1. Introduction

1.1. Background

The COVID-19 pandemic was first detected in December 2019 [1] . By October 2020 > 1.4 million deaths by COVID-19 were reported [2]. Due to the sheer number of lives taken by the COVID-19 virus or Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), this pandemic was pronounced as a global pandemic by the World Health Organization (WHO) [3]. Symptoms reported for those infected with COVID-19 include fever, dry cough, fatigue, and losing sense of taste and smell; many victims were referred to intensive care units for immediate mechanical ventilation [4]. Emergency countermeasures were required in order to mitigate the harms of this pandemic. Therefore, extensive change in public health system were required which included but not limited to diagnostics, clinical treatment, surveillance, and research [5, 6].

Utilizing current technologies in the fight against COVID 19 can enhance the public health system capability [7]. Mobile awareness apps that broadcast notifications regarding the spreading of COVID-19 and

Abbreviations: AI, Artificial intelligence; DL, Deep Learning; CNN, Convolutional Neural Network; COVID-19, Corona Virus 2019; CT, Computed Tomography; ULS, Ultrasonography; CXR, Chest X-Ray Radiography; RNN, Recurrent Neural Network; SARS-CoV-2, Severe Acute Respiratory Syndrome Coronavirus 2; WHO, World Health Organization.

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reported cases, wearable device for real-time tracking of infected cases can all help in this fight. Furthermore, unprocessed data can be analysed via Deep Learning (DL) to provide significant information in a relatively short period with little effort [8], augmenting public health capability against COVID-19. DL applications have slowly advanced since 1986, but post 2010 the DL field saw rapid growth due to the availability of high-performance tools such as graphics processing unit (GPU) and a massive amount of unstructured data [9].

DL is based on new structured algorithms allowing the development of intelligent machines and methods with less human interaction, some examples of DL mechanisms include smart reply regarding queries, plotting data in a meaningful way, or provide a highly accurate prediction for any matter [10]. Designing a sharp taxonomy for DL categorization is challenging as it relies on different aspects such as type of pursued object, learning from experience, exploring structured and unstructured data, and extracting required information and reasons from knowledge bases [8].

1.2. Problem and objective

Since the onset of COVID-19, many technology companies, governments, and institutes initiated urgent announcement for researchers to adopt AI applications to assist in COVID-19 mitigation [10]. From researchers point view, AI can contribute for fighting COVID-19 at certain levels: demographic level e.g. (prediction future forecasting infection), patient level e.g. (diagnose COVID-19 in early stage) [11].

As the scope of this review is limited to the use of DL against COVID-19, the reader may refer to comprehensive surveys about AI field [12] and lectures [13,14].

Huge amount of dataset can be manipulated and processed using AI features, in particularly, patient data can go through many stages such as analysing, segmentation, augmentation, scaling, normalization, sampling, aggregating, and sifting, in order to obtain accurate prediction that assists the healthcare ecosystem as well the rest of stakeholders in the public health. Recently, the number of DL studies have increased aiming to address and/or propose a solution for the COVID-19 pandemic [11]. However, most of these studies conducted during the COVID-19 pandemic are dispersed. We summarize the involvement of DL technologies in resolving challenges that related to COVID-19, an appropriate summarization will help new researchers to understand the present role of DL in the fight against COVID-19 opening new opportunities for researchers to continue with future work whilst building upon what has already been reported within the research community. Fig. 1 illustrates the most of DL techniques and dataset that have been used against COVID-19 [15].

Previous studies report on AI techniques that have been used to mitigate the COVID-19, [10,11,15–18]. The reported approaches are conducted in the form of systematic reviews or surveys [19–22] whilst focusing on the different applications of AI such as patient diagnosis, epidemiological monitoring, drug, and vaccine discovery. Nevertheless, a massive number of research papers are constantly published and overwhelming the electronic databases. Therefore, it is necessary to carry out an updated review that focuses on DL and its use in the COVID-19 pandemic. The aim of this review is to identify and illustrate the role of DL technology during the COVID-19 pandemic as illustrated in Fig. 1; Deep Learning; 1) Convolutional Neural Network (CNN): 2) Transfer Learning. The outcome can be used as a guidance in the healthcare sector for developers who consider the utilization of DL to improve the public health capability as a quick response to COVID-19.

2. Methodology

In order to ensure the transparency and reliability of this study, this scoping review is conducted following the guidelines of PRISMA Extension for Scoping Reviews (PRISMA-ScR) [23]. PRISMA-SCR is the most popular and comprehensive guidelines for scoping reviews, and it is highly recommended by Cochrane and the Joanna Briggs Institute (JBI) [24].The protocol outline in this review are detailed in the following sections.

