Predicting COVID-19 Using Deep Learning: A Comparative Study

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In 2020, WHO declared COVID-19, an infectious disease caused by SARS-CoV-2 virus as a global pandemic. With the increase in COVID-19 cases worldwide, it becomes very crucial to control and manage the spread of the virus. The disruption caused by the virus has impacted the lives of many people and affected various sectors beyond repair. Applications of Deep Learning Machine Learning can be used to detect various diseases including COVID-19. This study reviews recent studies on various machine learning applications for the detection of COVID-19 via CT and CXR images. This study consists of extensive research of 60 articles. Various aspects which include dataset preparation, feature extraction, classification algorithms, and model evaluation have been discussed in this study. Various ImageNet algorithms such as ResNet, VGG, AlexNet are discussed in literature review of this study. Some of the studies used techniques such as transfer learning and Support Vector Machines for classification purposes. It was found that Convolution Neural Networks (CNN) and Transfer Learning were the most used techniques. Many studies describe how overfitting and gradient vanishing problems can be avoided in a model. For model evaluation, various metrics such as accuracy, recall, specificity, precision, F1-Score, ROC curve, and cross-validation are used by many studies. All these studies conclude that the application of Deep Learning for early detection of COVID-19 can be a significant tool for the healthcare domain. Moreover, these techniques can save the time of radiologists in detecting the disease and necessary measures can be taken for the people diagnosed with COVID-19 quickly and effectively. Therefore, applications of these methods may prove effective in detecting the diseases in early stages thus saving time, cost, and lives, hence proving beneficial to mankind.

Keywords: Automated detection, Convolutional Neural Networks, COVID-19, Deep Learning, Diagnosis, Machine Learning, Medical imaging.

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1 Introduction

COVID-19(coronavirus disease 2019) caused by a SARS-CoV-2 virus was discovered in 2019 in Wuhan, China and declared a global pandemic by the WHO on February 11, 2020. This disease is highly contagious and has spread across the world. Therefore, detection of this disease becomes vital. This disease affects humans lethally causing death in serious cases. At the time of this writing, there are 340 billion COVID cases confirmed and 5 billion deaths due to COVID-19 reported by https://covid19.who.int/. Figure 1 shows a graph of the number of COVID-19 cases. The healthcare and research sectors must give this epidemic their full focus due to the rising death toll and economic implications [1]. The most common symptoms are fever, cough, loss of taste and smell, and fatigue. Less common symptoms include sore throat, headache, diarrhea, aches, and red or irritated eyes. Other serious symptoms include shortness of breath, loss of speech or mobility, and chest pain. On average, it takes 5-6 days for the symptoms to appear. This virus can affect people differently according to the age group and health conditions of the person. It was observed that people above 60 were severely affected by this disease, especially those above 80 years of age. Moreover, people suffering from diabetes, heart disease, or any other chronic disease are more prone to infection. In very severe situations it can lead to hospitalization even in young and middle-aged people. So, it becomes very important to take necessary measures at an early stage to avoid further complications in this disease. However, the increased number of COVID-19 cases places a significant burden on radiologists and clinicians, compelling researchers to investigate automated computer-aided systems for COVID-19 classification.

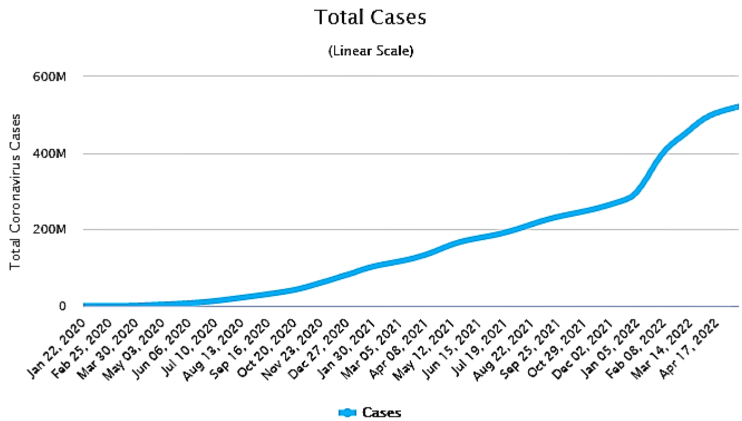

Fig. 1. Statistics of Coronavirus cases as of April 2022 [61]

There are various methods of detecting COVID-19 amongst which the primary method is the nucleic acid reagent test or RT-PCR test. This test is time-consuming as depending on the laboratory the results may take 3-4 hours, 1 or 2 days, or even a week in certain scenarios. Also, there are chances of false positives in this test. These tests do not always provide accurate results. Another method for detection of COVID is Chest X-Ray images (CXR). Although it is a quick and simple method to identify COVID-19, it is less effective in the early stages of the illness. Even before symptoms manifest, a chest CT scan is helpful because it can accurately identify any abnormal features in the images [2]. Recent research into the sensitivity of non-contrast chest CT has revealed that a reliable and long-lasting strategy for identifying disease features in CT is to identify focal or diffuse ground-glass opacities [3]. Furthermore, owing to the availability of radiology imaging systems and CT imaging systems in hospitals, these detection systems are a viable option to the COVID-19 testing kit shortage [4].

