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REVIEW ARTICLE

A systematic scoping review of the analysis of COVID-19 disease using chest X-ray images with deep learning models

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ABSTRACT

The significance of chest X-ray data in screening patients for COVID-19 has been recognised by medical experts. Deep learning (DL) technologies, particularly artificial intelligence (AI) algorithms, have emerged as efficient classifiers for diagnosing disease through the inspection of chest X-rays. Medical professionals may use deep learning skills to effectively allocate resources and prioritise patients, ensuring that people in critical need of medical attention receive it on time. In reviewed papers, chest X-ray images datasets are used in order to investigate if trained convolutional neural networks (CNNs) can be utilized to accurately classify COVID-19 cases. The study is made more fascinating by the availability of many kinds of new DL models designed specifically for this specific purpose. As the findings illustrate the efficacy of fine-tuned pretrained CNNs for COVID-19 identification using chest X-ray data, the usage of AI-based approaches for COVID-19 identification using chest X-ray data should see substantial growth, giving a more quick and cost-effective approach. The combination of CNN technology and the diagnostic capacity of chest X-ray imaging offers a lot of promise in the fight against COVID-19. Ultimately, the goal is to reduce the strain on healthcare resources and improve patient outcomes by providing medical practitioners with dependable technologies, such as those based on the artificial intelligence (AI), that can aid in real-time monitoring, rapid diagnosis, and patient triage. These advancements enable more effective use of healthcare resources, which benefits patients.

Keywords: chest X-ray; COVID-19; deep learning; CNN

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1. Introduction

Over the past few years, COVID-19 has emerged as one of the most significant disasters. The study of human nasal swabs by Real time polymerase chain reaction test (RT-PCR) is one of the widely used methods for the identification of COVID-19. The patient's care therefore depends on the early diagnosis of COVID-19. Due to the novel nature of this illness, there were no established methods for controlling it at first. The **Figure 1** shows the global deaths which are directly or indirectly related to COVID-19 pandemic[1].

As stated above the very first method for early detection of this viral disease is RT-PCR test which comes with its limitations of time consuming, costly and manual process[2]. Also, it was very difficult to avail the laboratory kits during pandemic time. Due to manual intervention the process of RT-PCR cannot be supposed to free from errors and biasing. Moreover, the early stage of COVID-19 detection by RT-PCR test has a low positive rate[3]. One alternative of RT-PCR test is the radiography image analysis such as Chest X-ray and CT (Computed Tomography) scans. Healthcare experts are using Chest X-ray images and CT scans for quick identification of COVID-19 but there are certain limitations of CT scan in terms of mobility, long term harm from screening, danger of contaminating healthcare professionals. Therefore, in comparison to CT scans Chest X-ray images (CXR) are better in terms of portability, quick response, affordable and widely accessible. Due to these advantages researchers are shifted towards the analysis of Chest X-ray images using Deep learning (DL) and Machine Learning (ML) and artificial intelligence (AI) based technology. As response of CXR is very slow which would result in time consuming of the overall analysis of the diagnosis process. Also, number of healthcare workers is less in comparison to number of ill people, which require assistance of AI based diagnostic systems in support of physicians in diagnosis process of COVID-19 disease. So, AI based approach such as Deep Learning and Machine Learning models are well suited for early diagnosis of COVID-19 disease. Therefore, the contribution of this paper is as follows:

- To review the role of Deep learning methods in monitoring of COVID-19 disease.
- To perform an empirical analysis of different deep learning models and a comparison of their accuracy with datasets namely National Institutes of Health (NIH) dataset, Kaggle (KAG) dataset, Chexpert dataset and many more as mentioned in the next parts of this paper.
- To present various challenges and future research directions by examining the best models and datasets used.

