ISSN: 0974-8571 Vol.14 No. 1 June, 2022

International Journal of Computational Intelligence in Control

An Analytical Study on Covid-19 Disease Analysis with Modern Machine Learning Methods

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Date of Submission: 27th October 2021 Revised: 09rd January 2022 Accepted: 30th January 2022

Abstract: The new coronavirus (Covid-19) created a worldwide pandemic and has become one of the most chronic and deadly diseases in the current century. Although Covid-19 vaccinations have been produced, machine learning and deep learning models have proven to be a key weapon in physicians' armories for automatically diagnosing Covid-19 and the deployment of intelligent internet of medical things (IoMT). In this study, we provide an overview of modern deep learning systems that use various medical imaging methods such as Computer Tomography (CT) and X-ray of Covid-19. We reviewed the existing works with an emphasis on improved training interval, reduced model complexity, multiple quality measurements, size of the dataset, and balancing of datasets. The study focuses on modern machine learning models for diagnosing Covid-19 with IoMT and gives information about benchmark datasets that were used in the models' training. For proper understanding, a taxonomy is created to categorize recent works. Finally, we discuss the limitations involved with using deep learning approaches for COVID-19 identification, as well as possible future developments in this field.

Keywords: Intelligent IoMT, COVID-19; Machine Learning; Deep Learning; Computer Tomography; XRay;

1 Introduction

The epidemic of Coronavirus Disease (Covid-19) has caused the world under immense strain since 2019. According to World Health Organization, more than four million individuals have been infected over the world, with nearly more than two lac verified mortality cases [1]. The spread of COVID-19 over the world caused social panic, disruption, and dread among health professionals due to a lack of information about the unusual virus [2]. COVID19 symptoms include high fever, pneumonia, dyspnea, bodily discomfort, and exhaustion, however, in many cases, no symptoms were found despite the presence of COVID-19 [3]. COVID-19 easily spreads between people [4] and can cause organ failure by impairing the respiratory and cardiovascular systems. Coronavirus has posed significant hurdles and has become a global threat [5].

In comparison with the RT-PCR test, chest radiography is widely available at a small price for screening for COVID-19 [6]. Chest radiology provides us to obtain chest imaging at a minimal cost [7]. Chest X-ray technology is beneficial to patients who are experiencing symptoms, but there is an overhead that images must be shown to a radiologist [8,9]. The challenge of appropriately detecting COVID-19 instances can be solved with a computeraided analysis system [10,11]. Deep Learning (DL) models are also available for the detection of COVID-9 [8-11].
In extracting attributes from biomedical images, DL models have demonstrated encouraging results [12].

There are existing Systematic Literature Reviews (SLRs) in the domain of covid-19. The published SLRs focused on image data [13], type of images (X-Ray/CT) [14], evaluation criteria [15], small dataset [13,16,17], or large dataset [14,15], code available publically [14], dataset available publically [13-17], as mentioned in Table 1. Despite having several published reviews on the detection of Covid-19 from X-ray or CT- images, studies either cover papers up to 2020 or focus more on high accuracy using biased datasets and less on model complexity and balancing datasets. Table 1 provides a comparison on the following dimensions: dataset size, training time, model complexity, evaluation methods, code available publically, correlation of data size with the layer used, and the public/private dataset. These observations help us in determining the necessity of this survey. The problem statement for this SLR is to review the existing works on diagnosing Covid-19 from CT scans or X-ray images by using modern machine learning models under the internet of things (IoMT), with an emphasis on improved training intervals, reduced model complexity, multiple quality measurements, size of the dataset, and balancing of the dataset.

Our comparative analysis is based on a survey of the material that has only been published in well-reputed journals (excluding conferences and workshops). Based on a systematic review criterion that is followed in this SLR, 44 research publications have been chosen for future usage. These publications are assessed on a variety of levels, both qualitatively and empirically. The novelty of this SLR is that it adds additional dimensions to the model complexity, training time, dataset balancing, and public/private dataset, which will help researchers and programmers in getting the best results from X-ray and CT images of Covid-19.

This SLR article is organized in the following sections. Section II confers related work and motivation, whereas Section III presents the research methodology we used for this review. Section IV presents the taxonomy of Deep Learning and the synthesis of reviewed literature. It also discusses the challenges and future trends of deep learning models. The article is concluded in section V.

2 Literature Review

Guixing and Leyang [13] reviewed the methods of COVID-19 automatic detection. The authors analyzed a stateofthe-art approach for auto-detection of COVID-19 and provided an analysis of its models, outcomes, and opinions onthem as well. The databases of CT and X-rays were also listed. A survey was conducted on issues connected with the automatic detection of COVID-19 and the results of the survey were published. The review's limitation is that survey questions were not related to issues and for models' comparison, only the accuracy factor was considered.

Ji, et al., [14], in their review, described the features for comparison of different models which includes learning rate, size of the batch, total epochs, and optimizer type for the best suitable model. For evaluation purposes, eight models were selected including VGG16, AlexNet, Resent50, Resnet34, SqueezeNet, MobileNetV2, and InceptionNetV3. After evaluation of the mentioned dimensions, ResNEt34 was determined best. The study's weakness is that the authors validated the results using a small sample of data.

Arash, et al. [18] emphasized the best DL model for lung segment recognition and COVID-19 prediction using DL approaches. The methods of segmentation, classification, and prediction were summarized. and DL models were compared in terms of image kind, dataset size, classifier, and accuracy. The shortcoming identified is that several of the selected articles have unbalanced datasets.

