Hyperparameters: learning rate Limit resources of images Small COVID-19 dataset	Das et al. (2020) Elzeki et al. (2021) Das et al. (2020); Liang et al. (2020); Wang et al. (2021) Misztal et al. (2020)
Feature	Both CT and CXR data should be used in this task Limit by the capacity to localize the disease	Das et al. (2020); Wang et al. (2021)
Methods	Fail to perform in the early stages of COVID-19 Many factors such as low signal-to-noise ratio and complex data integration have challenged DL's efficacy	Das et al. (2020) Wang et al. (2021)
Clinic	Not addressed categorizing into different severities Should use more types of clinical data with different feature	Li et al. (2020) Elzeki et al. (2021)
Others	Layer depth and degree of fine tuning CT's limitation: expensive and complex RT-PCR's limitation: the insufficient amount and quality of the clinical material from which the nucleic acids are isolated, which can result in false-negative results.	Lee et al. (2020) Das et al. (2020) Misztal et al. (2020)

themselves. A solution, a training strategy named Mix-aNd-Interpolate (MINI), was presented by generating a new training sample according to combining two authentic training samples from different domains (sources).

3.3.3. Hyperparameter tuning

Bahgat et al. (2021) concentrated on hyperparameter optimization. They introduced an Optimized Transfer Learning-based Approach for Automatic Detection of COVID-19 (OTLD-COVID-19) to optimize the network hyperparameters' for the CNN architecture. Experiments showed that DenseNet121 had the best performance and its accuracy can reach 98.47%. Lacerda et al. (2021) provided a method with Deep Transfer Learning on VGG-16 and a hyperparameter optimization technique, named Optuna, on the combined public datasets of CT images. They achieved an accuracy of 88% finally.

3.3.4. Discussion

The use of transfer learning was still very common in 2021. Some scientists concentrated on the power of transfer learning (Chakraborty et al., 2021; Fayemiwo et al., 2021; Gupta et al., 2022; Zhao et al., 2021). They employed various classical Deep Learning architectures with transfer learning and make a comparison about the networks' performance. Other researchers preferred to use transfer learning as an optimization part of their whole framework to further improve the effects (El-Kenawy et al., 2021; Bashar et al., 2021; Bahgat et al., 2021; Baltazar et al., 2021; Lacerda et al., 2021).

GANs were widely used by researchers in different domains like data augmentation, image segmentation and so on. Zhu et al. (2021) applied an optimization GANs methods (GACDN) to improve the feature extrac-

Table 5
Comparison of the proposed models and methodologies of research papers submitted in 2021

Author	Countries & Regions	Submit Time	Image Type	Main Model	Class Label and Sample Size	Accuracy (%)
El-Kenawy et al. (2021)	Egypt, Australia, Korea	Feb-21	Chest X-Ray	ResNet+ASSOA+MLP	more than 5863 for 3 classes	99.70
Baltazar et al. (2021)	Philippines	Feb-21	Chest X-Ray	Transfer Learning, Grid Search (InceptionV3, InceptionResNetV2, Xception, VGG, MobileNet)	629 COVID-19 1505 Viral Pneumonia 2786 Bacterial Pneumonia 194 Abnormal Non-Pneumonia 565 Non-COVID-19 Pneumonia 3593 Normal	Not Mentioned (Use other 3 variables)
Bahgat et al. (2021)	Egypt	Mar-21	Chest X-Ray	OTLD-COVID-19 (Based on DenseNet121)	2151 COVID-19 3187 P-virus 3047 P-bacteria 4548 normal	98.47
Fayemiwo et al. (2021)	Nigeria	Mar-21	Chest X-Ray	Deep Transfer Learning Model (DTL), (VGG-16,VGG-19)	1300 COVID-19 1300 normal 1300 viral a different set of 470 (70 COVID-19 200 viral 200 normal to test)	95.00
Lacerda et al. (2021)	Brazil	Mar-21	Chest CT	Transfer Learning (VGG-16), Optuna	856 COVID-19 1319 non-COVID-19	88.00
Park et al. (2021)	South Korea	Apr-21	Chest X-Ray	A novel ViT model, The Array-based Annotation Method (Toussie et al. 2020)	Pretraining: 224,316 CXR images Classification: 26846 Normal 1672 Other Infections 5755 COVID-19 Severity Quantification: 4782 CXR images	86.80
Chakraborty et al. (2021)	Bangladesh	May-21	Chest X-Ray	Transfer learning (VGG19, VGG16, DenseNet, AlexNet, GoogleNet), MongoDB with GridFS	1184 COVID-19 1294 Pneumonia 1319 Healthy	97.11
Zhu et al. (2021)	China	May-21	Chest CT	Generative Adversarial feature Completion and Diagnosis Network (GACDN)	1495 COVID-19 1027 CAP	91.31
He et al. (2021)	China, USA	May-21	Chest CT	GANs	Not Mentioned	Not Mentioned (Use other 6 variables)
Sangeetha et al. (2021)	India	Aug-21	Chest CT	Hybrid Swarm Intelligence and Fuzzy DPSO, Dropout CNN Classifier	Not Mentioned	99.00
Zhao et al. (2021)	China	Aug-21	Chest X-Ray	ResNet-50 × 1 with a Vanilla ResNet-v2 Architecture	2358 SARS-CoV-2-Positive 13993 SARS-CoV-2-Negative (8418 non-Pneumonia 5575 non-SARS-CoV-2 Pneumonia)	96.50
Bashar et al. (2021)	Arabia, Canada, USA	Sep-21	Chest X-Ray	A Method Combined Image Enhancement, Data Augmentation, Transfer Learning. (VGG19, VGG16, DenseNet, AlexNet, GoogleNet)	3616 COVID-19, 1345 Viral Pneumonia, 6012 Lung Opacity, 10192 Normal	94.23
Li et al. (2021)	China	Oct-21	Chest CT	Mix-aNd-Interpolate (MINI) + 3D ResNet-18	1046 COVID-19 652 CAP 475 non-Pneumonia	96.40
Gupta et al. (2022)	India	Oct-21	Chest X-Ray	Transfer Learning (VGG-19, ResNet, InceptionNet)	206 COVID-19 206 Normal	94.00

