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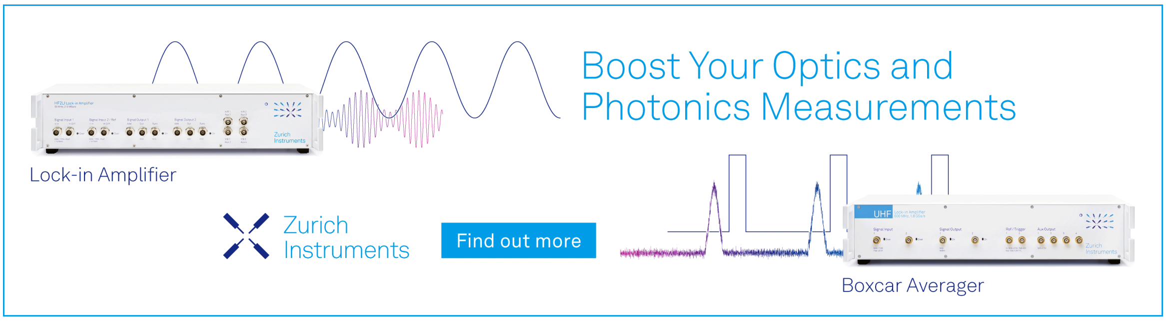

A Comprehensive Survey on Covid-19 Disease Diagnosis: Datasets, Deep Learning Approaches and Challenges

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Abstract. Millions of people were affected by the global health disaster brought on by the coronavirus (Covid-19) pandemic in December 2019, severely impacting the international economy. Deep learning (DL) methods successfully analyzed and detected infectious areas in radiological images. This research analyses the Covid-19 open-source datasets and Deep Learning methodologies and develops a categorization based on diagnostic approaches and learning methodologies at most using X-ray and CT imaging. Coronavirus diagnosis at image and region level analysis is systematically divided into classification, segmentation, and multi-stage procedures. Furthermore, a discussion of the significant obstacles and potential future research directions is included.

INTRODUCTION

Covid-19 is a highly infectious disease caused by the new coronavirus SARS-COV-2. It began in Wuhan, China, in December 2019 and has since spread worldwide. Droplets and aerosols generated during the speech, coughing, and sneezing from the mouth, nose, and throat are the principal methods of virus transmission. Another method of infection transmission is close contact with an infected person. Mild to severe Covid-19 symptoms include fever, coughing, shortness of breath, loss of taste or smell, and tiredness. Some people may be asymptomatic or have mild symptoms, but they can still spread the virus to others.

For this reason, testing is crucial in identifying and isolating infected individuals to prevent further transmission. RT-PCR is the most confirmatory test for diagnosing Coronavirus (real-time reverse transcriptase-polymerase chain reaction). RT-PCR detects the presence of the virus's genetic material in a sample taken from the patient's nose or throat (1). However, RT-PCR has a significant false-negative rate, which means it may miss the virus in some infected people. Additionally, RT-PCR can be costly, time-consuming, and not widely available in some regions, particularly developing countries. Medical imaging like Computer Tomography (CT scan) and X-ray images can be used as an alternative to detect COVID-19. CT scans can show characteristic lung changes indicative of the virus, such as ground-glass opacities. X-ray images can also show lung changes but are less sensitive than CT scans. Radiographic images, such as X-rays and CT scans, are widely available in low-income countries and commonly diagnose lung diseases, including COVID-19. However, it requires specific training to interpret the images and identify the changes indicative of the virus, and solving these images requires expertise and can be time-consuming. One disadvantage is that a specialized physician is needed to distinguish the infected area in the lung, which can be a limiting factor in areas with a shortage of radiologists or high demand for Covid-19 testing (2). Integrating Artificial intelligence / deep learning (AI/DL) techniques can help automate and speed up the process, allowing doctors to more quickly and accurately identify infected regions in the lung. As a result, AI/DL can offer assistance alongside conventional techniques using radiological images. By combining AI and DL approaches, clinicians can analyze X-rays and CT scans more rapidly and effectively. It is important to note that while AI/DL can be an excellent tool for detecting Covid-19, it should not replace traditional diagnostic methods. The performance of AI/DL models should be validated with clinical data and must be used in conjunction with other diagnostic tools, such as laboratory tests and clinical assessments. Also, a qualified radiologist or healthcare professional should always interpret the results from AI/DL models (3). The AI community made significant contributions in this area that could be used to diagnose, predict, and treat Covid-19. Deep learning (DL) algorithms use the data to train and modify models that address particular problems. This paper's significant contribution is a review of the current state of deep learning-based diagnostic tools for Coronavirus. The following views are covered in the article:

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- Collecting details about Covid-19 datasets that are public (textual data and medical images)
- Summarizing various DL methodologies, including customized CNN frameworks for Coronavirus diagnosis, Prediction, and treatment that utilize radiographic images like X-rays and CT scans.
- Exploring the challenges of the existing literature on Deep Learning approaches within the COVID-19 area and suggesting ways to resolve these drawbacks in the future.