Table 1: Comparison of existing Literature reviews with this Review Work

Reference	Dataset size/Large (	odel	Training Time	Balancing anc Unbalancing dataset of	Public/ Private dataset (case study)	Code Available Publically
[13]	Small	No	No	No	Public	No

[14]	Small	No	No	No	Public	No
[15]	Both	No	No	No	Public	No
[16]	Both	No	No	No	Public	No
[17]	Both	No	No	No	Public	yes
This SLR	Both	Yes	Yes	Yes	Both	yes

Tiwari et al. [17], covered the major aspects of the ML/AI approach for diagnosing Covid-19, data sources, software platforms, drug preparation, data perspective of research, detection, transmission prediction, and vaccine development. For the described element and medicine development, 14 AI and ML approaches were examined. However, the research has considered only seven online databases for review. Furthermore, the criteria of validation, accuracy, and assessment for ML/AI techniques were not taken into account.

Roberts et al. [15], used X-ray and CT scans to diagnose and prognostic Covid-19. The unbalanced datasets were checked using the PROBATE program. The validation type, properties of the data set, and sample size of the data were all examined.

It is identified that the SLRs in the existing literature have not considered all dimensions of categorization, detection, and outcome analysis used in deep learning-based solutions. Hence, there is a need to add extra dimensions to the categorization, detection, and outcome analysis (training duration, model complexity, dataset balancing) to assist researchers and programmers in generating the best results from biological images.

3 Materials and Methods

The protocol followed for systematic review in this work is enlisted in Fig. 1 as our research methodology. It is based on the systematic review guidelines given in [19].The problem statement of the SLR is analyzed systematically to minimize the possibility of any biased decision.

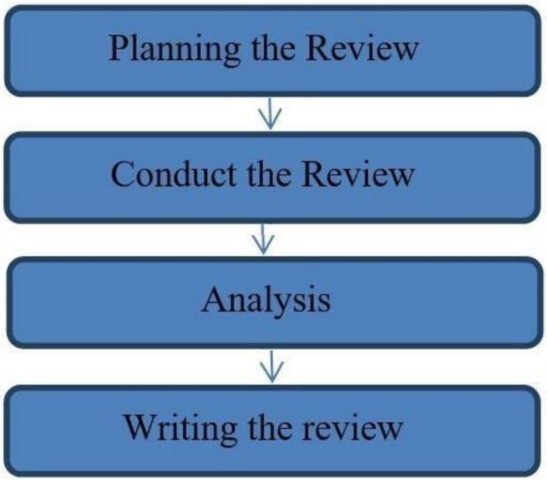


Figure 1: Research Methodology

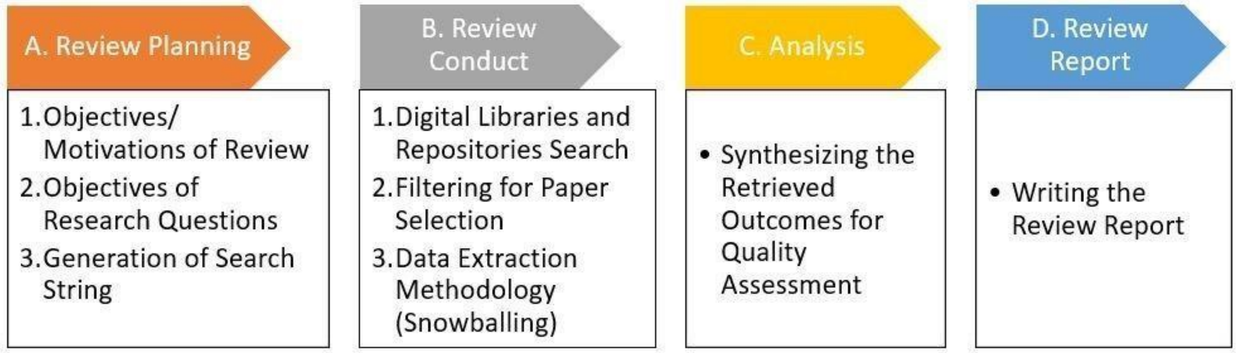


Figure 2: Strategy applied for the Systematic Literature Review

The systematic literature review is conducted under the strategy given in Fig. 2. The details are described below.

3.1 Review Planning of this SLR

The review plan of this SLR consists of the following three parts.

3.1.1 Objective/Motivation of Research

The objectives and motivations of this research are presented as research questions in Table 2. It presents four research questions as RQ1, RQ2, RQ3, and RQ4, The statement for each RQ is given in column two of Table 2.

3.1.2 Objectives of Research Question to Achieve the Goal

The objectives of the research questions are given in column three of Table 2. The purpose of each RQ is elaborated below.

RQ1: It tries to solve the issue of finding publication channels in the field of the biomedical image of Covid-19 for novice researchers. It makes CT/X-Ray image repositories available. Its major goal is to demonstrate the model's impact on public and private datasets.

RQ2: It asks for the approaches already used for the diagnosis of COVID-19 and how the findings were compared. It identifies the approaches, type of research, and evaluation methods used by the researcher to clearly define the gap in research.

RQ3: It provides detail for reducing the complexity of the model and reduction of training time for getting high accuracy.