tion step. [He et al. \(2021\)](#) developed an evolvable GAN framework by utilizing three different mutation operators, weight clipping and JS divergence, the Wasserstein distance, and so on, for the target of overcoming the limitation and problems of GANs.

In addition, some groups of scientists had come up with new ideas about the methods and their clinical application range. [Baltazar et al., \(2021\)](#) were concerned about the clinical prospective and mentioned the issues on clinical applicability, i.e., the unverified data quality, the insufficient COVID-19 positive cases, and the shortage of information on how the datasets were generated. Considering the clinical, methodical, and data standpoints, the writers aggregated a clinically validated CXR images dataset and a well-formulated study design based on an InceptionV3 architecture. They believed that it could be adopted by the re-

search community to advance and create practical AI solutions to mitigate COVID-19.

[Park et al. \(2021\)](#) claimed that CNN architecture could not be optimal for problems requiring high-level CXR disease classification because of the intrinsic locality of pixel dependencies in the convolution. They optimized and proposed a novel ViT model which utilizes ViT as a feature extractor for the low-level CXR feature corpus that contained the representations for common CXR findings as to the solution. Besides, they also expanded their model for COVID-19 severity quantification and localization, and a multi-task model to integrate these two tasks was addressed with a good performance.

Some other problems in the field of image processing could also be combined with image classification to aid detection. [Sangeetha et al.](#)

Table 6
Main Challenges experienced by researchers in 2021

Challenges Domain	Challenges	List of references
Data	Limit positive cases/ many models are trained or tested on a small dataset, featuring a small number of classes Some factors impede researchers to examine the validity of the medical images The lack of information on how these datasets were generated Most CXR images used for diagnostic purposes are not publicly accessible owing to privacy issues (Hard to collect data) The data source bias problem: dataset comprises only a single class of data	Baltazar et al. (2021); Bashar et al. (2021) Baltazar et al. (2021) Baltazar et al. (2021) Zhao et al. (2021) Li et al. (2021)
Method	GANs tend to be challenging to be trained The lack of model's compatibility from the development to a clinical translation The lack of model portability in which difficulty arises when migrating AI models to another host CNN architecture may not be optimal for problems requiring high-level CXR disease classification that require the integration of global relationship between pixels	He et al. (2021); Zhu et al. (2021) Baltazar et al. (2021) Baltazar et al. (2021) Park et al. (2021)
Clinic	Application in clinical scenarios still have some issues	Baltazar et al. (2021); Zhao et al. (2021); Zhu et al. (2021)

(2021) utilized Hybrid Swarm Intelligence and Fuzzy DPSO to preprocess inputs with the goal of lighting more meaningful information for lung segmentation and quantification at first. Second a new approach called Dropout CNN classification was used to detect abnormalities of lung images, so as to determine whether the patient was infected, which could be used to classify patients.

To sum up, we summarized the information of research in chest image classification in the period January 2021 - December 2021. See Table 5. From Table 5, we see that some of the sample sizes increased greatly, compared to studies before. With the passage of time, the algorithms gradually became more mature and diverse, and with the accumulation of data, more reliable models were presented.

