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Research Article

Covid-19 Diagnosis using Deep Learning Approaches: A Systematic Review

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ABSTRACT

The utilisation of deep learning techniques has witnessed a surge in popularity within the realm of medical image analysis, particularly in the context of identifying COVID-19. Following the occurrence of the COVID-19 pandemic, extensive investigations have been conducted to identify the existence of Sars-Cov-2 through the utilisation of several deep learning algorithms. The objective of this study is to conduct a comprehensive review of deep learning techniques utilised for the detection of COVID-19. "Can deep learning methodologies serve as a viable substitute for radiologists in the diagnostic process of COVID-19?" is the research inquiry. In order to compile research articles for the purpose of conducting a systematic review, two scientific databases were employed as primary sources. Databases such as PubMed and IEEE Xplore have been utilised for this purpose till January 2022. The published studies were examined in accordance with the PRISMA guidelines. The study established predetermined criteria for exclusion and inclusion, and subsequently identified relevant works based on these criteria. The findings indicated that a total of 543 out of the 634 articles that were initially retrieved were excluded due to their lack of conformity with the predetermined criteria. Conversely, 87 articles met the inclusion criteria and were retained for further analysis. The research articles presented in this compilation are categorised into three distinct groups: the types of visual representations utilised, the methods employed for applying deep learning techniques, and the programming languages that are most frequently utilised. The exclusive reliance on deep learning algorithms is insufficient for substituting the visual diagnostic performed by physicians and radiologists in the detection of COVID-19. Due to the lack of substantiation by the medical establishment. CT and x-ray imaging modalities are commonly utilised in various fields. However, alternative imaging techniques, such as Optical Coherence Tomography (OCT) and Ultrasonic imaging, are either overlooked or not given due consideration. The predominant focus of study is on retrospective (theoretical) rather than prospective (pragmatic) investigations. Consequently, there exists a significant need for researchers to enhance the practicality of their investigations.

1. INTRODUCTION

The SARS-CoV-2 outbreak in late 2019 affected 2.81 million people in a short period of time [1]. The first Covid-19 case was reported in China's Wuhan province. The virus's transmission then shifted from epidemic to endemic. Covid-19 is more likely to be an endemic illness and will not go extinct anytime soon due to a number of influencing variables [1]. Despite the absence of sufficient healthcare facilities, all countries throughout the world are fighting this pandemic. Fever, cough, dyspnea, sweating, and myalgia are frequent symptoms with SARS-Cov-2 infection. However, symptoms are not limited to covid.

Real-time reverse transcription-polymerase chain reaction (RT-PCR) is the gold standard and most often used method for detecting coronavirus. This approach, however, has significant disadvantages, including a scarcity of test kits, a 24-hour turnaround time, and a 30% false-negative rate. This means that it incorrectly identifies positive Covid-19 cases as negative. As a result of the insufficient number of healthcare facilities, practitioners in the healthcare sector confront numerous challenges, and many places have been closed down to prevent the spread of the virus [2]. Another way for diagnosing Covid-19 is to use chest radiography images such as X-rays and CT scans, which show particular characteristics such as ground-glass opacities and pleural thickening [3]. This medical imaging must be visually analysed by specialists, which is a tiresome and time-consuming task. As a result, researchers have created numerous algorithms to analyse radiologic pictures of the chest in order to distinguish between healthy and sick instances. Skin cancer detection [4][5], tumour classification [5, and lung segmentation [6] are among the challenges that must be addressed by artificial intelligence, machine learning, and,

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more specifically, deep learning. Figure 1 depicts artificial intelligence subsets. Extensive research has been undertaken in the Covid-19 era employing different deep learning approaches such as Generative Adversarial Networks (GAN) [7] [8], Lon-Term Short Memory (LSTM) [9][10], and Convolutional Neural Network (CNN)[11][12], and Recurrent Neural Network (RNN)[13]. There have been various narrative literature reviews on deep learning strategies for Covid-19 identification [14-17], but completing a systematic literature study that compiles and compares the existing approaches is still limited. As a result, we present a systematic evaluation of deep learning algorithms in Covid-19 identification using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) procedure [18]. Rather of a narrative literature review, the present work contributes by systematically reviewing deep learning-based research activities undertaken in the literature of Covid-19 detection.

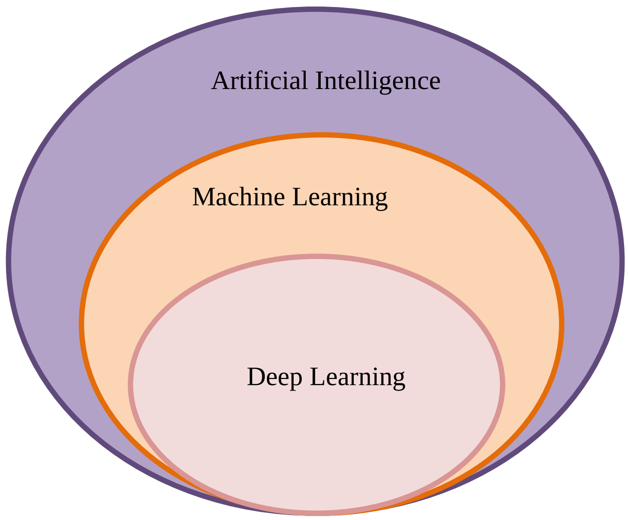


Fig. 1. Schematic representation of artificial intelligence sub-branches

The following is how the rest of the paper is organised: Section 2 provides the PRISMA protocol that was used to carry out this review. Section 3 presents the review's final results. Section 4 contains an in-depth explanation of the achieved outcomes. The main findings, limits, and future work have all been discussed in the last section.

2. METHODOLOGY

Deep learning is a subclass of machine learning that has recently acquired prominence in medical image analysis applications such as dermatology[19], ophthalmology[20][21], and gastroenterology[22][23]. Convolutional Neural Network (CNN) is an efficient deep learning technology that may be used in a variety of classification tasks using several picture modalities [24]. As the Coronavirus spread, researchers began to use CNN models to detect Covid-19 early. Transfer learning of pre-trained networks or developing a bespoke CNN architecture are the most common methods for implementing CNNs. The rationale for doing this systematic review is to review the literature on deep learning algorithms in Covid-19 detection in accordance with the PRISMA criteria, as seen in figure 2. The current study sought to identify the most prevalent deep-learning architectures utilised by academics to address Covid-19. This study was carried out in accordance with the PRISMA checklists (2009). In which a comprehensive literature search was conducted.