RQ4: It makes it possible for balancing the dataset. Its major advantage is to gain unbiased dataset results.

retrieve

3.1.3 Generation of Search String

We applied under-given criteria for phrase searching to retrieve more relevant papers.

- Based on RQs, the primary key terms are defined.
- The secondary keys are determined.
- An image type, such as CT or CXR, is chosen.
- Additional keywords are identified.
- For creating a search string, the Boolean operators, 'OR' and 'AND' are concatenated.

Table 2: Research Questions with Objectives

Research Question Title	Research Question Statement	Objectives of Research Question
RQ1	What are the Covid-19 biomedical image publication channels and which channel types and geographic locations are targeted by Covid-19's biomedical images?	To Find out • Covid-19 X-ray/CT image publications are held at the high-quality venue. • Covid-19 publication on CT/X-Ray during December 2019 to Nov-2021.
RQ2	Which methodologies are applied by researchers for diagnosing, prognosis, and detection of COVID-19?	To find out • Analysis based on evaluation methods, type of research, and approaches. • Deep learning models for Covid-19 images • Machine learning Algorithms for Covid-19 images • Hybrid approaches for Covid-19 images
RQ3	How to reduce the training time and complexity of the Model for getting high accuracy?	To identify • Create Simple Model • Reduce the training time • Getting high accuracy
RQ4	How to remove unbalancing of datasets	To identify • Getting high accuracy • Getting outstanding result of recognition

Our search query to retrieve the required articles from different digital libraries is shown in Table 3. Possible search string combinations for query terms are depicted in Figure 3. Here, the primary keywords are chosen with the secondary and additional keywords which are concatenated with the 'AND' Boolean operation. Whereas, all primary keywords, secondary keywords, and additional keywords are concatenated using the 'OR' Operator.

3.2 Review Conduct of this SLR

This review has been conducted in four stages, described below.

3.2.1 Digital Libraries and Repositories Search

In the first stage, relevant research articles are found in digital libraries and repositories. A systematic search for irrelevant and relevant papers was conducted. As a result, both manual and automated search methods have been used. Many digital libraries have been examined, however, only the most frequently visited digital libraries (enlisted below) have been chosen.

Table 3: Search Query Format used for different Digital Libraries

Digital Library	Search Query

Google Scholar	[Chest-Xray or CT or CXR] and [covid-19 or corona] and [deep learning or machine learning] and [automatic detection or automatic classification]
Springer Link	'Chest-Xray or CT and covid-19 or corona and deep learning or machine learning and automatic detection'
ArXiv	"Chest-Xray" or "CT" or "CXR" and "covid-19" or "corona" and "deep learning" or "machine learning" and "automatic detection" or "automatic classification"
ACM digital library	"covid-19"and "automatic detection" and "deep learning" and "cxr" and "affinity resemblance"
IEEE Explore	"Chest-Xray" or "CT" or "CXR" and "covid-19" or "corona" and "deep learning" or "machine learning" and "automatic detection" or "automatic classification"
PLOS ONE	Chest-Xray or CT and covid-19 or corona and deep learning or machine learning and automatic detection'
MDPI Health	"Chest-Xray" or "CT" or "CXR" and "covid-19" or "corona" and "deep learning" or "machine learning" and "automatic detection" or "automatic classification"
PubMed	("Chest-Xray*" or "CT*" or "CXR*") and ("covid-19*" or "corona*") and ("deep learning" or "machine learning") and ("automatic detection*" or "automatic classification*") using ("synthetic enrichment") or ("affinity resemblance")