2.1. Search strategy

2.1.1. Search sources

In this review, the research queries were conducted between the 10th and 13th of October 2020. The online database for this search as follow: IEEE Xplore and ACM Digital library. The search is mainly focused on the computer science database and due to the limitation of this research we excluded medical databases.

2.1.2. Search terms

Specified search terms were used to distinguish between related and unrelated studies that available on the targeted databases. these terms were chosen based on the target intervention “artificial intelligence and deep learning" and the target disease "Coronavirus and COVID- 19”. total retrieved studies in (Appendix A).

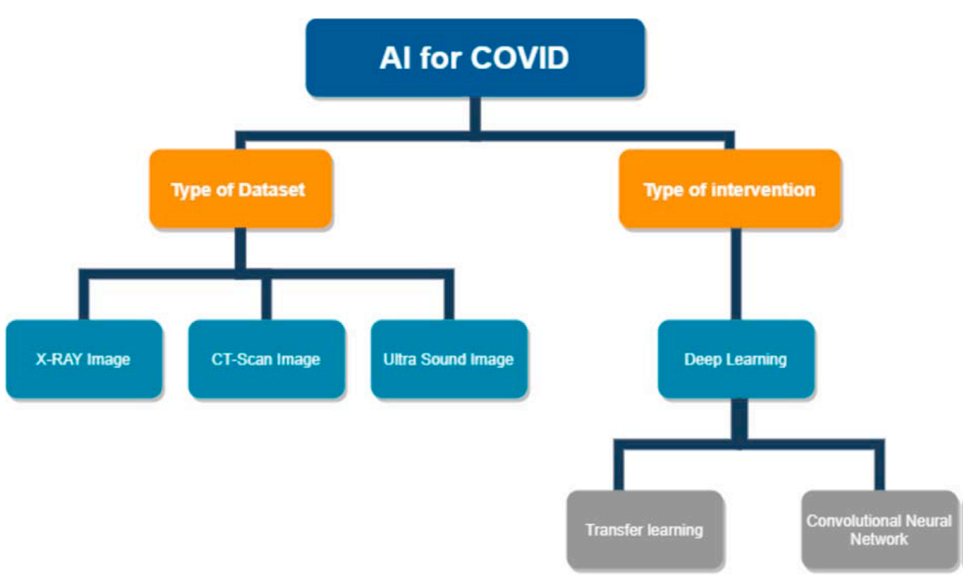

Fig. 1. DL technologies and datasets that used against COVID-19.

2.2. Study eligibility criteria

In this scope review, the main focus is the DL-based approaches or technology that used Chest X-Ray radiography (CXR), Ultrasonography (ULS), and Computed Tomography Scan (CT) for the purpose of detecting the COVID-19 in the early stage. In addition, studies with an overview such as scoping or systemic reviews were excluded. Furthermore, to assure the novelty of this review, we consider studies that have been published between (May-September 2020) which are written in English. The collected studies were limited to; 1) peer reviewed articles: 2) conference proceedings. However, the following publication types were excluded; 1) reviews: 2) conference abstracts: 3) proposals: 4) pre-printed studies.

2.3. Data extraction and data synthesis

Appendix B explains how the data extraction form is organized. the extracted data from selected studies includes the following characteristics: 1) DL models: 2) datasets used for the training and testing the model: 3) validation and evaluation of DL models. After we built the structured data, the narrative approach was used to synthesize it. In particular, we divided and described the DL model in the included studies based on the images used (e.g. XRAY, CT, ULS), DL branch (e.g. CNN and transfer learning), described the used dataset in term of source (e.g. public and private datasets). furthermore, validation and evaluation methods were described to determine the efficiency of each model. Excel sheet is used to manage data synthesis.

3. Results

3.1. Search results

53 studies were retrieved via the search within the selected database as shown in Fig. 2. Out of these studies no duplicate studies were found, we screened the titles and the abstracts for 53 studies, 23 studies were excluded during this step for reasons mentioned in Fig. 2. In last step during full-texts screening for 30 studies we have excluded 13 studies due to irrelevant and different study design. Finally, 17 studies were included in this review.

3.2. Characteristics of the included articles

In the included studies, 12 are peer-reviewed journals and 5 conference articles Table 1 In addition, a third (n = 5) of the studies are published in May 2020, and the rest of the studies are published in June, July, August, and September 2020. The included studies were conducted in 10 different countries, even though, a third of the studies were published in China as shown in Table 1.