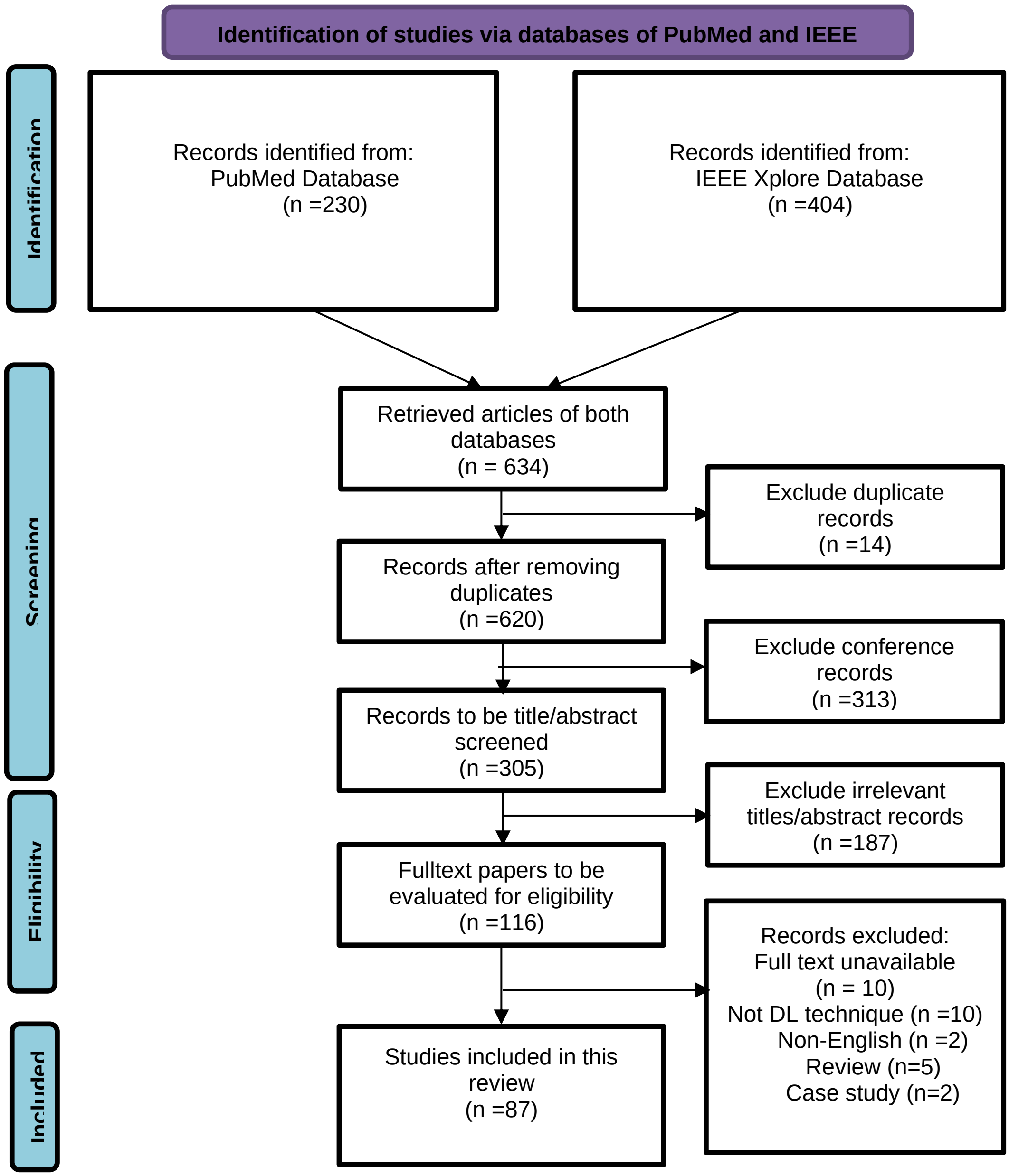


Fig. 2. PRISMA flow diagram

2.1 Search Criteria

The primary objective of this systematic review is to address the subsequent research inquiries: What are the current deep learning methodologies employed in the identification of COVID-19? What are the imaging modalities employed for the detection of COVID-19? What performance metrics are utilised for the detection of COVID-19?. The literature search was performed utilizing two different electronic databases which are IEEEXplore (https://ieeexplore.ieee.org), and PubMed (https://pubmed.ncbi.nlm.nih.gov). The search keywords of "artificial intelligence ", " machine learning", " deep learning", "coronavirus", "covid-19"," new coronavirus", " SARS-CoV-2", "X-Ray", "MRI", "CT", "classification", "detection", "diagnosis", and "image". Table 1 shows the search syntaxes used to retrieve publications from the literature sources and the number of retrieved articles from each source.

In the PubMed database, the provided syntax has been used for searching in titles and abstracts of published materials in Medline journals retrieving 230 articles. To broaden our search, we apply search filters to be from the outbreak date of coronavirus 2019/12/12 to 2020/12/29. However, the number of returned works of literature in the search engine of IEEE

Xplore is 404 research items. Firstly, the article duplications were removed from both digital archives. Secondly, the title and abstract of the articles were screened to exclude review articles from both databases.

TABLE I. LITERATURE SEARCH DETAIL

Database	**Search syntax**	**Search in**	**No. of retrieved articles**
PubMed	((artificial intelligence)OR(machine learning)OR(deep learning))AND((covid-19)OR(coronavirus)OR(SARS-CoV-2)OR(new coronavirus))AND((diagnosis)OR(detection)OR(classification))AND((x-ray)OR(CT)OR(MRI)OR(image))	Title/abstract	230
IEEE	("Abstract":artificial intelligence OR "Abstract":machine learning OR "Abstract":deep learning) AND ("Abstract":covid-19 OR "Abstract":coronavirus OR "Abstract":SARS-CoV-2 OR "Abstract":new coronavirus) AND ("Abstract":diagnosis OR "Abstract":detection OR "Abstract":classification) AND ("Abstract":x-ray OR "Abstract":CT OR "Abstract":MRI OR "Abstract":image)	abstract	404

2.2 Eligibility criteria (inclusion/exclusion criteria)

After conducting a comprehensive review of pertinent literature, papers that do not meet the specified eligibility criteria are omitted from the analysis. The eligibility criteria established for this systematic review are as follows: The articles must be published in a peer-reviewed academic journal. The articles are required to utilise an image dataset as the primary source for their specified methodology. The articles must possess a scientific or scholarly quality, while excluding commercial works. Evaluate the methodology by employing a minimum of one performance statistic. Articles, publications, surveys, review papers, and correspondence written in languages other than English are prohibited. The combination of artificial intelligence and mathematical or statistical models is prohibited. Conventional machine learning methodologies are prohibited. Exclude studies that employ deep learning methodologies for non-significant tasks such as image generation and data augmentation.

2.3 Study selection

This section describes the process of choosing studies. During the initial round of searching, a large number of research articles were obtained as a wide range of search keywords were used. Initially, the titles of the papers were checked to exclude irrelevant ones, as well as the article reviews. The abstract was then examined to determine the studies that were included in the purview of this review, such as statistical and mathematical ways to dealing with Covid-19. The complete text was then downloaded and thoroughly analysed to see whether or not they met the eligibility criteria. The PRISMA protocol outlines the stages for selecting research, such as identification, screening, eligibility, and included studies. Table 2 displays the number of papers returned by the PubMed and IEEE Xplore search engines..

TABLE II. NUMBER OF PAPERS RETRIEVED FROM JOURNALS AND CONFERENCES

PubMed Journals	**IEEE Xplore Journals and Conferences**
230	404

2.4 Data extraction

Tables 3 and 4 exhibit the extracted data from papers from the PubMed and IEEE databases that match the eligibility criteria, respectively. CNN models were found to be the most commonly utilised models in the Covid-19 era. Deep learning has arisen to address two major problems: classification and segmentation. To that goal, several imaging modalities such as CT scans, MRI, and ultrasound are used.

1) Title screening

The title was screened as the initial stage of the search approach. At this stage, irrelevant papers such as comparative analysis/study, survey, critical review and analysis, and predictive analytics were eliminated. We also omitted indirectly relevant papers such as exploratory investigations, deep learning applications, deep learning technology evaluation, and design studies. Other publications, such as data imbalance analysis, performance analysis, and exploratory investigations, were also removed. Mathematically related publications such as Polynomial Based Linear Regression Model to Predict COVID-19 Cases and partially unrelated COVID-19 Severity prediction were also eliminated.

