International Journal of Advanced Technology and Engineering Exploration, Vol 9(90)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2021.874887

Review Article

A narrative review of medical image processing by deep learning models: origin to COVID-19

Mareeswari V[1*], Vijayan R[2], Sathiyamoorthy E[3] and Ephzibah E P[2]
Assistant Professor (Senior), School of Information Technology and Engineering (SITE), Vellore Institute of Technology (VIT), Vellore, Tamilnadu, India[1]
Associate Professor, School of Information Technology and Engineering, VIT, Vellore, Tamilnadu, India[2]
Professor, School of Information Technology and Engineering, VIT, Vellore, Tamilnadu, India[3]

Received: 28-September-2021; Revised: 19-May-2022; Accepted: 22-May-2022

Abstract
A rapid diagnostic system is a primary role in the healthcare system exclusively during a pandemic situation to control contagious diseases like coronavirus disease-2019 (COVID-19). Many countries remain lacking to spot COVID cases by the reverse transcription-polymerase chain reaction (RT-PCR) test. On this stretch, deep learning algorithms have been strengthened the medical image processing system to analyze the infection, categorization, and further diagnosis. It is motivated to discover the alternate way to identify the disease using existing medical implications. Hence, this review narrated the character and attainment of deep learning algorithms at each juncture from origin to COVID-19. This literature highlights the importance of deep learning and further focused the medical image processing research on handling the data of magnetic resonance imaging (MRI), computed tomography (CT) scan, and electromagnetic radiation (X-ray) images. Additionally, this systematic review tabulates the popular deep learning networks with operational parameters, peer-reviewed research with their outcomes, popular nets, and prevalent datasets, and highlighted the facts to stimulate future research. The consequence of this literature ascertains convolutional neural network-based deep learning approaches work better in the medical image processing system, and especially it is very supportive of sorting out the COVID-19 complications.

Keywords
Deep learning, Image processing, COVID-19, CT scan, X-ray image, Convolutional neural network (CNN), Neural nets, MRI scan, Diagnostic system, Healthcare.

1.Introduction
In the recent digital era, people and machines accessed medical-based applications through varieties of computers, mobile phones, internet of things (IoT) devices, and more. Hence, different kinds of enormous data have to be stored, processed, and analyzed according to various medical-based queries. For example, computational intelligence techniques have been used in big data processing [1] such as analysis of medical images, E-health record management, patient genomics different device logs and sensor data analysis, and cognitive information processing. Whichever, a healthcare system concerns to reduce the rate of the infected population by any disease as well as reducing the mortality rate.

The recent years back, the world health organization (WHO) stated the new family of coronavirus disease-2019 (COVID-19) outbreak as a pandemic category on 11th March 2020. Around the world, cumulatively 376,478,335 people were affected by COVID-19 and 5,666,064 people passed away as of 1st, Feb 2022, collected from world health organization (WHO) official website https://covid19.who.int/. It hence brought notice to all the countries to take speedy actions. At this stage, the reverse transcription-polymerase chain reaction (RT-PCR) test helps to detect the COVID-19 positive cases, and those can be isolated from normal people. But it is time-consuming, and high cost of testing kits and supporting materials, which makes diseases will spread to others at a faster rate [2]. Therefore, the healthcare system needs to find an alternate way of computational intelligence techniques to detect infectious diseases, thus, deep learning cares for them the way of medical image processing. Henceforth,

*Author for correspondence

the objective of this review is to show the computational intelligence techniques for analysis, disease identification, monitoring, prediction, and risk assessment of medical data used in healthcare and discussed in further sections.

Machine learning achieved many developments in various fields from the concerns of researchers and industries. Machine learning is transformed into deep learning by integrating the features of an artificial neural network (ANN). These sets of algorithms and approaches are applied to determine or learn the problematical solutions from the enormous data. Only it proves that deep learning-based applications can able to resolve problems from the history of results or experiences [3]. Deep learning is specifically challenging in processing big data, and it has attained a lot of achievements in several areas, including Bioinformatics. Since the flexible deep learning software environments provide a blast of computing power and strength of neural networks, which produces better results than earlier. Moreover, deep learning models make a footprint in various fields like computer vision, language modeling, prediction, and robotics. The successor of machine learning leads to a top ranking in the healthcare system by the overtaking of ANN techniques [4].

1.1Objectives and research questions

Recently, deep learning has perceived the dramatic developments and attention to the medical and software industries, academicians, and researchers. Additionally, during this COVID-19 pandemic period, to defend the people from infectious disease, there is a drive to do research and developments. Moreover, everyone has a social responsibility to get well from this pandemic. Because many countries want to treasure the substitute to RT-PCR test to diagnose the COVID-cases due to insufficient test equipment. During this, deep learning assists a lot by resolving complicated problems, deep through the existing huge data sets, and makes the developments to help the healthcare professionals.

Though, as an academician, some of the following research questions are raised and further sections are organized to discuss on the same. The section 1.2 presents the fundamentals of deep learning algorithm. The section 2 investigates the research studies published in medical image processing using deep learning approaches and how to sort out the significant articles from reputed publishers. The section 3 summarises the existing methodologies used in medical image processing by literature studies. The section 3.1 identifies how the magnetic resonance imaging (MRI) scan images are handled and the section 3.2 lists what are the methods for handling computed tomography (CT)-scans by deep learning approaches. *Table 1* tabulates to identify what are the standing datasets and working drives. The section 3.3 analyzes how the lung nodule is detected and how it's linked with COVID-19. The section 3.4 investigates how to diagnose COVID-19 by chest CT scan / electromagnetic radiation (X-Ray) images. *Table 2* and *Table 3* list to identify what is the purpose, methods, and outcomes of the previous research. The section 3.5 discoursed to decide what dataset is suitable doing research associated with COVID-19 and compared the popular datasets in *Table 4.* The last section 4 discussed the gaps highlighted to do future research.

1.2Deep learning fundamentals

Deep learning and bio-inspired computing can learn a lot from each other and produce promising results. Such applications are assisting doctors in healthcare, smoothening the overall business process, the automated grading system in education, smart features added in autonomous vehicles, predicting pricing patterns in travel and other industries, personalization in social media, and more.

Figure 1 explains the origin of deep learning. Artificial intelligence (AI) also called machine intelligence, which makes intelligent agents or software to perform the intellectual abilities of humans or any living entity such as thinking, learning, and problem-solving. The challenges of AI are automated reasoning, knowledge representation, automated planning, scheduling, machine learning, processing human language, and machine perception. Machine learning is the application or a subclass of AI. A machine can learn from the training data to perform specific operations short of explicit programming, but depends on patterns and implications. Mostly, this hybrid scientific algorithm and statistical model is motivated by prediction-based applications in different fields such as agriculture, banking, Bioinformatics, financial sector, healthcare, telecommunication system, speech recognition, and more. Machine learning has a set of algorithms and models. The learning algorithms have been classified into supervised, unsupervised, reinforcement, self, future, sparse dictionary, anomaly detection, and association rules. Such type of learning algorithm used in various fields depends on the kind of data and operations to resolve. Moreover, machine learning built a model and examined it in multiple applications. Such models are the ANN, decision trees, support vector machine (SVM), regression analysis, Bayesian networks, and genetic algorithms.

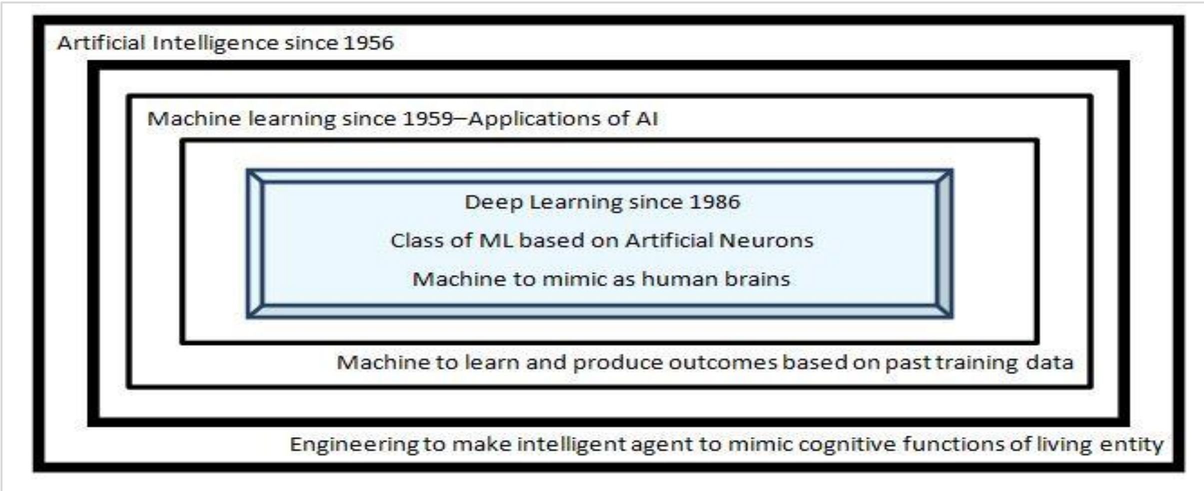

Figure 1 Origin of deep learning

Deep learning is an innovative area that leads machine learning towards achieving the goals of AI using an ANN model. Deep learning was introduced in 1959, but it booms everywhere in the year 2010. The neural network is inspired by the human brain for processing information and solving complex tasks. Deep learning practices several neural network layers to achieve the best outcomes in various concepts, such as voice recognition, computer vision, natural language processing, predictive analytics, and image processing. The intelligent system exhibits comparable results or, occasionally, higher than human experts.

Figure 2 shows the importance of deep learning algorithms compared with old learning algorithms based on the metrics' performance and accuracy. However, deep learning overcomes the problems and proves higher efficiency when the vast data to process, practice the bigger models, more computation, and concerns to small, medium, and large companies. Hence, the strength of deep learning is scalability.

The goal of deep learning with brain replications is to promote machine learning through AI, stated as outperforming, and improving the learning algorithms are much better in several fields. These learning algorithms might supervise, unsupervised, or semi-supervised. It could construct based on one among the deep neural networks (DNN), deep belief networks (DBN), recurrent neural networks (RNN), and convolutional neural networks (CNN).