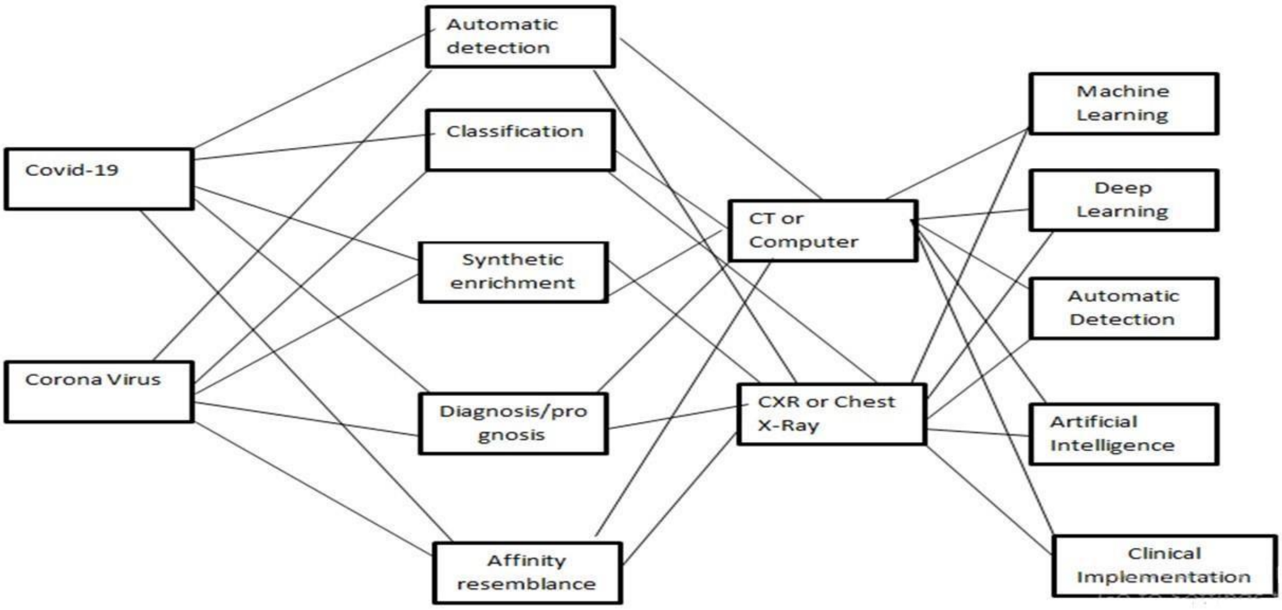


Figure 3: Search String

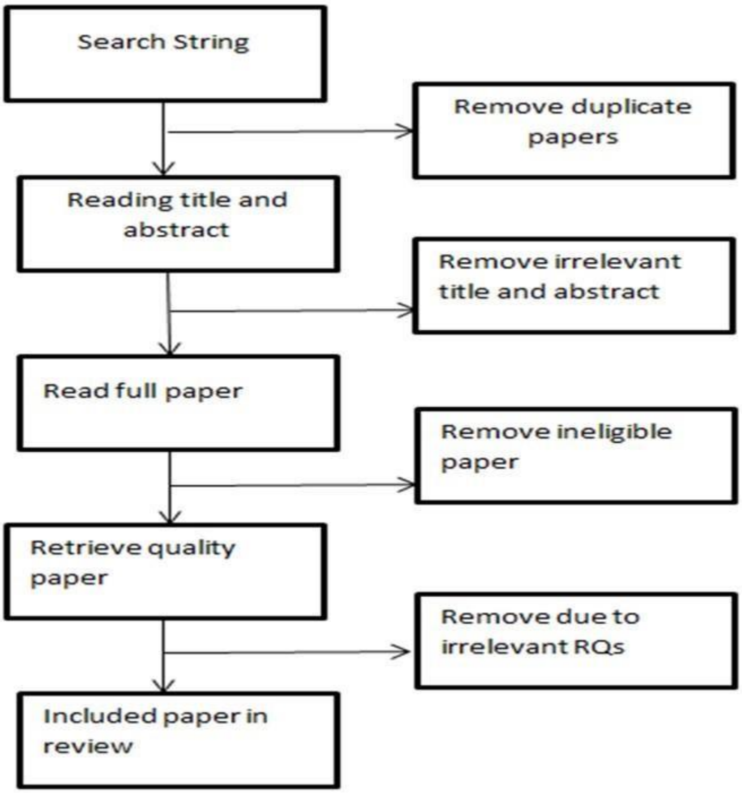
- Springer Link(https:// link.springer.com)

- Google Scholar(https://scholar.google.com)
- ArXiv(https:// arxiv.org)
- ACM digital library(https:// dl.acm.org)
- IEEE Explore(https:// ieeexplore.ieee.org)
- PLOS ONE(https:// journals.plos.org)
- MDPI Health(https:// www.mdpi.com)
- PubMed(https:// pubmed.ncbi.nlm.nih.gov)

At the start, a manual search is carried out to acquire the literature relevant to the identification and prognosis of COVID-19 biomedical imaging. The search queries mentioned in Table 3 cannot exclude irrelevant papers. Therefore, in the next step, we applied the inclusion and exclusion criteria, defined below, for the selection of relevant papers.

3.2.2 Filtering for Paper Selection: Inclusion and Exclusion Process

In the second stage, the inclusion and exclusion process is applied under the defined criteria for filtering searched papers concerning relevancy. The criteria are defined according to the guidelines given in [15]. The process is depicted in Fig. 3.2.2.



The inclusion of the returned papers is done under the following criteria.

- Select papers related to COVID-19 image detection/prognosis.
- Only those papers included which are research question specific.
- Papers published in journals and high-quality conferences are only included in the review.

- Papers on CRX or CT image dataset are included in the selected paper set.
- Papers related to COVID-19 image dataset properties are included.

Exclusion of the retrieved papers is done under the following rules.

- Remove any duplicated paper.
- Remove irrelevant titles and abstracts.
- Remove the ineligible paper.
- Remove papers with irrelevant Research Questions.

Table 4: Results for Selection and Filtering Phases

Phase	Selection	Selection Criteria	Google Scholar	Springer Link	ArXiv digital	ACM	IEEE Explore	PLOS ONE	MDPI Health	Pub Med	Total
1	Search	Keywords	499	3056	48	29347	12	101	239	4251	37553
2	Filtering	Title	127	32	9	187	7	29	10	131	532
3	Filtering	Abstract	21	15	5	21	5	8	8	20	103
4	Filtering	Introduction, Conclusion	11	11	4	13	3	6	5	14	67
5	Filtering	Full Article	8	8	3	9	1	4	3	8	44

3.2.3 Data Extraction Methodology: Snowballing

In the third stage, snowballing is used to extract more key papers relevant to our RQs. After conducting a quality evaluation approach, we applied snowballing for the extraction of more literature relevant to this work. However, only those papers included which passed the inclusion and exclusion criteria defined in the above section. After reading the abstract and title, inclusion and exclusion criteria are applied. As an outcome, we choose 44 primary studies in total, which are enlisted in Table 4, depicting the result of each filtering phase.

3.3 Analysis: Synthesising results for Quality Assessment

For quality assessment, we applied the under-given points scoring system. A study has awarded Two (2), One (1), or zero (0) marks for the four cases as given below.