AI's effectiveness and advantages in healthcare have been proved numerous times [5]. AI has been used in various healthcare domains to improvise performance and automate the detection of many diseases. Global healthcare systems have developed in various different areas to improve the rates of diagnosis and detection with the prime aim of being minimally invasive [6]. Such computer-aided systems have been developed for various applications in the medical domain like detecting brain tumors, lung cancer, Alzheimer’s disease, Parkinson’s disease etc.

Moreover, these techniques can act as a second opinion for the clinicians’ identification of diseases. Deep Learning (DL), a component of machine learning systems, is primarily focused on automatically extracting and classifying image features [4]. Deep Learning models can interpret medical images like X-rays, CT scans, MRI images to perform diagnosis. Such deep learning models can be proposed to automate COVID-19 detection and provide positive results. With the prompt referral of patients to care facilities and quarantine, non-contact automated diagnosis technologies may prove to be a crucial instrument in restricting the viral transmission (even among healthcare staff) [6]. As only those patients can be referred for viral nucleic tests that test positive with these models, this could reduce the number of RT-PCR tests needed [6]. A large amount of dataset is publicly available for these imaging systems which can be useful while designing such automated systems using deep learning. In recent studies, Convolutional Neural Networks (CNNs) are widely used for image classification. A CNN is a neural network based on convolutional layers. It can have one or more convolutional layers that are utilized for feature extraction, classification, and picture segmentation. Rich and discriminative features can be extracted from the images using CNN. These techniques can prove to be beneficial in terms of better accuracy and resource utilization. In this regard, this study has presented various state of art deep learning techniques which can be used for automated detection of COVID-19 disease.

2 Datasets

This section gives an overview of the popular datasets used by the studies in the Literature Review for Predicting COVID-19. Table 1 gives a detailed analysis of the datasets used by the studies along with the number of images, imaging method and special note about the dataset.

Table 1. Common datasets used in various studies.

Datasets	Number of images	Imaging method used	Special Note about dataset
Kaggle, Mendeley, Italian Society of Medical and Interventional Radiology (ISMIR), Radiopaedia [7]	It has total 400 images, 1000 of each type (Bacterial, Viral, Normal and COVID-19)	X- Ray images	Data augmentation techniques like random rotation, random reflection, random shear is applied, and images are resized in 299 x 299 pixels.
NCBI nucleotide website [8]	The dataset consists of 1261 SARS-COV-2, 4699 SARS, and 136 MERS sequences.	Sequences are in FASTA format.	These sequences were further converted into polynomial datasets with 30000 attributes.
Zhongnan Hospital Wuhan University(ZH	It contains a total of 2000 images.	CT images.	Normalization of images into a range from 0 to 255 and conversion into PNG format of 512 x 512.

WU), ISMIR [9]			
Royal Melbourne Hospital [10]	Images of 70 patients.	Lung Ultrasound (LUS) images.	LUS videos were acquired at six anatomical zones.
Italian COVID-19 Lung Ultrasound Database (ICLUS-DB) [11]	60 videos from 29 patients.	LUS videos.	Out of these 60 videos, 39 were from convex probes and 21 from linear probes.
Montgomery County and Shenzhen No. 3 People's Hospital, dataset released by Kerman, GitHub [12]	1840, 433, 394, 2780 and 1345 images belong to normal, COVID-19, TB, BP and VP classes respectively.	CXR images.	Pre-processing and data augmentation (shifting, scaling, and rotating) and post-processing is performed (filling holes, removing small objects).
MosMedData [13]	1110 images.	CT images.	Due to imbalance data random oversampling and random under sampling is performed.
MedSeg-29 [14]	2 public datasets, first containing 9 volumetric CT scans, second containing 20 volumetric CT scans.	Annotated volumetric CT scans.	Images were converted from JPG to Nifti format and infections are segmented and evaluated by radiologists.
LUNA16 [14]	888 annotated 3D thoracic CT scans.	3D CT scans.	Lung nodules were annotated by 4 radiologists. 7 cases containing broken lung masks and noisy scans were excluded.
Massachusetts General Hospital, Boston, Massachusetts [15]	2448 reports.	CT reports.	Data augmentation and removal of duplicate reports was performed to obtain these 2448 CT reports.

Fig. 2. Concept map for COVID-19 prediction.

3 COVID-19 detection techniques

There are two techniques that are commonly used for prediction of COVID-19: Machine Learning and Deep Learning. Figure 2 shows a concept map of Datasets, Machine Learning and Deep Learning Techniques, Hardware, Software and Evaluation parameters used for COVID-19 detection and this section gives a detailed overview of these techniques.