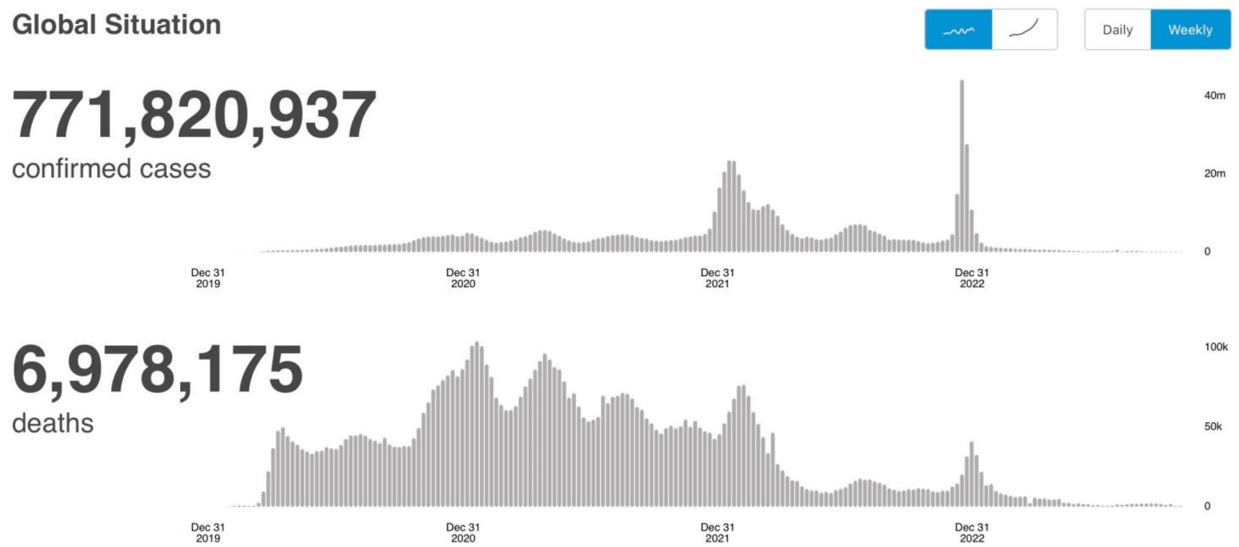

Figure 1. A graph shows the data of global deaths due to COVID-19 pandemic. (Source: World Health Organization)

Organization of paper:

To give an in-depth analysis of the subject, the paper is divided into five sections. Section 1 "Introduction" presents role of deep learning in COVID-19 detection, which gives general idea and scope of this disease and different techniques to detect and diagnosis of it. This section is subtitled "Search Criteria" where many search engines, databases, and archives were used to compile pertinent information for the study are described in this section. The section 2 "Methodology," explores the strategy used to produce the desired outcomes. In order to guarantee consistency and reliability in the results achieved, it includes a full description of the processes used across all the research articles included in the study. A comprehensive examination of the chosen research papers is provided in the section 3 "Discussion and Results". The specific models used for the categorization of the analysed images are described in detail, along with any pre-processing methods that were employed on the datasets. Section 4 "Challenges and Future Scope" discusses the challenges that were faced while doing the research. This section also considers how the current approach may be improved and offers additional technologies that might be used in the future to produce better results. At last, Section 5 depicts the Conclusion of paper. It compares several models and analyses the possible results that might be attained by using the methodology that is suggested.

Search criteria

In this paper, various studies have been systematically analysed. It was discovered that PubMed, Web of Science, and Scopus were the databases with the largest number of research papers relevant to the current goal of the study. The search method employed the following keywords: "COVID-19", "Deep Learning", "Machine Learning", "Artificial Intelligence", "COVID-19 Detection", "COVID-19 Diagnosis", and "X-rays & COVID-19". **Figure 2** shows the number of research article that were searched for the above-mentioned keywords.

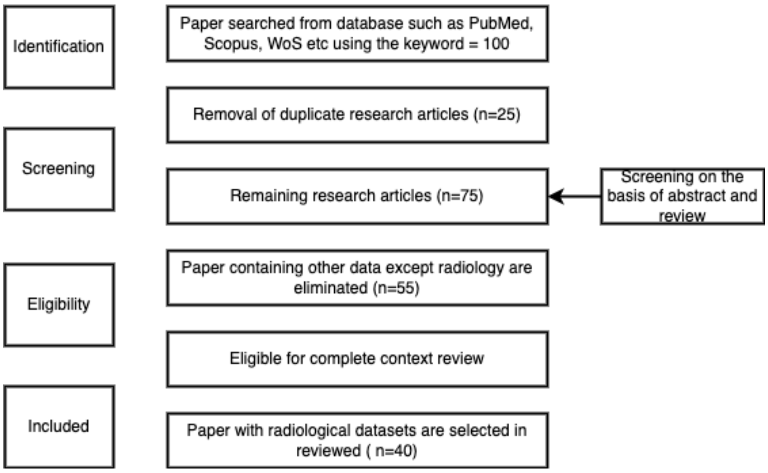

Figure 2. Search and selection of systematic research article review.

A plethora of articles have been meticulously accumulated, all of which delve into the topic of COVID-19 detection through the ingenious utilisation of ML and DL models. The screening of articles removed duplicate studies as well as those that depended on findings from sources other than the fields of radiology, like sequences of proteins and lab findings. Following this thorough selection process, a thorough contextual analysis was used to categorise the remaining articles. It is significant that these revolutionary articles were published within the timeframe of 2020 to 2022, freezing their relevance in the ever-evolving landscape of COVID-19 research.