3.3. Deep learning

Deep learning is the current trend in dealing with medical images. It is intended to assist radiologists in giving a more precise diagnosis by giving a quantitative analysis of worrisome lesions and allowing for a faster clinical workflow. Deep learning has already demonstrated performance in recognition and computer vision tasks that may overcome humans' abilities [25]. The architecture of deep learning algorithm is more complex compared to the traditional algorithm (machine learning). DL architecture is composed of 3 main stages; the first step is done through pre-process and enhancement for each input. The second step is used to extract the features of that input. The third step is related to the classification process for each input based on different classifiers. As shown in Fig. 3, deep learning model minimizes human intervention, processes a complex data that might be challenging in machine learning and produce accurate results in a short time [26]. Most of the studies used Convolutional Neural Network (CNN) and Transfer Learning for

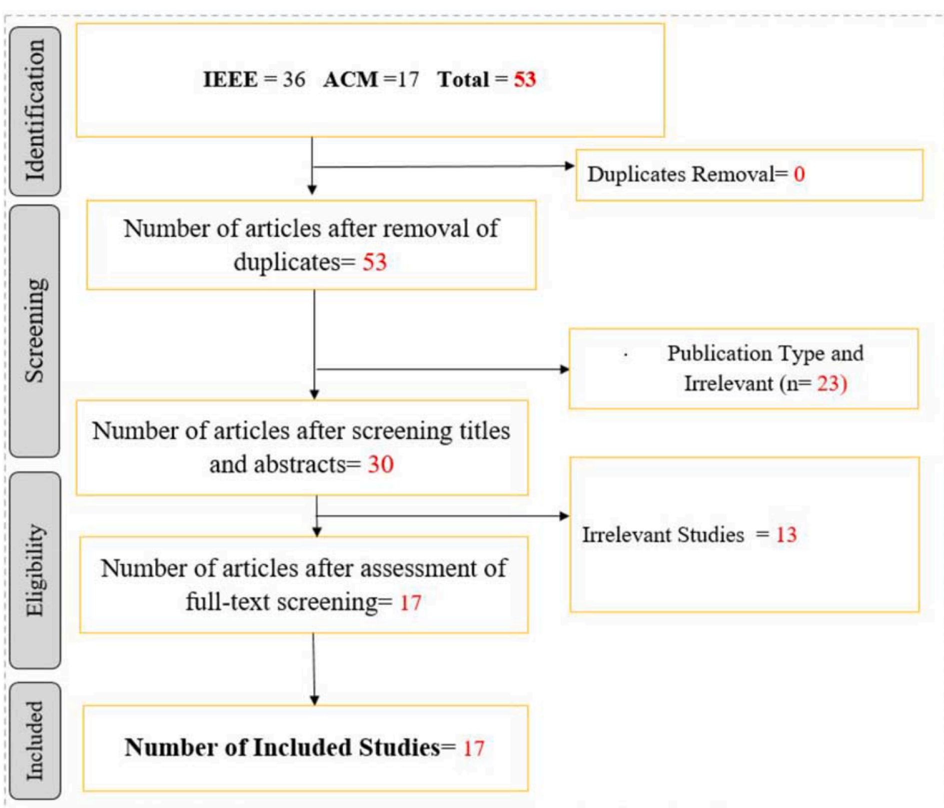

Fig. 2. PRISMA chart.

Table 1
General characteristics of the included studies.

Characteristics	Number of Studies				
Publication Type	Journal:12		Conference:5		
Submission Month	May:5	June:4	July:2	August:2	September:4
Country of publication	China:2 Italy:1 India:1 Korea:1	China:1 USA:1 Morocco:2	Malaysia:1 Thailand:1	China:1 India:1	China:1 India:1 Greece:1 Australia:1

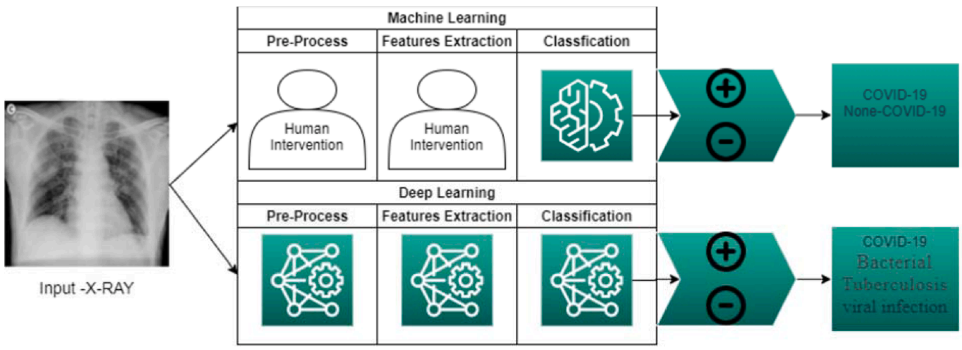

Fig. 3. Comparison Deep Learning and Machine Learning.