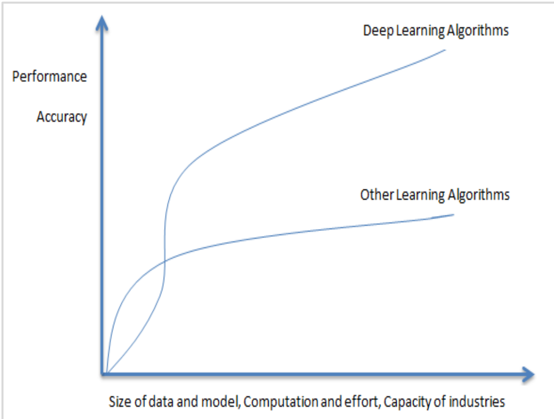

Figure 2 Importance of deep learning algorithms

Figure 3 shows the working principle of deep learning algorithms in general. A horse is an input image given in a deep learning framework. The features are picked out and classified as to whether it is kind of horse family-related, and further, it will be processed and produced the final output as a horse or no horse. Such input is image, text, numerical, binary, set, and time-series features. The input data is processed at multiple interconnected layers in all directions by deep learning algorithms such as ANN, CNN, DBN, RNN, and extreme learning machine (ELM). It has been used in such applications as computer vision, robotics, natural language processing (NLP), and business process.

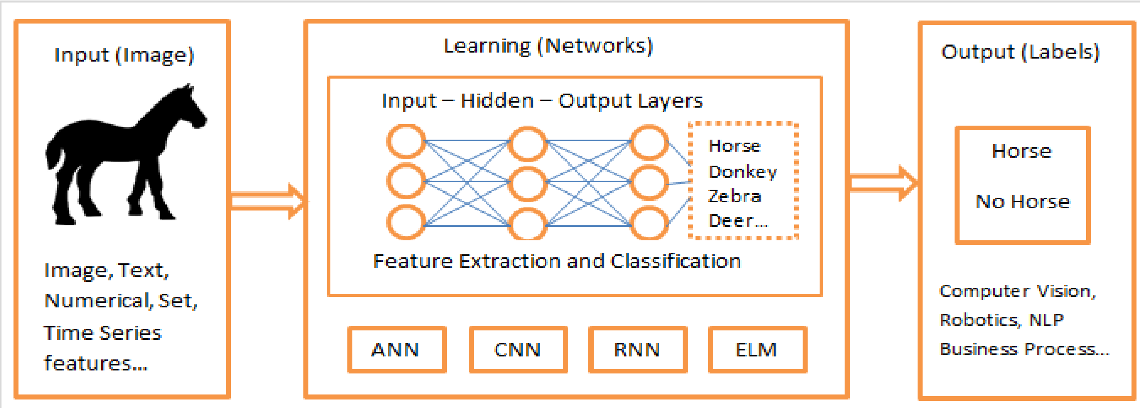

Figure 3 Working principle of deep learning algorithms

An underlying neural network defined as a computational prototype founded on the perceptions of the animal brain is to solve complex operations by the processing of simple connected components. In ANN, the artificial neurons are connected and communicated through the signal. The connection between the neurons is called a synapse, each neuron, and synapse have weight; it will differ depending on the input signals. Also, each neuron has a state represented in the range of 0 and 1. Neurons are organized layer-wise; each layer transmits the input and output signals between them in a neural network. Usually, it consists of a thousand to million units of neurons and millions of connections, even though this scale is less compared with the human brain. Still, the performance is higher than the human mind, especially in image recognition [5]. For better performance, it will do back-propagation in the opposite direction between the layers and process the data to solve a problem.

The DNN has many interconnected layers in which inputs are processed and calculated the probability of output in each layer and transferred to the next layer, repeating the process until to produce the final solution is based on a threshold value. For example, a car image is an input which processed in many layers and identified as a type of car at a certain point. DNN is usually a feed-forward network, which means the data is processed in a forward direction towards the final output layer.

The RNN is a kind of ANN that creates a directed graph by neurons and connections. It processes the data in both ways; mainly, it has been used in language modeling [6]. For this application, a long short-range of memory is utilized effectively. Typically, RNN uses internal memory to process the continuous data. Hence it is effectively used in speech recognition [7] and handwritten recognition [8]. Moreover, it has a footprint in several areas, such as time series forecasting [9], robot control, and prediction techniques in the medical system.

The CNN is a kind of DNN that comprises a lot of input, output, and hidden layers with varied weights in each layer. It analyses the image by using the dot product of data. Notably, it offers better performance in picture and video analysis in the medical field. Every neuron is in each layer connected with all other neurons in the subsequent layer. It is inspired by the biological process like the visual cortex in the animal brain, which is linked by the eye to visualize the image. Hence, CNN is defined as a neural network that works with the linear mathematical dot operation to recognize the image. Specifically, it is worthy of computer vision, image classification, and such related applications [10]. The DBN is a unique category of DNN that consists of a group of layers, including hidden layers. Each layer is interconnected between them like a direct acyclic graph model excluding hidden elements. This DBN is composed of simple unsupervised networks, where a sub-layer is processed over a period greedily and further extracted and classified depending on it leads to final results. Hence, it has performed well among the other deep learning approaches. It is used in such a realistic scenario as monitoring the electrical activity of the brain called electroencephalography [11] and drug discovery [12].

An extreme learning machine is a feed-forward network that contains one or many hidden layers in which units are needed not regulated. It gives better results and is faster than backpropagation networks and SVM [13]. This linear model is used for classification, clustering, regression, compression, approximation, and predictive learning. The artificial immune system (AIS) is motivated by the biological immune system which protects against disease. Likewise, AIS has the learning abilities and better utilization of memory to apply in problem-solving. Naturally, it is composed of intelligent computation and rule-based machine learning algorithms.

Summary of ANN in Healthcare

The ANN is composed of multiple computational parts called neurons, which are organized with multiple layers. The simple nonlinear function or activation function is applied in each input layer and produced the output layer and then the same is repeated to reach the specific final output. It is called a multilayer perception/feed-forward network. Hence, the medical data fed into the network is trained at each layer and produced the specific label depending on the application. At each layer, trained outputs were recorded and predicted results verified by anyone of the objective function among mean absolute error (MAE), mean squared error (MSE), and cross-entropy loss (CEL). In backward propagation, the inconsistency is propagated back to the network to improve the performance and make the changes in weights and try to produce an accurate label [14]. Nowadays, these deep learning models are developing futuristic approaches in various domains such as recognition of images, text, speech, and video in computer vision, robotic mechanisms, medical diagnosis, predictive analytics, and recommendation system.

2.Research methodology

The authorized research methodologies followed in this systematic review of medical image processing from origin to present COVID-19. It starts with collecting the existing concern articles with the following inclusion criteria and depicted using PRISM representation, refers to *Figure 4*.

- Published articles collected from 2015 to 2022. Especially, peer-reviewed journal articles published in increasing order like 119 and 176 in the year 2020 and 2021 respectively were covered.
- The journal articles were nominated from peer-reviewed journal databases such as Scopus, ScienceDirect, Springer, institute of electrical and electronics engineers (IEEE), multidisciplinary digital publishing institute (MDPI), and the national center for biotechnology information (NCBI).
- Only open access journals were selected from the Computer Science and Engineering subject areas.
- The final stage of journal articles considered and excluded the conference proceedings and book series.
- Limited in the selection where it's written in the English language.
- Journal articles are screened by appropriate title and abstract.
- Qualified full-text articles were investigated and formulated for this review article. The prevalent deep learning methods, purposes, accuracy, and dataset are identified and tabulated in further sections
- *Figure 5* represents the distribution of publishers in articles selection, in which 35% of the Elsevier journals were selected for this review, and peer-reviewed journals were selected from other publishers such as 10% of Springer, 17% of IEEE, 7% of Wiley online library, 12% of PubMed publishing, 11% of MDPI and 9% journals from rest of the reputed publishers.

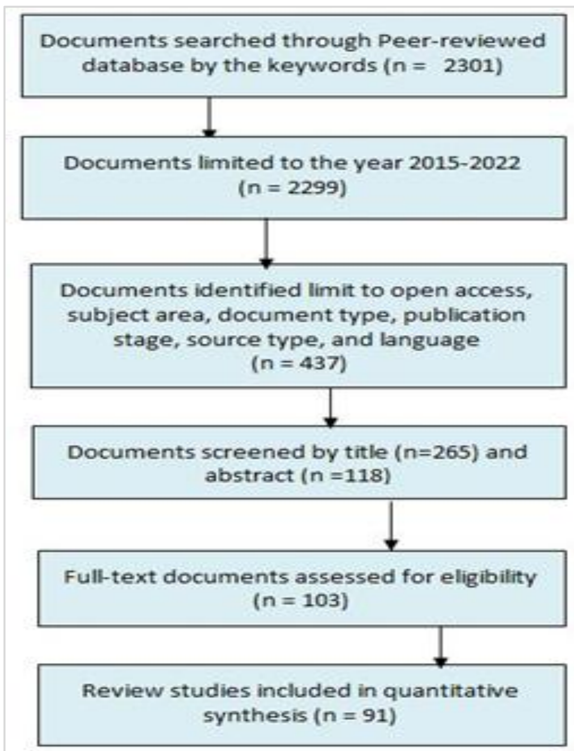

Figure 4 Articles screening

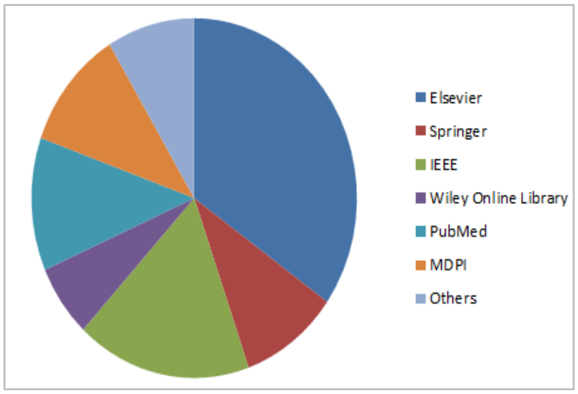

Figure 5 Distribution of publishers in article selection

3.Methods of medical image processing

3.1Methods for handling MRI data

CNN is one type of ANN. It maintains a relationship among data in a grid format with limited connections between layers. Hence, it is an excellent technique to input image data and learns image representation. It contains many convolution layers and activation functions, where so many pooling windows are processed to make future maps to produce the output layer. Particularly in medical imaging CNN works outperformed in image retrieval and image prediction. They [15] used deep learning concepts in MRI-based applications. They split the entire process into two steps. First, the image input signals are processed at multiple stages and registered at each. Second, apply deep learning algorithms in the segmentation of medical images, identification of disease, prediction of disease, analyzing text reports, and concentrate on such organs as the spine, brain, kidney, and prostate. Deep learning applied in medical image processing, which has four processing steps, is shown in *Figure 6*. Consider a patient fed into an MRI scan. The biological parts are scanned and signals are transformed into k-space grid formatted data. This image is reconstructed into magnitude and phase. Then the noise is reduced at the image restoration stage—finally, the images are registered according to multi-parameters like structural three-dimension t1-weighted MRI (sMRI), diffusion-weighted MRI (dMRI), and functional-bold MRI (fMRI). Here, sMRI means structural three-dimension T1-weighted MRI, dMRI means diffusion-weighted MRI, which is an overlay on sMRI indicated in blue color, and fMRI means functional-bold MRI highlighted by red color.