3.1 Machine Learning techniques for COVID-19 detection

Decision Trees: A supervised machine learning system called a decision tree continuously splits data based on predetermined criteria [16]. The topmost node is the root node, each node represents an attribute test, the branches display the test results, and the leaf node represents the overall results, or the target class labels. In this way, decision trees give information about important parameters for prediction. Decision trees have the capability of handling high dimensional data, and they provide a good accuracy in general.

Naïve Bayes: Naive Bayes classifiers are a collection of supervised Machine Learning algorithms based on Bayes theorem for classification problems. It predicts on the ground of probability of objects which defines it as a probabilistic classifier. The assumption in Naive Bayes is that each data item is having a set of attributes and all the attributes are independent of each other, therefore each attribute is going to contribute for classification. It is a simple and productive Machine Learning algorithm which helps in making robust and quick classifications.

Random Fores: Random forests [17] are ensemble based techniques that use multiple decision trees instead of a single tree for prediction. It is based on bagging(Bootstrap and Aggregation) and provides the means of the classes of all the trees as an output [18]. Randomly sample subsets of input features are used for the construction of classification trees in random forest [19]. Sample datasets for every model are formed by performing random row sampling and feature sampling. Random forests generally perform better than decision trees as they do not rely on a single tree for prediction.

Support Vector Machine: SVM [18] is a non-probabilistic supervised Machine Learning linear classifier [3]. It finds a hyper-plane dividing different categories of data. The dimension of this hyper-plane is selected depending on the number of features so if there are only two features, the hyper-plane is a line and if there are 3 features, the hyper-plane is a 2D plane and so on. As the number of features increases, it becomes difficult to apply SVM for classification. SVM can only be used for binary classification except for certain techniques that can be used for multi-class classification.

K-Nearest Neighbors: A supervised machine learning technique called K-Nearest Neighbors bases its operation on similarities between data. The K-NN algorithm places new data points in the most relevant category depending on the categories that are currently available by comparing new data points to existing data points. It determines how far away that data point is from training samples and makes a prediction about the class to which it belongs based on k of the closest data points [16]. It does not make any assumption on underlying data; therefore, it is a non-parametric algorithm. It can be used both for regression and classification, but it is more suitable in classification problems.

Logistic Regression: Logistic Regression is a supervised Machine Learning algorithm of a generalized linear model class. It is a regression algorithm which does classification. It takes features and labels from the training data and instead of giving the result it gives the logistic of the result. It determines the likelihood that a class will contain members and provides values between 0 and 1. Logistic Regression models assume the data flow to be a sigmoid function just like Linear Regression assumes to be Linear function.

XGBoost: XGBoost [20], an iterative ensemble learning method based on boosting turns poor learners into strong learners [20][21]. Creation of the decision tree in this algorithm is in sequential form and an important role is played by weights which are assigned to the independent variables. These independent variables are fed into the decision tree to predict results. If the predicted weights are wrong, then weights are increased and fed to the second decision tree. This increases the performance DT classifiers and introduction of regularization parameters reduces the overfitting [16].

3.2 Deep Learning techniques for COVID-19 detection

Convolutional Neural Networks: Convolutional Neural Networks(CNNs) [22][23] is an artificial neural network that consists of several layers, each layer having neurons which function similar to human brain neurons. CNN is the backbone of most of the deep learning algorithms used for image segmentation. Convolutional neural networks (CNNs)-based deep learning techniques have shown to be effective for a variety of computer vision applications in the field of medical imaging [6]. CNNs can be used for various tasks like feature extraction, image classification, image segmentation and signal processing. CNN's primary advantage is that it identifies key features automatically and without human involvement [24]. The Convolutional Layer, which has numerous kernels and each neuron acting as a kernel, is the fundamental component of CNN. By using convolution, various kernels and filters can manipulate images in ways including edge detection, blurring, and sharpening [25]. In this layer filters are applied to the original image for feature extraction. Another is the pooling layer, which is typically sandwiched between two subsequent convolutional layers to reduce the size of the feature map while preserving crucial features. This reduces the computational load and memory usage when the size of the input images is very large, limits the risk of overfitting, and helps to limit the likelihood of overfitting.

Activation function is used in CNN as it defines how the weighted sum of input is transformed into output and learns intricate patterns. The performance of the model is highly dependent on the choice of activation function. Currently, the most used activation function is ReLU, and it is used in almost all the CNNs across the world. Batch normalization layer is used because every layer in the network does learning more independently that helps in normalizing outputs of the previous layer. It also increases the pace of deep learning processes with the help of covariance shift. Covariance shift is the shift in distribution of input data between training environment and actual environment. Dropout proposed by Hinton [26] is a regularization technique that ignores randomly chosen neurons during training. Dropout works by "turning off" some neurons with a probability "1 – p", and using only the reduced network helps to minimize overfitting and hence generalization error[27]. The fully connected layer makes use of the high-level characteristics that the convolutional or pooling layers produce from the data. The input images are classified into various groups based on the dataset with the help of fully connected layers. Unpooling layer is employed to capture example specific structures by returning to image space from the original places with strong activations. This helps in effectively reconstructing the detailed structure. The convolutional operation at a point (x, y) in the image can be given as:

$$O(x,y) = I(x,y) * f(x,y) = \sum_n \sum_m I(n,m) f(x-n, y-m) \quad (1)$$

Where I is the input image, f is the filter and O is the output feature map. Figure 3 shows the working of a Basic CNN architecture.