detection COVID-19 because they are the backbone methods for dealing with medical image in deep learning [25]

3.3.1. Convolutional neural networks (CNNs)

Convolutional neural networks (CNNs) is an artificial neural networks that consist of several layers and each layer has multiple neurons that operate similarly like human brain neurons. CNN proofed its efficiency in the medical image classification [26]. In addition, CNN is the backbone for all proposed models that used for detection COVID-19 via three imaging modes chest X-Ray radiography (CXR), Ultrasonography (ULS), and Computed Tomography Scan (CT) scan. Fig. 4 illustrate the basic concept of how the dataset is passed into CNN to train the model and used for COVID-19 prediction. [27].

3.3.2. Transfer learning

Transfer learning is a deep learning method that can utilize the gained knowledge from the previous training and apply it on the new training set as shown in Fig. 5 In this review Transfer learning is developed based on the CNN model and they are called pre-trained model [27].

3.4. Evaluation metrics and validation

In the collected studies, the performance of each model is evaluated using confusion matrix. Hence, folds-cross validation is included in some studies for validation purpose [28,29]. The assessment measurements for model are used to ensure the efficiency for recognizing COVID-19. Table 2 explains how the evaluation metrics and validation methods are used within the reviewed studies.

3.5. Evaluation metrics and validation

3.5.1. Classification of DL- based detection approaches

As shown in Table. 3. In all studies DL approaches are aimed to detect COVID 19 in the early stage based on three indicators, 10 studies used X-Ray radiography (CXR) [26,27,29–36], 5 studies used Computed

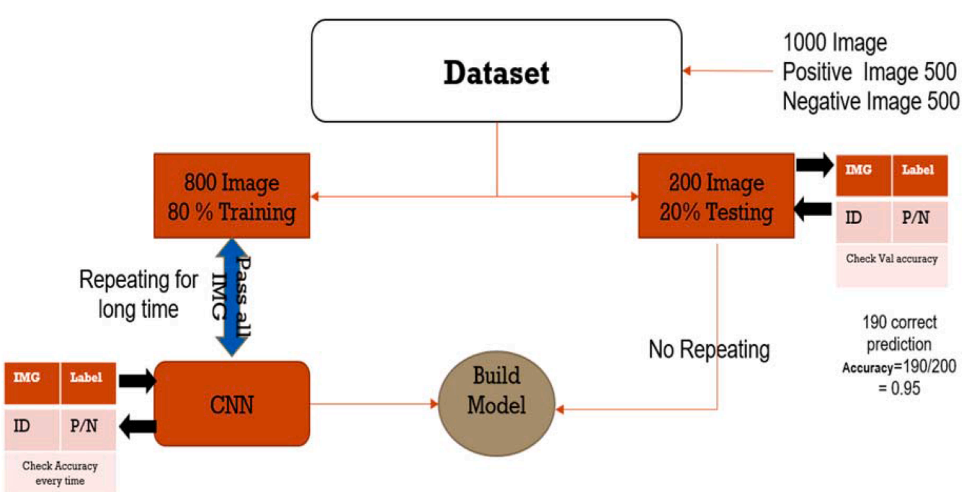

Fig. 4. CNN in Image classification.