[label=()]Based on the availability of dataset details like geographic area, size, image type, and dimension.

1. • Two (2) marks; if dataset parameters are available.
   - one (1) marks; if dataset parameters are partially declared or just size is defined
   - zero (0)marks; if a dataset is not defined.
2. Based on evaluation metric defined.
   - If the evaluation metric is defined clearly, assign two (2) marks.
   - If partially defined or missed some parameter, assign one(1) mark.
   - Assign zero(0) marks if the evaluation metric is not defined.
3. If a step-by-step technique solution is discovered, assign (1), otherwise (0)
4. If the paper is published in a journal, it is assigned two (2), if in the conference of AI assign one (1), otherwise assign zero (0) marks.

3.4 Review Report

Table 4 lists all research repositories for finding papers that used deep learning and machine learning techniques to detect and prognosis covid-19 CXR and CT imaging. To find relevant documents, 8 digital repositories have been chosen. The search query returned a large number of results. We filtered the articles based on relevancy in the title, abstract, introduction, and conclusion. Finally, we choose only 44 articles that earn a high score in the quality assessment.

4 Results

This section presents the assessment of each research question defined as the motivation and objective for this research.

Assessment of RQ1: "What are the Covid-19 biomedical image publication channels? Which channel types and geographic locations are targeted by Covid-19's biomedical images?"

The analysis considers biomedical image datasets, models, detection, prognosis, and other problem areas for researchers to solve upcoming challenges. For this purpose, high-quality articles' venues are searched. A scientometric analysis was applied based on meta-information in the domain of Covid-19 X-Ray/CT images. In this regard, the publication sources, years, research types, methodology, and channels of publication of selected studies were considered.

The studies selected after the analysis phase are given in Table 5. The resultant publication sources are the world's largest professional societies. More than 40 scholarly publications are selected belonging to the computing and medicine discipline. A maximum number of publications are searched for the year 2020, which presents a better working of detection and prognosis of this research. Table 5 also presents the overall classification results and Quality Assessment of the selected publications. For assessment of these publications, we consider five features (solution proposal, model, datasets, published in a journal or conference, experimentally validated statistical results or not, and performing surveys or not), and awarded scores to each one. When analyzing Covid-19 images, useful information was found through the Quality Assurance (QA) based ranking of Articles. The articles published in the Q1 category received the highest score, while those published in the low category of journals received a lower score. We have included articles with lower scores as it is likely that they may contain useful information. If those articles were ignored, the relevant studies may be missed, which might risk the SLR's quality requirements, so we have incorporated them. Ultimately, those articles got a minimum score out of the 44 studies.

Fig. 4 is showing that the maximum number of articles are selected from the journal and the minimum number of articles are selected from conferences. Workshop articles and reports are excluded from selection. The geographical division of selected articles is shown in Fig. 5. It shows that the maximum of publications are selected from Asia because the 1st Covid-19 has been detected in an Asian country, China. Furthermore, while we only included technically completed SLRs in our selection, Table 5 also presents the approaches used by the chosen studies that are not SLRs.

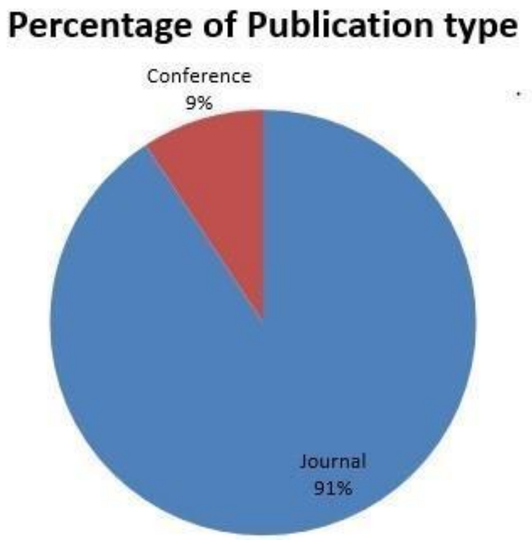


Figure 4: Percentage of Publication Count out of Journal and Conference Type Publications

Table 5: Classification of Articles

Ref.	Classification					Quality Assessment				
	P.Channel	P.Year	Research type	Empirical	Method	a	b	c	d	score
[1]	Journal	2019	Corona virus	No	Review	1	0	1	2	4
[2]	Journal	2020	Types virus	yes	types	2	0	0	2	4
[3]	Journal	2020	symptoms	yes	Review	2	1	0	2	5
[4]	Journal	2021	Features	Yes	Formal	1	1	1	2	5
[5]	Journal	2020	diagnosing	yes	Formal	2	2	1	2	7
[6]	Journal	2021	diagnosing	yes	Formal	1	2	1	2	6
[7]	Journal	2020	diagnosing	yes	Formal	1	2	2	2	7
[8]	Journal	2021	diagnosing	yes	Formal	2	2	2	2	8
[9]	Journal	2021	diagnosing	yes	Formal	2	1	1	1	5
[10]	Journal	2020	diagnosing	yes	Formal	1	1	1	2	5
[11]	Journal	2021	diagnosing	yes	Formal	1	1	1	2	5
[12]	Journal	2021	diagnosing	yes	Formal	1	2	1	2	6
[13]	Journal	2013	diagnosing	yes	Review	2	1	1	1	5
[14]	Journal	2020	SLR	NO	Review	1	1	1	2	5
[15]	Journal	2020	SLR	Yes	Formal	2	2	2	2	8
[16]	Journal	2021	SLR	Yes	Formal	2	1	1	2	6
[17]	Journal	2020	SLR	NO	Formal	1	2	1	2	6
[18]	Journal	2020	SLR	NO	Formal	1	2	1	2	6
[19]	Journal	2020	SLR	NO	Formal	1	1	1	2	5
[20]	Journal	2020	SLR	NO	Formal	2	2	2	2	8
[21]	Journal	2020	SLR	NO	Formal	2	1	1	2	6
[22]	Journal	2021	SLR	NO	Formal	1	2	1	2	6
[23]	Journal	2021	SLR	NO	Formal	1	2	1	2	6
[24]	Journal	2019	diagnosing	NO	Formal	1	1	1	2	5
[25]	Journal	2020	diagnosing	Yes	Formal	2	2	2	2	8
[26]	Journal	2020	SLR	NO	Formal	2	1	1	2	6
[27]	Journal	2021	Prognosis	Yes	Formal	2	2	2	2	8
[28]	Journal	2021	Diagnosis	Yes	Formal	1	2	1	2	6