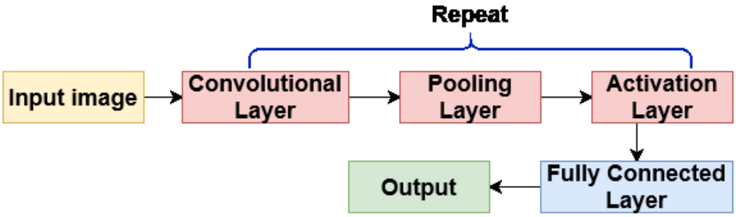

Fig. 3. Basic CNN architecture.

3.3 Innovation in CNN architecture: The various innovations made in CNN architecture are listed below

AlexNet: *AlexNet [28]* one of the deep neural networks that has been used to classify images [27]. Hinton and Alex Krizhevsky, champions of the 2012 ImageNet competition, created AlexNet [29]. Five convolutional layers and three dense layers with various kernel sizes make up its architecture. The kernel size of the first layer is 11 x 11 and that of the second layer is 5 x 5. The kernel size of layers three to five each is 3 x 3. ReLU is the activation function that is used after each fully connected and convolutional layer. For overfitting, AlexNet uses dropout as opposed to regularization [27].

VGG (Visual Geometric Group): VGG is a deep neural network which can be used for tasks like object detection and feature extraction. The first and original model of VGG is VGG-16 [30] which has 16 layers, 13 convolutional layers and 3 dense layers. The training of VGG-16 was done on 14 million images corresponding to 1000 categories [31]. The kernel size of convolutional layers is 3 x 3 and that of the dense layers is 3 x 3. This low kernel size of VGG-16 makes it different from AlexNet. VGG-19 is an advanced and in-depth version of VGG-16 which has 19 layers consisting of 16 Convolutional layers, 3 fully connected layers, 5 MaxPool layers and 1 SoftMax layer.

GoogleNet (Inception-V1): GoogleNet [32], the winner of ILSRVRC 2014, is an architecture different from others in terms of computational efficiency. It consists of features like 1 x 1 convolutional layers to decrease the number of parameters, Global Average Pooling which averages the 7 x 7 feature map to 1 x 1. This improves the performance of the model.

Inception-V3: The third version of GoogleNet is Inception-v3 [33]. Its architecture contains 48 layers [7]. The training of architecture is on the ImageNet repository consisting of more than million images [33]. The architecture has the capability of classifying images into 1000 categories [7]. The architecture of Inception V3 is like that of Inception V2 with some changes like introduction of RMSprop optimizer in the architectures, 7 x 7 factored convolution, Label smoothing regularization and application of Batch Normalization in fully connected layer of auxiliary classifier.

ResNet: ResNet [34] architecture consists of a convolutional layer for feature extraction and a pooling layer for feature processing [29].ResNet was designed to solve the vanishing/exploding gradient problem which was faced by many deep learning models. The idea of ResNet is to use a technique called skip connection which skips the training from certain layers and redirects to the output. This allows the layers to learn residual mapping instead of underlying mapping. The advantage of using skip connection is that if a certain layer is hindering the performance of the model, it can be skipped by regularization.

MobileNet: MobileNet [35] is a lightweight model with few parameters which gives better performance on a real-time basis due to fast inference power [36].MobileNet architecture uses the concept of Depth convolution and Point convolution which makes it different from the normal CNNs. Another unique features of MobileNet are smaller neural networks, low latency, low computational cost which makes it a robust architecture with higher accuracy [25].

DenseNet: DenseNet [37] was built by extending the architecture of ResNet with the help of concatenation as cross-layer connections and by making every layer densely connected to the previous layer in those connections [37].The main advantage of DenseNet networks is that they are essentially feed-forward networks [24]. They reduce the number of parameters by intensifying feature propagation and stimulating feature extraction. DenseNet is a lightweight model which enhances the network's capacity is feature reusing, resulting in extremely compact versions [24].

SqueezeNet: SqueezeNet [38][39] is a CNN consisting of 68 layers which includes two convolutional layers, eight fire modules(fire2-fire9), two max pooling layers, one global average pooling layer and last SoftMax layer [4]. A squeeze convolutional layer is a layer which has only 1 x 1 filter. A fire module consists of a squeeze convolution layer that feeds in an expand layer. Expand layer is the layer which consists of a mixture of 1 x 1 and 3 x 3 convolutional filters. SqueezeNet can perform 3 x faster and 500 x smaller than AlexNet which reduces the depth of the model and improves their performance.