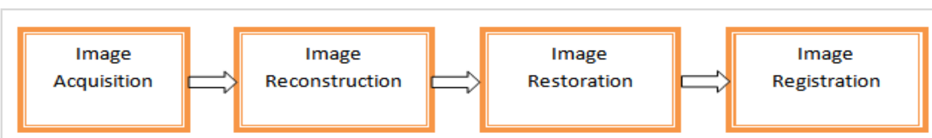

Figure 6 Medical image processing by deep learning

CNN and RNN are efficient methods in many image restoration and registration [16] to reconstruct the cardiac MRI from available complex-valued k-space undersampled data, which are cultured by spatial-temporal dependencies. For dynamic MRI reconstruction, multiple CNN is employed together at deep to reduce operational complexity. In real-time, that is 200 ms per slice used for image reconstruction by applying a parallel CNN image analysis approach [17]. These k-space image data are learned from a person's knee MRI recordings and transferred as trained models over variant networks to reconstruct the images [18]. The image restoration happened at 30 ms by reducing the noise rate, and learning features of an image by using the least square generative adversarial network (GAN) framework [19] and hands-on resources available at github.com/js3611/Deep-MRI-Reconstruction. This research [20] developed an automated transform by manifold approximation (AUTOMAP) framework for image restoration, in which MRI results are gathered from the human connectome project and processed deep in a fully connected feed-forward neural network.

Quantitative susceptibility mapping (QSM) is a rising technique in the study of MRI examinations to identify the affected tissue parameters. These authors [21] developed a QSMnet based on U-net architecture using a 3D convolution neural network for susceptibility from magnetic data. These data's collected from 60 scan reports from 12 well healthy volunteers. Moreover, DeepQSM is used to analyze the brain MRI reports over multiple image processing steps within a second [22]. These researchers [23] used deep learning approaches for de-noising to investigate the brain MRI scans of 33 patients. At each stage, a DNN is applied, and images are classified as a pathology, healthy, and vessel experts. Furthermore, the DNN was used to learn the knee

MRI images in DeepResolve [24] for which 124 patients were tested. Hence, deep learning approaches are beneficial in the diagnosis of the biological parts and detection the diseases for radiologists and medical practices.

For women, the menopausal stage transition is more concerned with health issues, which leads to hurting their lifestyle in different ways. Hence, [25] proposes a framework to predict the rigorousness of menopausal signs using the ANN technique, and provide healthcare services for women and clinical practice. For which nine inputs were gathered from hospital records such as age, body mass index (BMI), education, income, and chronic disease, applied ANN technique and predicted the Kupperman menopause index (KMI) score as output to analyze the menopause severity with accurate prediction results.
They [26] presented a hybrid system by ANN guided by an evolutionary algorithm (EA) for the estimation of cardio-metabolic risk (CMR). If CMR was predicted earlier, this could prevent atherosclerosis and cardiovascular diseases. However, it is prevalent that more than 10 million cases per year in India alone. This estimation is beneficial to prevent more death. Hence, the above said authors implement the intelligent CMR system using Matlab codes on which multiple ANN as trained with EA and proved above 90% accuracy. They highlight that the results might vary on regional inputs.

3.2For processing CT-scan images

Lung cancer is the most the vulnerable disease, which causes more new cases worldwide around 17 million in 2018, announced to the world cancer research fund. The highest number of cancer patients is in Hungary and the lowest in India [27]. Mostly, smoking habits affect the lung, which increases lung cancer incidence and mortality rate as of now highest among men smokers tailed by the women smokers [28]. The other risk factors for cancer are unprocessed biomass fuels, air pollution, exposure to the nuclear environment, and asbestos mines. This review [29] reports the lung cancer epidemiology, statistics and compares the cancer patients worldwide economically, socially, and biologically.

In medical imaging, a computed tomography (CT) scan takes one's place with the best diagnosis system, which is the combination of X-rays taken from different angles on organs, bones, and tissues. Deep learning models vital support diagnosis, detection by processing the CT scan images quickly rather than manual screening by radiologists. Mainly, it is applied to detect the painful nodules of the lung in CT scan images. Compared with manual screening, deep learning quickly detects the diagnosis even if it is of different shapes and appearances, a considerable part of CT scan images, the tiny nodule less than 10mm in diameter. Hence DL offers high confidence to the radiologist to make the accurate diagnosis detection. In general, this computer-aided detection process consists of pre-processing of CT images, lung segmentation (throax extraction and lung extraction), nodule detection (candidate detection and feature extraction), and classification. These researchers [30] study the recently published work between 2009 and April 2018 on lung nodule detection in CT images and reports the analysis beginning with feature engineering to deep learning approaches. Finally, they suggest that deep learning approaches, especially CNN-based algorithms, are widely applied in lung nodule detection, segmentation, and categorization. In specific nodule categorization, the multi-view-multi-scale, CNN achieves higher accuracy of 90.3-92.3% varies in the dataset [31].

The pre-trained visual geometry group (VGG-s) model combined with CNN achieves 76.79% of accurateness and 0.87 of receiver operating characteristic (ROC) curve [32], Applied CNN at the decision level with 96.65% of the area under curve (AUC) [33], and genetic algorithm centered on CNN with 94.66% of sensitivity 94.78% of accuracy [34]. For nodule segmentation, in the data-driven-associated machine learning model experiments the central focused CNN (CF-CNN) scored 82.15% in the dice score varies in the dataset [35]. The 3-D CNN applied to the fusion method produces a 94.4% sensitivity score in lung nodule detection [36] for classification. *Table 1* reports the significant published research work over 2018-2022 for lung nodule detection experimented with deep learning approaches experimented on the lung image database consortium (LIDC) / image database resource initiative (IDRI) dataset and other popular datasets.

Table 1 Comparison of recently published articles on lung nodule detection centered on its performance

Purpose	Methods	Results
Nodule classification [37]	• The knowledge-based collaborative deep model learns 3-D lung nodules, • Experimented on LIDC/IDRI, • Utilized three pre-trained ResNet-50 networks, classified 3-D nodule to nine stable views	• Accuracy = 91.60%, • AUC =95.70%
Nodule detection, malignancy classification [38]	• 3D CNN experimented on lung nodule analysis (LUNA)16 and Kaggle Data Science Bowl challenges	• Dice coefficient= 0.40, • Precision =0.25 • Recall= 0.93 • AUC= 0.87, • Overall performance =0.94
Nodule detection and classification [39]	• Two deep three-dimensional (3D) customized mixed link network (CMixNet) architecture, • Nodule detections by faster regions with CNN (RCNN) and classification by gradient boosting machine • Evaluated on LIDC-IDRI datasets	• Sensitivity=94% • Specificity =91%, • Accuracy=94.17%
Nodule detection [40]	• 3D Deep CNN (DCNN), evaluated on LIDC-IDRI datasets	• Sensitivity=87.94% • Competition performance metric (CPM) score =0.7967
Lung nodule detection [41]	• CNN's and CT image segmentation, evaluated on LIDC-IDRI datasets	• Sensitivity= 92.8% • 8 false positives (FP) per scan
Segmentation and classification [42]	• DCNN and conditional random field algorithm (CRF), evaluated on LIDC-IDRI datasets	• accuracy =89.48%
Nodule 3D visualization by detection and segmentation for [43]	• Mask R-CNN (Mask region-convolutional neural network) and ray-casting volume rendering algorithm, • Utilized resnet50 as the backbone and applied feature pyramid network, region proposal network experimented on LIDC-IDRI datasets	• Sensitivity= 88.1% at 1 FP / scan • Sensitivity=88.7% at 4 FP / scan,
Nodule detection [44]	• CNN's-based classifier, experimented on the TIANCHI AI dataset [D1], LUNA-16 dataset, and extra other hospitals 2470 chest scans	• Sensitivity = 0.968 • Sensitivity 75.6% • CPM=0.903
Nodule classification [45]	• Semi-supervised adversarial classification (SSAC) model	• Accuracy = 92.53% • AUC= 95.81%
Nodule segmentation [46]	• Semi-supervised 3D deep neural network: Residual U-Net	• Dice Coefficient =71.9%
Nodule detection and classification [47]	• Fuzzy particle swarm optimization algorithm with CNN (FPSOCNN)	• Accuracy= 94.97%, • Sensitivity= 96.68, • Specificity= 95.89
Nodule classification [48]	• 3D DenseNet architecture filters and pooling kernels practiced CT scan images of lung nodule analysis 2016 (LUNA16) dataset, a subgroup of the LIDC/IDRI dataset	• Accuracy=92.4% • Sensitivity=87% • Specificity=96%
Lung nodule classification [49]	• Bilinear CNN, used VGG-16, VGG-19 and SVM classifier, • Practiced on LIDC/IDRI dataset	• Accuracy= 91.99% • Sensitivity= 91.85% • Specificity = 92.27% • F1-score = 93.76% • FP rate = 7.72%

Purpose	Methods	Results
Nodule detection [50]	• Used Alexnet Faster R-CNN and ResNet, • Practiced on LIDC/IDRI dataset	• Accuracy=98% • True Positive Rate=98.9%
Nodule segmentation [51]	• CoLe-CNN: 2D Context-learning CNN, multiple convolution layers on U-Net, segmentation mask, soft asymmetric loss function for accuracy, efficiency, and stability	• F1score = 3.3% • IoU = 4.7%
Nodule classification [52]	• Developed multi-model ensemble learning architecture associated with 3D CNN, to classify the malignant or benign nodule, • Practiced the VGGNet, ResNet, InceptionNet, and Multinetwork, • LIDC-IDRI dataset used	• Accuracy=90.60% • Sensitivity=83.7% • AUC=93.90%
Nodule classification [53]	• Utilized the residual attention network (RAN) and squeeze-and-excitation network (SEN) to take out spatial and contextual features, • The gradient boosting machine algorithm for classification, • LIDC-IDRI dataset practiced.	• Accuracy=91.9% • Sensitivity=91.3% • FP rate=8.0% • F1-score=91.0%
Nodule classification [54]	• Exercised the transferable texture CNN with nine convolutional layers and an energy layer, • LIDC-IDRI and MNIST (modified national institute of standards and technology) datasets are • practiced	• Accuracy=96.69% • Error rate =3.30% • AUC=99.11% • Recall=97.19%

3.3Popular CNN nets

The ImageNet is the extensive accessible image database arranged rendering to WordNet. It collects the list of web images for each synset of wordnet. Just, it is available at https://www.image-net.org, which directs through URL to access web images provided by someone providing images. The first famous CNN architecture is LeNet was developed by LeCun et al. [55] in 1998. *Table 2* lists the top 5% error rate of pre-trained CNN Nets.