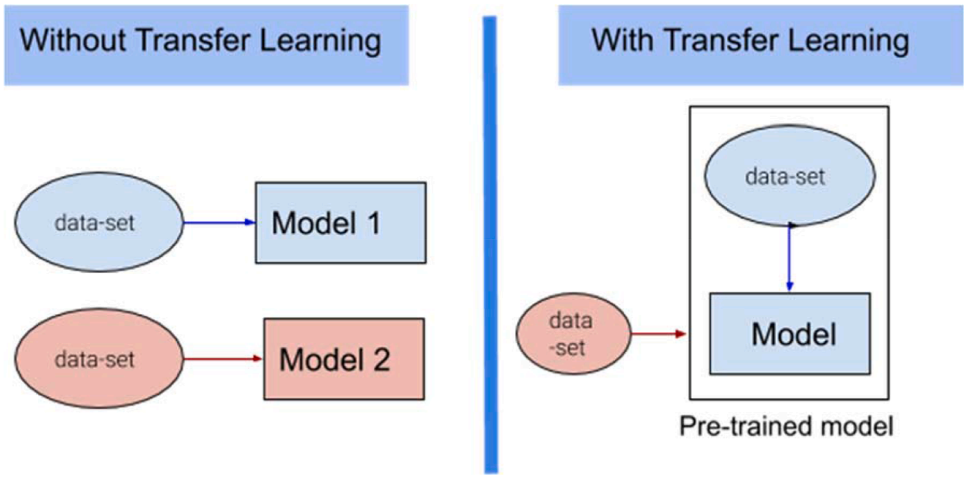

Fig. 5. Transfer Learning Pre-trained model.

Table 2
Evaluation and validation method.

Evaluation	Methods	Definition	Number of studies
	Accuracy	(TN+ TP)/(TN + TP + FN + FP)	$N = 17$
	Precision	TP/(TP + FP)	$N = 14$
	Recall / Sensitivity	TP/(TP+ FN)	$N = 11$
	F1 score	2(Precision * Recall)/ (Precision + Recall)	$N = 13$
	Specificity	TN/(TN + FP)	$N = 10$
	Cohen0s kappa	(p_0 - p_e)/(1 + p_e)	$N = 2$
Validation	Folds-cross validation	To identify how many folds the dataset is going to be splitted . Every fold gets chance to appear $N = 5$ during training where (k-1).	$N = 5$
Abbreviations	TP: True Positive; TF: True Negative. FP: False Positive; FN: False Negative. p_0: Observed agreement. p_e: Expected agreement N: Number of Studies		

Tomography Scan (CT) [37–41], and 2 studies used Ultrasonography (ULS) [42,43]. In addition, 5 of the studies build their model from scratch using CNN [35–37,39,43] while other 12 studies used pre-trained model to build their model [26,27,41,42,29–34,38,40]. Further, 5 of the studies used private dataset [30,37,39,40,43] and 12 of the studies used public access datasets [26,27,41,42,29,31–36,38]. In seven studies data segmentation is used to improve the accuracy of the model [29,30,37–40,43] in nine of the studies, data augmentation is used to overcome the overfitting [26,27,31–36,41,42], and in one study no segmentation either augmentation is applied [36]. moreover, only 5 studies adopted folds-cross validation [36,38,39,41,43]and 13 studies used F1-score as evaluation metrics [26,29,41–43,30–35,39,40]. For better visualization for the infection area in the lung, the visual explanation technique Gradient Weighted Class Activation Mapping (Grad--CAM) is adopted in five studies [26,29,30,41,43].

3.5.2. Features of used DL- models

All proposed studies are summarized in Table 4, where most of the studies achieved high accuracy and evaluation metrics, validation, and visualization are implemented. However, the different were in two aspects; first the used dataset and how divided into training and testing, the second aspect is the weight of the used model. furthermore, models that have been built based on VGG16 and VGG19 model in [26,32,38, 42] as backbone are considered as high weight due to the high number of parameter, while models are built based on ResNet [29,40] are considered as medium weight and models that build based on Xception, InceptionV3, and MobileNet [27,30,33] are considered as lightweight models. The challenge is obtaining high accuracy and process huge dataset with lightweight model as achieved in [30] for X-RAY, in [40] for CT scan using medium weight model, and in [43]for the ULS using customized model. Most of the studies [26,27,29,31–34,37,40]split the dataset into 70–80% for training and 30–20% for testing, while other studies [38,39,43]split the dataset into 50% for training and 50% for testing. However, study that split dataset into 40% for training and 60% for testing therefore high Recall (Sensitivity) was obtained. Only three studies[33–35] obtained 98% accuracy and two studies [34,42]obtained 89% as F1-score, for highest Precision score only one study [42]achieved 99%, and [32]obtained best score for Specificity. Gradient-based visualization method (Grad-CAM) is applied on all type of images as proven in [26,29,30,41,43] to show regions in lung where the model highlighted during the classification.

3.6. Characteristics of used datasets for training and testing of DL models

As provided in Table 5, Public datasets (e.g. Kaggle, GitHub, Twitter) are the mostly used source in selected studies. Public Radiograph

Table 3
Features of DL-based approaches used for detecting COVID-19.