2. Methodology

In this section the methodology used for detection of COVID-19 disease has been presented. In order to achieve this demanding classification task, the researchers employed modern methods built on the principles of deep learning (DL) and Artificial Intelligence. The common procedures followed across all these articles, which cover the way for consistent and reliable results, are succinctly outlined below:

2.1. Dataset selection

In this work radiological modalities such as Chest X-rays are used as the main resources however CT scans are also used in order to obtain the difference between better rate of detection of COVID-19. A range of sources, including open repositories, such as PubMed, were used to gather the data. The database is primarily categorised into three groups: COVID-19, viral/bacterial pneumonia, and healthy individuals.

2.2. Pre-processing techniques

Overfitting, which is brought on by a lack of labelled training data or a data imbalance, is frequently a consequence of the dearth of available datasets. The datasets with the fewest samples are often pre-processed or enhanced utilizing a variety of methods to address this issue. Additionally, a particular sort of machine learning framework called Generative Adversarial Network (GAN) has been used in various research studies[4] to produce new images.

2.3. Segmentation

For COVID-19 to be detected effectively the region of interest (ROI) must be verified. With the use of U-Net architecture[5] a much better segmentation can be achieved by the researchers which will solely base on CNN. To improve segmentation performance, this architecture incorporates data from the up sampling and down sampling channels. In order to extract contextual information from Chest X ray images, researchers have also employed a 3D representation of the U-Net architecture[6]. With the use of these techniques, COVID-19-relevant areas in medical imaging may be precisely located and defined.

2.4. Feature extraction

Deep learning models are widely used for feature extraction from X-rays and CT scans in most research papers due to their inherent self-learning ability. The extracted features are used to train deep learning model in order to solve the classification problem at hand. Numerous feature extraction techniques, including VGG, Inception, ResNet, DenseNet, Xception, and EfficientNet, have been employed by various research article writers. Here is a quick explanation of a few of these methods:

- VGG[7]: VGG is a deep CNN which primarily consists of stacked convolutional layers with small 3 × 3 filters, followed by a non-linear activation function like ReLU (Rectified Linear Unit). **Figures 3** and **4** depicts the ReLu function and VGG architecture respectively. Mathematically this can be written as

$$f(x) = \max(0, x) \tag{1}$$

where it yields a zero output for any negative input and returns input value itself for any positive value x.

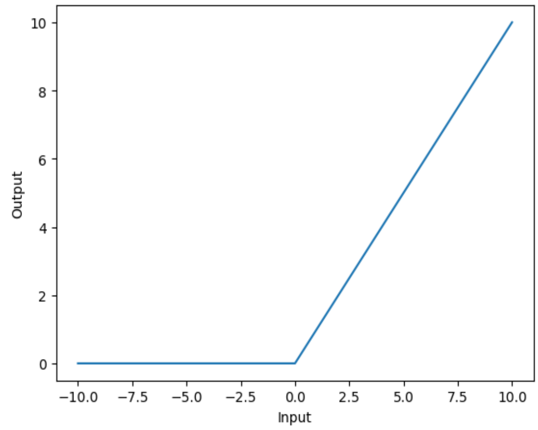

Figure 3. Graph of ReLu function.

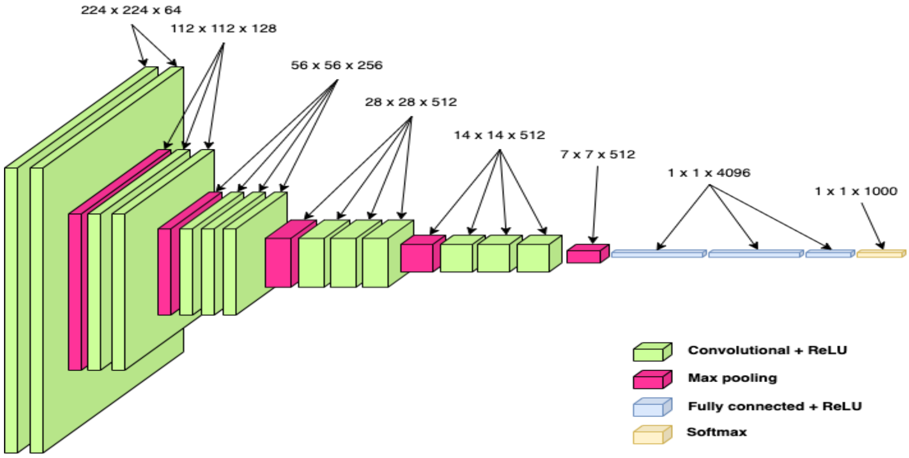

Figure 4. VGG architecture.