2) Abstract screening

The abstracts of retrieved publications were thoroughly evaluated in the second round of the screening. The fundamental reasons for the exclusion of research at this level include the following criteria. The first rationale for exclusion was employing deep learning techniques for goals other than classification and segmentation, such as data augmentation and image synthesis using versions of Generative Adversarial Network (GAN). The second issue was the absence of performance measures in the abstracts of chosen research. Furthermore, research on detecting severity and progression, as well as predicting morbidity and mortality, were ruled out. Traditional machine-learning techniques, as well as articles focused on statistics and mathematics, were also rejected.

3) Full-text screening

Non-English publications were rejected at this step because the complete text of several of the qualified studies in abstract screening was written in a non-English language. Some of the publications chosen do not provide enough information regarding the deep-learning approaches employed in Covid-19 detection. As a result, it was rejected with reviews and case studies.

3. RESULTS

The current analysis examines 89 chosen papers out of 634 investigations. Figure 2 displays information about the research selection. In spite of the fact that Covid-19 and artificial intelligence were referenced in their titles and/or abstracts, the literature searches turned up (230+404) entries, of which 545 had to be excluded since they had flagged serious inclusion criteria violations. Some of the proposed approaches' datasets and source code were not directly supplied in their papers; therefore, we indicate that they are publicly available rather than providing a reference. As an illustration, it was said that the code for Karakanis and Leontidis [25] and Javor et al. [26] will be accessible on the github repository.

TABLE III. PUBMED SELECTED PAPERS

Ref.	Modality	DL technique	Task	Performance metric	Code	Language	Validation
[27]	CT	BigBiGAN	classification	AUC=97.2 Sensitivity=92 Specificity=92	https://github.com/MI-12/BigBIGAN-for-COVID-19	Python	A
[28]	X-ray	VGG 19	classification	Precision=95.15 Recall=96.55 F1-score=95.8	Not available	Not specified	MNA
[29]	CT	COVNet	classification	Sensitivity=84 Specificity=56	https://github.com/bkong999/COVNet	Python	A
[30]	CT	U-Net	segmentation	Sensitivity=100 F1-score=97	Not available	Not specified	A
[31]	CT	EfficientNet NasNetLarge NasNetMobile Inception V3 ResNet 50 SeResNet 50 Xception DenseNet 121 ResNext 50	classification	Accuracy=85 Precision=85.7 Recall=85.4	Not available	Python	NM
[32]	X-ray	Resnet 32	classification	Accuracy=91.08	Not available	Python	NM
[33]	X-ray	Resnet 32	classification	Accuracy=90.2	https: //github.com/Perceptron21/CovXNet	Python	MNA
[34]	X-ray	Inception V3	classification	Accuracy=99.06	Not available	Not specified	MNA
[35]	X-ray	VGG 19	classification	Sensitivity=98.33	Not available	Python	MNA

				Specificity=98.68 Accuracy=96.91			
[36]	X-ray	DarkNet [37]	Classification	Accuracy=87.02 Sensitivity=85.35 Specificity=92.18 Precision=89.96 F1-score=87.37	https://github.com/muhammedtalo/COVID-19	Python	MNA
[38]	X-ray	MobileNet V2 SqueezeNet	Classification	Accuracy=98.25 Sensitivity=97.04 Specificity=99.15 F1-scorel=97.09	https://github.com/mtogacar/COVID_19	Python MATLAB	MNA
[39]	CT	U-Net ResNet 50	Segmentation Classification	Accuracy=96.74	Code not available/An online CT-based diagnostic platform for COVID-19 derived from our proposed framework is now available	Not specified	MNA
[40]	X-ray	SqueezeNet	Classification	Accuracy=98.3 Specificity=99.1 F1-score=98.3	Not available	MATLAB	MNA
[41]	X-ray	VGG 16	Classification	Accuracy=92.53 Specificity=95.1 Sensitivity=86.1	Not available	Not specified	MNA
[42]	X-ray	U-Net[43] ResNet 152[44]	Segmentation classification	AUC=97.27 Sensitivity=95.91 Specificity=91.99	https://github.com/ChenWWWeixiang/diagnosis_covid19	Python	A
[45]	X-ray	InceptionNet [46]	classification	F1-score=99.97	https://drive.google.com/fle/d/1-oK-eeEgdCMCny kH364IkAK3opmqa9Rvasx/view?usp=sharing	Python	NM
[11]	X-ray	COVID-Net	classification	Precision=93.33 Accuracy=93.3	https://github.com/lindawangg/COVID-Net	Python	NM
[47]	CT	DenseNet 201[48]	classification	Precision=96.29 Recall=96.29 F1-measure=96.29 Specificity=96.21 Accuracy=96.25	Not available	Not specified	NM
[49]	CT	3D U-Net [50] 3D ResNet [44]	Segmentation Classification	Accuracy=93.3 Sensitivity=87.6 Specificity= 95.5	Not available	Python	NM
[51]	CT	3D ResNet34 [52]	Classification	AUC=94.4	Not available	Python	MNA

				Accuracy=87.5 Sensitivity=86 Specificity=90 F1-score=82			
[53]	CT	Custom an attention-based deep 3D multiple instance learning (AD3D-MIL)	Classification	Accuracy=94.3 AUC=98.8 F1-score=92.3 Precision=95.9 Recall=90.5 Cohen-Kappa=91.1	https://github.com/zhyhan	Python	MNA
[44]	CT	ResNet 50[44]	Classification	Specificity=95 Sensitivity=90 AUC=96	https://github.com/bkong999/COVNet	Python	NM
[55]	CT	EfficientNet B4 [56]	Classification	Accuracy=96 sensitivity=95 Specificity=95 ROC=95	http://github.com/robinwang08/COVID19.	Python	A
[57]	X-ray	CV19-Net	Classification	AUC=92 Sensitivity=88 Specificity=79	https://github.com/uw-ctgroup/CV19-Net	Python	A
[58]	X-ray	DenseNet-121 [59] ResNet-50 [44] InceptionV3 [60] InceptionResNet V2[67] Xception[62] EfficientNet-B2[56] (DeepCOVID-XR)	Classification	Accuracy=83 AUC=90	https://github.com/ IVPLatNU/deepcovidxr	Python	A
[63]	X-ray	VGG 16[64] VGG 19 [64] InceptionNet v3 [60] MobileNet V2[65] ResNet 50[44] DenseNet 121 [59]	Classification (2 classes)	ROC=96.51 Sen=93.84 Spec=99.18 Acc=98.50	Not available	Not specified	NM
[66]	X-ray	Custom	Classification (3 classes)	Acc=91.34 F1-score=89.66 Recall=88.33 Prec=91	Not available	Not specified	MNA
[67]	CT	U-Net[43] DenseNet 121[59]	Segmentation classification	AUC=90 Sen=78.93 Spec=89.93	https://github.com/ wangshuocas/COVID-19	Python	MNA
[68]	CT	Multi-task U-Net[43]	Segmentation	Dice coefficient=85	https://www.jianpeicn.com/category/yuepianjiqiren	https://www.simpleitk.org	A
[69]	X-ray	InceptionResNet V2[67] InceptionNet v3 [60] NasNetLarge[70]	Classification	Acc=97.87 Acc=97.87 Acc=96.24	Not available	Not specified	MNA
[71]	CT	ConvLSTM	Classification	Acc=96	Not available	Python	MNA
[72]	X-ray	Inception V3 ResNet	Classification	Acc=66.43 Acc=59.81	Not available	Not specified	NM
[73]	CT	Custom	Classification Segmentation Reconstruction	Acc=94.67 Dice coefficient=88	Not available	Python	MNA