Table 2 Popular CNN nets

Network & type	Depth	Layers	Purpose	P. (10^6)
LeNet-5:Simple CNN	5	2 Convolutional layers and 3 fully connected layers	Digits classification on image [55]	0.06
AlexNet: Feedforward CNN	8	5 Convolutional layers and 3 fully connected layers	1 million images are classified into 1000 classes by Alex Krizhevsky [56]	61.0
VGG-16: DCNN	16	13 Convolutional layers and 3 fully connected layers	14 million images are classified into 1000 classes by Karen Simonyan and Andrew Zisserman [57]	138
VGG-19:Very DCNN	19	16 Convolution layers and 3 fully connected layers	Image classification [57]	144
SqueezeNet: compact CNN	18	3*3 to 1*1 Convolutional kernels	For image and video recognition [58]	1.24
GoogleLeNet : DCNN	22	9 Inception modules	Developed by Google [59]	7
MobileNet-V2: Inverted Residuals and Linear Bottlenecks	53	3×3regular convolution in 1st layer, followed by 13 times the above building block. No pooling layer	Developed by Google For image classification, detection, and segmentation [60]	3.5

Network & type	Depth	Layers	Purpose	P. (10^6)
ResNet : Residual CNN	18,34, 50, 101, 152	5 Version of convolution	Image recognition by [61]. It has introduced an identity shortcut connection that bounces one or more layers.	11.7 -44.6
Xception : eXtreme CNN	71	Depth wise convolution followed by a point-wise convolution	350 million images and 17,000 classes [62]	22.9
3D DenseNet	48×48×48 image volume	a convolutional layer, 5 Fully connected dense blocks, 4 Four transition blocks, a pooling layer and a softmax layer	888 CT scan images in LUNA16 244,527 spiral CT images in LIDC/IDRI [48]	200 EPO

These popular CNN Nets are used by many researchers and also develop the new Nets with other mechanisms. Though, COVID-19 is infected in both the upper respiratory tract and the lungs. Mostly chest x-ray (CXR) images are employed to diagnose lung diseases and are now proven to detect COVID-19 disease. These authors [63] practiced the popular CNN Nets such as ResNet18, ResNet50, ResNet101, VGG16, and VGG19 for feature extraction, and SVM classifier for feature classification. This model was inspected in the dataset comprised of 380 CXR images of COVID19 patients and healthy persons. They conclude that 94.7% of the highest accuracy is attained when combining the ResNet50 and SVM classifier with the linear kernel function. Similarly, they [64] practiced the ResNet34 at the semi-supervised segmentation learning process on axial CT scan images to sense COVID-19 and named as FSS-2019-nCov's segmentation model. This model uses a public data set and tried to improve the generalization efficiency, even if it could not achieve accurate segmentation. But this drawback will be overcome by practicing a large volume of 3D, CT images of COVID-19. In many research experiments LIDC-IDRI dataset, [49] the one of the research proved SVM classifier achieved better results than the k-nearest neighbor (KNN), soft-max, and other classifiers.

3.4 For processing chest images of COVID19

It is essential to maintain a healthcare system concerning reduces the rate of the population who are affecting any disease as well as reduces the mortality rate. As of now, all the countries and territories around the world face severe diseases caused by a novel coronavirus. This pandemic disease has such stages in order as investigation, recognition, initiation, and acceleration. The peak of sickness starts at the end of the acceleration stage. However, these stages drive contrast, among countries and also varied among different states in the same country depending on the characteristics of the coronavirus and the public health reaction. Moreover, it is going to spread fast from one person to more persons, and humans do not infect it before. So, this state of affairs poses a severe public health risk and challenge for entire systems, especially health care systems.

People who are affected by lung disease may be threatened with dreadful illnesses from COVID-19. Hence, cancer patients and their families will be distressed by the coronavirus outbreak. Moreover, for a person who has less immunity is challenging to fight coronavirus infection. As well as, the coronavirus rapidly spreads among people around the world. In this situation, a regular diagnostic tool as a clinical test is very time-consuming and expensive; even if it requires high equipped labs for analysis. However, at this initial stage, none of the medicines and treatment is proposed. As per suggestion from WHO, RT-PCR test on molecule confirms the positive COVID-19 case [65]. While this is rapidly spreading among the people, some countries which have a lower number of test kits used the CT scan to detect the coronavirus. Hence, medical image processing through CT scan is utilized to detect the COVID-19 patient alongside RT-PCR [66]. In addition to that, the radiologist faces a struggle to distinguish between the identification of COVID-19 infections and other CT findings (influenza, severe acute respiratory syndrome (SARS), middle east respiratory syndrome (MERS)) during this express coronavirus spread swifts their workload [67]. *Figure 7* shows the samples of nodule segmentation with 3 labels in COVID-19 CT axial slice by a radiologist. Here blue denotes the ground-glass opacities with a mask value of 1, consolidation with a mask value of 2 in yellow and pleural effusion with a mask value of 3 in green. These labels promote boosting the prognosis estimation for COVID-19 patient screening instead of the RT-PCR test [68].

Computer-aided diagnosis (CAD) supports the radiologist to detect the abnormalities in the lungs even could not be perceived by visual infection [69]. As of our earlier discussion on this study, deep learning plays a vital role in medical image processing, especially in lung disease diagnosis. These researchers [70] proved by experimental results of 0.899 AUC that CNN works better than a beep belief network to detect the malignant lung nodule. This research [71] practiced CNN on CT images to differentiate the COVID19 and non-COVID19 infections. Also, they analyzed 10 CNN architectures and concluded that ResNet-101 and Xception performed well with an AUC of 0.994, among other CNN nets. The radiological image-based diagnostic system produces better results than RT- PCR testing. *Table 3* describes the research published on COVID-19 cases.

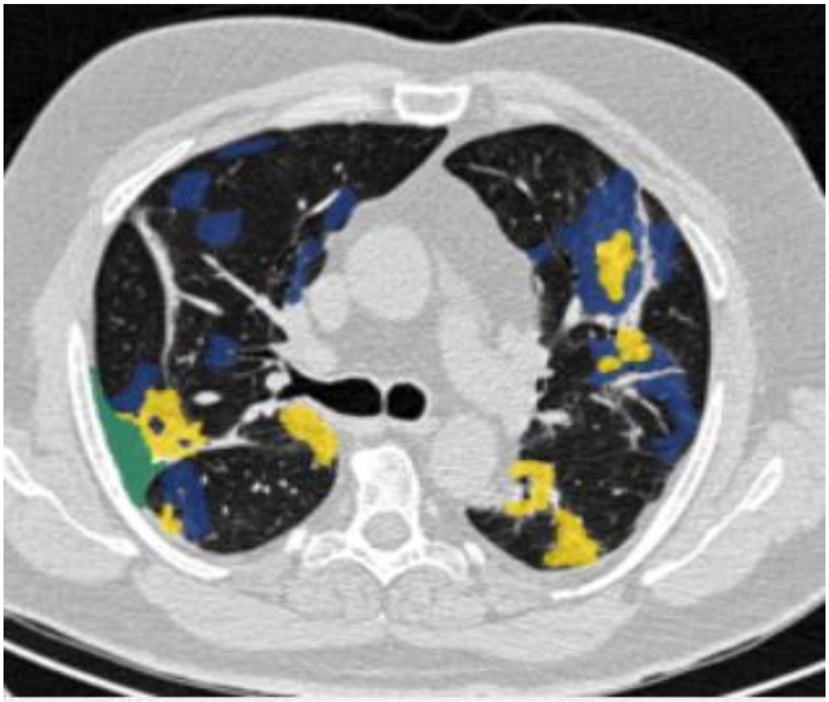

Figure 7 Example of one COVID19 CT slice

Table 3 The comparative outcomes of futuristic methods exercised in COVID-19 cases

Purposes	Methods	Outcomes
Find the misdiagnosis rate of Radiologists and calculate the attainment of chest CT images practiced in the diagnosis and management of COVID-19 [72].	• The authors look over the clinical contents and CT images. • Differentiate COVID-19 with other viruses.	• Shallow false rate (3.9%) diagnosis rate based on chest CT on COVID-19 (2/51 patients)
Categorized the images for macular degeneration and diabetic retinopathy and differentiated bacterial and viral pneumonia on CXRs [73].	• Used transfer learning techniques of deep learning	• Sensitivity and specificity were attained at a 0.05 error rate and 95% of confidence • Rapid and accurate explication of the X-ray images
The deep learning methods extract the radiological graphical features to diagnose COVID-19 [74].	• The inception migration neuro network model	• The internal validation-accuracy: 82.9%, specificity: 80.5%, sensitivity: 84%. • The external testing dataset – accuracy: 73.1%, specificity: 67%, sensitivity: 74%
A fully automatic analytical method for frontline clinical doctors distinguishes COVID-19 pneumonia among Influenza-A	• It states that pulmonary CT images are classified employs a location-attention classification model and infection type	• Overall accuracy 86.7%