COVID-19 DATASETS

One of the main issues in Covid-19 research is the scarcity of accurate and sufficient data. Since data is a crucial element of Deep Learning techniques, the quality of data representation significantly impacts how well these models perform. As a result, the availability of large amounts of data with balanced representation offers opportunities to develop high-performing detection and prediction model (4). We categorize the Covid-19 datasets into two primary groups: the medical image and the textual datasets.

Covid-19 Medical Image Datasets

Medical imaging (Radiology) uses techniques to visualize inside body structures for therapeutic and diagnostic purposes. These allow healthcare providers to identify and treat conditions (4). The modalities that fall under the medical imaging category include CT scans, X-rays, and ultrasounds. A comparison of these modalities can be found in **Table 1**. This information can assist in selecting the appropriate imaging technique for a patient's specific condition.

TABLE 1. A comparison of medical imaging modalities(5)

Modalities	Radiation exposure	Processing cost	Image processing time	Appropriate organ for scanning
CT scan	exposure to less harmless radiation restriction for children and pregnant woman	its prices are 10 times higher than X-ray	usually completed within 5 minutes	lung and chest imaging and others
X-rays	exposure to dangerous ionizing radiation	x-ray is relatively cheaper	a few seconds	primarily used to examine broken bones
ultrasound	higher frequency sound waves are used for imaging	price higher than an X-ray and lower than ct scan	usually takes about 5-10 minutes	used for internal organs of the body

Medical image datasets are commonly used in the screening and diagnosis of Covid-19. These data sets can be classified based on the type of medical imaging modality used. Table 2 summarises publicly available data sets of CT, X-ray, and ultrasound images of healthy individuals, individuals with Covid-19, and other types of Pneumonia. These datasets can be utilized to train deep-learning algorithms for accurate disease identification in future patients.

TABLE 2. Summary of publicly available Covid-19 medical image datasets

Ref	Modality	Dataset name	Metadata	Lung masks	Infection masks
(6)	CT scan	Covid-19 and common pneumonia CT dataset	-	-	-
(7)	CT scan	Large Covid-19 CT scan slice dataset	□	-	-
(8)	CT scan	Covid CTset	□	-	-
(9)	CT scan	Mosmeddata	□	-	□
(10)	CT scan	Medseg	-	□	□
(11)	CT scan	Segmentation of covid 19 CT scan images	-	□	-
(12)	CT scan	Funding & measuring lungs	-	□	-
(13)	CT scan	COVID-CT	□	-	-
(14)	CT scan	COVID CT MD	□	-	-
(15)	CT scan	CC-CCII	□	-	-
(16)	CT scan	Sarscov2-CT scan-dataset	-	-	-
(17)	CT scan & X ray	SIRM dataset	□	□	□
(18)	CT scan & X-ray	-	□	-	-
(19)	CT scan	Per-COVID-19 dataset	□	-	-
(20)	Ultrasound	POCUS data set	-	-	-
(21)	Ultrasound	DL4covid (ICLUS-DB)	-	-	-
(22)	Ultrasound	Covid-19_ ultrasound	□	-	-
(23)	X-ray	COVID-19 Radiography Database	□	-	-
(24)	X ray	CheXpert	-	-	-

TABLE 2. Summary of publicly available Covid-19 medical image datasets

Ref	Modality	Dataset name	Metadata	Lung masks	Infection masks
(25)	X ray	COVID-Net –Dataset	□	□	-
(26)	X ray	COVID19-vs-normal dataset	-	-	-
(27)	X ray	QaTa-Cov19 dataset	-	-	□
(28)	X ray	COVID-QU Dataset	-	□	-
(29)	X ray	COVID-QU-Ex	-	□	□
(30)	X ray	Actualmed- COVID chest X ray dataset	□	-	-
(31)	X ray	Augmented COVID 19 X ray images	-	-	-
(32)	X ray	Curated Dataset for COVID19 Posterior Anterior Chest Radiography	□	□	-
(33)	X ray	RADIOGRAPHY	□	-	-
(34)	X ray	ChestXray	□	-	-
(35)	X ray	Covid19 chest x-ray	-	-	-
(36)	X-ray	Covid19 x-rays	□	□	□
(37)	X ray	Chest-XRay-pneumonia	□	□	□
(38)	X ray	Covid chestxray dataset	□	□	□

Covid-19 Textual DataSets

Since the outbreak of the COVID-19 pestilence, there has been a significant increase in the development and use of textual data sets for various purposes. These datasets have been utilized for multiple objectives, including predicting and displaying the spread of the coronavirus epidemic according to reported cases, analyzing the public's views, sentiments, and opinions by tracking social media posts, and researching mobility's impact on viral transmissions. Constructing these datasets was essential for comprehending and responding to the pandemic. They continue to be used to follow the transmission of the virus and understand its societal impact. **Table 3** displays publicly accessible textual ground truth data for analyzing human emotions and concerns regarding Covid-19.