Characteristics	Number of Studies					
Dataset Source	Public:12			Private:5		
Model Backbone	CNN:5			Transfer Learning:12		
Diagnosis Method	X-RAY:10		CT scan:5		ULS:2	
Data Segmentation	UNet:3	FC-DenseNet103:1		Ensemble model:1		Unknown: 2
Data Augmentation	Rescale, Resizing, Rotation, Flipping, Over-sampling, and Distortion: 9					
Validation Method	Five-Fold Cross Validation: 4			Four-Fold Cross Validation:1		
Evaluation Metrics	F1-Score:13	Accuracy:16	Precision:14	Recall:15	Specificity:10	Cohen's kappa:2
Visualization Method	Grad-CAM:5					

Table 4
Summary of DL-Models in the selected studies.

	Studies	Used Model	Data Segmentation	Data Augmentation	Dataset Source	Training Dataset	Testing Dataset	Accuracy	F1-Score	Precision	Recall	Specificity	Kappa	Validation	Grad-CAM
XRAY	Oh et al. [29].	ResNet-18	FC-DenseNet103	Not specified	Public	354	99	0.88	0.84	0.83	0.85	0.96	N/A	N/A	Yes
	Waheed et al. [31].	CovidGAN	N/A	ACGAN	Public	932	192	0.95	0.93	0.96	0.90	0.97	N/A	N/A	No
	Rajaraman et al. [30]	Customized -Inception- V3	N/A	Not specified	Public Private	14,997	1703	0.97	0.97	0.97	0.97	N/A	N/A	N/A	Yes
	Makris et al. [32].	VGG-16	N/A	Not specified	Public	180	44	0.95	0.96	0.96	0.96	0.98	N/A	N/A	No
	Phankokkruad et al. [27].	Xception based	N/A	Increase Number of Images	Public	258	65	0.97	N/A	N/A	N/A	N/A	N/A	N/A	No
	Sethi et al. [33].	MobileNet	N/A	Not Specified	Public	4686	1563	0.98	0.87	0.87	0.87	0.87	N/A	N/A	No
	Qjidaa et al. [26].	VGG-16	N/A	Resizing Image	Public	240	60	0.87	0.88	N/A	0.87	0.93	0.81	N/A	Yes
	Qjidaa et al. [34].	Ensemble-CNN	N/A	Rotation, Flipping Shifting, Rescale	Public	396	170	0.98	0.98	0.98	0.98	N/A	N/A	N/A	No
	Babukarthik et al. [35].	GDCNN	N/A	Rotation, Flipping, Sampling, Distortion.	Public	2031	3040	0.98	0.96	0.93	1	0.97	N/A	N/A	No
	Abdani et al. [36].	SPP-COVID-Net	N/A	Not Specified	Public	N/A	N/A	0.94	N/A	N/A	N/A	N/A	N/A	Five-Folds	No
CT	Wang et al. [37].	DeCoVNet	UNet	Random affine, color jittering	Private	499	133	0.90	N/A	0.97	0.95	0.95	N/A	N/A	No
	Hu et al. [38].	Modified VGG	N/A	Cropping, Rotation Reflection, Adjust contrast	Public	40	20	0.94	N/A	0.95	0.93	0.93	N/A	Five-Folds	No
	Han et al. [39].	AD3D-MIL	N/A	Random affine, color jittering	Private	276	184	0.97	0.97	0.97	0.97	N/A	0.95	Five-Folds	No
	Li et al. [40].	3D ResNet-18	N/A	Not Specified	Private	2028	518	N/A	0.90	0.97	0.84	N/A	N/A	N/A	No
	Wang et al. [41].	Redesign COVID-Net	N/A	Cropping, Flipping	Public	N/A	N/A	0.90	0.90	0.95	0.85	N/A	N/A	Five-Folds	Yes
ULS	Roy et al. [43].	Regularised Spatial Transformer Networks (Reg-STN)	Ensemble model	Sampling, rotation scaling, shearing blurring, flipping additive noise	Private	1005	426	0.96	N/A	N/A	N/A	N/A	N/A	Five-Folds	Yes
	Horry et al. [42].	VGG19	N/A	Rotation, Flipping, Shifting	Public	N/A	N/A	N/A	0.98	0.99	0.97	N/A	N/A	N/A	No