Purposes	Methods	Outcomes
viral pneumonia and healthy cases[75].	• Total confidence scores were determined using Noisy-or Bayesian function.	
Detection of doubted COVID-19 thoracic CT features and classified into COVID-19 and Non-COVID-19 and reviewed at 3D[76].	• Used robust 2D and 3D deep learning models	• AUC=0.996, • Sensitivity=98.2%, • Specificity=92.2%
Finding COVID-19 cases from CXR images, and making it a public dataset [77].	• DCNN	• Comprising 13,975 CXR images across 13,870 patient cases • Accuracy of 92.4%
Identification of positive COVID-19 case and. framework based on capsule networks, being capable of handling small datasets of X-ray images [78].	• CNN	• Accuracy= 95.7%, • Sensitivity= 90%, • Specificity=95.8%, • AUC of 0.97
A lightweight DNN-based mobile app used for screening COVID19 cases from noisy snapshots of CXR images[79].	• Knowledge transfer and distillation (KTD) framework	• Used by three roles as a pre-trained attending physician network, a fine-tuned resident fellow network, and a trained lightweight medical student.
Build open-access datasets and distinguished the COVID19 cases and pneumonia cases using CNN [80].	• Progressive resizing, cyclical learning level calculation, and discriminative learning rates to train quick and precise residual neural networks. • A 3-step technique is to adjust a pre-trained ResNet-50 model to enhance model performance	• Accuracy=96.23%
Developed a diagnostic system for COVID19 by medical image processing [81].	• Bayesian optimization of deep learning techniques	• The overall accuracy of 98.6%
Infected COVID-19 cases were identified from CXR images [82].	• VGG-16 net encoder used to capture unbiased features, Siamese network for concluding sort out of COVID-19 cases. • This meta COVID model achieves the best accuracy in 3-way and 10-shot learning settings.	• 95.6% of model accuracy, • 90% of specificity, • 96.80% of sensitivity, • AUC of 0.97
Build COVID-19 multi-task network (COMiT-Net), an automated end-to-end network that screens COVID-19[83].	• Predict the features of COVID-19 from the patient's CXR and mark the lung regions by segmentation to identify the COVID-19 symptoms. 2513 frontal CXR images were examined to build the dataset COMiT-Net and published for researchers.	• 90% of specificity and • 96.80% of sensitivity
CovNet-19: 3- Way classification model to identify normal, pneumonia, and COVID-19 and 2-Way classification model to COVID or Non-COVID [84].	• Ensemble DCNN applied in 6214 CXR images from 5 different datasets brought together by open-source software.	• 98.28% accuracy in 3-way classification, 98.33% of average precision 98.33% in Recall, 99.71% accuracy in 2-way classification model.
CCSHNet: Model built by analyzing the 1164 patient chest CT images and classified into COVID-19, healthy person, pneumonia, and secondary pulmonary tuberculosis[85].	• The pre-trained model employs to learn features, and (L, 2) transfer feature learning algorithm practiced to extract features, deducted layers with hyper-parameter and combine these to conclude the best model assisted with discriminant correlation analysis.	• Attained above 95% of sensitivities, precision, and F1 scores in each categorization • Micro-averaged F1 score measures the model accuracy as 97.04%.

Purposes	Methods	Outcomes
FSS-2019-nCov: semi-supervised few-shot segmentation approach for COVID-19 detection from few CT-scan images [64].	• ResNet34 at the semi-supervised segmentation learning process on axial CT scan images to spot COVID-19. • It comprises a feature encoder module practiced by ResNet34, a context enrichment module projected by smoothed atrous convolution block and multi-scale pyramid pooling block, and a feature decoder module. • Tried recombination and recalibration be combined with transferring learned information.	• Dataset1 contains 110 axial CT slices belonging to 60 patients and dataset2 contains the group of 1600 unannotated axial CT images used. • Tried to improve the highest generalization efficiency on limited images.
DeepCoroNet: Tracing COVID-19 cases using the long short term memory (LSTM) model from 1061 CXR above 45 years old [86].	• During the initial process, practiced the Sobel gradient and marker-controlled watershed segmentation operations to improve the performance. • LSTM employed instead of the transfer learning and deep feature extraction methods	• Declared complete accuracy, sensitivity, specificity and F1 score achieved.
A 2-step cascaded 3D UNet to slice the contaminated area from the lungs[87].	• The first 3D UNet discharged the lung parenchyma from the CT volumes followed by pre-processing and augmentation. • The second 3D UNet discharged the infected 3D volumes.	• In first stage, sensitivity= 93.47%, specificity= 98.64%, accuracy=98.07%, dice score=92.46%. • In second stage, sensitivity=83.33%, specificity= 99.84%, accuracy=99.20%, dice score of 82%
REMBRANDT Brain cancer, NIH chest X-ray, COVID-19 CT scan [88].	• A new adaptive momentum optimizer with stochastic gradient descent (SGD) and additional adaptive optimizers Adam and RMSprop to train CNN	• Boost SGD performance by falling classification error from 6.12 to 5.44%, • Convergence speed is 20% higher than the conventional SGD
A deep adversarial model employs CT images for segmentation-assisted COVID-19 diagnosis [89].	• Precisely predict the COVID-19 infective probability and • Bring lesion regions in CT images with limited training data, • Collected from [68]	• Accuracy= 99.2%, • Precision= 98%, • Recall= 96.0%, • F1 score= 97.96%
Multi-channel feature deep neural network algorithm to recognize COVID19 chest X-ray images (MFDNN)[90].	• MFDNN algorithm to screen the COVID19 patients. • The oversampling method was used in the model to equalize all types of input at pre-processing. • The MFDNN model is used for feature extraction.	• Attained an average test accuracy of 93.19% in all data compared with VGG19, GoogLeNet, ResNet50, and Densenet201. • Produces 1.91% higher accuracy than the CoroDet model
USTM-Net: Weakly-Supervised Segmentation of COVID19 Infection with Scribble Annotation on CT Images [91].	• COVID-19 segmentation by scribble-level observation • An uncertainty-aware mean teacher framework established for training • Regularize the model with a transformation-consistent strategy	• MAE=0.086 • Practiced on three datasets as uAI 3D dataset, IS-COVID dataset, [92], Lesion segmentation (CC-COVID) dataset [93].

3.5Dataset

The selection of the dataset plays a major role in research works. *Table 4* lists the popular dataset practiced for COVID19 diagnosis, which discussed the number of medical images collected from hospitals, websites, and search engines, developer information, available location, and credits of dataset release by citation and usability. It will be encouraged to develop the new dataset and practiced it for future research. The common decision-making system for the health care diagnosis system depends on supervised learning approaches. But it requires large labeled datasets; moreover, it is an expensive and time-consuming approach. When picking the small size dataset it produces an over-fitting problem and convergence problem at great risk during training the model. Meanwhile, the unsupervised learning approaches like transfer learning achieved more accuracy in feature extraction. Hence balanced dataset controls the false positive rate in such scenarios [50]. Besides, chose the dataset contains high-quality resolution images with required labels for the lung nodule detection of COVID cases and similar situations. Most of the dataset description includes the suitability of techniques and related features of the dataset. So, the appropriate deep learning techniques can train our model efficiently and produce accurate results in both training and testing.

Table 4 Comparative discussion on COVID19 popular datasets

Initial release	**Dataset**	**Contents**	**Creator**	**Available**	**Credits (as on search)**
2021	Novel Corona Virus 2019 Dataset	• Country-wise COVID cases • India - https://www.kaggle.com/sudalairajkumar/covid19-in-india • South Korea - https://www.kaggle.com/kimjihoo/coronavirusdataset • Italy - https://www.kaggle.com/sudalairajkumar/covid19-in-italy • Brazil - https://www.kaggle.com/unanimad/corona-virus-brazil • USA - https://www.kaggle.com/sudalairajkumar/covid19-in-usa • Switzerland - https://www.kaggle.com/daenuprobst/covid19-cases-switzerland • Indonesia - https://www.kaggle.com/ardisragen/indonesia-coronavirus-cases	Data are gathered from the google pages associated with Johns Hopkins university	https://github.com/CSSEGISandData/COVID-19	9.71 usability
2021 [92]	Covid-19 CT scan dataset	• By merging 7 public datasets • The dataset contains COVID-19, Normal, and CAP CT slices and their metadata. • In total, group of 7,593 COVID-19 images of 466 patients, 6,893 normal images of 604 patients, and 2618 CAP images of 60 patients. • To investigate different classes of medical images, detached CAP labels to acquire higher performance in binary classification.	Maftouni and her colleagues,	Kaggle	8.2 usability.
2020 [68]	COVID-19 CT segmentation dataset	• A set of 100 axial CT images of 60 COVID-19 patients. • It has three segmentation labels of ground glass with a mask value of 1, consolidation with a mask value of 2, and pleural effusion with a mask value of 3.	H. Jenssen	http://medicalsegmentation.com/covid19	15
2020 [93]	IS-COVID dataset	• A set of 110 axial lungs CT slices of 40 COVID-19 patients that transformed from openly accessible JPG images.	The entire CT slices were gathered by the Italian Society of Medical and Interventional Radiology.	https://github.com/DengPingFan/Inf-Net	473 citation
2020 [94]	Chest CT Image Investigation (CC-CCII)	• 1544 CT images of 929 COVID-19 positive patients • 1556 images of 964 Common Pneumonia (negative) patients • 1078 CT images of 849 Normal Lung (negative) patients	A huge CT dataset incorporating patient cohorts from the China Consortium	http://ncovai.big.ac.cn /download	498 citation