3.4 Strategies for Training Deep Learning Models: The common strategies for training Deep Learning models are

Transfer Learning: Transfer Learning is a machine learning technique that applies the knowledge discovered while resolving one problem to another that is related to it. It is mainly used in CNN techniques where it is not possible to train the entire model from scratch due to small size of dataset and with the help of Transfer Learning it can be trained with less data along with speeding up the training time. Also, when the neural network is having large numbers of parameters or collected samples are very less, using Transfer Learning the model can be adjusted with fewer training data [40].Transfer Learning can be performed in two ways. First method is using the technique as a feature extractor, in which a pre-trained model is used as a feature extractor to handle the CNN [25]. Here both the learned parameters and the model architecture is retained from the pre-trained model [6]. The second method includes modification in the model or fine-tuning, in which the last Fully Connected layer is replaced by a new fine-tuned layer. Other blocks can also be replaced by new fine-tuned layers to improve the performance. Backpropagation is allowed only up to FC layers and the Convolutional Layers are frozen for preserving the rich filters learned by the Conv layers [6].

Ensemble Learning: Ensemble Learning is a technique applied on classification tasks in which features from various Deep Learning models are fused to obtain a high-grade classifier, improving the performance [7]. Ensemble Learning techniques mostly consist of bagging, boosting, and stacking. These techniques can be divided into two types. First is the heterogeneous classifier in which each different learning algorithm is applied to the same dataset. Another is the homogeneous classifier where the same learning algorithm is applied to different datasets. The advantage of using ensembles is that it leverages the information from various classifiers and combines them to produce a robust model.

4 Related Work

The diagnosis and treatment has been made easier with the help of modern technologies [41]. Disease diagnosis tasks have been made more accurate with the help of large datasets and successful Deep Learning techniques available [41]. This section highlights the work done by various researchers and groups in the field and Machine Learning and Deep Learning for detection of COVID-19.

Authors in paper [42] proposed a modified MobileNet and ResNet for classification of COVID-19 using CXR and CT images respectively to solve the problem of overfitting and gradient vanishing. The modification made in the MobileNet and ResNet model which predicts COVID-19 using CXR and CT images is that a point-wise convolutional block is used to process the outputs from the first four blocks of the original model to minimize the dimension and a dropout layer is introduced after the added outputs from the previous layer which reduces the input dimensions by global average pooling and solves the overfitting problem. On the five-category CXR image dataset, the approach achieved test accuracy of 99.6%, and on the CT image dataset, test accuracy of 99.3%.

F. Ahmad et al. [7] introduced an ensemble method for detection of COVID-19 using CXR images. Images are resized split into training and testing sets followed by data augmentation. Two best deep learning models (MobileNetV2, InceptionV3) are chosen and merged using ensemble learning. Dense and dropout layers are added to overcome the problem of overfitting along with fine tuning which improves the model's performance. Dataset consists of bacterial, viral, COVID-19 and normal images. J.F Hemandez Santa Cruz et al. [5] proposed a model for the detection of COVID-19 with the help of CT images by using transfer learning and ensemble techniques for training artificial neural networks. The accuracy of the model was 86.86%, an F1 score of 85.86% and an AUC of 90.82%. Authors in paper [43] proposed a Bag-Of-Feature ensemble model for the classification of COVID patients and normal patients using the algorithms linear SVM and cosine KNN. Best performance is observed using the ensemble subspace discriminant model with 200 visual words having an accuracy, sensitivity, and precision of 98.6%, 99.4% and 97.7% respectively.

Authors in paper [44] aim on prediction of COVID-19 and severity based on machine learning models. Two methods were used: (i) Principal Component Analysis (PCA) (ii) k-means cluster analysis. The outliers were removed using a graphical method of leverage versus student residuals. Four ML algorithms were applied: Artificial Neural Networks, Decision Tree, k-nearest Neighbors, discriminant analysis by partial least squares. The model evaluation was done using sensitivity, specificity, and accuracy. ANN was the model with the best performance having an accuracy of 94%.

A CNN based method for distinguishing between three different classes of viruses i.e. SARS-COV-2, MERS and SARS was proposed by [8] in which genomic and protein sequences of these viruses are converted into polynomial and binary image datasets. The final nucleotide sequence was selected by most attribute weighted models. The three coronaviridae virus members could be classified with 100% accuracy due to machine learning methods.

W. Li et al. [9] proposed a method which focuses not only on the important details of an image but on every small pixel to detect minor symptoms of COVID using CT images. To build a new model and to extract discriminative representations from CT images from both source (limited labeled images) and target domains (unlabeled images), a Network in Network and Instance Normalization is used. To implement infected region adaptation from source domain to target domain in an Adversarial Learning manner, a domain classifier is utilized. This model achieves an accuracy of 96.85%, Sensitivity of 94.2% and Specificity of 99.5%.