With the use of ReLU it is probable that a particular unit within the network may not activate which will reduce the overfitting and noise. In order to reduce the dimensionality of the feature maps and to decrease the computational complexity VGG network make use of 1×1 convolutional filters. It also uses local response normalization (LRN) which helps in enhancing the contrast between different features and improving the network's ability to generalize across different inputs.

- Inception-v3[8]: It was introduced as part of the Inception series by Google researchers and is a CNN model. The key feature is the use of inception modules or layers. **Figure 5** shows the effective architecture of Inception V3.

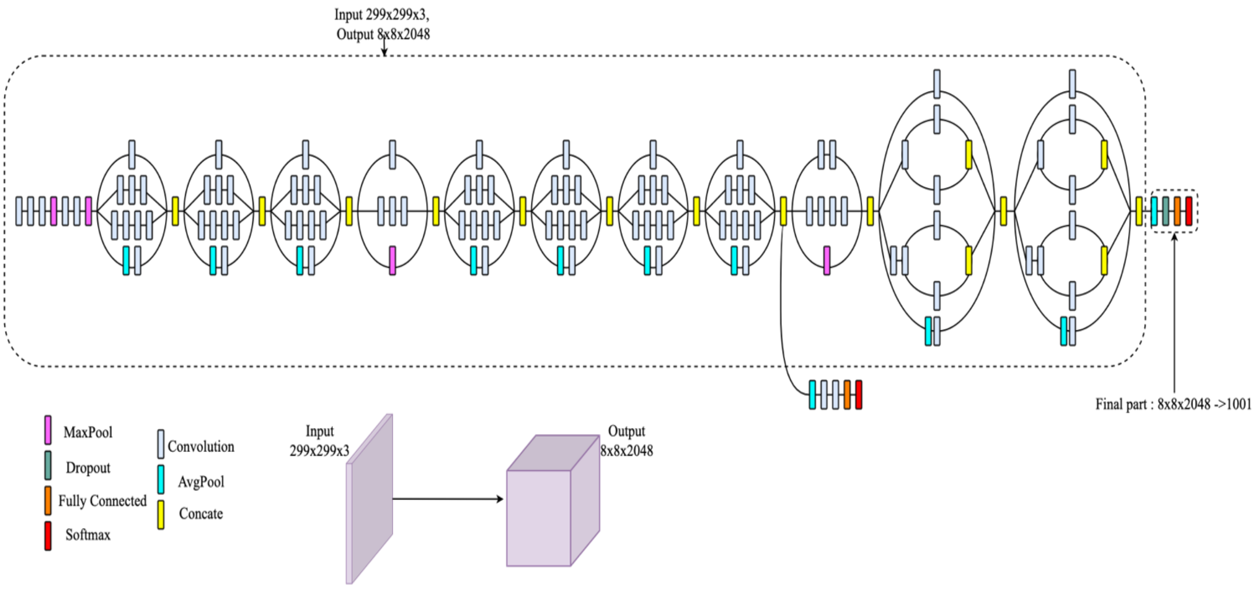

Figure 5. Inception V3 architecture.

- ResNet[9]: ResNet, a well-known CNN design used to address the vanishing gradient problem which arises as neural networks involve back propagation method where new weights are calculated with old weights of layers and product of learning rate and gradient of loss function as

$$w\_new = w\_old - \eta * \partial Loss/\partial w \tag{2}$$

As the number of layers in the networks increases, the product of derivatives experiences a fall in value due to which the partial derivative of the loss function approaches a value close to zero, ultimately resulting in the vanishing of the partial derivative. This phenomenon is commonly referred to as the vanishing gradient problem. ResNet architecture adds skip connections between layers. These connections allow for the weights at a given layer to be derived from the combination of the weights from the previous layer and the one preceding it, which remains unaltered. In the event when the weights of the current layer are comparatively less than those of the preceding layer, the inclusion of weights from the unaltered layer will effectively counteract the diminution of the weights, resulting in an exponential reduction in magnitude. Consequently, this approach effectively addresses the issue of the vanishing gradient. Resnet architecture is represented in **Figure 6**.