Initial release	Dataset	Contents	Creator	Available	Credits (as on search)
2020 [95]	COVID-CT-Dataset	• The group of 349 COVID-19 CT images of 216 patients and 463 non-COVID-19 CTs • they practiced multi-task learning and self-supervised learning on this dataset, • Achieved an 0.90 F1 score, 0.98 an AUC, and 0.89 an accuracy.	COVID19-associated papers crawled from medRxiv, bioRxiv, NEJM, JAMA, Lancet, etc. attested by a senior radiologist in Tongji Hospital, Wuhan, China	https://github.com/UCSD-AI4H/COVID-CT	175 citation
2020 [96]	Cord-19: The covid-19 open research dataset	• 1,000,000 scholarly articles, embraces over 350,000 with full text, about COVID-19, SARS-CoV-2, and connected coronaviruses.	The White House and a coalition of leading research groups	Kaggle	492 citation 8.82 usability
2020 [97]	SARS-COV-2 Ct-Scan Dataset	• A group of 1252 CT scans of SARS-CoV-2 infection (COVID-19) and 1230 CT scans of non- SARS-CoV-2, • can decide if a person is diseased by SARS-CoV-2 through the investigation of their CT scans	gathered from genuine patients in hospitals in Sao Paulo, Brazil	www.kaggle.com/plameneduardo/sarscov2-CT scan-dataset	205 citation
2020 [98]	COVID-19 Image Data Collection	• It contains 123 frontal view X-rays to diagnose the COVID19 by deep learning model like a radiologist. • Image content linked with clinically relevant features in a public dataset for designing models and development of tools.	Joseph Paul Cohen, Paul Morrison, Lan Dao Collected from websites and hospitals	https://github.com/ieee8023/covid-chestxray-dataset	707 citation
2020 [99]	COVID19 chest X-ray dataset	• The set of images includes 3616 COVID19 confirmed cases, 10,192 healthy, 6012 non-COVID but lung infected cases, and 1345 viral pneumonia cases.	developed by 12 authors and practiced by [90]	kaggle	408 Citation
2020 [100]	SIRM COVID-19 database	• Out of 384 radiographic images, 94 chest X-ray images and 290 lung CT images with 71 confirmed COVID-19 cases.	*Italian Society of Medical and Interventional Radiology (SIRM) COVID-19 DATABASE*	https://sirm.org/category/covid-19/	6
2019 [101]	Repository of molecular brain neoplasia data (REMBRANT) dataset	• 110.020 MRI descriptions of 130 tumor patients with multi-class classification. • these images are organized by patient id in the format of a DICOM image.	Georgetown University's G-DOC System	https://www.cancerimagingarchive.net/	1375 citation
2017 [102]	NIH Chest X-ray Dataset	• 112,120 X-ray images of 30,805 unique patients • down-scaled to 600×600 and encoded as 1-channel jpegs. • It doesn't have other patient information such as age, and sex. • format of TFRecords highly applicable for CNN training with multi-label classification	National Institutes of Health Clinical Center	https://nihcc.app.box.com/v/ChestXray-NIHCC Kaggle	*2319 citation* *7.3 usability*
2011 [103]	LIDC/IDRI	888 CT scans with the size of 124 GB and considered the slice thickness greater than 2.5 mm	53 authors of the diagnostic image analysis group, department of radiology and nuclear medicine, Radboud university medical center, Nijmegen, The Netherlands	https://luna16.grand-challenge.org.	1347 citation

4.Discussion

Several research studies reviewed many research works on lung nodule detection through CT scans by machine and deep learning techniques [104, 105]. Even though, our research studies reviewed the entire research work carried out from lung nodule detection, classification, segmentation, popular nets, datasets, and COVID-19 research grounded on medical image processing.

From the analysis, the various issues, concerns, and outcomes related to deep learning techniques exercised on COVID-19 have been tabulated, which will help to improve the research studies and further developments of applications or models expected to regulate the tragic situations. Many researchers stated that the investigation of the chest images is better for COVID-19 diagnosis rather than expensive RT-PCR testing. Moreover, many researchers practiced the CNN and hybrid of CNN techniques for medical image processing and they achieved higher accuracy in their nodule detection and further diagnosis investigation.

Rendering to the research justifications, most of the articles are measures the significant accuracy, sensitivity, specificity, precision, and F1 score. Even some other characteristics such as scalability, robustness, security, and convergence time of models are not discussed. Most of the research has been done by Python libraries and supporting tools. Still, more visualization is needed to enhance their research to gain a deep understanding of concepts and consequences. Many research models have been done on small-scale datasets and can achieve good accuracy, even though they should be improved by practicing a large volume of CT-scan/ CXR images.

The major drawback of many kinds of research in the healthcare system, the models have insufficient interaction between the researchers and concerned clinical experts about their studies and results. Moreover, some of the features needed to consider the multimodal data in like COVID-19 infectious disease cases such a location of patients, clinical histories of a patient, population density, and environmental studies. According to the investigation, most of the researchers have analyzed the issues and have not developed any real-time application or product to drive support the detection and surveillance throughout the disaster phases. Hence this investigation analyzed the stated interpretations of cited research. Further, this study will be scrutinizing the recent research on application-oriented, methods of handling healthcare data and formulate a comparative analysis. A complete list of abbreviations is shown in *Appendix I.*

5.Conclusion and future work

As far as discussed, this review narrated the origin of deep learning, the fundamental concepts of deep learning networks, and discussed how it is utilized in healthcare systems. Deep learning algorithms perform a vital role in processing the medical images for the detection of injurious, characterization, classification, and making a rapid decision for diagnosis. Hence this comprehensive review focused on the recent research works carried on specifically processing the medical images gathered from MRI scans, CT scans, and X-ray images through deep learning networks, and highlighted how it will help to diagnose COVID-19 from the state-of-art approaches, presenting the famous CNN nets with working constraints and lists the popular dataset with its credits. This study aims to learn about the automated process of diagnosis systems, their comparative studies, and how it has been implemented using artificial intelligence-based approaches in the future. This review concludes with a highlighted point as the medical image processing-based diagnostic system produces a better result in COVID-19 cases. Like and more novel deep learning models should be developed and expected to detect and control infectious diseases to avoid the pandemic situation in the future.

Acknowledgment

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Author's contributions statements

Mareeswari V: Conceptualization, investigation, writing – original draft, writing – review, and editing. **Vijayan R**: Data curation, writing – original draft, analysis, and interpretation of results. **Sathiyamoorthy E:** Supervision, investigation on challenges and validation. **Ephzibah E P:** Study conception, data collection and visualization.

References

[1] O leary DE. Artificial intelligence and big data. IEEE Intelligent Systems. 2013; 28(2):96-9.

[2] Castiglioni I, Ippolito D, Interlenghi M, Monti CB, Salvatore C, Schiaffino S, et al. Artificial intelligence applied on chest X-ray can aid in the diagnosis of COVID-19 infection: a first experience from Lombardy, Italy. MedRxiv. 2020.

[3] Schmidhuber J. Deep learning in neural networks: an overview. Neural Networks. 2015; 61:85-117.

[4] Bengio Y, Courville A, Vincent P. Representation learning: a review and new perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2013; 35(8):1798-828.

[5] Silver D, Huang A, Maddison CJ, Guez A, Sifre L, Van DDG, et al. Mastering the game of Go with deep neural networks and tree search. Nature. 2016; 529(7587):484-9.

[6] Gers FA, Schraudolph NN, Schmidhuber J. Learning precise timing with LSTM recurrent networks. Journal of Machine Learning Research. 2002:115-43.

[7] Anumanchipalli GK, Chartier J, Chang EF. Speech synthesis from neural decoding of spoken sentences. Nature. 2019; 568(7753):493-8.

[8] Graves A, Liwicki M, Fernández S, Bertolami R, Bunke H, Schmidhuber J. A novel connectionist system for unconstrained handwriting recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2008; 31(5):855-68.

[9] Hewamalage H, Bergmeir C, Bandara K. Recurrent neural networks for time series forecasting: current status and future directions. International Journal of Forecasting. 2021; 37(1):388-427.

[10] Zang J, Wang L, Liu Z, Zhang Q, Hua G, Zheng N. Attention-based temporal weighted convolutional neural network for action recognition. In IFIP international conference on artificial intelligence applications and innovations 2018 (pp. 97-108). Springer, Cham.

[11] Movahedi F, Coyle JL, Sejdić E. Deep belief networks for electroencephalography: a review of recent contributions and future outlooks. IEEE Journal of Biomedical and Health Informatics. 2017; 22(3):642-52.

[12] Gawehn E, Hiss JA, Schneider G. Deep learning in drug discovery. Molecular informatics. 2016; 35(1):3-14.

[13] Huang GB, Zhu QY, Siew CK. Extreme learning machine: theory and applications. Neurocomputing. 2006; 70(1-3):489-501.

[14] Smolensky P. Information processing in dynamical systems: foundations of harmony theory. Colorado Univ at Boulder Dept of Computer Science; 1986.

[15] Lundervold AS, Lundervold A. An overview of deep learning in medical imaging focusing on MRI. Zeitschrift für Medizinische Physik. 2019; 29(2):102-27.

[16] Qin C, Schlemper J, Caballero J, Price AN, Hajnal JV, Rueckert D. Convolutional recurrent neural networks for dynamic MR image reconstruction. IEEE Transactions on Medical Imaging. 2018; 38(1):280-90.

[17] Chen F, Taviani V, Malkiel I, Cheng JY, Tamir JI, Shaikh J, et al. Variable-density single-shot fast spin-echo MRI with deep learning reconstruction by using variational networks. Radiology. 2018; 289(2):366-73.

[18] Knoll F, Hammernik K, Kobler E, Pock T, Recht MP, Sodickson DK. Assessment of the generalization of learned image reconstruction and the potential for transfer learning. Magnetic Resonance in Medicine. 2019; 81(1):116-28.

[19] Mardani M, Gong E, Cheng JY, Vasanawala SS, Zaharchuk G, Xing L, et al. Deep generative adversarial neural networks for compressive sensing MRI. IEEE Transactions on Medical Imaging. 2018; 38(1):167-79.

[20] Zhu B, Liu JZ, Cauley SF, Rosen BR, Rosen MS. Image reconstruction by domain-transform manifold learning. Nature. 2018; 555(7697):487-92.

[21] Yoon J, Gong E, Chatnuntawech I, Bilgic B, Lee J, Jung W, et al. Quantitative susceptibility mapping using deep neural network: QSMnet. Neuroimage. 2018; 179:199-206.

[22] Bollmann S, Rasmussen KG, Kristensen M, Blendal RG, Østergaard LR, Plocharski M, et al. DeepQSM-using deep learning to solve the dipole inversion for quantitative susceptibility mapping. Neuroimage. 2019; 195:373-83.

[23] Benou A, Veksler R, Friedman A, Raviv TR. Ensemble of expert deep neural networks for spatio-temporal denoising of contrast-enhanced MRI sequences. Medical Image Analysis. 2017; 42:145-59.