website is also used to obtain different type of images for different type of Pneumonia. Most of private dataset which are not available for researchers are collected in particular, from certain hospital either in China or Italy. In addition, each mode of dataset (X-ray, CT scan, and ULS) are also classified to different class (COVID-19, healthy, viral infection, bacterial infection). As shown in Table 5, most of studies [26,27,29,31–36] used IEEE-COVID-19 dataset [44] for the following reasons; 1) Dataset is collect for the purpose of AI based application to detect and recognize the type of infection: 2) Dataset classes are labelled and arranged in a hierarchy including type of viral, type of bacteria, and fungal: 3) Data is collected from public sources also indirect collection from hospitals and physicians: 4) Dataset project is established for the purpose of fighting COVID-19. Therefore, most of the studies found that IEEE-COVID-19 dataset [44] meets their requirement to develop a COVID-19 detection model. However, there is a trade-off between using public dataset and private dataset, for example by using public dataset, Images are randomly collected without consideration for the end researchers, but the result can be evaluated and future work can be carried out by other researcher. On other hand, by using private dataset, images can be collected carefully based on the researcher requirement and many images can be taken for one patient with less noise and blurrily. However, the work that implemented on private dataset cannot be evaluated and the future work is limited.

4. Discussion

4.1. Principal findings

The use of DL was investigated in this scoping review and its usage against the COVID-19 virus. Only 17 publications that met our predefined inclusion criteria were reported via the targeted database libraries (ACM and IEEE). This is not extraordinary due to (a)In such a pandemic, most of the studies are published in medical databases (eg. MEDLINE, EMBASE, PsycInfo), (b) COVID-19 was only identified in January 2020, (c) Lack of data to support scientific researchers, and (d) Underestimate the danger of this pandemic. Most of the studies were published in China which was not surprising since studies suggest COVID-19 originated in that region and as a result data was available in that region. We noted most DL studies were used to detect COVID-19 through radiology images and none of the included studies used DL for other purposes such as tracing of the infected cases, future broadcasting, or applying DL to robotics to deal with suspected cases. The selected studies did not mention any type of real-life implementation, the studies were proposals and not empirically tested. The number of training datasets are still small (less than 500 in half of the studies). The heterogeneity and quantity of data show a shortage in the public dataset, consequently, COVID-19 eliminate 1.46 million as of the time of writing. Therefore, the call for immediate sharing of individual participant data from COVID-19 studies worldwide are still open.

Table 5
Features of used datasets.

Dataset Type	Public Dataset	Private Dataset
X-RAY	JSRT Database: Japanese Society of Radiological Technology. [29] SCR Database: Segmentation in Chest Radiographs. [29] USNLM Dataset: National Library of Medicine Data Distribution. [29] Corona Hack: Chest X-Ray-Dataset (Kaggle). [29] IEEE COVID-19 Image Data Collection (GitHub). [26,27,29,31–36] COVID-19 Radiography Database (Kaggle). [31] COVID-19 Chest X-ray (GitHub). [31] RSNA CXR DATASET (Kaggle). [30] TWITTER COVID-19 CXR DATASET (Twitter). [30] CheXpert Chest X-ray Dataset. [35] COVID-19 Database Italian Society of Radiology. [36] Chest X-Ray Images Pneumonia (Kaggle). [32,36]	PEDIATRIC CXR DATASET (Guangzhou Women and Children's Medical Center in Guangzhou)
CT Scan	The Cancer Imaging Archive (TCIA) Public Access. [38]	Local hospital Union Hospital, Tongji Medical College [37]
	SARS-CoV-2 (Kaggle). [41]	Designated COVID-19 hospitals in Shandong. [39]
	COVID-CT (GitHub). [27]	10 medical centres China. [40]
ULS	POCOVID (GitHub). [42]	5 Local Italian hospital COVID-19 Lung Ultrasound Database (ICLUS-DB). [43]

4.2. Future work and research implications

In future, DL Technologies must be integrated with public education, current DL proposed approaches are somewhat treated with caution due to the lack of understanding on how DL function at the most profound level. May ethical points are raised and require further clarification before the acceptance of DL approaches is likely to see an upsurge. Furthermore, most of DL studies that detect COVID-19 are not described consistently which makes the comparison between studies more challenging. In this review, we found out that only 70% of these studies disclose how the training-testing dataset is split, 30% implement validation method while other 70% did not mention how the validation is conducted, more than 50% of the studies did not provide their work for public sharing, 30% of the studies are missing significant evaluation metrics. The scientific community and developers need to standardize a protocol in an attempt to minimize the huge volume of studies for COVID-19 that can be confusing to interested researchers and provide robust studies by following Criteria: 1. Collect proper dataset from different medical centers including many images for each patient. 2. Dataset pre-processed phase should be improved in term of the used model such as using FC-DenseNet103 for segmentation instead of UNet, also in the reviewed studies data augmentation is either excluded completely or not significant in size. 3. In the case of COVID-19 pandemic, researchers should provide light- weight models to be used by developers and researchers in countries that have constraint resources. 4. Researchers should focus on ULS images instead of XRAY and CT scan. However, some studies have successfully show this thing by using two type of modes (X-RAY, CT scan) and this requires further examination. 5. All evaluation metrics should be used for the aim of COVID-19 detection to come up with a solid prototype that can detect different type of diseases based on images. We found that, Recurrent Neural Network (RNN) and Reinforcement learning is not used in the field against COVID-19 and rather considered as new direction for future work.