Table 6 below, shows a summary of the challenges experienced by researchers in 2021. More attention was paid to clinical and practical applications.

4. Summary of datasets

In Deep Learning, the quality and quantity of data can greatly affect the modelling outcome. For this reason, finding high-quality accessible datasets is critical. In this Section 3, we summarize the public datasets used by researchers in Table 7 below, as well as point out some popular datasets with a brief description.

As you can see from Table 7 above, there are many different public datasets, among which the followings are most used by researchers:

- Daniel Kermay, Kang Zhang, and Michael Goldbaum built a dataset called Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification in January 2018 with thousands of images (Kermay & Zhang, 2018).

- Chest X-Ray Images (Pneumonia) was a dataset first updated by Mooney on Kaggle in March 2018. It has 5863 images in 2 categories (Mooney, 2020).
- A team of researchers from Qatar University, Doha, Qatar, and the University of Dhaka, Bangladesh along with their collaborators from Pakistan and Malaysia in collaboration with medical doctors created a database of chest X-ray images for COVID-19 positive cases along with Normal and Viral Pneumonia images, which was COVID-19 Radiography Database (Rahman et al., 2020).
- Chung first uploaded Figure 1 COVID-19 Chest X-ray Initiative dataset on GitHub in May 2020 and their team was working continuously to grow this dataset as new data becomes available (Chung, 2020).
- Cohen et al. created a public COVID-19 CXR image data collection in 2020, which contains 679 frontal chest X-ray images and 82 lateral chest X-ray images of 5 types from hospitals across 26 countries. It is the most popular dataset from our review (Cohen et al., 2020).

5. Discussion

In Section 5, we discuss the contribution, challenges, limitations, and gaps in the research of chest image classification for COVID-19 identification and then sum up with a brief description of the future direction in the next few years.

5.1. Contribution to literature

This literature review summarizes an overview of a wide range of existing studies in 2020-2021. Over the past two years, many researchers have paid attention to theoretical aspects such as data sample size, feature extraction, hyperparameter tuning, and architecture optimization. Significant progress in the amount of data is considerable, and the model's accuracy, sensitivity, and specificity have greatly improved. This paper provides a systematic and detailed conclusion of the development of the COVID-19 image classification project so that future scientists can keep up with the project's progress as soon as possible. Besides, we also put forward the aspects still lacking in this research project, which can help scientists to better select topics and make up for the deficiency in the field.

5.2. Challenges

Some methods of hyperparameter optimization and feature extraction have been proposed and reviewed before. However, in the field of COVID-19 image classification and even Deep Learning, finding suitable hyperparameters and feature extraction methods will always be a complex and necessary topic for scientists to explore and study.

Also, lack of data for research purposes has been around for as long as researchers have been focusing on understanding what the data is telling them. Compared to the time when the pandemic first began in January 2020, the quantity and quality of datasets have greatly improved, and many methods have emerged to address issues such as data imbalances. Nonetheless, the problems of relatively few positive cases, the lack of standardized large-scale datasets, and data augmentation methods still exist. And it is these problems that influence the results of the experiments and model validity.

As for methods and models, some solutions with the application of Deep Learning techniques, reported poor interpretability, transparency, and efficiency. These are the disadvantages of using deep learning techniques. More suitable architectures such as GANs were proposed by researchers in the two years, 2020-2021. But in most cases, the compatibility and portability of the CNN framework and related models still need to be further studied. Researchers still need to prove that their models can still run well when migrating their models to other platforms. In a nutshell, researchers need to consider how to achieve good model performance when using other datasets from other sources.

