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Contents

Advancement of Deep Learning and Its Substantial Impact on the Diagnosis of COVID-19 Cases

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Abstract. A subset of machine learning is called Deep Learning (DL). Due to its intelligent behavior, it is used in various applications like speech recognition, face recognition, detection of an image, Natural Language Processing (NLP), analysis of video images, etc. Medical image processing is one of the significant area where deep learning network performance is proved outstanding. DL is used in image classification, dimensionality reduction, feature learning, detection, etc. The large volume of image data is processed and analyzed to predict disease is absent/present.

In 2019, the COVID-19 virus was detected and started spreading through the community transmission rapidly, and several people lost their lives due to lack of treatment. Almost all hospitals all over the countries were overloaded heavily, and the Medical Health Care System was affected significantly. To fight against such a tough time, many researchers put their efforts day and night into designing effective deep learning models that can accurately speed up the COVID-19 viral diagnosis process.

With this knowledge, a review of various deep learning algorithms and techniques for diagnosing Covid-19 cases is presented in this paper. It starts with the introduction of deep learning, its architecture, and different deep learning algorithms used to diagnose COVID-19 cases with key issues and challenges that significantly impact the detection of COVID-19 cases.

Keywords: Medical image processing · Deep learning · Applications · COVID-19 · Issues · Challenges

1 Introduction

Medical image processing is a broad area of computer vision that has emerged since the 1970s. Then, medical images were represented, stored, and processed digitally. In late 1990, more advanced image analysis approaches changed the way of medical image processing. The introduction of neural networks and machine learning techniques has brought another big revolution in medical image processing. In addition, a variety of optimization algorithms are available, which can help get more accurate results.

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Neural networks are designed to mimic a human brain containing input nodes, called Neurons. These Neurons are then connected to the intermediate nodes (Neurons), connected to the output nodes. These networks are widely used in the visualization of images [1]. The network is initially trained with a set of images to extract features and identify image categories; for example, an X-ray image is with or without pneumonia. Once training is over, the model is ready to identify any X-ray image category. Then, deeper neural networks were used to predict results with more accuracy. The model draws discrete features from the images at each layer as deep inside the model, just like doctors do while examining images like X-Ray to determine the presence/ absence of the diseases. These models are known as Deep Neural Networks. Deep Neural Networks have changed the way of Medical image processing. They are widely used in the detection and classification [2] segmentation retrieval [3, 4] of images. Today, medical image processing focuses on acquiring an image, extracting more detailed features, and improving the accuracy rate of the prediction. Looking at the wide range of existing and new deep learning algorithms, the diagnosis process of COVID-19 cases has been drastically improving. This paper aims to study different deep learning models used to detect COVID-19 and its impact on the diagnosis process. The contents of this paper are organized as follows: Sect. 2 introduces deep learning and its basic architectures with essential features and a brief review of existing deep learning methodologies used in the diagnosis of the COVID-19 cases. Section 3 highlights different challenges in the existing deep learning methodologies and future scope. Finally, in Sect. 4, conclusions are discussed.

2 The Literature Survey

2.1 Deep Learning Architecture with Its Important Features

The deep learning model discovers unique features and a combination of features for building an integrated feature extraction and classification model (Table 1).

Table 1. Basic Deep Learning Architecture with its important features.

Network	Features
Deep forward Neural Network [5]	It has simple and basic deep architecture. All Nodes are connected in the forward direction. A complex nonlinear relation can be modeled more efficiently. The most popular learning strategy used to train this model is back-propagation with gradient descent. Problems like overfitting and vanishing gradient might occur if a network is not trained properly. Use of Regularisation [6], dropout [7], batch normalization, and proper selection of initial values of weights improves Network performance. "The outcome generated by layer i is written as, Xi + 1 = fi (WiXi + bi). weight and bias can be simplified by formula, New = W − η∂E/∂W bnew = b − η∂E/∂b" [8]

(*continued*)

Table 1. (*continued*)