TABLE 3. Lists Covid-19 textual datasets

Type	Ref	Modality	Details
Report	(39)	Textual	Include 29 columns about patients
	(40)	Textual	The textual dataset collected from 13202 paper
	(41)	CSV	Google Mobility
	(42)	Textual	In South Korea, 62 people's health reports and symptoms were collected.
	(43)	Textual	Patient symptoms
	(44)	Textual	Patient symptoms
	(45)	Textual	cases for patients with covid-19
social media	(46)	Instagram posts	Covid-19 instaPostIDs
	(47)	Tweet	Corona worry
	(48)	Tweet	Covid twitter
	(49)	Tweet	Corona Tweet Ids
	(50)	Tweet	Corona Arabic Tweets
	(51)	Tweet	Tweets from institutions and news outlets related to the COVID-19 social science research project
	(52)	Tweet	COVID 19 symptoms identification
	(53)	Tweet	Covid Tweets dataset
	(54)	Tweet	Coronavirus tweets
	(55)	Tweet	Coronavirus Multilanguage Tweets Dataset
	(56)	Tweet	Coronavirus Twitter dataset
Mobility	(57)	Dashboard and CSV	Coronavirus Mobility Trends Reports Apple
	(58)	Dashboard	Covid-19 GeoDSLab@UW-Madison
	(59)	Dashboard and CSV	Covid19 Community Mobility
	(60)	Dashboard	National migration details
	(61)	Dashboard	COVID Reports | IDMOD

COVID 19 DIAGNOSIS USING ARTIFICIAL INTELLIGENCE

The analysis and forecasting of the Coronavirus can be improved with the help of artificial intelligence. At the moment, several researchers and the studies that they have conducted demonstrate that Artificial Intelligence (AI) has been widely utilized for Coronavirus problems employing ML (Machine Learning) and DL (Deep Learning) (62). Artificial intelligence (AI) encompasses a wide range of subfields, two of the most important of which are machine learning (ML) and deep learning (DL). Both of these subfields have been extensively utilized in the search for Covid-19-positive cases. In most cases, DL approaches are used to learn hierarchical features from the underlying data. As a result of the hierarchal feature learning concept, the DL approaches can efficiently handle complicated patterns. Radiological imaging has revealed that an infection caused by the Coronavirus manifests in several ways, including GGO, pleural effusion, consolidation, and bilateral lung involvement. Discovering these patterns that are unique to Covid-19 can be done by utilizing several different architectures for deep learning. Because the Deep Learning models could diagnose diseases with better sensitivity and specificity, it is generally agreed that they have higher accuracy. It also has the potential to minimize the percentage of false negatives and positives, providing medical professionals and radiologists with an efficient, inexpensive, and trustworthy diagnostic option. Deep learning can be developed and trained from scratch to learn features, or it can leverage a previously known model to save time and adapt it for Corona analysis-related tasks. Either way, deep learning can learn features. (63). **Figure (1)** provides a summary of a comprehensive system for the detection and analysis of the Coronavirus epidemic