A CNN based model was proposed by the authors of paper [45]]to predict whether a cartilage defect is present or not using MRI images. Here three networks were proposed, first (CNN-1) was trained on sagittal and coronal view of MRI images. Second (CNN-2) was trained on images of sagittal views, third (CNN-3) was trained on images of coronal views. Xception CNN architecture was used to train CNN-2 and CNN-3. Then CNN-1 was trained using SVM to combine both architectures. The accuracy of CNN-1, CNN-2 and CNN-3 were 89.66%, 79.31% and 82.76% respectively.

Authors in paper [46] proposed a method for identifying COVID-19 with the help of CT images. After training the database, it is tested, the noise removal step is applied, and then gray level co-occurrence (GLCM) is used to extract features. Total 10 features are extracted from each GLCM matrix. The accuracy of the model is 94% for detecting the infection and location of the infection. Another CNN based method for diagnosing COVID-19 using CT images was proposed in paper [47] where VGG16 was used as the backbone in which attention modules(Pyramid Convolution module(PCM), Multi-reception Spatial attention block(SAB), Multi-receptive Channel attention Block(CAB)) were added before each pooling layer. The model provided accuracy rate of 97.12%, specificity of 96.89%, and sensitivity of 97.21%.Authors in paper[16] proposed a bi-level COVID detection method unlike the state-of-art detection methods.VGG19 and Transfer Learning is used for feature extraction. For the classification step, the first level classified the images into normal or infected and the second step classified infected images as COVID and Pneumonia using Logistic Regression and XGBoost respectively. The proposed model gave an accuracy of 99.26%.

A CNN based model was built in paper [48] for predicting COVID-19 using X-Ray images where data augmentation was applied and GRAD-CAM was used to determine the importance of each channel with respect to the target class. The accuracy obtained in this model was 98% and a training accuracy of 96% at the end of 15th epoch. ReLU was used to maintain the features that had a favorable impact on the final map. S. Chakraborty and K. Mali[49] proposed a framework to segment the radiological images(CT images, Chest X Ray). This can help in quickly screening the suspected patients of COVID positive and negative cases.

I.Shiri et al. [50] proposed a method to predict survival in COVID-19 patients using CT images. Feature extraction was performed using PyRadiomics. To understand the prognostic importance of each feature, univariate and multivariate machine learning analysis was performed, and multivariate analysis provided better information about features and in that lung+lesion+clinical had the highest AUC, Accuracy, sensitivity, specificity. Bootstrap techniques were used for XGBoost hyperparameters tuning implemented with 1000 repetitions. The model was able to locate the best features which could provide better results. Authors of paper [51] presented a morality prediction model of hospitalized COVID-19 patients based on lung densitometry. Univariate Logistic Regression (ULR) was carried out with patients having $p<0.2$ and then Multivariate Logistic Regression was carried out (MLR) and final model variables were found. It was found that CT_model and COMB_model performed better than other two models.

A. Oulefki, S. Agaian, T. Trongtirakul et al. [52] invented a new image contrast algorithm using linear and logarithmic stiching parametric algorithms for automatic COVID-19 measurement and segmentation using CT images. This work can quantify COVID-19 lesion, visualize infected area, track disease changes along with detecting abnormal regions with low intensity contrast between lesion and healthy tissues. The statistical measures' means that were calculated using the accuracy, sensitivity, F-measure, precision, MCC, Dice, Jacquard, and specificity were 0.98, 0.73, 0.71, 0.73, 0.71, 0.71, 0.57, 0.99 respectively. Authors in paper [53] studied the patterns of the changes in detection of Acute abdominal pathology. To classify the presence of acute appendicitis (AA), acute diverticulitis (AD), or bowel obstruction (BO), a random forest model was used, and 5-fold cross validation was used for performance assessing. Even decreasing significantly in the case of acute appendicitis, acute abdominal pathologies did not increase, which shows that patients put off getting treatment during the COVID-19 pandemic's initial peak.

A thorough study was conducted and analysis was done which has been summarized across parameters as mentioned in Table 2, which gives a completed overview on the methodology used, application, Dataset used and Results of the study.

Table 2. Literature Review

Deep Learning Method	Application	Dataset used	Results
Transfer Learning + CNN(Inception-v3, Multi-Layer Perceptron) [54]	Detecting COVID-19 using breathing sounds, CXR image and Rapid Antigen Test (RAnT)	Publicly available	Accuracy-80% (Breathing sound analysis), Accuracy-99.66% (CXR dataset).
CNN(feature extraction) + Spatial Transformer Network(ML) [10]	Detecting Pleural Effusion using LUS (frame based, video based)	Royal Melbourne Hospital	Accuracy-99.97% (Frame based),Accuracy-99.93%(Video based), F1-Score-99.98%
K-Means(feature extraction) + SVM(classification) [55]	COVID-19 prediction using CXR images.	Publicly available.	Accuracy-99.34%.