Network	Features
Restricted Boltzmann Machines [5]	It is a Stochastic Artificial Neural Network. It can analyze the enter possibility distribution each in supervised and unsupervised mode. Restricted Boltzmann Machine is a form of Boltzmann machine. The intra-layer link between the units is restricted. Different variants are available Applications: Classification problems [5], Reduction in image dimensions [10, 11], Feature extraction, Creating regression model, Topic modeling, Collaborative filtering
Deep Belief Networks (DBN) [9]	It is a generative graphical model with multiple layers with input observations of hidden features. "Like an RBM model, the top two layers of DBN are undirected. All connections in DBN other than last are directed graphs [4]. A DBN network with L of hidden layers, the combined distribution in its visible layer v, and the hidden layer h can be defined as, where l = 1,2,… L as follows: "$p\left(v, h^1, \ldots, h^L\right) = p\left(v \vert h^1\right)\left(\prod_{l-1}^{L-2} p\left(h^l \vert h^{l+1}\right)\right)p\left(h^{L-1}, h^L\right)$" [8] The network's performance is better since hidden layers of the network can extract some abstract features. Most widely used in the classification problem Applications: Prediction of Failure, Detection of images, Natural Language Comprehension, Retrieval of information
Autoencoders	It is a three-layer neural network with unsupervised machine learning techniques. At the output layer, it reconstructs the input. It follows deterministic distributions instead of stochastic. Issues in the network can be reduced by training each layer of a deep autoencoder as a normal autoencoder using back-propagation. "The equation for coding: $y' = f(wx + b)$, where variable w, b is called weight and bias respectively, which are needed to be adjusted. ***f*** is an activation function, and x is an input vector. Equation for decoding: x' = f(w' y' + c), where w' is the transpose of the weight vector, c is the bias value to the output layer, x' is the reconstructed input defined at the output layer." [30] With multiple hidden layers, a deep autoencoder can be created. When hidden layers are more, then training is more complicated. Different variations in autoencoders are Denoising, Sparse, Variation Auto-Encoder (VAE), Contractive (CAE) Applications: Dimensionality reduction, Information Retrieval, Anomaly detection
Recurrent Neural Network (RNN)	It is derived from a Deep Feedforward Neural network. Outputs generated in the previous step are served as input in the present step. Typically, in a neural network, all the inputs and outputs are not dependent on each other. But for example, when it is required to guess the next word in a sentence, the previous words are essential therefore required to remember them. An RNN is a Neural network that can recall all the information it encounters over time. Such networks can be improved, trained, and extended by adopting a standard back-propagation algorithm known as BPTT (back-propagation through time) [12] Applications: Speech and Handwriting Recognition

(*continued*)

Table 1. (*continued*)

Network	Features
LSTM/GRU Network	LSTM/GRU Network was designed and developed by Hochreiter and Schmidhuber. "A memory unit in LSTM is known as a cell. A cell comprises three ports called gates, responsible for governing the movement of data in and out of a cell. A cell can preserve its value for the required time duration depending on its input. This is how a unit to remember its last value is calculated" [8]. Back-propagation through a time algorithm is adopted in the training process to obtain optimized weights The Gated Recurrent Unit (GRU) has two gates. GRU network can be constructed using a standard RNN with an initial value of the reset gate set to 1 and then updating the gate to 0. Compared to the LSTM, the working of the GRU model is very simple. GRU model has fast learning capability. In terms of execution, it is considered to be more efficient Application: Image captioning, Gesture recognition, Handwriting recognition, Natural language text compression, and Speech recognition [13]
Convolutional Neural Network CNN	It preserves the spatial structure of an image. Therefore, it is extensively used for image/object recognition and classification. In a typical CNN model containing an input layer, hidden layers comprise a stack of connected layers such as conv, pooling, fully connected layers, and an output layer. Image(s) can be given as input in a matrix of pixel values. Earlier hidden layers initially extract the features of an image, such as edges. Later layers recombine the features collected into high-level attributes, and the fully connected layer help in the classification and identification of image output. Back-propagation algorithms are used to train the model efficiently. "Back-propagation with gradient descent [14, 15] is the most widely used learning algorithm while training this model" Applications: Analysis of the Document, face detection, image identification, analysis of video data, parallel processing on GPU, face recognition, pose recognition [6], deep reinforcement, image captioning, re-rendering of the image

Essential characteristics of deep learning models are-

1) Used in wide range of applications
2) It is a neural network with two or more layers, known as a deep Network
3) Higher learning capability
4) Massive datasets are required to enhance results more effectively
5) All desired features are extracted from the input data
6) It performs complex computation tasks with high speed and accuracy without human interference
7) Optimized results are obtained
8) Performance of the deep networks is highly dependent on the structure of a network, activation function, and data representation used while training a model
9) The overall performance of the deep studying version may be stepped forward through hyperparameter tuning

10) It can efficiently process high dimension data like 2D/ 3D images/audio/video
11) The network is not dependent upon labeled data before it is processed.