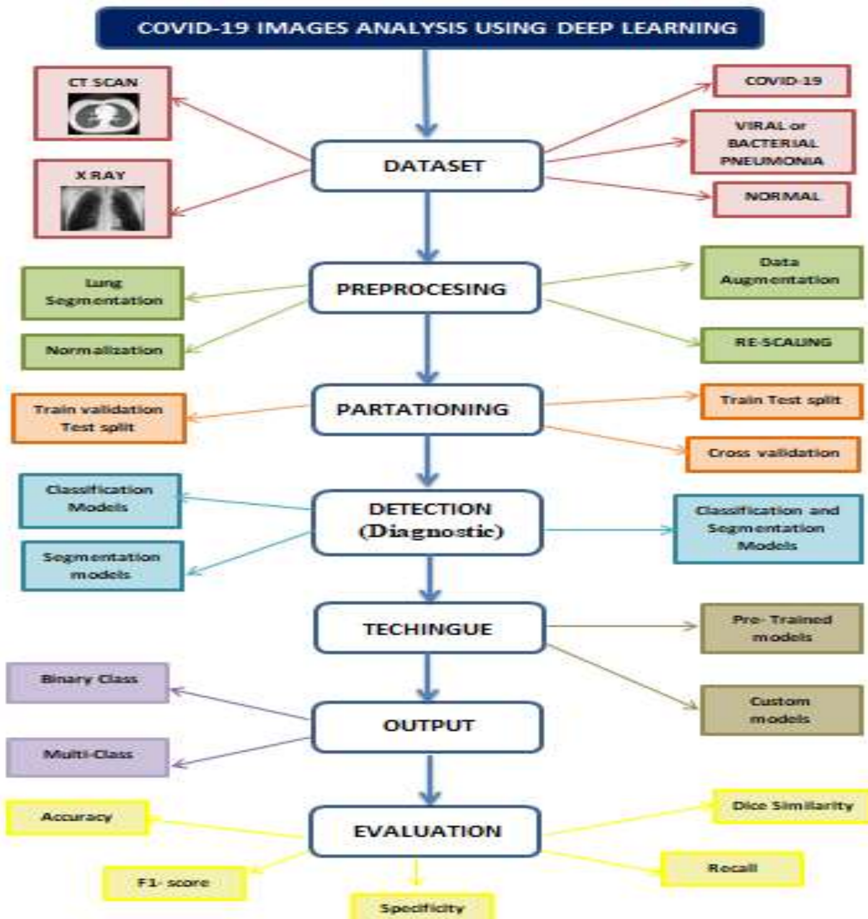

FIGURE 1. Summary of the workflow for Covid-19 medical images analysis using DL

COVID-19 Diagnostic Strategies

Techniques based on deep learning help assess and isolate infectious areas in radiology images, and these techniques have relied on two distinct levels for diagnosing the presence of Covid-19 contagion:

Image Level Diagnosis of Covid-19 images

Image level prediction is achieved with this approach by labelling an individual with the whole radiological image of Covid-19. To stop the pandemic, these approaches can be employed for the preliminary screening of people who suspect they have Coronavirus, for detection and diagnosis, and for isolating people who have Covid-19 from healthy individuals. Deep Learning models for classification have been used in medical image-based analytic techniques for disease diagnosis (64). A diagnosis that is performed on an image may assign a binary class (which differentiates images that are infected with Covid-19 from those that are healthy) or many classes (which determine images that are infected with Coronavirus from those that are healthy, viral Pneumonia, and bacterial Pneumonia).

Region-Level Diagnosis of Covid-19 images

Instead of labelling entire images, region-level diagnosis creates illness predictions by dividing the radiological image into specific patches or portions. Each pixel in the photo is classified as Covid-19 or other to help identify the area of interest. It can provide a thorough understanding of the patterns that the Coronavirus generated and how it spread; the region-level diagnosis involves Deep learning-based instance and semantic segmentation approaches. (64)

Categorical of DL Techniques for Covid-19 Diagnosis

Radiologists must be trained to look at Covid-19-infected images or areas by hand. However, because the number of coronavirus cases and other lung illnesses is growing daily, getting enough radiologists puts much stress on medical care. So, Deep learning-based schemes have been used to diagnose disease automatically. Deep Learning techniques are divided into three methods for Coronavirus analysis at the image and region levels.

Classification Techniques

Diseases can be diagnosed, managed, and treated more rapidly with classification. Examining X-ray and CT scan imagery requires considerable effort from radiology specialists. Deep Learning techniques can quickly address this problem by automating the screening for coronavirus-infected medical images. These will free up more time for medical professionals to assist more Corona patients in critical condition. Binary and multi-class classification are two primary methods for classifying coronavirus images (65).

Segmentation Techniques for Coronavirus Infection

The segmentation of medical images of individuals infected with Covid-19 assists medical professionals in diagnosing the disease and determining the severity of the condition (categorized as mild, moderate, or severe stages). Regarding segmentation, a CT scan is preferable over an X-ray because it provides a superior image of the three-dimensional areas of the lungs. Manual segmentation, which requires expert radiologists and might take many hours to complete, is required to distinguish diseased anomalies from CT scans reliably. Therefore, it is necessary to create automated methods to differentiate the lesions detected in the CT scans of the lungs of Covid-19 patients. In the wake of the Corona epidemic, several custom-based Convolution Neural Networks and Transfer Learning -based fine-tuned Convolution Neural Networks have been implemented to segregate patients' CT scans. These procedures are utilized to remove the contaminated tissue most of the time. They either use binary segmentation labels, such as "Infected with Covid-19 or healthy case," or multi-class segmentation labels, such as "GGO, consolidation, crazy paving pattern, or linear opacity," or both(66).

Multi-stage Techniques

Using a system that has numerous steps, COVID-19-infected areas are categorized and isolated from one another. In Deep Learning models that use multi-stage approaches, there is no predetermined order for the classification and segmentation processes. The multi-stage framework, conversely, made it much simpler to execute computations and boosted the efficiency of COVID-19 disease lesion recognition and analysis. Multiple research investigations have found that using a multi-stage framework for model diagnosis is superior to using a single-stage framework. The researchers who conducted these experiments classified the data using Covid-19 after completing segmentation (67). Each diagnostic method is built on two different kinds of deep learning architectures. A pre-trained model incorporating deep transfer learning and a custom deep learning framework to identify Corona disease in X-ray and CT imaging modalities (68). Many frameworks, including VGG16, MobileNet, ResNet, and InceptionV3, have been purposefully developed to screen, classify, detect, and identify diseases.