[29]	Journal	2020	Detection	Yes	Formal	2	2	2	2	8
[30]	conference	2020	Detection	Yes	Formal	2	2	2	2	8
[31]	Journal	2020	Detection	Yes	Formal	2	2	2	2	8
[32]	Journal	2021	Detection	Yes	Formal	1	2	1	2	6
[33]	Journal	2020	Detection	Yes	Formal	2	2	2	2	8
[34]	Journal	2020	Detection	Yes	Formal	2	1	1	1	5
[35]	Journal	2021	Detection	Yes	Formal	2	2	2	2	8
[36]	Journal	2020	Detection	Yes	Formal	1	2	1	2	6
[37]	Journal	2021	Detection	Yes	Formal	2	2	2	2	8
[38]	Journal	2021	Detection	Yes	Formal	2	1	1	1	5
[39]	Journal	2021	Diagnosis	Yes	Formal	2	2	2	2	8
[40]	Journal	2020	Detection	Yes	Formal	1	2	1	2	6
[41]	Journal	2021	Detection	Yes	Formal	2	2	2	2	8
[41]	Journal	2021	Detection	Yes	Formal	2	1	1	1	5
[42]	Journal	2021	Detection	Yes	Formal	2	2	2	2	8
[43]	Journal	2021	Detection	Yes	Formal	2	2	2	2	8
[44]	Journal	2021	Detection	Yes	Formal	2	2	2	2	8

Assessment of RQ2: "Which methodologies are applied by researchers for diagnosing, prognosis, and detection of COVID-19?"

Machine learning and deep learning are two approaches used for the detection of COVID-19, but deep learning performs better than machine learning algorithms in automatic detection. In DL, we do not need to change the values because the model itself learns from the data, forwards the outcome from the previous layer to the next layer, and extracts the features themselves from the image. In a hybrid approach, the deep learning model is used to extract the features and then a machine learning model is used to classify the image into a category. Withthe increase of the data, the accuracy of this approach increases. These results are extracted from the data given in Table 6. It is deduced that if we implement Deep Learning Techniques, it promises results compared to machine learning algorithms.

Table 6: Classification of Articles

Ref.	Deep Learning	Result (Accuracy)
[27]	LSTM-CNN	98.3%
[28]	ResNet-50, VGG-16, VGG-19	8.3%, 89.8%, 94.9%
[29]	VGG-16, ResNet-50, EffieciNetB0	93%, 96.23%, 96.80%
[30]	SVM+ Sobel Filter	99.06%
[31]	ResNet34	99.99%
[33]	CoroNet	89.6%
[34]	Ensemble(ResNet50+DF Computation)	91.6%

[35]	NasNetMobile	82.90%(CT) 93.94%(X-ray)
[37]	GSA-DensNet121	98.38
[38]	ResNet101	97.77%
[45]	MetaCOVID	95.6%
[42]	DL model+SVM	94.7%
[43]	DL+ML	99.65%
[44]	Reinforcement (CoDe)	99.8%

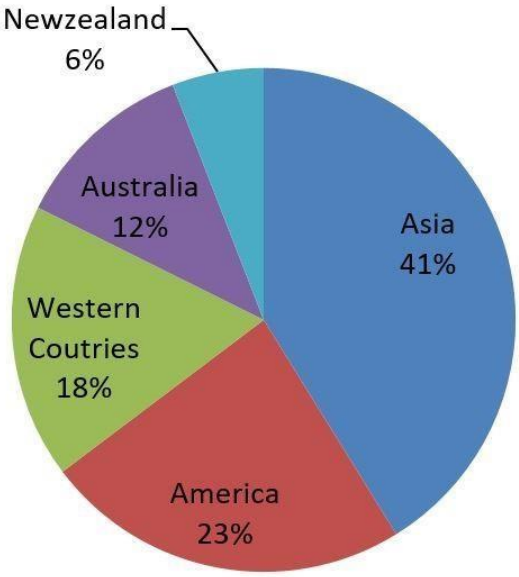


Figure 5: Geographic area Percentage

Assessment of RQ3: "What are the dataset repositories for X-ray and CT images? What is the effect of model implementation on data public and private datasets?"