Table 7
Summary of public datasets utilized in the papers

Author	Submit Time	Image Type	Dataset
Wang et al. (2020)	Mar-20	Chest X-Ray	COVID-19 image data collection.(Cohen et al. (2020) Figure 1 COVID-19 Chest X-ray(Chung et al. (2020) Actualmed COVID-19 Chest X-rays(Chung et al. (2020) COVID-19 Radiography Database(Rahman et al. (2020) RSNA pneumonia detection challenge(2019)
Ozturk et al. (2020)	Apr-20	Chest X-Ray	COVID-19 image data collection (Cohen et al. (2020) Chestx-ray8 (Wang et al, 2017)
Ucar & Korkmaz (2020)	Apr-20	Chest X-Ray	COVID-19 image data collection (Cohen et al. (2020) Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification. Mendeley Data, V2(Kermany et al. (2018)
Apostolopoulos et al. (2020)	Apr-20	Chest X-Ray	COVID-19 image data collection(Cohen et al. (2020) Radiological Society of North America (RSNA), Radiopaedia, the Italian Society of Medical Interventional Radiology (SIRM).
Waheed et al. (2020)	Apr-20	Chest X-Ray	COVID-19 database.(S.I. S. o. M. a. I. Radiology.2020) IEEE COVID Chest X-Ray Dataset.(2020) COVID-19 Radiography Database (Rahman et al. (2020) COVID-19 Chest X-ray (Chung et al. (2020)
Das et al. (2020)	May-20	Chest X-Ray	COVID-19 image data collection (Cohen et al. (2020) Chest X-Ray Images (Pneumonia)(Mooney P. 2020) Tuberculosis chest X-ray image data sets(U.S. National Library of Medicine)
Ismael & Şengür (2021)	May-20	Chest X-Ray	GitHub. (2020). COVID-19 [dataset]. Retrieved March 10, 2020 Kaggle. (2020b). X-ray chest [dataset]. Retrieved March 10, 2020 X-ray Chest images [dataset].(Radiology Assistant, 2020)
Perumal et al. (2021)	Jul-20	Chest CT & X-Ray	Chestx-ray8 (Wang X. et al 2020) Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification. Mendeley Data, V2(Kermany et al. (2018)
Misztal et al. (2020)	Aug-20	Chest CT & X-Ray	COVID-CT-Dataset(J.Zhao et al.) COVID-19 image data collection (Cohen et al. (2020) SIRM, COVID-19 Resource site for Imaging and Radiology, EURORAD, Radiopaedia, Radiology Assistant, Cases RSNA, APP, RAD2share, Yxppt, COVID-19 Chest X-ray
Elzeki et al. (2021)	Oct-20	Chest X-Ray	COVID-19 in X-Ray Images (Faizan S.2020) Chest X-Ray Images (Pneumonia)(Mooney P. 2020) COVID-19 X-ray images (Bachir 2020) Chest x-ray images with three classes: COVID-19, normal, and pneumonia, Mendeley Data v3 (Shams et al. 2020a)
Lee et al. (2020)	Oct-20	Chest X-Ray	RSNA pneumonia detection challenge (Oak Brook,IL, 2018) COVID-19 image data collection (Cohen et al,2020) COVID-19 Chest X-ray (Chung et al. (2020) Actualmed COVID-19 Chest X-rays (Chung et al. (2020) COVID-19 Radiography Database (Rahman et al. et al. (2020)
Liang et al. (2020)	Dec-20	Chest X-Ray	COVID-19 Radiography Database.(Rahman et al. (2020)
Menon et al. (2020)	Dec-20	Chest X-Ray	Chest X-Ray Images (Pneumonia)(Mooney P. 2020) COVID-19 image data collection (Cohen et al. (2020)
El-Kenawy et al. (2021)	Feb-21	Chest X-Ray	COVID-19 Image Data Collection: Prospective Predictions Are the Future (Cohen et al. (2020) Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification. Mendeley Data, V2 (Kermany et al. (2018) COVID-19 image data collection (Cohen et al, 2020)
Baltazar et al. (2021)	Feb-21	Chest X-Ray	The Medical City Institutional Review Board (TMC IRB)
Bahgat et al. (2021)	Mar-21	Chest X-Ray	COVID-19 image data collection (Cohen et al, 2020) Pneumonia (virus) Vs. COVID-19 (Mahasin, 2020) COVID-19 X-ray images using CNN (Srikar, 2020). COVID-19 X-ray Images (Das, 2020). COVID-19 Patients Lungs X Ray Images 10000 (Sajid, 2020) COVID-19 Chest X Rays (Sreeraman, 2020). COVID-19 Dataset (Riaz, 2020). Curated Chest X-Ray Image Dataset for COVID-19 (Sait, 2020).
Lacerda et al. (2021)	Mar-21	Chest CT	MosMedData: Chest CT Scans With COVID-19 Related Findings Dataset. (Morozov, S.P. et al. (2020), The LUNA16 challenge. (Setio,A.A.A. et al. 2017), Open Source Imaging Consortium (OSIC). OSIC Pulmonary Fibrosis Progression Kaggle Challenge; 2020.
Park et al. (2021)	Apr-21	Chest X-Ray	Valencian Region Medical Image Bank [BIMCV] (De La Iglesia Vay'a et al. (2020), Brixia (Signoroni et al. (2020b) National Institutes of Health [NIH] (Wang et al. (2017) CheXpert
He et al. (2021)	May-21	Chest CT	COVID-19 CT Lung and Infection Segmentation Dataset, v1.0. (M.Jun, G.Cheng, 2020) MosMedData: Chest CT Scans with COVID-19 Related Findings, 2020 COVID-19 radiology-data collection and preparation for Artificial Intelligence (H. B. Jenssen, 2020)
Sangeetha et al. (2021)	Aug-21	Chest CT	Radiological Society of North America (RSNA)
Zhao et al. (2021)	Aug-21	Chest X-Ray	The RSNA International COVID-19 Open Radiology Database (RICORD). (Tsai, E.B. et al. 2021) RSNA Pneumonia Detection Challenge.(2019)
Gupta et al. (2022)	Oct-21	Chest X-Ray	Chest X-ray & CT dataset (Kermany et al. (2017) COVID-19 image data collection (Cohen et al. (2020)