DenseNet(features) + SVM, XGB, RFC(classification) [19]	COVID-19 and severity prediction using CT images.	Publicly available.	Precision Recall-0.99, F1-Score-1.00, ROC-1.00.
Transfer Learning + CheXNet [56]	Predicting COVID-19 on CT images using small-sized dataset.	COVID-CT-Dataset [57]	Accuracy-87%, F1-Score - 0.86.
RestNet-50 [58]	Diagnosis of COVID-19 using 3D CT scans.	Mosmed-1110 + CCAP datasets.	AUC-96%.
DenseNet_169 + Generative Adversarial Network(GAN) [59]	COVID-19 Chest CT image analysis	Publicly available CT dataset + LUNA16 (Lung cancer)	Accuracy - 98.09%, Recall - 97.80%, Precision - 97.37%, F1-Score - 97.92%.
3D UNet++(classification) + RestNet-50(segmentation) [60]	COVID-19 prediction using CT images.	5 hospitals in Wuhan.	Sensitivity - 0.974, specificity - 0.922.
CNN Model + GRAD CAM [48]	COVID-19 detection using CT + CXR images	Kaggle + Open source dataset by Dr. Joeph Paul	Accuracy – 98%
VGG16 + GRAD CAM [47]	COVID-19 detection using CT images	DTDB dataset provided by the Beijing Ditan Hospital Capital Medical University	Accuracy - 97.12%, specificity - 96.89%, sensitivity - 97.21%.

5 Evaluation Parameters

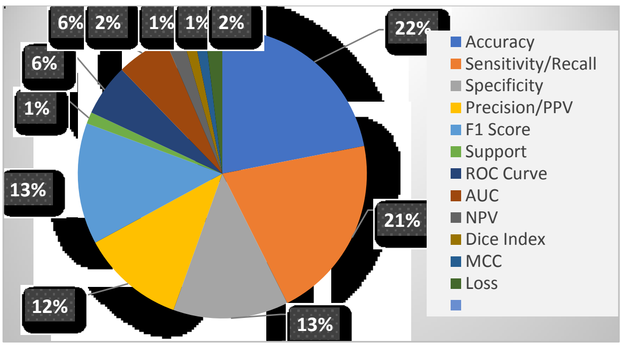

Fig. 4. Summary of evaluation parameters selected by the reported studies.

Figure 4 gives the summary of various common evaluation parameters used by the reported studies and this section gives a detailed overview of these parameters.

5.1 Confusion Matrix

Confusion Matrix is a NxN matrix, where N is the number of classes to be predicted. It gives a summary of predicted and actual values.

	Actual Positive	Actual Negative
Predicted Positive	True Positive	False Positive
Predicted Negative	False Negative	True Negative

True Positive: Correct prediction of positive class.
True Negative: Correct prediction of negative class.
False Positive: Incorrect prediction of positive class.
False Negative: Incorrect prediction of negative class.

5.2 Accuracy

Accuracy is the measure of correctness of the model. It is given by the formula:

(True Positive + True Negative) / Total number of samples (2)

5.3 Sensitivity or Recall

It is the true positive rate or how well the model can predict positive values. It is given by the formula:

True Positive / (True Positive + False Negative) (3)

5.4 Specificity

It is the true negative rate or how well the model can predict negative values. It is given by the formula:

True Negative / (True Negative + False Positive) (4)

5.5 Precision or Positive Predictive Value (PPV)

It is the ratio of correctly classified positive samples to the total number of classified positive sample which can be either correct or incorrect. It is given by the formula:

True Positive / (True Positive + False Positive) (5)

5.6 Negative Predictive Value (NPV)

It is the ratio of correctly classified negative samples to the total number of classified negative sample which can be either correct or incorrect. It is given by the formula:

True Negative / (True Negative + False Negative) (6)

5.7 F1 Score

F1 Score is the harmonic mean of Precision and Recall. It is given by the formula:

$$2 * \frac{(Precsion * Recall)}{(Precision + Recall)} \tag{7}$$

5.8 Receiver Operating Characteristics Curve (ROC Curve)

ROC curve gives us the insight of model performance on different threshold values by combining confusion metrics. It is a plot of True Positive Rate vs False Positive Rate.