Survey papers [16–19, 20–23] highlighted different deep learning models and its significance in the era of Medical image processing.

Different classical deep models are designed to perform various tasks in image processing, e.g., LeNet, AlexNet, GoogleNet, VGGNet, R-CNN, YOLO, SSD, SqueezeNet, ResNet, DenseNet SegNet, and DCGAN [16, 17]. Massive size image datasets are used to train such models. Typically, GPUs are designed for such CNN-based applications to get accurate results quickly. Keras [17], caffe2: deployable on CPU/GPU, a popular software platform used to implement deep learning architecture. Torch, Pytorch: It is a Python-based library supported by Facebook's AI Research and powerful cloud platforms. TensorFlow: developed by Google. Paddle (Baidu) (Parallel Distributed Deep Learning): is an efficient, flexible, and extensible deep learning framework. CNTK: The Microsoft Cognitive Toolkit (https://cntk.ai). MXNet (Amazon): Apache MXNet (MXNet) is a deep learning open-source framework. Deep neural networks can be defined, trained, and deployed on various platforms, including cloud infrastructure and mobile devices. Special hardware can be used to speed up training and estimate deep learning workloads. Different specialized hardware platforms are available at low cost to speed up the training of a deep learning model and monitor its behavior. Tensor Cores in NVIDIA's latest Volta GPUs and Google's Tensor Processing Units are examples of GPUs, FPGAs, and ASICs (TPUs).

2.2 Overview of Deep Learning Algorithms in the Diagnosis of COVID-19 Cases

On March 11, 2020, the World Health Organization (WHO) [24] found a new contagious virus called the COVID-19 and declared it a pandemic. It has created a heavy load on the local public health system and forced the entire world into an unavoidable lockdown. To test COVID-19, samples were collected via nasopharyngeal swab, throat swabs, and sputum. In addition, a laboratory-based RTPCR test is performed [25]. As this test is time-consuming, other alternative tools such as X-ray and computed tomography (CT), Ultrasound are also conducted to speed up the line of treatment as the number of patients grew exponentially. A brief review of existing deep learning methodologies used in the diagnosis of the COVID-19 cases is as given below (Table 2):

Table 2. Overview of deep learning algorithms in the diagnosis of COVID-19 cases

Citation	Method/ Framework	Modality	Segmentation technique applied	Feature extraction model	Performance evaluation model	Result obtained	Limitations and recommendations
[26]	ResNet18 with location-attention model	CT	RPN (region proposal Network) used for ROI with a 3D bounding box	VNet with Inception residual	Noisy-OR Bayesian function	Accuracy: 86.7%	Diagnosis of COVID-19 had similarities with other pneumonia-like IAVP
[27]	COVID19 Net (DenseNet), CT	CT with EGFR gene sequencing	COVID-19Net for 3D ROI segmentation	Transfer learning	Multivariate Cox proportional hazard mode, Kaplan–Meier analysis, and log-rank test	ROC score: 0.87 and AUC score: 0.88 obtained from validation sets, respectively	Information like death or date of admission in ICU was not considered. The line of treatment for severe and mild COVID-19 cases is different, so examining the COVID-19 prognosis in these two groups might be beneficial. The thickness of each slice if an image is not uniform. To solve the issue, a generative adversarial network can be used
[28]	ShuffleNet V2	CT	Random cropping operation. Using ShuffleNet V2, segmentation for pixel-level analysis	ShuffleNet V2	95% confidence interval	Avg accuracy: 91.21% AUC: 96.89%	Dataset size was small. More samples can be tested from different hospitals to generalize and make the model more robust and accurate.“ [8]

(*continued*)

Table 2. (*continued*)