Additionally, with the assistance of CNN, three additional methods—ensemble, fusion, and segmentation—significantly increase the overall classification performance. Table 4 provides an overview of the various Deep Learning architectures utilized in Covid-19, along with a comparison to other architectural styles. Additionally, we investigate multiple deep-learning CNN architectures developed from scratch using The X-Ray and CT scan imagery datasets. The fifth column provides information regarding the model's name (method), which is dependent on deep learning frameworks such as a custom architecture, a standard model, a pre-trained model, and pre-train custom models, as well as their (Accuracy, F1-score, Specificity, Precision, and Recall).

TABLE 4. Summary of the various Deep learning architectures used in Covid-19

			DL		Performance				
Ref-year	**Modularity**	**Purpose (problem)**	**Datasets**	**Model's name(technique)**	**Accuracy (%)**	**F1-score (%)**	**Precision (%)**	**Specificity (%)**	**Recall (%)**
(69)-2021	CT-scan	Screening	Collected from various hospitals	2D CNN	89.50	-	-	88	87
(70)-2021	CT – scan	Diagnosis	Private dataset of 320 CT images	5L-DCNN-SP-C	93.64	93.62	93.96	94.00	-
(71)-2021	X-ray	Diagnosis	Six Public Databases	AlexNet	96.5	-	-	91.7	-
(72) - 2021	CT scan	Diagnosis	A whole novel set of data consisting of 2481 chest CT scans	CO-IRv2 Adam	94.97	95.24	96.90	96.52	93.63
(72) - 2021	CT scan	Diagnosis	A whole novel set of data consisting of 2481 chest CT scans	CO-IRv2 Nadam	96.18	96.28	95.35	95.08	97.23
(72) - 2021	CT – scan	Covid-19 classification	A whole novel set of data consisting of 2481 chest CT scans	CO-IRv2 RMSProp	96.18	96.13	99.16	99.18	93.28
(73)-2021	X-ray	Diagnosis	ChestX-ray8	CO-ResNet	98.99	0.60	0.45	-	0.90
(93)-2021	CT – scan	Covid-19 Detection	SARS-CoV-2CT-scan	VGG-19	95.75	95.75	-	-	97.13
(77)-2021	CT-scan	Diagnosis	A Dataset Comprising Actual Patient Images	DenseNet-121	92	-	-	-	95
(91) - 2021	CT – scan	Covid-19Diagnosis	COVID-CT-Dataset	S.R.G.A.N. +VGG16	98.0			94.9	
(82)-2021	X-ray	Covid-19 Diagnosis	Two dataset Datasets from Kaggle Dataset1 of 3050 and Dataset2 of 1203 chest X-ray sc	mAlexNet + SPEA-II	99.13	-	-	99.15	-
(84)-2021	CT-scan	Detection	ARS-COV-2 CT-Scan & Covid-CT Scan datasets	MobileNet	94.12	96.11	96.11	-	-
(89)-2021	X-ray	Covid-19 identification	Three datasets Dataset1 from GitHub	ResNet101	94.7	68.6	98.9	99.9	52.5

TABLE 4. Summary of the various Deep learning architectures used in Covid-19

DL					Performance				
Ref-year	**Modularity**	**Purpose (problem)**	**Datasets**	**Model's name(technique)**	**Accuracy (%)**	**F1-score (%)**	**Precision (%)**	**Specificity (%)**	**Recall (%)**
(89)-2021	X-ray	Diagnosis	Three datasets Dataset1from GitHub	ResNet152	92.8	60.9	75.7	98.0	51.0
(89)-2021	X-ray	Corona Diagnosis	Three datasets Dataset1from GitHub	ResNet50	99.7	98.5	98.3	99.8	98.8
(85)-2022	X ray	Covid-19 Detection	The data for the specialized database came from three different medical facilities.	Modified Inception	89.5	77	-	87	88
(86)-2022	X-ray	Coronavirus detection	Two public dataset	DCNN	95.2	-	95	-	-
(74)-2022	X-ray	detection	Two separate public datasets	DarkCovidNet, , ResNet18 COVID-Net, , VGG-19	95.20	95.20	95.0	-	-
(75)-2022	CT-scan	Diagnosis for Covid	A Private Dataset of 296 lung window images	DC-Net-RVFL	90.91	90.41	95.70	96.13	-
(83)-2022	CT – scan	Covid-19 Diagnosis	SARS-CoV-2Ct-Scan Dataset	mAlexNet + TSA-ANN	98.54	98.41	99.09	99.23	-
(87)-2022	X-ray	Covid-19 x-ray Image Recognition	two datasets, a total of 6252 images	multi-scale spatial attention mechanism with CNN	97.96	-	100	100	-
(88)-2022	CT-scan	Diagnosis	Dataset1 of 3530 chest CT slices and Dataset2 of 280 chest CT scans	PAM-DenseNet	94.29	-	93.75	96.77	-
(90)-2022	CT scan	Detection	COVID-CT Dataset	ResNet50+Attention+mixup	95.57	-	-	-	-
(92)-2023	X-ray	Diagnosis for covid-19 classification and Prediction for covid-19	Four public dataset	VGG-19+RNN	97.8	-	-	-	-
(76)-2023	CT scan		Big Dataset of 2482 CT - images of actual patients	DenseNet-121) model (Dense CNN)	93.78	0.942	0.951	0.942	-