[74]	CT	U-Net[43]	Segmentation	Dice coefficient=97	Not available	Nora software	MA
[75]	X-ray	StackNet-DenseVIS GAN[76] DenseNet-121 [59] VGG 19 [64] InceptionResNet V2[67] SEResNeXt50-32 × 4d [77]	Augmentation Segmentation Classification	Acc=95.07 Sen=99.40 Spec=94.61	Not available	Python	MNA
[78]	CT	U-Net++[79]	Classification	Acc=100 Sen=81.82 Spec=92.59 Prec=88.89 Recall =100	https://github.com/endo-angel/ct-angel	Python	A
[80]	X-ray	SE-ResNeXt-50-32x4d [77] (COV19NET)	Classification	AUC=81 Sen=85 Spec=72 Prec=55 Recall=92	http://www.radiology.hku.hk/MAIL/pages/covid19.html (Upon request)	Python	A
[81]	X-ray	AlexNet[82] MobileNet V2[83] SuffleNet[84] SqueezeNet[85] Xception[62]	Classification	Recall=93 Precision=94 F1-score=93.5	Not available	MATLAB	MNA
[86]	X-ray	VGG 16[87]	classification	Acc=95 Prec=88.33 Recall=95 F1-score=91	Not available	Allen Institute for AI	NM
[88]	X-ray	Custom	classification	AUC=99.79 Acc=98.27	Not available	MATLAB	MNA
[26]	CT	ResNet 50[44]	classification	Sen=84.4 Spec=93.3	[44]	Python	A
[25]	X-ray	Custom ResNet 8	classification	Acc=98.3 Sen=99.3 Spec=98.1	Will be Publicly available	Python	NM
[89]	X-ray	Xception[62]	classification	Prec=95 Recall=96.9 F1score=95.6 Acc=95	https://github.com/drkhan107/CoroNet	Python	MNA
[90]	X-ray	ResNet 18[44] ResNet 50 [44] SqueezeNet[85] DenseNet 121[59]	classification	Sen=98 Spec=90.7	https://github.com/shervinmin/DeepCovid.git	Python	NM
[91]	CT	VGG 16[64] Inception V3[60] ResNet 50[44] DenseNet 121[59] DenseNet 201	classification	Acc=88.34 AUC=88.32 F1-score=86.7	Not available	Python	NM
[92]	X-ray	Custom	classification	AUC=81 Prec=68 Recall=81	Not available	CAD4TB v6 software	A
[93]	X-ray	VGG 16 [64]	classification	Acc=83.6	https://github.com /jurader/covid19_xp	Python	MNA
[94]	X-ray	ResNet 18[44] ResNet 50[44] COVID-Net [95] DenseNet 121 [59]	classification	Sen=88 Spec=94 AUC=97 BA=91 DOR=112.93	https://github.com/EIDOSlab/unveiling-covid19-from-cxr	Python	NM
[96]	CT	U-Net[43] ResNet 50 [44] (COVID-AL)	Segmentation classification	Acc=95	Not available	Not specified	NM
[97]	CT	U-Net[43] ResNet 50 [44] (IDANNet)	Segmentation classification	Acc=81 Sen=81 Spec=82	https://github.com/LittleRedHat/COVID-19	Python	A

				Prec=94 Recall=57			

TABLE IV. IEEE SELECTED PAPERS

Ref.	Modality	DL technique	Task	Performance metric	Code	Language	Validation
[98]	CT	U-Net[43] AlexNet[99] ResNet[44] (DeCoVNet)	Segmentation Classification	AUC=96.7 ROC=95.9 Accuracy=90.1 Precision=84 Recall=98.2	https://github.com/ sydney0zq/covid-19-detection	Python	A
[100]	CT	DenseNet 121 DenseNet 169 DenseNet 120 VGG 19[64]	Classification	Accuracy=97.35 Precision=97.52 Recall=98.80 F1-score=98.6	https://github.com/qianliu1219/iMP	Python	NM
[101]	CT X-ray	Squeezenet [85] MobileNet[83] VGG 19[64] ResNet 18 Inception V3 ResNet 101 ChexNet DenseNet 201	Classification	Accuracy=99.40 Precsion=99.40 Recall=99.40 F1-score=99.40 Specificity=98.84	Not available	MATLAB	MNA
[102]	CT	VB-Net [103]	Segmentation Classification	Accuracy=91.79 Sensitivity=93.05 Specificity=89.95 Sensitivity=93.05 AUC=96.35 Precision=93.10 F1-score=93.07	Not available	Not specified	NM
[104]	CT, X-ray, Ultrasound	VGG 16[64] VGG 19[64] Xception[62] InceptionResNet[67] Inception V3[60] NASNETLarge[70] DenseNet 121[59] ResNet 50 V2[64]	Classification	F1-score(X-ray, Ultrasound, and CT)=(79, 99, and 79)	Not available	Python	MNA
[65]	X-ray	GAN Darkcovidnet [36]	Generate synthetic images	AUC=95.25	Not available	Python	MNA
[106]	CT, X-ray	DenseNet 121[59] VGG 16[64] InceptionResNet v2[46] ResNet 50 [70]		Accuracy (X-ray, and CT)=(91.79.8) Sensitivity (X-ray, and CT)=(77.7, 76.5) Specificity (X-ray and CT)=(95.4, 80.1)	Not available	Python	NM

				AUC(X-ray, and CT)=(96.6, 81.9)			
[107]	X-ray	MobileNet[65] VGG 16[64] VGG 19[64] Xception[62] InceptionResNet V2[67] DenseNet 121[59] DenseNet 201 DenseNet 201[48] DenseNet 169 [59]	classification	Accuracy=98.46 F1-score=98.46	Not available	Python MATLAB	NM
[108]	X-ray	DenseNet 121[59] (CSEN)	classification	Accuracy=96.35 Sensitivity=98.86 Specificity=91.71	https://github.com/meteahishali/methods-early-cov19	Python	MNA
[109]	CT	GAN U-Net[43] ResNet 18[44]	Segmentation Classification	AUC=88.3 Dice=57.5 Accuracy=88.4 F1-score=64	https://github.com/guaguabujianle/COVID-19-GAN	Python	NM
[110]	CT X-ray	Genetic Deep Learning Convolutional Neural Network (GDCNN)	classification	Accuracy=98.84 Precision=93 Sensitivity=98.84 F1-score=93 Specification=98.84	https://github.com/ BABUKARTHIKRG/covid19.git	Python	MNA
[111]	X-ray	COVID-Net[95]	classification	Sensitivity=95.27 Precision=94.53	[95]	Python	NM
[112]	CT	U-Net[43] Inception [46]	Segmentation Classification	Dice coefficient=83.25 Sensitivity=84.06 Specificity=99.88 Intersection over Union (IOU)=74.2	Not available	Python	NM
[113]	CT	U-Net[43]	Segmentation	Dice coefficient=78.3 Recall=77.6	https://github.com/lzx325/COVID-19-repo.git.	Python	NM
[114]	CT	Mobilenet V2 [83]	Classification	Accuracy=99.38 Precision=99.20 Recall=99.60 F1-score=99.40 AUC=99.58	Not available	MATLAB	MNA
[115]	X-ray	CovFrameNet Custom	Classification	Precision=85 Recall=85 Accuracy=100 Specificity=100 AUC=50 F1-score=90	https://github.com/NathanielOy/covid19cnn	Python	NM
[116]	CT	VGG 16[64] VGG 19[64]	Classification	Accuracy=58.21 Sensitivity=95.8	Not available	Not specified	NM