Citation	Method/ Framework	Modality	Segmentation technique applied	Feature extraction model	Performance evaluation model	Result obtained	Limitations and recommendations
[29]	U-net, ResNet-50, CT	CT	ROI of lung, lesion detection U-Net for segementation with ROI	Resnet-50 for classification, Grad-cam visualization technique for o/p	Positive ratio with threshold, volumetric network-activation maps to get corona infection score	Accuracy: 99.6% sensitivity:98.2%, specificity:92.2%	Progress and regression of outcomes could be checked more statistically and consistently. For screening and early detection, more advanced tools can be used
[30]	Multimodal Network	CT, X-Ray		MobileNet, Xception, DenseNet, InceptionV3, VGGNet,InceptionResNetV2, ResNet, NASNet with transfer learning	AdaBoost, Decision Tree, XGBoost, Bagging tree, LightGBM [23].bagging tree	DENSENET-121 with bagging tree outperformed with accuracy:99.00%	Select proper deep feature extraction method in CNN
[31]	DenseNet201 VGG16, ResNet152V2 and Inception-ResNetV2	CT	DenseNet201 based deep transfer learning			Accuracy using DenSENet-121: 97% AUC = 97%	Combination of deep learning and feature extraction techniques like color, texture, form, meta-heuristic algorithms, and picture filters. A larger dataset and a more complex feature extraction algorithm can improve performance
[32]	A 3-D CNN	CT	Automatic segmentation and quantification of the lung area using VB-Net	Combining cross-channel features via convolution method	Dice similarity coefficient, percentage of infection calculation	A human-in-the-loop (HITL) to enhance automatic annotation accuracy 91.6% ± 10.0%	suffers from hyperparameters tuning issue

(*continued*)

Table 2. (*continued*)

Citation	Method/ Framework	Modality	Segmentation technique applied	Feature extraction model	Performance evaluation model	Result obtained	Limitations and recommendations
[33]	Multi-task deep learning model, pre-trained Networks,	CT, X-ray	Inception-v3	Inception-v3, DeepLab-v3 + for ROI	Multi- label classifier,	Dice similarity coefficient, mean Intersection over Union reconstruction. Multi-tasking reduces overfitting and improves results accuracy by 94.67%	Insufficient data with poor annotation information. Because the databases are from different sources, variations in images and sometimes are noisy. U-NET and other classification models can improve the model's performance even if annotated data are limited
[34]	DeCoVNet, CT	CT	UNet; generate 3D lung mask without having annotated lesions	DeCoVNet	progressive classifier	ROC AUC:95.%9 PR: AUC:97.6% Sensitivity:90.7% specificity:91.1%	3D image segmentation with detailed annotated images by radiologists improves segmentation quality. Dataset is from a single hospital; therefore, the result cannot be generalized due to a lack of cross-center validations. AI experts can refer to automatic machine learning (AutoML)
[35]	ResNet18, ResNet50, ResNet101, & SqueezeNet, CT	CT	Stationary wavelet 2 stage method, abnormality localization	ResNet18, ResNet50, ResNet101, & SqueezeNet, CT	Transfer learning	ResNet18 proved best model with Sensitivity:99.4%, Specificity: 98.6%, AUC:.99.65%	Fast and exact recognition of COVID-19 infection A large volume of COVID-19 positive CT scans of patients is needed to train the model

(*continued*)

Table 2. (*continued*)

Citation	Method/ Framework	Modality	Segmentation technique applied	Feature extraction model	Performance evaluation model	Result obtained	Limitations and recommendations
[14]	AD3D-MIL	CT	Outperformed in the classification of images even with weak labels semantically generate deep 3D instances	AD3D-MIL,	Cohen kappa metric	Accuracy:97.9%, AUC: 99.0%, Cohen kappa metrics: 95.7%	Weakly supervised method Using advanced image processing algorithms can reduce the time of the processing
[36]	Weakly supervised deep learning framework, CT	CT	Multiview U-Net for detecting different lesions Fixed-size sliding window method to minimize data bias problem	Multiview U-Net, integrated gradient method to extract accurate features	categorical-specific saliency maps to highlight multiple lesions obtained from gradient value of prediction,		Difficult to discriminate between the CAP (community-acquired pneumonia) from COVID-19. Individual image slices input in training that could add noises in training. Higher backbone design, similar to ResNet and Inception, might help. No patient-wise CT images were set in the training stage un-infected CT image slices need to identify before training enhance results
[37]	AlxNet DeTraC deep CNN	X-Ray	DeTraC-ResNet-18 deep CNN Transfer learning with ResNet	AlexNet, Class composition method to enhance classification	K-means clustering,	Accuracy:95.12% sensitivity:97.91% specificity: 91.87%	ImageNet parameters may not be well suited for X-ray images