TABLE 4. Summary of the various Deep learning architectures used in Covid-19

		DL			Performance				
Ref-year	**Modularity**	**Purpose (problem)**	**Datasets**	**Model's name(technique)**	**Accuracy (%)**	**F1-score (%)**	**Precision (%)**	**Specificity (%)**	**Recall (%)**
(81)-2023	X-ray	COVID 19 classification	Two unbalanced datasets total 5935 photos each, and one balancing dataset with 5002 images.	LDDNet	99.55	85	100	-	73
(81)-2023	CT scan	Covid 19 classification	a dataset of 1043 CT	LDDNet	99.36	99	100	-	98

There is numerous research to segment Corona lung infection radiological images by utilizing various Deep Learning-based Infection Segmentation and a multi-stage framework using classification and segmentation techniques with CT scans and X-Ray images. These techniques are summarised in **Tables 5 and 6**; the performance of these models has been evaluated using standard performance metrics in addition to Dice Similarity (DS)metric.

TABLE 5. Summary of DL-based Infection Segmentation Techniques for Corona Diagnosis Using X-Ray & CT Scans

		DL			Performance		
Ref-year	**Modularity**	**Purpose (problem)**	**Datasets**	**Model's name(technique)**	**Accuracy (%)**	**Dice Similarity (%)**	**Specificity (%)**
(94),2020	CT scan	predict multi-class lesion segmentation the covid-19 patients	548 CT scans were collected from 204 patients at the First Hospital of Changsha who suffered from Covid-19	2D UNet with Resnet-34 backbone	97.5	74.0	90.49
(98),2020	CT scan	detection of viral pneumonitis in CT scan, which trained for binary lesion lung segmentation	The custom dataset collected from Renmin Hospital in China	UNet++ architecture	95.2	-	93.6
(66),2020	CT scan and X-ray	automatically identify infected regions with covid-19 from CT scan images.	Six PUBLIC COVID-19 IMAGING DATASETS	Two Model Inf-Net Semi-Inf-Net	 - -	 57.9 59.7	 97.4 97.7
(38),2020	CT scan	segmentation of coronavirus infections	two public datasets and one local dataset	USTM-Net	-	73.6	0.958
(95),2021	CT scan	semantically segmenting infected tissue areas in CT lung to distinguish infected/non-infected tissues	COVID-19 CT Segmentation Dataset	SegNet and UNet (SegNet shows better results)	95.4	74. 9	95.4

TABLE 5. Summary of DL-based Infection Segmentation Techniques for Corona Diagnosis Using X-Ray & CT Scans

			DL	Performance			
Ref-year	**modularity**	**Purpose (problem)**	**Datasets**	**Model's name(technique)**	**Accuracy (%)**	**Dice Similarity (%)**	**Specificity (%)**
(96),2021	CT-scan	To distinguish between healthy tissues and the pathological site induced by COVID-19.	Using seven datasets, such as LUNA16 Coronacase Radiopaedia NSCLC lung segmentation	NormNet based on 3D UNet	89.5	-	87.9
(97),2021	CT-scan	Covid-19 infection segmentation	The custom dataset collected from 8 hospitals	COVIDENet (ensembling two and 3-dimensional CNNs)	-	70.0	-
(102), 2021	CT-scan	automatically segmenting and quantifying infection areas on CT images.	From the Ethics Committees of the Shanghai Public Health Clinical Center and additional centers beyond Shanghai.	VB-Net	73.4	91.6	-
(99),2021	CT scan	Automatic COVID-19 CT segmentation	The two datasets utilized in the studies were obtained from the Italian Society of Medical & Interventional Radiology: covid-19 CT image segmentation dataset	U-Net Model	-	83.1	-
(100), 2021	CT-scan	segmentation and measurement for Covid-19 lung-infected region	COVID CT dataset with newly collected data from the EL-BAYANE centre for Radiology and Medical Imaging.	automatic tool for segmentation	98	73	99
(104), 2021	CT-scan	Covid-19 contaminated areas are segmented from CT scans.	Covid CT Lung and infection segmentation Dataset	U-net	-	89	-
(101), 2022	CT-scan	the covid-19 segmentation and detection cases	four publicly datasets from different sources	CGAN	99.8	96.77	-
(103), 2022	CT-scan	segment covid-19 lung infections	two publicly datasets	SD-UNET	99.0	86.96	99.32
(105), 2022	CT scan	determine the boundaries of the lung and the covid 19 related symptoms in the lung area.	Corona and Benchmark CT Lung Infection Segmentation datasets are used here.	U-net	95	-	-