[24] Chaudhari AS, Fang Z, Kogan F, Wood J, Stevens KJ, Gibbons EK, et al. Super-resolution musculoskeletal MRI using deep learning. Magnetic Resonance in Medicine. 2018; 80(5):2139-54.

[25] Li X, Chen F, Sun D, Tao M. Predicting menopausal symptoms with artificial neural network. Expert Systems with Applications. 2015; 42(22):8698-706.

[26] Kupusinac A, Stokic E, Kovacevic I. Hybrid EANN-EA system for the primary estimation of cardiometabolic risk. Journal of Medical Systems. 2016; 40(6):1-9.

[27] Youlden DR, Cramb SM, Baade PD. The international epidemiology of lung cancer: geographical distribution and secular trends. Journal of Thoracic Oncology. 2008; 3(8):819-31.

[28] Thun MJ, Carter BD, Feskanich D, Freedman ND, Prentice R, Lopez AD, et al. 50-year trends in smoking-related mortality in the United States. New England Journal of Medicine. 2013; 368:351-64.

[29] Barta JA, Powell CA, Wisnivesky JP. Global epidemiology of lung cancer. Annals of Global Health. 2019; 85(1).

[30] Halder A, Dey D, Sadhu AK. Lung nodule detection from feature engineering to deep learning in thoracic CT images: a comprehensive review. Journal of Digital Imaging. 2020; 33(3):655-77.

[31] Liu X, Hou F, Qin H, Hao A. Multi-view multi-scale CNNs for lung nodule type classification from CT images. Pattern Recognition. 2018; 77:262-75.

[32] Paul R, Hawkins S, Schabath MB, Gillies RJ, Hall LO, Goldgof DB. Predicting malignant nodules by fusing deep features with classical radiomics features. Journal of Medical Imaging. 2018.

[33] Xie Y, Zhang J, Xia Y, Fulham M, Zhang Y. Fusing texture, shape and deep model-learned information at decision level for automated classification of lung

nodules on chest CT. Information Fusion. 2018; 42:102-10.
[34] Da SGL, Da SNOP, Silva AC, De PAC, Gattass M. Lung nodules diagnosis based on evolutionary convolutional neural network. Multimedia Tools and Applications. 2017; 76(18):19039-55.
[35] Wang S, Zhou M, Liu Z, Liu Z, Gu D, Zang Y, et al. Central focused convolutional neural networks: developing a data-driven model for lung nodule segmentation. Medical Image Analysis. 2017; 40:172-83.
[36] Dou Q, Chen H, Yu L, Qin J, Heng PA. Multilevel contextual 3-D CNNs for false positive reduction in pulmonary nodule detection. IEEE Transactions on Biomedical Engineering. 2016; 64(7):1558-67.
[37] Xie Y, Xia Y, Zhang J, Song Y, Feng D, Fulham M, et al. Knowledge-based collaborative deep learning for benign-malignant lung nodule classification on chest CT. IEEE Transactions on Medical Imaging. 2018; 38(4):991-1004.
[38] Ozdemir O, Russell RL, Berlin AA. A 3D probabilistic deep learning system for detection and diagnosis of lung cancer using low-dose CT scans. IEEE Transactions on Medical Imaging. 2019; 39(5):1419-29.
[39] Nasrullah N, Sang J, Alam MS, Mateen M, Cai B, Hu H. Automated lung nodule detection and classification using deep learning combined with multiple strategies. Sensors. 2019; 19(17).
[40] Gu Y, Lu X, Yang L, Zhang B, Yu D, Zhao Y, et al. Automatic lung nodule detection using a 3D deep convolutional neural network combined with a multi-scale prediction strategy in chest CTs. Computers in Biology and Medicine. 2018; 103:220-31.
[41] Wang Q, Shen F, Shen L, Huang J, Sheng W. Lung nodule detection in CT images using a raw patch-based convolutional neural network. Journal of Digital Imaging. 2019; 32(6):971-9.
[42] Savitha G, Jidesh P. A holistic deep learning approach for identification and classification of sub-solid lung nodules in computed tomographic scans. Computers & Electrical Engineering. 2020; 84.
[43] Cai L, Long T, Dai Y, Huang Y. Mask R-CNN-based detection and segmentation for pulmonary nodule 3D visualization diagnosis. IEEE Access. 2020; 8:44400-9.
[44] Wang J, Wang J, Wen Y, Lu H, Niu T, Pan J, et al. Pulmonary nodule detection in volumetric chest CT scans using CNNs-based nodule-size-adaptive detection and classification. IEEE Access. 2019; 7:46033-44.
[45] Xie Y, Zhang J, Xia Y. Semi-supervised adversarial model for benign–malignant lung nodule classification on chest CT. Medical Image Analysis. 2019; 57:237-48.
[46] Liu M, Jiang X, Liu Y, Zhao F, Zhou H. A semi-supervised convolutional transfer neural network for 3D pulmonary nodules detection. Neurocomputing. 2020; 391:199-209.
[47] Asuntha A, Srinivasan A. Deep learning for lung cancer detection and classification. Multimedia Tools and Applications. 2020; 79(11):7731-62.
[48] Zhang G, Lin L, Wang J. Lung nodule classification in CT images using 3D densenet. In journal of physics: conference series 2021 (pp. 1-8). IOP Publishing.
[49] Mastouri R, Khlifa N, Neji H, Hantous-Zannad S. A bilinear convolutional neural network for lung nodules classification on CT images. International Journal of Computer Assisted Radiology and Surgery. 2021; 16(1):91-101.
[50] Liang J, Ye G, Guo J, Huang Q, Zhang S. Reducing false-positives in lung nodules detection using balanced datasets. Frontiers in Public Health. 2021.
[51] Pezzano G, Ripoll VR, Radeva P. CoLe-CNN: context-learning convolutional neural network with adaptive loss function for lung nodule segmentation. Computer Methods and Programs in Biomedicine. 2021.
[52] Liu H, Cao H, Song E, Ma G, Xu X, Jin R, Liu C, Hung CC. Multi-model ensemble learning architecture based on 3D CNN for lung nodule malignancy suspiciousness classification. Journal of Digital Imaging. 2020; 33(5):1242-56.
[53] Xia K, Chi J, Gao Y, Jiang Y, Wu C. Adaptive aggregated attention network for pulmonary nodule classification. Applied Sciences. 2021; 11(2).
[54] Ali I, Muzammil M, Haq IU, Khaliq AA, Abdullah S. Efficient lung nodule classification using transferable texture convolutional neural network. IEEE Access. 2020; 8:175859-70.
[55] Lecun Y. LeNet-5, convolutional neural networks. URL: http://yann. lecun. com/exdb/lenet. 2015.
[56] Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems. 2012.
[57] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556. 2014.
[58] Iandola FN, Han S, Moskewicz MW, Ashraf K, Dally WJ, Keutzer K. SqueezeNet: alexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size. arXiv preprint arXiv:1602.07360. 2016.
[59] Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, et al. Going deeper with convolutions. In proceedings of the IEEE conference on computer vision and pattern recognition 2015 (pp. 1-9).
[60] Sandler M, Howard A, Zhu M, Zhmoginov A, Chen LC. Mobilenetv2: inverted residuals and linear bottlenecks. In proceedings of the IEEE conference on computer vision and pattern recognition 2018 (pp. 4510-20).
[61] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In proceedings of the IEEE conference on computer vision and pattern recognition 2016 (pp. 770-8).
[62] Chollet F. Xception: deep learning with depthwise separable convolutions. In proceedings of the