The study deduces that the layers of the CNN model are related to the number of images in the data. Thus keeping in view the models and results given in Table 6, we can optimize our results according to the size of the data used and the number of layers of the model implemented on it. According to the survey, if we apply the method mentioned in the papers, we can make new datasets for implementation. Table 7 shows that [27,28,43,44] used an integrated dataset to reduce the overfitting problem by increasing the dataset. Whereas [28],[35], and [43] article's dataset comprises a private dataset according to the case studies they discussed. In [29],[31], the authors collected datasets from public repositories and combined them with privately collected data.

Assessment of RQ4: "How to reduce the training time and complexity of Model for getting high accuracy?" The approach presented in [44] optimizes the model's efficacy and is found to be of significant value due to its simple design. It reduces the model complexity and improves the efficacy of the model compared to the available deep learning model.

Table 7: Dataset and Types of data

Ref.	Size of Dataset	Public / Private	Type of Image
[27]	4575	Public (integrated from the different repository)	X-Ray
[28]	402(dataset1), 954(dataset2)	Public (integrated from different repository)	X-Ray
[29]	2686	Publically	X-Ray
[30]	333	Private database	X-Ray
[31]	16756	Private + Public combined	X-Ray
[33]	1251	Private + Public combined	X-Ray
[34]	1441	Publically	X-Ray
[35]	400, 400	Publically	X-Ray,CT
[37]	121	Private	CT+X-Ray
[38]	1832	Public	X-Ray
[45]	16000	Publically	X-Ray
[42]	380	Private	X-Ray
[43]	3100	(integrated from the different repository)	X-Ray
[44]	1000	(integrated from the different repository)	X-Ray Images

Many of the existing systems, according to this study, utilized the COVID-19 X-ray image and two of them used CT images [34,36]. All proposed solutions utilized benchmark available data for experiment purposes; however, real-time data was not used by any developer. There are only 22 instances of Covid-19 in the dataset [36]. Although several frameworks utilized large image datasets, the datasets had a small number of covid-19 cases in comparison to their size. The approach proposed by EfficientB0 achieves the best results on the smallest dataset [28] when correlating the data set and the small number of layers. The performance study revealed that the strategy proposed in [44] worked effectively, reducing training time and model complexity while achieving good accuracy. X-raybased systems outperformed CT-based systems when they pertained to detecting Covid-19. Finally, it is difficult to determine the precise information of the utilized datasets because the information of the datasets is getting modified regularly as the volume of COVID-19 images grows.

5 CHALLENGES, DISCUSSION, AND FUTURE TREND

The goal of this research was to find modern approaches for automatically detecting COVID-19 from X-ray and CT images. The results of the systematic literature review are summarised and discussed in this section. The critical analysis was performed on the selected articles and constructed a taxonomy as shown in Fig. 6 using the coding scheme as mentioned in Table 6, with eliminated those studies (SLRs) that have not experimentally proven their techniques. We explored improvements and problems in areas including detection, diagnosis, and prognosis. Moreover, these features are further subdivided into several sub-levels, demonstrating the depth of each feature and its importance in improving Covid-19 identification from X-ray/CT images.

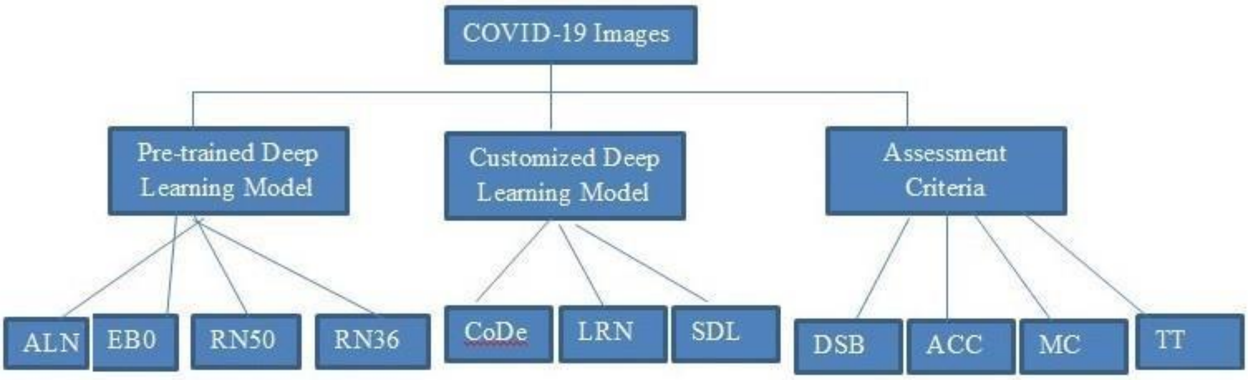


Figure 6: Taxonomy of AI Techniques Applied on X-ray and CT images.

5.1 Open Discussion

In this research, 44 research works were examined for IoMT training and testing. The 29 works are using pretrained models like deep learning and customized deep learning architecture. The remaining 15 were focused on machine learning models.