Table 8
Future Research Opportunities for Chest Classification for Identifying Covid-19

Future works	List of references
Apply or optimize GANs for data augmentation or image quality improvement	Bahgat et al. (2021); Menon et al. (2020); Waheed et al. (2020)
Improve hyperparameter tweaking	Fayemiwo et al. (2021)
Increase/Refine the input datasets	Das et al. (2020); Ismael & Şengür (2021); Ozturk et al. (2020); Ucar et al. (2021); Zhao et al. (2021)
Expand the number of classification classes	Li et al. (2021); Zhu et al. (2021)
Extend the classification to other diseases	Bahgat et al. (2021); Das et al. (2020); Ismael & Şengür (2021)
Use better methods to optimize their models	Ismael & Şengür (2021); Li et al. (2021); Tuncer et al. (2021); Wang et al. (2020)
Expand to clinical, practical or other domains	Bashar et al. (2021); Das et al. (2020); Ozturk et al. (2020); Ucar & Korkmaz (2020); Wang et al. (2021); Wang et al. (2020); Zhao et al. (2021)
Consider the technique to classify the cases according to the severity	Lacerda et al. (2021); Zhu et al. (2021)
Expand the applications to other medical image processing cases	Ucar & Korkmaz (2020)

What's more, most of the models that have been developed and published, have not yet been validated in the clinical setting. Further, CT scans and X-Ray image limitations have also impeded the development of Chest X-Ray classification for Covid-19 identification.

5.3. Future research directions

We have reviewed many published papers for COVID-19 detection. Most of these papers contain solutions that apply Deep Learning models with excellent result. But, to fight against the Covid -19 disease, chest radiological image classification still has enormous potential since researchers have been raising new limitations and issues in the past two years. Some problems identified by previous researchers have been solved by recent scholars, while some of the problems have not yet been solved. Table 8 below shows some future directions which have not been solved yet or could have room for improvement.

An important task in the future will be to build larger and more authoritative COVID-19 radiological images datasets. Also, enhancing the deep-learning methods such as data augmentation and Transfer Learning are also achievable approaches to overcome the limited data-related shortcomings. Further, applying innovative methods for hyperparameter tuning, feature extraction, and so on will make a difference in the accuracy of algorithm performance. Furthermore, transferring accessible solutions from other topics to the problem of Chest Image Classification for identifying Covid-19 can prove to be effective. In addition, it is possible that we can learn from other pandemics, or even from fields other than medicine. The target should be to fill the gaps that existing models have.

The other vital task is for researchers to expand the narrow diagnostic scope. Most research can only classify COVID-19 patients from 2-4 categories of chest images and achieve a strong result in the lab, which is far from real clinical applications. Researchers need to make their models still work with a robust performance at a practical level. Researchers need to build models that are adaptive for many different application scenarios. Maybe

6. Conclusion

This paper provided a comprehensive review of chest radiological images classification related to COVID-19, covering 30 studies. It included the basic deep learning methods, the most common datasets used, the challenges experienced by researchers, and the future direc-

tion. We believe that this paper will assist future researchers in the field of chest image classification to better understand and have an overview of a wide range of studies that were performed in the last two years, 2020-2021.

It is the ultimate goal of every researcher to diagnose COVID-19 patients by using chest image classification so that patients can receive timely treatment and the spread of the disease can be better controlled. However, Image classification based on Deep Learning is a big topic with many processes, hyperparameters and deep learning methods. As a conclusion, our perspective is, rather than focusing on building a complex model that will lead to a breakthrough by achieving good performance and at the same time overcome the many problems presented in this review, we encourage future researchers to be more realistic and to focus on one of the current challenges or limitations.

As shown in our review, there are still many worthwhile opportunities for future researchers to explore in the field of Chest Image Classification for Covid-19. The COVID-19 pandemic offers people both challenges and opportunities, and progress in the whole field requires the concerted efforts of many individual researchers or groups.

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.

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