		ResNet 50 [117] AlexNet[118] Inception [119]		Specificity=28.44 Precision=51.75 Recall=87.74 F1-score=67.02			
[120]	CT	The deep learning model of 3D lesion segmentation and classification for diagnosing COVID-19 (DeepSC-COVID)	Segmentation Classification	Dice Coefficient=73.3 Sensitivity=80.2 normalized surface Dice (NSD)=71.8	https://github.com/XiaofeiWang2018/DeepSC-COVID	Python	MNA
[121]	CT	Details Relation Extraction neural network (DRENet) ResNet 50 [44]	Classification	Accuracy=93 Precision=93 Recall=93 Specification=93 F1-score=93	http://biomed.nscc-gz.cn/model.php Code not available	Python	MNA
[122]	X-ray	U-Net[43]	Segmentation Classification	Accuracy=94.67 AUC=98.42 Sensitivity=94.34 Precision=94.97 F1-score=94.65 Matthews Correlation Coefficient (MCC)=89.34	https://github.com/sivaramakrishnanrajaraman/Iteratively-pruned-model-ensembles-for-COVID19-detection-in-CXRs	Python	NM
[123]	CT	U-Net[43] VGG [64]	Segmentation Classification	Accuracy=82.2 Precision=69.93 Sensitivity=74.9 Specificity=89.46 AUC=87.9	Not available	Python	NM
[124]	X-ray	ResNet 18[44] Inception[60] VGG 19[64]	Classification	Accuracy=92.5 Sensitivity=65.01 Specificity=94.3	https://github.com/asmaa4may/4S-DT	Python MATLAB	NM
[125]	CT	Multi-scale discriminative network(MSD-Net) U-Net[43] U-Net++[79] U-Net + CBAM [126] Attention U-net [127]	Segmentation	Dice coefficient=87.79 Sensitivity=84.45 Specificity=98.89	Not available	Python	NM
[128]	X-ray	Multiscale Attention Guided deep network with Soft Distance regularization (MAG-SD)	Classification	Accuracy=96.94 F1-score=96.23 Specification=94.93 Sensitivity=97.83	https://github.com/JasonLeeGHub/MAG-SD	Python	MNA

[129]	X-ray, CT	Multilevel deep-aggregated boosted network (MDA-BN)	Classification	Accuracy=95.38 F1-score=95.57 Specification=92.53 Sensitivity=98.14 Precision=93.16 AUC=98.55	https://github.com/Owais786786/MDA-BN-Model	MATLAB	MNA
[130]	CT	Lung Infection Segmentation Deep Network (Inf-Net)	Segmentation	Dice coefficient=57.9 Sensitivity=87 Specificity=97 Precision=50 Mean Absolute Error (MAE)=47	https://github.com/DengPingFan/InfNethttps://github.com/DengPingFan/Inf-Net (Both dataset and code are the same	Python	NM
[131]	CT, X-ray	VGG 16[64]	Classification	Accuracy=97 F1-score=98 Sensitivity=99 Specificity=99 Recall=99 Precision=97	Not available	Python MATLAB	NM
[132]	CT	ResNet 50[44]	Classification	Accuracy=95.21	Not available	Python	MNA
[133]	Ultrasound	U-Net++[79] Inspired by [134]	Segmentation Classification	Precision=70 F1-score=61 Recall=60	https://github.com/mhugTrento/DL4covidUltrasound.	Python	A
[135]	CT, X-ray	DenseNet-169[59]	Classification	Accuracy=93.44 Precision=90.97 Recall=93.8 F1-score=92.06 CK-score=88.85	Not available	Python	NM
[136]	X-ray	modified multi-crossover genetic algorithm (MMCGA) DenseNet 264[137]	Classification	Accuracy=99.34	Not available	MATLAB	NM
[138]	X-ray	ResNet-50[44]	Classification	Accuracy=71.4 AUC=78.4 Sensitivity=71.3 Specificity=71.5	Not available	Not specified	MNA
[89]	CT	ResNext+ inspired by ResNext[139] called COVID-Attention-Net	Classification	Accuracy=77.6 Precision=81.9 F1-score=81.4 Sensitivity=85.5 Specificity=79.3	Not available	Python	MNA
[140]	X-ray, Ultrasound	capsule network	Classification	Precision=98.33 F1-score=98 Sensitivity=98 Specificity=97.66	[141]point of care ultrasound (POCUS)	Not specified	NM
[142]	CT	U-Net	Segmentation	Hausdorff Distance=17.12 Relative Volume Error=15.96 Dice coefficient=80.72	https://github.com/HiLab-git/COPLE-Net	Python	NM

[143]	CT	U-Net	segmentation	Dice coefficient=88.02 Sensitivity=89.38 Precision=87.59	Not available	Not specified	NM
An et al.	X-ray	U-Net DenseNet	Segmentation classification	Accuracy=98.83 Precision=98.91 Recall=98.53 F1-score=98.71	Not available	Python	NM

3.1 Image modalities

Several imaging methods have been utilised to detect the presence of the coronavirus. The image modalities examined in this literature review encompass Ultrasound, CT, MRI, and X-ray pictures. Figure 3 displays the chest X-ray (CXR), computed tomography (CT), and ultrasound images, in that order. The detection of COVID-19 has been facilitated by the utilisation of a range of medical imaging tools in conjunction with RT-PCR in response to the outbreak of the disease. The radiographic modalities encompass Positron Emission Tomography (PET)/Computed Tomography (CT), X-ray, and Ultrasonography pictures. The subsequent section offers a concise elucidation of each of them in a succinct manner.

1) X-ray

In addition to reverse transcription polymerase chain reaction (RT-PCR), X-ray imaging serves as an alternate modality for the identification of COVID-19. The utilisation of chest X-ray (CXR) as a readily accessible and expeditious method for the visual identification of COVID-19, in collaboration with radiologists, is well-established. Nevertheless, there exist several limitations associated with chest X-rays (CXR) in relation to the detection of viral persistence, mostly due to its restricted sensitivity. Additionally, it should be noted that X-ray imaging is unable to effectively identify anomalies in soft tissues. Hence, it is not the optimal selection for the purpose of COVID-19 screening [144]. Moreover, the early phases of infection are characterised by the inability to identify Ground Glass Opacity (GGO) and consolidation. While X-ray imaging has demonstrated the ability to identify some uncommon presentations of pleural effusions and pneumothorax in COVID-19 cases, it is not effective in detecting lung lesions and pneumonia, including both bacterial and viral pneumonia [145], [146]. Moreover, X-ray imaging lacks the ability to distinguish between pneumonia cases caused by the corona virus and those resulting from other forms of pneumonia.