TABLE 5. Summary of DL-based Infection Segmentation Techniques for Corona Diagnosis Using X-Ray & CT Scans

DL				Performance			
Ref-year	**modularity**	**Purpose (problem)**	**Datasets**	**Model's name(technique)**	**Accuracy (%)**	**Dice Similarity (%)**	**Specificity (%)**
(106) ,2022	CT scan	segmentation for corona lesion lung	Covid-19 CT scan segmentation	U-Net (AA-U-Net)	-	78.4	98.4
(107) ,2022	CT scan	segmentation for corona lesion lung area	Radiopedia and Coronacases Initiative datasets are used for training, and the SRIM dataset is used for testing.	FCN networks	-	78.0	95.1

TABLE 6. Summary of Multi-Stage Techniques for Coronaviruse Diagnosis Using Both CT Scans & X-Ray Images:

DL					Performance							
					Classification						Segmentation	
Ref-year	**modularity**	**Purpose (problem)**	**Datasets**	**Model's name(technique)**	**Accuracy (%)**	**F1-score (%)**	**Sensitivity (%)**	**Precision (%)**	**Specificity (%)**	**Recall (%)**	**DS (%)**	**IOU (%)**
(108), 2020	x-ray	lung infection segmentation and classification into multiple classes	Two datasets COVID-19 portable C.X.R. dataset and Kaggle C.X.R. dataset	Classification: VGG16 Segmentation: Custom CNN	88	-	91.0	-	93	-	97.2	95.6
(109), 2020	CT scan	Segmentation and classification of covid-19 infected	SIRM Dataset	Class: CoV-CTNet Seg: CoV-RASeg	98.8	99.0	99	99	99	-	95.2	98.7
(110), 2021	CT scan	Detection for covid-19 Pneumonia	the data came from 5 hospitals in Beijing and Wuhan.	Segmentation: (FCN-8s, U-Net , V-Net , and 3D U-Net++) models the best is 3D U-Net++ and classification: ResNet, Inception	92.2	-	97.4	-	92.2	-	75.4	-

TABLE 5. Summary of DL-based Infection Segmentation Techniques for Corona Diagnosis Using X-Ray & CT Scans

DL					Performance							
					Classification						Segmentation	
Ref-year	**modularity**	**Purpose (problem)**	**Datasets**	**Model's name(technique)**	**Accuracy (%)**	**F1-score (%)**	**Sensitivity (%)**	**Precision (%)**	**Specificity (%)**	**Recall (%)**	**DS (%)**	**IOU (%)**
(111),2021	CT scan	Diagnosis for coronavirus	(COVID-CS) dataset	JCS system	-	-	95.0	-	93.0	-	78.5	66.4
(112),2021	X-ray	Multi-classification DL model for diagnosing lung cancer, Pneumonia, and COVID-19	covid-19x-ray-dataset	Segmentation U-Net classification: three CNN architectures (VGG, ResNet, and Inception) VGG19 and CNN models achieved the best accuracy	98.0	88	-		-	-	98.2	-
(113),2021	CT scan	Covid-19 infection automatic segmentation	Many public datasets	DNN	-	-	70.1	-	94.2	-	75.7	-
(114),2022	CT scan	automatically segment &classify COVID-19 CT	COVID-19 LUNG CT SCANS PUBLIC DATASET FROM KAGGLE	CNN_Seg	93.9	75.8	75.3	-	75.3	92.3	-	-
(115),2022	CT scan	Diagnosis	Many public datasets for diagnosis & segmentation task	The model comprises a segmentation network (SSN) & n (SADN.)	99.2	97.9	-	-	-	96.0	-	58
(116),2022	CT scan	methodology for detecting and quantifying Covid-19 infection and screening for Pneumonia	data from the Corona-cases Initiative and Radiopaedia	CNN and U-Net	0.98	-	-	-	-	-	0.98	-

CHALLENGES AND FUTURE DIRECTIONS

Challenges

There are a lot of Deep Learning techniques to diagnose covid-19. CNN was used in most of these ways to screen and analyze Coronaviruses. All of these techniques facing several obstacles, which we will talk about below:

1. **Lack and unavailability of large-scale labelled, annotated datasets:**
   Most AI-based DL approaches used CNN to screen and analyze COVID-19, which strongly depends on enormous annotated datasets to generate reliable results. Because Corona is a novel illness, there are not enough radiographic images in a consistent format for CNN models to train and test. As a result, there are not enough datasets available for AI.