4.3. Strengths and limitations

4.3.1. Strengths

This study reviews DL techniques that used for detection COVID-19, without restriction on the characteristics, country, and study design. To the best of our knowledge this review is the first comprehensive study in the field of DL approaches and their application for COVID-19 detection. This scoping review can aid researchers to understand how DL was and is being used efficiently during COVID-19 pandemic. Comparing with other similar reviews [19,21,28,45,46], this review is unique in its field as it describes and summarizes features of the identified DL models, datasets, evaluation, and validation. Furthermore, in comparison to previous reviews [19,21,28,45,46] it follows the scientific of PRISMA-ScR [23]. Finally, we limited the studies to the most popular computer science databases in order to determine the most relevant studies as possible.

4.3.2. Limitations

We excluded proposals of DL techniques; as a result, we have likely excluded other applications of DL for COVID-19 detection. Research was conducted only on two digital libraries (ACM and IEEE) so we could not highlight all potential DL studies. Due to the search query that did not include special terms that related to each technique such as CNN, image classification, and transfer learning. Thus, it is possible that we dropped some studies that used previous terms in their abstract or title instead of the terms that we used (DL, AI, and deep learning). This number of studies was identified using only 2 databases, which are the most popular computer science databases, further, we restricted our search to a specific period (May-September). To address this limitation, the findings in this review are based on the results that are provided in each study, the reliability of the given information in the studies may affect the findings of this review.

5. Conclusion

In this review, 17 studies on DL against COVID-19 are provided to form the scoping review, published date and country are included to clarify how this pandemic is tackled by various entities, with a pre-knowledge that many of the proposed mechanisms, are not clinically implemented. The used approaches are described based on medical diagnosis (early detection of COVID-19), the exciting works are summarized and represented including deep learning methods. we have noticed that most of medical diagnosis for image classification are handled via CNN and transfer learning. This review covered all models and algorithm that used and discussed the validation and evaluation not ovulation process. We provided a specific section to cover the dataset that used in most of the studies, including public and private datasets. However, due to the huge number of studies that daily updated to the online database, this review can be further extended to cover other research direction such as treatment and vaccines discovery, and prediction of patient outcomes.

Declaration of Competing Interest

None declared.

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No fund to be declare.

Contributors

Mahmoood Alzubaidi, Haider Zubaidi and Ali Abdulqader Bin-Salem analyzed the papers and drafted the article. Mowafa Househ, Alaa A Abd-Alrazaq, Arfan Ahmed revised it critically for important intellectual content. All the authors approved the final version of the manuscript.

Appendices

APPENDIX A: used search terms and total number of retrieved studies per database

Database name	Used research terms.	Number of retrieved studies
ACM	(“COVID-19″ OR “COVID19”) **AND** (" artificial intelligence " OR " Deep learning)	17
IEEE	(“COVID-19″ OR “COVID19”) **AND** (" artificial intelligence " OR " Deep learning)”	36
Total studies 2020		**53**

Appendix B: Data extraction form

Concept	Definition
Study Characteristics	
Author	The first author of the study.
Year Submission	The year in which the study was submitted.
Country of publication	The country where the study was published.
Publication type	The paper type (i.e., peer-reviewed, conference or preprint).
Deep Learning technique characteristics	
Detection modality	What type of medical images are used (e.g., XRAY, CT, and ULS)?
DL branches	The branches/areas of that were used (e.g., CNN, Transfer learning).
AI models/ algorithms	The specific AI models or algorithms that were used (e.g., VGG).
Dataset Characteristics	
Data sources	Source of data that were used for the development and validation of AI models/ algorithms (e.g., public and private databases, clinical settings, government sources).
Dataset size	The total number of data that were used for the development and validation of AI models/ algorithms.
Type of validation	How the dataset was split/used to develop and test the proposed models/ algorithms (e.g., Train-test split, K-fold cross-validation, External validation).
Proportion of training set	Percentage of the training set of the total dataset.
Proportion of test set	Percentage of the test set of the total dataset.
Evaluation metrics	Any evaluation method that are used to check the performance of the model .(e.g., accuracy, precision, F1 score, recall and Kappa).
Visualization method	Type of used visualization method

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