2) CT

During the current COVID-19 pandemic, computed tomography (CT) has been recognised as a fundamental imaging technique for the diagnosis of the virus [147]. Moreover, the utilisation of CT imaging characteristics, such as peripheral Ground Glass Opacification (GGO) and lower and middle lung consolidation, has been extensively employed for the diagnosis of COVID-19 [148], [149]. Computed tomography (CT) scans have a higher level of sensitivity in comparison to X-rays when it comes to detecting ground-glass opacities (GGO) and consolidative opacities. The COVID-19 disease exhibits a higher susceptibility to the development of pulmonary symptoms, lymphadenopathy, and pneumothorax. Although X-ray imaging was incapable of detecting these manifestations. Hence, health practitioners generally prioritise the utilisation of CT scans for the detection of infection in individuals who are asymptomatic but have serious health issues. Chest computed tomography (CT) has a notable degree of sensitivity when employed for the purpose of diagnosing lung disease symptoms, including bacterial and viral pneumonia. Numerous studies have demonstrated that computed tomography (CT) imaging results exhibit superior performance compared to reverse transcription polymerase chain reaction (RT-PCR) results. Furthermore, it has been shown that a significant number of patients who initially tested negative for SARS-CoV-2 using reverse transcription polymerase chain reaction (RT-PCR) had positive results after lung abnormalities were seen in their computed tomography (CT) scans of the lungs [150], [151], [152]. Multiple studies have indicated that the rate of misdiagnosis for the coronavirus is significantly reduced in comparison to the RT-PCR test. Moreover, computed tomography (CT) is a suitable modality for the timely detection of COVID-19 [153]. While computed tomography (CT) is a valuable and efficient method for promptly diagnosing COVID-19, it is unable to differentiate COVID-19 from other infectious diseases such as Severe Acute Respiratory Syndrome (SARS) and Middle East respiratory syndrome (MERS) [151][153]. Additionally, there is a potential risk of disease transmission from suspected patients to healthcare practitioners [154]. Finally, it should be noted that CT imaging subjects patients to a significant amount of radiation.

3) Ultrasound

Ultrasound represents an additional modality employed in the diagnostic assessment of lung pathology. The diagnostic accuracy of lung diseases, such as acute respiratory disorders, pneumothorax, and hyperinflation, is comparatively higher than that of X-ray and CT scans [146], [155]. Ultrasound is a non-invasive imaging modality utilised for surface examination, capable of identifying artefacts such as pleural visceral structures. The ultrasonographic findings observed in individuals with COVID-19 include pleural abnormalities characterised by the progressive thickening of pleural lines with irregularities, peripheral consolidation, and the presence of B-lines and A-lines. Although ultrasonic radiography offer several benefits, they are unable to effectively identify lesions located in the core regions of the lung. Ultrasonography is limited in its ability to detect pneumonia that has spread deeper into the body. Therefore, a computed tomography (CT) scan is considered to be highly favourable in such instances (156). Ultrasound imaging has the capability to detect viral infections in their early stages by identifying abnormalities in focal B-line patterns and the thickness of the pleural line, which indicates lung involvement in cases of pneumonia. Lung ultrasonography plays a pivotal role in the detection of COVID-19 owing to its cost-effectiveness, absence of radiation, and safety considerations. Figure 3 illustrates the distribution of studies that employ X-ray, CT scan, and Ultrasound techniques.

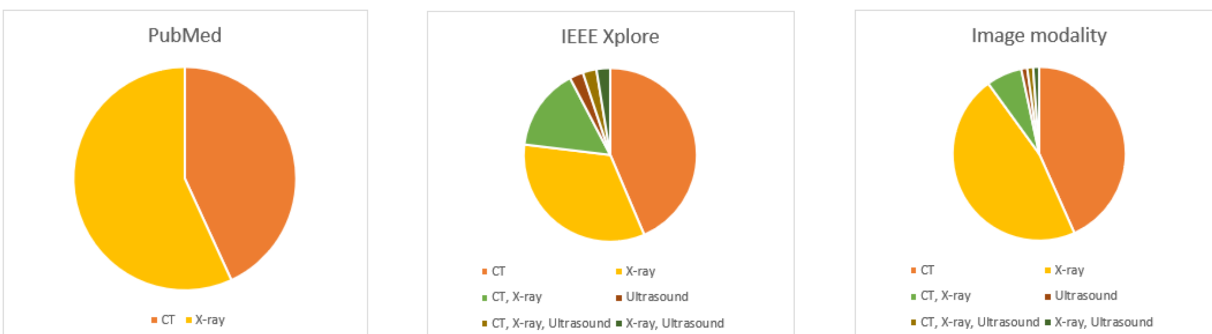
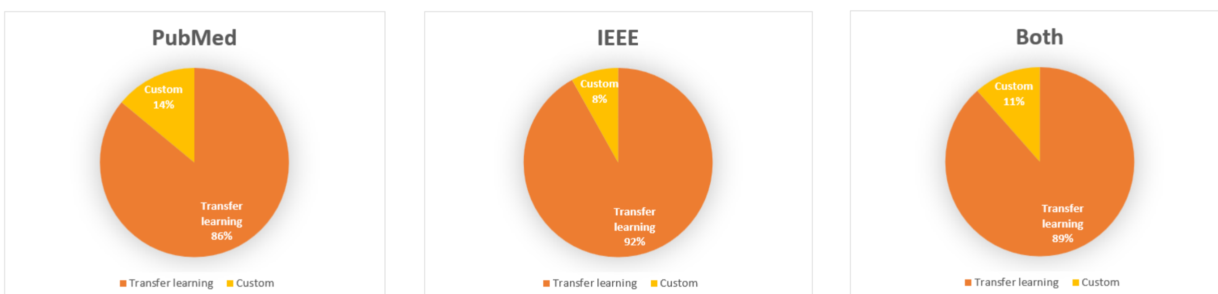


Fig.3. Image modalities, (a) PubMed, (b) IEEE Xplore, (c) Both databases.

3.2 Deep learning architectures

The convolutional neural network (CNN) is a fundamental component of deep learning and falls within the supervised domain of deep learning. The topic of Artificial Neural Networks (ANN) has witnessed significant advancements. Since 2012, it has resurfaced as a pivotal element in diverse computer vision jobs, encompassing medical-related issues. The introduction of AlexNet in 2012 brought about a significant transformation in the domain of convolutional neural networks (CNNs) by introducing novel layers in contrast to the conventional layers seen in artificial neural networks (ANNs). The primary objective of Convolutional Neural Networks (CNNs) is to acquire knowledge pertaining to the distinctive characteristics present within a given dataset by use of convolution operations. The Convolutional Neural Network (CNN) is composed of multiple layers which receive an input image, undergo a sequence of processes, and ultimately make a prediction regarding the class of the input image. Instead of doing manual feature extraction, Convolutional Neural Network (CNN) layers employ a sequence of convolution, Rectified Linear Unit (ReLU), and pooling operations to automatically extract features. Convolutional Neural Networks (CNNs) often consist of various types of layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layer functions as a feature extraction mechanism, wherein several filters are employed to acquire knowledge about distinct features. The production of feature maps is achieved by convolving the filters across the entirety of the image. Every individual neuron within the convolutional layer establishes connections with a limited area of the input image, referred to as the receptive field. The pooling layer is responsible for reducing the dimensionality of feature maps through downsampling in the dimensionality reduction technique. The pooling layer encompasses various forms, including max pooling and average pooling. The initial operation extracts the maximum value from the feature map, whereas the subsequent operation computes the average value of the activation map elements. Similar to artificial neural networks (ANNs), every neuron inside this particular layer is connected to all the neurons present in the preceding layer. The final layer of the Convolutional Neural Network (CNN) employs the "softmax" activation function in order to make predictions regarding the class of the given input image. The subsequent enumerations include descriptions of contemporary CNN architectures that have been extensively employed to address the COVID-19 pandemic. The CNN architectures most frequently employed in various applications include Alexnet Krizhevsky et al. [158], Visual Geometry Group (VGG16) [159], GoogleNet [46], ResNet [160], and DenseNet [59]. Transfer learning and bespoke deep learning techniques were grouped in this study. The first is supervised machine learning that solves deep learning challenges. As shown, deep learning architecture training from scratch involves a lot of data and time. Therefore, Zhang et al. [32], Mahmud et al. [33], Das et al. [34], Ozturk et al. [36], Howard et al. [65], Chiu et al. [80], Xie et al. [97], Song et al. [121], Zheng et al. [125], and Woo et al. [126] have used transfer learning in Covid-19 detection to accelerate the training process and solve the problem of a small dataset. Some writers preferred specialised architectures to train the network from scratch. For example, Echtioui et al. [66], Hu [71], Amyar [73], Irmak [88], Karakanis and Leontidis [25], Murphy [92], Babukarthik [110], Li [128], Qwais [129], and Fan [130]. Figure 4 illustrates the percentage of writers using custom and transfer learning methodologies in this review.