(*continued*)

Table 2. (*continued*)

Citation	Method/ Framework	Modality	Segmentation technique applied	Feature extraction model	Performance evaluation model	Result obtained	Limitations and recommendations
[39]	Pertained networks,	CT	AlexNet, GoogleNet, VGG-16, SqueezeNet,VGG-19, ResNet-18, ResNet-50, MobileNet-V2, ResNet-101, Xception	high spatial resolution method for image reconstruction	Kolmogorov-Smirnov testing for normal value distribution. *t*-test and chi-square test, for gender, age distribution	ResNet-101 outperformed AUC:99.4%	Demographic information is also considered in the detection process Lengthy & costly process
[40]	VGG19, Cascade-SEMEnet (ResNet50, SEME-DenseNet169	X-ray	U-Net: for Feature extraction SEME-ResNet50 for classification SEME-DenseNet169 for detailed classification	CLAHE, MoEx, and histogram equalization to improve image quality hash trac, K-means clustering	Grad-CAM visualization tool, Squeeze-Excitation method for accuracy improvement	AUC:99.6, F1-score: 97%	Dataset size is small
[41]	Transfer learning	X-ray	Inception-v3, Inception ResNet-v2,NASNetLarge,. DenseNet-169 Reinforcement learning	Random oversampling,	weighted class loss function to balance no. of images	NasaNetLarge outperformed Accuracy: 98% AUC:99%	Three datasets are used [41, 42] More advanced Pre-processing techniques may help to get better results
[43]	Transfer learning	X-ray	AlexNet, modified CNN	Transfer learning	imageNet parameters and random parameters	Sensitivity for x-ray 100% for CT 92% accuracy: Pre-trained Net 98% Modified CNN 94.1%	5 different datasets [38] The data size used is limited; the same feature extraction method is used for both modalities
[44]	VGG-16, X-ray		Bounding box around infection, histogram equalization for image enhancement	transfer Learning using VGG16	Object Detection using CLAHE	Sensitivity: 94.92%, specificity:92.00%	The transfer learning method is used

3 Discussion

3.1 Challenges

Corona virus is a contagious disease that spreads worldwide very rapidly and impacts human life and the medical health system very severely. Deep learning models play an essential role in the diagnosis of patients rapidly with great accuracy. While doing so, researchers face many challenges like dataset availability, design architecture, algorithm, hyper parameters, cost, the time required to train model, accuracy, platform available, etc. The fundamental challenges and their significant impact on the detection of COVID-19 cases are:

- Lack of uniform dataset: Different Researchers have used datasets available from different modalities like CT, X-ray, and Ultrasound. So the result obtained cannot be generalized.
- Size of dataset: Huge size datasets are one of the most significant ingredients in training the Deep learning network. The amount of the dataset used to train the model significantly impacts its accuracy.
- Dataset availability: Most of the datasets are private, and images need to be annotated by the radiologist, which is time-consuming, especially when COVID-19 is at its peak level.
- Advanced models: Using more advanced models like the weakly supervised method, a dataset with poor annotation or without annotation can also be used to train the model effectively.
- Pre-trained models: No pre-trained models like Resnet, VGG, etc., are specifically available for medical image processing.

3.2 Open Research Areas

Deep learning models help effectively diagnose other medical emergencies like tumor detection and identify infections in the different parts of the body quickly. However, more research, good architecture with hyperparameter tuning, modern image pre-processing algorithms probably contribute more to the enhancement of accuracy and efficiency of the model.

4 Conclusion and Future Scope

An overview of different deep learning models in the detection of COVID-19 has been provided in this study. Undoubtedly, DL models excel in diagnosing COVID-19 detection, and their impact on diagnostic outcomes has been growing significantly.

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