conference on computer vision and pattern recognition 2017 (pp. 1251-8).
[63] Ismael AM, Şengür A. Deep learning approaches for COVID-19 detection based on chest X-ray images. Expert Systems with Applications. 2021.
[64] Abdel-Basset M, Chang V, Hawash H, Chakrabortty RK, Ryan M. FSS-2019-nCov: a deep learning architecture for semi-supervised few-shot segmentation of COVID-19 infection. Knowledge-Based Systems. 2021.
[65] https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/laboratory-guidance/. Accessed 3 March 2020.
[66] Chung M, Bernheim A, Mei X, Zhang N, Huang M, Zeng X, et al. CT imaging features of 2019 novel coronavirus (2019-nCoV). Radiology. 2020; 295(1):202-7.
[67] Taylor-phillips S, Stinton C. Fatigue in radiology: a fertile area for future research. The British Journal of Radiology. 2019.
[68] https://medicalsegmentation. com/about, 2020. Accessed 3 March 2020.
[69] Castellano G, Bonilha L, Li LM, Cendes F. Texture analysis of medical images. Clinical Radiology. 2004; 59(12):1061-9.
[70] Sun W, Zheng B, Qian W. Automatic feature learning using multichannel ROI based on deep structured algorithms for computerized lung cancer diagnosis. Computers in Biology and Medicine. 2017; 89:530-9.
[71] Ardakani AA, Kanafi AR, Acharya UR, Khadem N, Mohammadi A. Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: results of 10 convolutional neural networks. Computers in Biology and Medicine. 2020.
[72] Li Y, Xia L. Coronavirus disease 2019 (COVID-19): role of chest CT in diagnosis and management. Cardiopulmonary Imaging, Original Research. 2020; 214(6):1280-6.
[73] Kermany DS, Goldbaum M, Cai W, Valentim CC, Liang H, Baxter SL, et al. Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell. 2018; 172(5):1122-31.
[74] Wang S, Kang B, Ma J, Zeng X, Xiao M, Guo J, et al. A deep learning algorithm using CT images to screen for corona virus disease (COVID-19). European Radiology. 2021; 31(8):6096-104.
[75] Wang Z, Li H, Li J, Yang C, Guo X, Hu Z, et al. Elevated serum IgM levels indicate poor outcome in patients with coronavirus disease 2019 pneumonia: a retrospective case-control study. Available at SSRN 3557987. 2020.
[76] Gozes O, Frid-Adar M, Greenspan H, Browning PD, Zhang H, Ji W, et al. Rapid AI development cycle for the coronavirus (COVID-19) pandemic: initial results for automated detection & patient monitoring using deep learning CT image analysis. arXiv preprint arXiv:2003.05037. 2020.
[77] Wang L, Lin ZQ, Wong A. Covid-net: a tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. Scientific Reports. 2020; 10(1):1-12.
[78] Afshar P, Heidarian S, Naderkhani F, Oikonomou A, Plataniotis KN, Mohammadi A. Covid-caps: a capsule network-based framework for identification of covid-19 cases from x-ray images. Pattern Recognition Letters. 2020; 138:638-43.
[79] Li X, Li C, Zhu D. Covid-mobilexpert: On-device COVID-19 screening using snapshots of chest x-ray. arXiv preprint arXiv:2004.03042. 2020.
[80] Farooq M, Hafeez A. Covid-resnet: A deep learning framework for screening of covid19 from radiographs. arXiv preprint arXiv:2003.14395. 2020.
[81] Ucar F, Korkmaz D. COVID iagnosis-net: deep bayes-squeezenet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images. Medical Hypotheses. 2020; 140.
[82] Shorfuzzaman M, Hossain MS. MetaCOVID: a Siamese neural network framework with contrastive loss for n-shot diagnosis of COVID-19 patients. Pattern Recognition. 2021.
[83] Malhotra A, Mittal S, Majumdar P, Chhabra S, Thakral K, Vatsa M, et al. Multi-task driven explainable diagnosis of COVID-19 using chest X-ray images. Pattern Recognition. 2022.
[84] Kedia P, Katarya R. CoVNet-19: A deep learning model for the detection and analysis of COVID-19 patients. Applied Soft Computing. 2021; 104.
[85] Wang SH, Nayak DR, Guttery DS, Zhang X, Zhang YD. COVID-19 classification by CCSHNet with deep fusion using transfer learning and discriminant correlation analysis. Information Fusion. 2021; 68:131-48.
[86] Demir F. DeepcoroNet: a deep LSTM approach for automated detection of COVID-19 cases from chest X-ray images. Applied Soft Computing. 2021; 103.
[87] Aswathy AL, SS VC. Cascaded 3D UNet architecture for segmenting the COVID‑19 infection from lung CT volume. Scientific Reports. 2022.
[88] Aytaç UC, Güneş A, Ajlouni N. A novel adaptive momentum method for medical image classification using convolutional neural network. BMC Medical Imaging. 2022; 22(1):1-12.
[89] Yao HY, Wan WG, Li X. A deep adversarial model for segmentation assisted COVID-19 diagnosis using CT images. EURASIP Journal on Advances in Signal Processing. 2022.
[90] Pan L, Ji B, Wang X, Peng S. MFDNN: Multi-channel feature deep neural network algorithm to identify COVID19 chest X-ray images. medRxiv. 2021.
[91] Liu X, Yuan Q, Gao Y, He K, Wang S, Tang X, et al. Weakly supervised segmentation of covid19 infection with scribble annotation on ct images. Pattern Recognition. 2022; 122.
[92] Maftouni M, Law AC, Shen B, Grado ZJ, Zhou Y, Yazdi NA. A robust ensemble-deep learning model for covid-19 diagnosis based on an integrated CT scan images database. In IIE annual conference. proceedings 2021 (pp. 632-7). Institute of Industrial and Systems Engineers (IISE).

[93] Fan DP, Zhou T, Ji GP, Zhou Y, Chen G, Fu H, et al. Inf-net: automatic COVID-19 lung infection segmentation from CT images. IEEE Transactions on Medical Imaging. 2020; 39(8):2626-37.

[94] Zhang K, Liu X, Shen J, Li Z, Sang Y, Wu X, et al. Clinically applicable AI system for accurate diagnosis, quantitative measurements, and prognosis of COVID-19 pneumonia using computed tomography. Cell. 2020; 181(6):1423-33.

[95] Zhao J, Zhang Y, He X, Xie P. Covid-CT-dataset: a CT scan dataset about COVID-19. arXiv preprint arXiv:2003.13865. 2020.

[96] Wang LL, Lo K, Chandrasekhar Y, Reas R, Yang J, Eide D, et al. Cord-19: the COVID-19 open research dataset. ArXiv. 2020.

[97] Angelov P, Almeida SE. SARS-CoV-2 CT-scan dataset: a large dataset of real patients CT scans for SARS-CoV-2 identification. MedRxiv. 2020.

[98] Cohen JP, Morrison P, Dao L. COVID-19 image data collection. arXiv preprint arXiv:2003.11597. 2020.

[99] Chowdhury ME, Rahman T, Khandakar A, Mazhar R, Kadir MA, Mahbub ZB, et al. Can AI help in screening viral and COVID-19 pneumonia?. IEEE Access. 2020; 8:132665-76.

[100]Rahman T, Khandakar A, Qiblawey Y, Tahir A, Kiranyaz S, Kashem SB, et al. Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images. Computers in Biology and Medicine. 2021.

[101]https://wiki.cancerimagingarchive.net/display/Public/REMBRANDT. Accessed 3 March 2022.

[102]Wang X, Peng Y, Lu L, Lu Z, Bagheri M, Summers RM. Chestx-ray8: hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In proceedings of the IEEE conference on computer vision and pattern recognition 2017 (pp. 2097-106).

[103]Armato III SG, McLennan G, Bidaut L, McNitt-gray MF, Meyer CR, Reeves AP, et al. The lung image database consortium (LIDC) and image database resource initiative (IDRI): a completed reference database of lung nodules on CT scans. Medical physics. 2011; 38(2):915-31.

[104]Gu Y, Chi J, Liu J, Yang L, Zhang B, Yu D, et al. A survey of computer-aided diagnosis of lung nodules from CT scans using deep learning. Computers in Biology and Medicine. 2021.

[105]Li R, Xiao C, Huang Y, Hassan H, Huang B. Deep learning applications in computed tomography images for pulmonary nodule detection and diagnosis: a review. Diagnostics. 2022; 12(2):1-21.

Dr. Mareeswari V is working as Assistant Professor (Senior) at the School of Information Technology and Engineering (SITE), Vellore Institute of Technology (VIT), Vellore, Tamilnadu, India. She received her Ph.D. in Information Technology and Engineering from VIT University, India in the area of Web Service and has produced several national and international articles in reputed journals and conferences. Her area of interest includes Programming, Web Services, Image Processing, Ad-Hoc Networks, and Data Analytics.
Email: vmareeswari@vit.ac.in

Dr. Vijayan R is working as Associate Professor at the School of Information Technology and Engineering, VIT, Vellore India. He is a life member of the Computer Society of India (CSI). He has produced several national and international research articles in reputed journals and conferences. His research interest involves Web Technologies, Wireless Networks, Adhoc Networks, Computer Networks, Cloud Computing, and Data Analytics.
Email: rvijayan@vit.ac.in

Dr. Sathiyamoorthy E is working as a Professor at the School of Information Technology and Engineering, VIT, Vellore, India. He received Ph.D. from VIT University, India. His research interests include E-business, software agents, web services, information security, and cloud computing. He has research publications in national, and international journals & conferences. He is serving as an editorial board member for reputed journals. He chaired many International conferences' and delivered invited, technical lectures along with keynote addresses.
Email: esathiyamoorthy@vit.ac.in

Dr. Ephzibah E P received her Ph.D. from mother Teresa Women's University, Kodaikanal, India. She is currently working as an Associate professor in the School of information technology and engineering, VIT, Vellore. She has over 20 years of academic and research experience. Her research area includes Artificial Intelligence, Soft Computing Techniques, Blockchain Technology, Classification, Clustering, and Prediction.
Email: ep.ephzibah@vit.ac.in

Appendix I

S. No.	Abbreviation	Description
1	AI	Artificial Intelligence
2	AIS	Artificial Immune System
3	ANN	Artificial Neural Network
4	AUC	Area Under Curve
5	AUTOMAP	Automated Transform by Manifold Approximation
6	BMI	Body Mass Index
7	CAD	Computer-Aided Diagnosis
8	CEL	Cross-Entropy Loss
9	CF-CNN	Central Focused CNN
10	CMixNet	Customized Mixed Link Network
11	CMR	Cardio-Metabolic Risk
12	CNN	Convolutional Neural Network
13	COVID-19	COronaVIrus Disease-2019
14	CRF	Conditional Random Field algorithm
15	CT	Computed Tomography
16	CXR	Chest X-Ray
17	DBN	Deep Belief Networks
18	DCNN	Deep CNN
19	dMRI	Diffusion-Weighted MRI
20	DNN	Deep Neural Networks
21	EA	Evolutionary Algorithm
22	ELM	Extreme Learning Machine
23	fMRI	Functional-Bold MRI
24	FP	False Positive
25	FPSOCNN	Fuzzy Particle Swarm Optimization Algorithm with CNN
26	GAN	Generative Adversarial Network
27	IEEE	Institute of Electrical and Electronics Engineers
28	IoT	Internet of Things
29	IDRI	Image Database Resource Initiative Dataset
30	KMI	Kupperman Menopause Index
31	KNN	K-Nearest Neighbour
32	KTD	Knowledge Transfer and Distillation
33	LIDC	Lung Image Database Consortium
34	LSTM	Long Short Term Memory
35	LUNA	Lung Nodule Analysis
36	MAE	Mean Absolute Error
37	MDPI	Multidisciplinary Digital Publishing Institute
38	MERS	Middle East Respiratory Syndrome
39	MFDNN	Multi-Channel Feature Deep Neural Network Algorithm to Identify COVID19 Chest X-ray Images
40	MNIST	Modified National Institute of Standards And Technology
41	MR-CNN	Mask R-CNN
42	MRI	Magnetic Resonance Imaging
43	MSE	Mean Squared Error
44	NCBI	National Center for Biotechnology Information
45	QSM	Quantitative Susceptibility Mapping
46	RAN	Residual Attention Network
47	RCNN	Regions with CNN
48	REMBRANT	Repository of Molecular Brain Neoplasia Data
49	RNN	Recurrent Neural Networks
50	ROC	Receiver Operating Characteristic
51	RT-PCR	Reverse Transcription Polymerase Chain Reaction
52	SARS	Severe Acute Respiratory Syndrome
53	SEN	Squeeze-and-Excitation Network
54	SGD	Stochastic Gradient Descent
55	sMRI	Structural Three-Dimension T1-weighted MRI
56	SSAC	Semi-Supervised Adversarial Classification
57	SVM	Support Vector Machine
58	VGG	Visual Geometry Group
59	X-Ray	Electromagnetic Radiation
60	WHO	World Health Organization