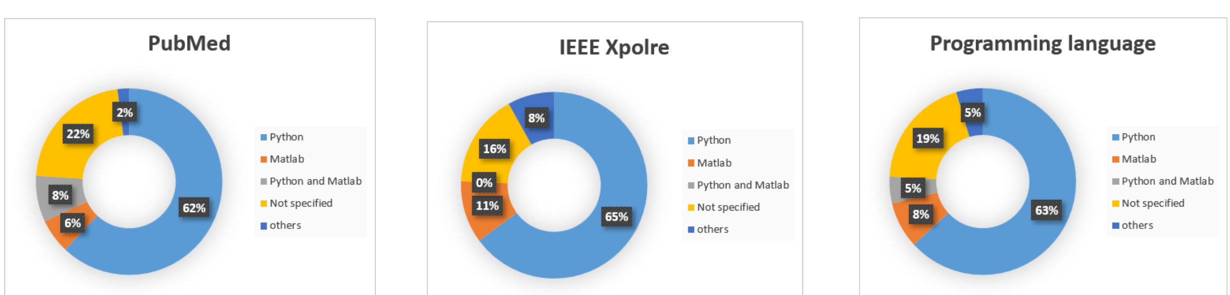


(a) (b) (c)

Fig. 4. deep learning models (a) PubMed, (b) IEEE Xplore, (c) Both databases.

3.3 Programming languages

The findings derived from the accessed literature in the review indicate that a range of programming languages have been employed to enact the recommended approaches, including Python, MATLAB, and other languages. Several writers disclosed the programming languages employed and made them available for public utilisation. The prevailing programming language in widespread usage is Python, followed by MATLAB. It is worth noting that several writers have not explicitly indicated the programming language they employed.



(a) (b) (c)

Fig. 5. Programming languages, (a) PubMed, (b) IEEE Xplore, (c) Both databases.

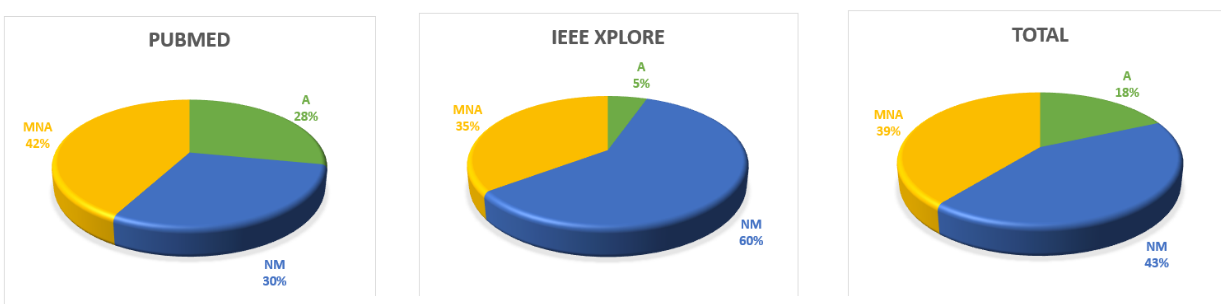
3.4 Types of studies

Javor The primary aim of this literature review is to ascertain the proportion of studies employing deep learning techniques that have been implemented in practical applications within the medical domain. The terms A, MNA, and NM correspond to the categories "Approved," "Mention but not Approved," and "Not Mentioned," respectively. Figure 4 displays the proportion of studies obtained from each database archives as well as the combined retrieval. The majority of the studies conducted in this field are retrospective in nature, however a subset of the data utilised has been annotated by radiologists, as demonstrated by Yu et al. [161]. While the methodologies have received validation from radiologists, several approaches merely categorise COVID-19 instances as positive or negative, as indicated by reference [97]. The code, as referenced by [27], is accessible to health providers in the absence of a specific platform for utilisation. This section will include an analysis of some papers that have been assessed by resident radiologists in the sequel.

The AI-based system CAD4COVIDX-ray, developed by Murphy et al. [92], was trained using a dataset consisting of 24,678 pictures. The obtained outcomes of the artificial intelligence (AI) system are afterwards juxtaposed with the findings of six radiologists. The model's performance was assessed using the Receiver Operating Characteristic (ROC) curve measure. The system exhibits precision and recall rates of 77% and 76%, respectively. Nevertheless, the collective outcome determined by the radiologist indicates precision and recall rates of 72% and 78% respectively. In a separate study, Anastasopoulos et al. (74) gathered data from a scholarly hospital in order to create an artificial intelligence (AI)-driven software capable of segmenting and quantifying CT lung opacities. The study's project team consists of eight physicians. The proposed methodology is accessible in the form of an open-source web application and has been developed using the Nora medical software development platform. The system's performance was evaluated in comparison to a manual diagnosis of COVID-19 conducted by resident radiologists. The utilisation of performance indicators such as the Dice Coefficient and Hausdorff Distance has been seen.

Chiu et al. (80) proposed the utilisation of a deep learning (DL) methodology known as COV19Net for the identification of coronavirus in X-ray pictures. The model was trained and evaluated using a publicly accessible dataset. The assessment of the outcomes of the created algorithm was conducted by three radiologists who are certified by a professional board. The validation cohort was assessed by radiologists in a blinded manner, with no prior knowledge of RT-PCR or any other patient-related information. In order to establish consensus among readers of radiography, a method of majority voting has been employed to determine the presence or absence of COVID-19 in a given image. The proposed COV19Net demonstrates a positive predictive value (PPV) of 55% and a negative predictive value (NPV) of 92%. In comparison, radiologists exhibit a PPV of 44% and an NPV of 78%. Chen et al. [78] presented an additional approach for CT images that utilises deep learning techniques. The proposed system was put out by a collective of researchers, and the source code for the suggested approach can be accessed by interested researchers at the following public repository: https://github.com/endo-angel/ct-angel. Furthermore, the system is accessible to physicians through an open-access website, which may be found at the following URL: https://121.40.75.149/znyx-ncov/index. The CT images were obtained from a cohort of patients who were prospectively enrolled at Renmin Hospital of Wuhan University. The research was granted approval by both Qiangjiang Central and Renmin Hospital of Wuhan University. Within this study, a model was constructed based on the UNet++ framework [79]. The model's performance was assessed in comparison to human performance in terms of both time and accuracy. During the course of the studies, it was observed by the researchers that the average duration required by the expert radiologist dropped by 65%.