5.9 Area Under ROC Curve (AUC)

AUC is the area under the ROC curve between (0,0) and (1,1). An example for Area Under ROC curve is given in figure 5:

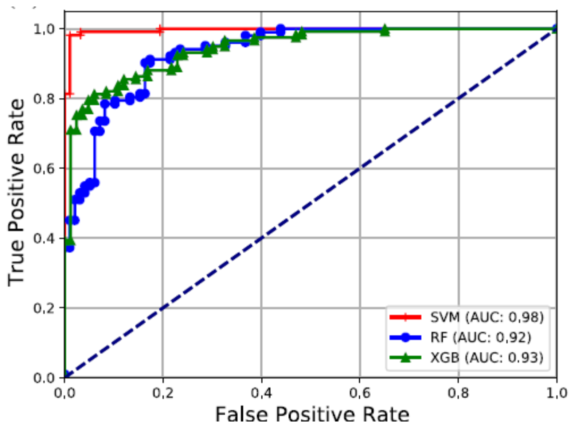

Fig. 5. Example for Area Under ROC Curve [19]

6 Loss Functions

A loss function provides an overview of how well the algorithm models the given data. Loss functions are divided into two types: Regression Losses and Classification Losses. This section highlights the common loss functions used in Machine Learning.

6.1 Regression Losses

In all the equations given below,
 i – i^{th} training sample in dataset
 n – total number of training samples
 y(i) – actual output of i^{th} training sample
 y-hat(i) – predicted output of i^{th} training sample

Mean Squared Error. It is the average of the squared difference between predicted and actual observations. It is given by the formula:

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n} \qquad (8)$$

Mean Absolute Error. It is the average of sum of absolute difference between actual and predicted values. It is given by the formula:

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \qquad (9)$$

Mean Bias Error. It is same as MSE but less accurate. It could determine if the model has positive or negative bias. It is given by the formula:

$$MBE = \frac{\sum_{i=i}^{n}(y_i - \hat{y}_i)}{n} \qquad (10)$$

6.2 Classification Losses

Cross Entropy Loss. It is the most common loss for classification problems. The value of cross entropy loss increases as the predicted probability diverges from the actual label. The formula is given as:

$$Cross\ Entropy\ Loss = -(\mathrm{y}_i \log(\hat{\mathrm{y}}_i) + (1 - \mathrm{y}_i)\log(1 - \hat{\mathrm{y}}_i)) \qquad (11)$$

7 Discussion

Automated detection of COVID-19 has proven to be beneficial for healthcare industry and professionals. It reduces the efforts of the radiologists in analyzing the images and thus supporting early and efficient diagnosis of the disease. In this study, various methods are discussed for automated detection of COVID-19. The transformations made in those techniques increased the performance of the model, but there are certain limitations and improvements to be made in the current techniques. The most common issue is the availability of data for COVID-19 prediction. Numerous research has employed data augmentation techniques to address this issue, including flipping, rotating, translating, scaling, and cropping.; color augmentation techniques like brightness, contrast, saturation, hue, and pre-processing to increase the size of the dataset, along with that Generative Adversarial Networks (GANs) which can generate new/output images from input images. But identifying the best data augmentation technique is difficult because of the data bias and compromise in the quality of output. Another problem encountered is the computational cost and time, and quality of images which has a great impact on the performance of the model. As Deep Learning deals with large amounts of data, the hardware and the processor requirements are very high. One solution to this can be the GPUs used for deep learning viz. Tensor Processing Units (TPUs) developed by google for enhancing deep learning, Xavier processors by Nvidia which uses only 30 watts of power and is capable of 30 trillion operations per second. Another solution is to make the neural network sparse with the help of techniques like pruning and quantization so that it requires less computation. Finding compact deep learning architectures that are computationally more efficient could be another option, for example training a bigger "teacher model" and then training a smaller "student model" which mimics the behavior of the "teacher model" [61]. Another major issue encountered is differentiation of COVID-19 from other similar diseases such as Pneumonia, Lung Cancer etc. As COVID-19 has features like Pneumonia, in many studies the model is not able to differentiate between the diseases resulting in lower accuracy. As a solution to this, [41] proposed a method that used Gene Ontology to identify functional similarity of genes. Disease Genes can be differentiated using ML classifiers by hidden semantic similarities. Another solution could be a bi-level classification, [17] uses this technique in which first level is to classify the images into normal or infected and second step is to further classify infected images in COVID and Pneumonia which improves the performance. Paper [13] solves this issue using a model named MANet that focuses on the relevant features instead of the whole image. In the first stage of this model, the image is taken as an input and predicts the corresponding lung masks. These first stage predicted masks are employed as spatial attention maps to modify the CNN features for classification in the second stage. Additionally, preprocessing techniques to learn the fine-order differentiating features can be added into the models to enhance overall performance[45]. Most of the proposed models are not integrated in web applications or mobile applications, which signifies the unavailability of the models to the public. As a part of future work, these models should be integrated in applications which could demonstrate the efficacy of the research.

8 Conclusion

This review gives an overview of 60 studies on Machine Learning and Deep Learning for COVID-19 detection. In many studies, the proposed mechanism is not clinically implemented which gives a scope of future work. Most of these studies used different CNN architectures in their model. This review is a detailed discussion on various ML and DL techniques, common datasets used by them, evaluation parameters and loss functions. Innovations are made in state-of-art methods by various studies for improving the performance, which is discussed in Related Work. Considering the updates in requirements and techniques, the review can be further extended to include new techniques and updated dataset.

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