2. **Variance in the Quality of covid-19 datasets**
   One of the biggest problems with covid-19 is the lack of high-quality datasets. Many factors that can affect data sharing are limited, such as (1) closed-source and unpublished datasets, (2) privacy concerns that prevent data sharing, and (3) the scattered nature of covid-19 datasets. Also, Another problem related to collecting datasets is that the distributed and heterogeneous nature of many data sources contributes to data lack.

3. **Keeping data privacy :**
   Collecting information about a person's privacy is incredibly hard in the big data and Artificial Intelligent era. Many administrations want to gather personal data from individuals, including phone numbers, ids, patient histories, and personal data, to address public health issues like the covid-19. This private and secure information must be confidential at all costs, and severe steps must be taken to avoid data leaks.

4. **Unbalance datasets:**
   Data imbalance is a problem that arises as a result of the lack of covid-19 data. Compared to Pneumonia caused by other viruses, the number of patients with covid-19 Pneumonia (positive samples) is significantly smaller. This problem is experienced by many researchers and can impact the accuracy of disease diagnosis.

5. **Shortage in the crossing of computer science and medicine fields(lack of interdisciplinary cooperation):**
   The majority of AI researchers are trained in computer science. However, expertise in various fields, including virology, bioinformatics, clinical biology, and medical imaging, is necessary. The in-depth study on COVID-19 must be conducted in collaboration with specialists from other fields. This knowledge barrier can be avoided by interdisciplinary research. To improve the studies, medical experts and machine learning engineers should collaborate.

6. **Severity level**:
   Several studies focus on using classification after segmentation to separate Coronavirus patients from those who did not have Covid-19 without focusing on segmentation to predict the severity level and get Coronavirus confirmed cases. Furthermore, it lacks a dataset of severity level where Infective or non-infective labels were typically present in the majority of datasets for the output classes that might be produced, thus for monitoring a patient's recovery. It is necessary to have an annotated dataset to represent the disease's severity level.

7. **Scarcity of Technology Infrastructure**
   The availability of Information Technology (IT) infrastructure is essential for the early diagnosis, tracking, and monitoring of patients. IT infrastructure aids in locating hotspots and crowd gathering, enabling administrators to make decisions and implement them more quickly. The lack of infrastructure severely limits using Artificial Intelligence (AI) for detection and earlier tactics in developing countries like Iraq.

Possible Future Directions

This section discusses Many future research ideas:

A dataset enrichment: while annotating training samples takes time and professional medical personnel, for this in the future, we can construct annotating data and enrich datasets with it through generating masks (ROI) for both lung and lesion that are very important for estimating the proportion of the infected area of the lung, which is an essential measure for quantifying the severity of Covid-19 infection.

Automated Diagnosis: The entire procedure can be performed remotely using various automation approaches. It can help to prevent needless interaction with radiologists and other medical personnel.

Medical validation: Several Deep Learning models have proved promising outcomes in Covid-19 screening, diagnosis, and Prediction; these models will be used in a real-world setting (such as emerging services, hospitals, and treatment centers.) soon after extensive validation by medical experts.

Simulation: Artificially-powered Deep Learning systems may be employed in various virtual simulations to identify and track multiple aspects of Coronavirus detection, such as using the Internet of Things (IoT) for covid-19 monitoring.

CONCLUSION

The global Covid-19 epidemic is still going strong and continuing to have an impact. Analysis of radiological images is thought to be a rapid screening method. However, radiological imaging only shows a portion of the information regarding people who have Coronavirus infection. Therefore, combining the clinical review of radiological images with Deep Learning approaches can help us gather information from many sources and subsequently aid in developing an accurate detecting and diagnostic system. Deep learning-based medical image (X-Rays and CT scans) analysis is crucial for a precise and speedy diagnosis. As a result, we offer a comprehensive analysis of the Covid-19 public datasets created and obtained from various countries, which may be divided into two primary categories: text data and medical images. Our research on numerous Deep Learning approaches based on image and region-level analysis of Covid-19 contagion also includes classification, segmentation, and multi-stage approaches for identifying and diagnosing disease-contaminated radiological images.

Furthermore, provide a summary of each study by detailing the dataset, model structure, model similarity type, and performance evaluation criteria. Finally, we are concentrating on some significant challenges and future directions that aid in diagnosing Covid-19. Consequently, this research may provide important insights for Deep Learning and radiological imaging that will aid in developing a comprehensive and consistent approach for detecting and evaluating Coronavirus. Therefore, it can assist physicians and radiologists in detecting and combating COVID-19 variants like Omicron and future pandemics.

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