Javor and colleagues (2019) proposed a model based on the ResNet50 architecture, implemented using the fastai deep learning framework (Howard et al., 2018). In order to assess the resilience of the model, a comparison was made between the obtained outcomes and those of two radiology specialists. In order to mitigate potential bias in the diagnostic process, the individuals responsible for interpreting the radiographs were intentionally kept unaware of the incidence of COVID-19 infection among the subjects. The approach has been evaluated using performance criteria such as AUC, ROC, specificity, and sensitivity. The authors demonstrated the superiority of the model by attaining an average specificity of 94.45%. Nevertheless, it is worth noting that the sensitivity of manual diagnosis surpasses that of automatic identification by the model, with a rate of 81.1%. The fundamental framework of the proposed Identification and Analysis of New covid-19 Net (IDANNet) [97] comprises the utilisation of UNet and ResNet-50 models. The researchers employed a five-fold cross-validation technique to assess the reliability and stability of the developed deep learning model. The obtained outcomes are examined by three proficient radiologists through a process of re-diagnosing the CT images in a blinded manner, wherein they are unaware of the previous results of RT-PCR testing for the prospective participants. The performance measurements utilised in this study are positive predictive value (PPV), negative predictive value (NPV), specificity, sensitivity, and accuracy. The average values obtained for these metrics are 90.33%, 51.33%, 66.66%, 79.66%, and 76.33%, respectively. Nevertheless, the proposed model has an accuracy, sensitivity, precision, and recall of 81%, 81%, 82%, 94%, 94%, and 57% respectively. In a separate study, the researchers in [27] devised a diagnostic algorithm for COVID-19 utilising the BigBiGAN model [163]. The system underwent training and testing using a specialised dataset of CT images. Cardiothoracic radiologists who have accumulated a decade of expertise have begun to discern visual manifestations depicted in medical imaging. The conclusive determination regarding the presence or absence of the virus has been reached following an agreement among professionals in the field of radiography. The proposed method demonstrates a specificity of 88% and a sensitivity of 85%. In comparison, radiologists achieve an average specificity of 75% and an average sensitivity of 77% in their diagnostic results. The approach provided by Ni et al. [30] involved the utilisation of a bespoke dataset comprising CT scan images. A clinical reading of CT images, which have been previously blinded to patient circumstances, was conducted by a group of three radiologists. The mean values for accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and F1-score, following the establishment of a consensus among residents, are 88%, 84.33%, 78%, 93%, and 86% correspondingly, for the metrics listed above.



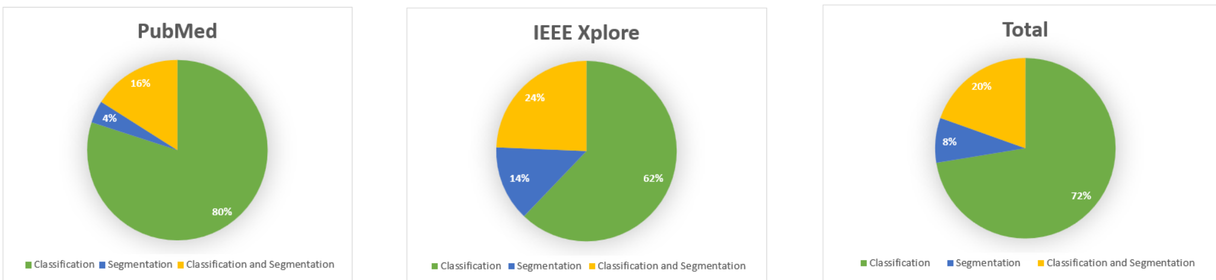
(a) (b) (c)

Fig. 6. Types of studies which validated the results with radiologists mentioned, mentioned but without validation, and did not mention (a) PubMed, (b) IEEE Xplore, (c) Both databases.

Figure 4 depicts the distribution percentage of chosen articles among scholars who validate the study findings with radiologists (A), scholars who acknowledge the potential usefulness of the study in aiding healthcare professionals (MNA) but do not endorse it, and scholars who do not mention it at all (NM). The distribution of retrieved publications to A, MNA, and NM from both the PubMed and IEEE databases is depicted in the left and middle sub-figures, respectively. Based on the analysis of the sub-figure on the right, it is evident that a total of 34 studies, accounting for 43% of the sample, did not indicate the potential practical implications of their research. Additionally, a total of 37 papers, accounting for 39% of the sample, indicate that their research findings are deemed valuable but lack validation from radiologists. In conclusion, a total of 16 publications, representing 18% of the researchers, successfully obtained validation from medical practitioners for their conducted studies. This validation serves to reinforce the researchers' stance on the ailment in question.

3.5 The core tasks

Figure 7 illustrates the fundamental activities undertaken by researchers in their investigations, namely classification and segmentation. The quantity of scholarly articles obtained from the PubMed search engine pertaining to the topics of classification, segmentation, and the combination of both is 40, 2, and 8, respectively. The classification, segmentation, and joint performance metrics for the task at hand have been reported as 23, 5, and 9, respectively, in works published by the Institute of Electrical and Electronics Engineers (IEEE). The utilisation of deep learning techniques for classification was observed in 72% of the studies, while segmentation was employed in 8% of the studies. Additionally, a combination of classification and segmentation approaches was implemented in 20% of the investigations.



(a) (b) (c)

Fig. 7. Performed tasks (classification, segmentation), (a) PubMed, (b) IEEE Xplore, (c) Both databases.

4. DISCUSSION

Deep learning approaches have been utilised to a significant degree in addressing the challenges posed by the Covid-19 pandemic at varying rates. The aforementioned systematic review yields the following conclusion. The majority of the conducted experiments utilised deep learning techniques primarily for classification tasks as opposed to segmentation activities. Although each image modality has its own merits and downsides, certain modalities, such as X-ray, have been more widely utilised than others. Certain types of imaging, such as ultrasonography, are often disregarded due to their infrequent utilisation. Furthermore, the use of transfer learning approaches has been extensively employed as opposed to the proposition of a novel convolutional neural network (CNN) architecture and the training of the model from its initial state. The justification for this can be attributed to the significant computational expense associated with training the model from the beginning. Based on the categorization of studies in this review, a limited proportion of the literature has received validation from healthcare professionals and is deemed suitable for their utilisation. The predominant body of research produced in this field tends to be retrospective in nature, rather than prospective. This observation suggests that the findings of these studies may not provide health practitioners with adequate assistance. This suggests that there remains a practical gap in the utilisation of various techniques.

5. CONCLUSION

The primary objective of this work was to investigate the utilisation of deep learning techniques in the diagnosis of Covid-19. This was achieved through a comprehensive examination of relevant literature available in two prominent databases, namely IEEE and PubMed. The investigation encompassed several facets of the study, such as the exploration of CNN architectures, visual modalities, programming languages, and other relevant factors, in order to address the research inquiries. The research findings will be of interest to researchers and health practitioners, as they explore the potential of deep learning technologies in aiding doctors with the diagnosis of Covid-19-related diseases. An additional finding of this study pertains to the preference for transfer learning over the development of a custom architecture, owing to its practicality and user-friendly nature. Moreover, X-ray is considered the most extensively utilised image modality, although alternative modalities such as ultrasound exhibit somewhat lower levels of popularity. Furthermore, it is worth noting that the literature reviewed in this study mostly focuses on approaches based on Convolutional Neural Networks (CNNs), whereas other deep learning techniques, including Generative Adversarial Networks (GANs), Long Short-Term Memory (LSTM), and Recurrent Neural Networks (RNNs), have not been adequately explored.

One of the notable findings derived from this study is that relying exclusively on deep learning techniques is still not a viable substitute for healthcare professionals. This is mostly due to the fact that many of the studies examined in this research neglected to consider the practical implementation aspect of the proposed methodology. Hence, it is imperative to conduct a thorough investigation into the connections between deep learning researchers and healthcare professionals specialising in Covid-related illnesses.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study

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Conflicts Of Interest

I declare no conflicts of interest and other authors have no conflicts of interest to declare.

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