The findings of each system are provided for clarity. For data samples, two typical testing methods are used: CT and X-ray. Most of the systems focused on a single source of data, while a few others focused on numerous sources. We summarised the created systems based on characteristics such as training time, dataset size, the correlation between data size and the number of layers, publicly accessible code, publicly available data, deep learning/machine learning approach for detection and prognosis, and performance metrics. A few of the methods utilized a large number of images, whereas the COVID-19 instances have a limited number of samples as shown in Table 6. For diagnosis, the data were separated into X-ray and CT images. The use of machine learning, deep learning, and hybrid models is considered and most systems applied these models or variants of them for diagnosis. Throughout the review, the typical assessment measures found are accuracy, precision; AUC, F1score, and ROC-AUC. Table 6 and Table 7 summarises the results of the X-ray and CT image datasets based on COVID-19 detection and diagnostic using machine learning, deep learning, and hybrid approach respectively. The results show that [37,41] utilized real-world data collected from different hospitals. The public data set used IEEE8023 chest datatset[38] ,Kaggle repository “Chest X-Ray Images (Pneu-monia)” and open source Github repository by Joseph [33],IEEE8023 chest datatset and Kaggle repository “Chest X-Ray Images (Pneu-monia)” [34], open source Github repository by Joseph [37],Chest X-ray Images (Pneumonia)” [38] and others used 4575 images [27],4000 images by Hall, L. O., Paul, R., Goldgof, D. B., Goldgof, G. M. [30],GitHub repository, hospital-oriented datasets, and Kaggle repository [41],Wang X, Peng Y, Lu L, Lu Z, Bagheri M, Summers RM. ChestX-Ray8 [42] combined the data from both private and public sources. The reviewed study systems have used images with a minimum and maximum size of 121 [36] and 16000 [38], respectively, for evaluation. Most of the systems were developed to be classified into normal and Covid-19, but some of them [24,34,36], are classified into pneumonia, normal, and covid19. While evaluating the performance of the developed system used LSTM [27], ResNet50, VGG-16 and VGG-19 [28],VGG16, ResNet50, and EfficientNetB0 backbones [29],fusion of CNN,SVM and Sober filter [30],Xception with SVM [34],InceptionV3 [36],GSA-DenseNet121 [37],pre-trained models[38],ResNet18 [41], ResNet50 model and SVM classifier [42], COVID-in-Depth CoDe [44] attained high accuracy, F1 score, precision, and AUC having these results of more than 91%. Moreover, ResNet34 and CoDe attain the highest accuracy of 99.99% and 99.80%, respectively.

5.2 Future Trends

The use of deep learning techniques and algorithms to detect new coronaviruses (COVID-19) presents several distinct obstacles. Despite the encouraging findings of modern techniques-based detection of COVID-19 from X-ray and CT images, wider adoption is still limited, and the following problem needs to be addressed.

- How could a proper assessment protocol be designed to avoid inaccurate results when many datasets with large discrepancies are combined?

- How can lung segmentation improve the detection of covid-19?
- How does an explanatory model may help in screening Covid-19 for the clinical physician?
- How can the data-centric approach help in creating a large dataset?
- How do you interpret a black-box prediction in COVID-19 images?

The lack of standard data is a major challenge for diagnosis because COVID-19 is so new to research and imaging data for COVID-19 patients is inadequate, noisy, confusing, and in some cases incorrectly labelled. The designed systems received data from various sources on the web, processed it in their own method, and then assessed their systems using evaluation metrics. As a result, it is difficult to say definitively which method generates the maximum COVID-19 detection results. Clinical data is currently limited and highly regulated because of the COVID-19 pandemic's relative newness. As a result, datasets relevant to them are rare. In the training phase, a small dataset leads to a decreased approximation, and in the testing phase, an optimist as well as large variable predictions of the efficiency of deep learning-based COVID-19 diagnostic systems. Depending on the nature of the deep learning architecture, a small dataset produces an underfit or overfit problem, which impairs the performance of the developed system. Another major difficulty with deep learning-based COVID-19 diagnosing systems is class inequality. COVID-19 has substantially fewer images in chest X-rays and CT scans than other prominent lung illnesses. During the training phase of deep learning algorithms, data imbalances frequently cause bias. The target sample has grown increasingly difficult to balance as the percentage of positive samples has decreased. While both problems may be observed in developed systems, the problem with insufficient datasets is more serious than the issue of class imbalance.

While accuracy is a useful criterion for assessing the performance of deep learning models, it should not be the only one utilized. For deep learning-based COVID-19 diagnostic systems, the lack of a confidence interval is particularly problematic. Using flipping, rotation, cropping, random noise addition, and other techniques from the provided pictures, the data augmentation approach [18] produces new diseases from the given COVID-19 samples. However, in the event of supplemented data, the overfitting problem may develop. Furthermore, because manually classifying COVID-19 imaging data is an expensive and time-consuming task, self-supervised deep learning algorithms are highly suggested. More datasets comprising Sputum Smear Microscopy Images and Histopathology Images of COVID-19 and other lung illnesses might be created in the future.

6 Conclusions

COVID-19 is still a pandemic, with new records being set every day in terms of worldwide infection counts and death tolls. This paper presents the latest COVID-19 diagnostic work based on deep learning approaches applied to two types of imaging modalities: CT and X-ray samples. This document also specifies all of the utilized dataset's sources, making them clearly understandable and accessible to the academic community for the deployment of intelligent IoMTs. The greatest accuracy of the model produces 98% by balancing the datasets. COVID-19 in-depth (CoDe) is a customized model used to decrease the training and time and the model complexity for achieving high accuracy. Furthermore, alternative ways to solve the present problems are suggested to inspire and encourage researchers interested in contributing to this field. It is envisioned that deep learning specialists would collaborate proactively with radiologists and medical professionals soon to develop appropriate support systems for detecting COVID-19 infections, particularly in the early stages of the disease, or determining the severity of the infection.

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