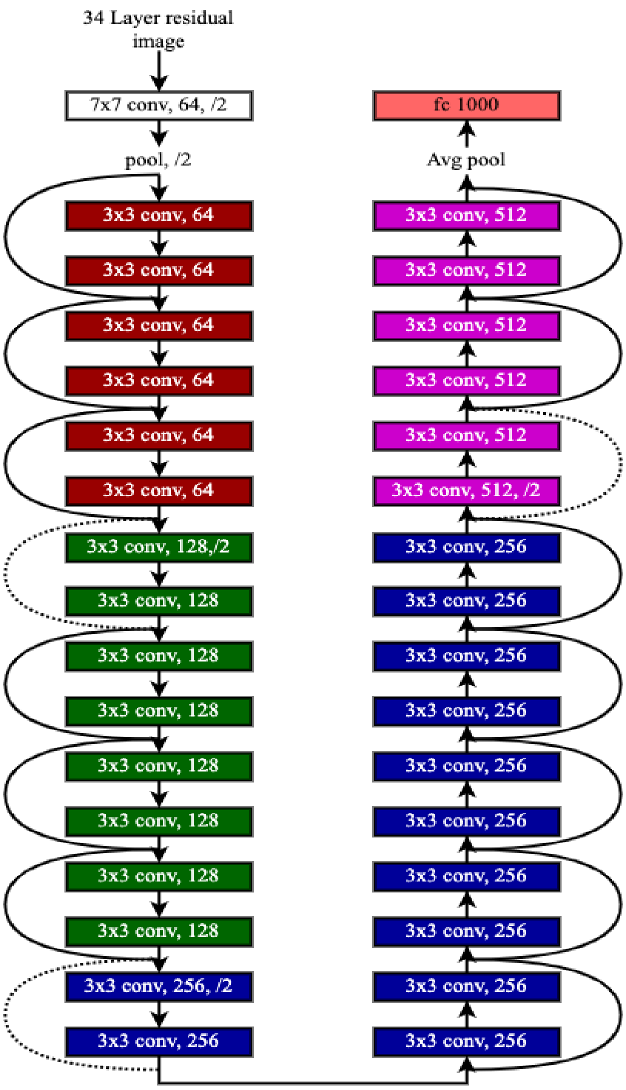

Figure 6. Resnet architecture.

- DenseNet[10]: A densely connected CNN called DenseNet significantly improves feature propagation, allows for feature reuse, and lessens the problem of vanishing gradients. It does this by creating a feed-forward connection between every layer and every other layer. **Figure 7** depicts the DenseNet architecture.

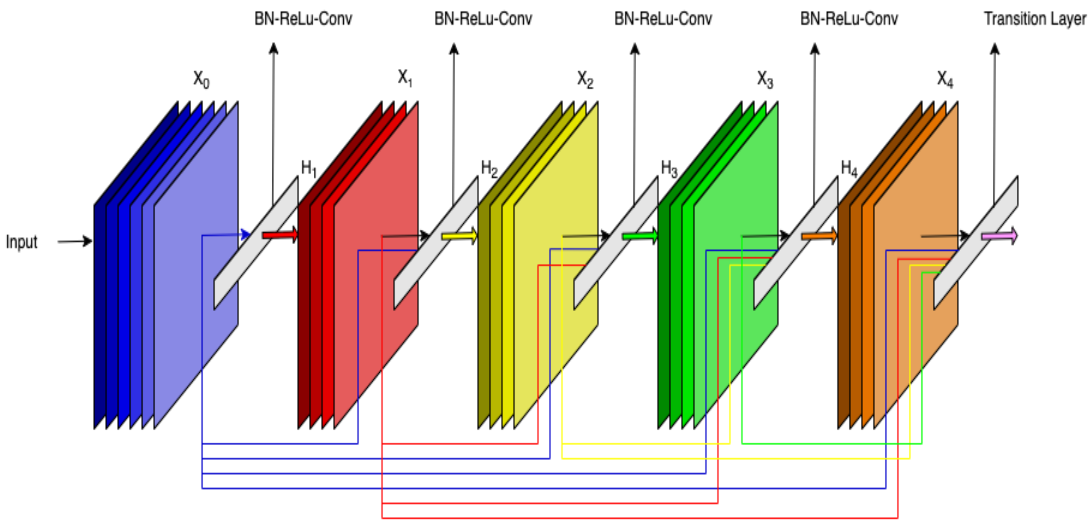

Figure 7. DenseNet achitecture.

- MobileNet[11]: MobileNet is a lightweight CNN architecture that utilizes depth-wise separable convolutional layers. This design choice reduces the computational complexity and enables efficient inference on resource-constrained devices. MobileNet V1 architecture is shown in **Figure 8**.

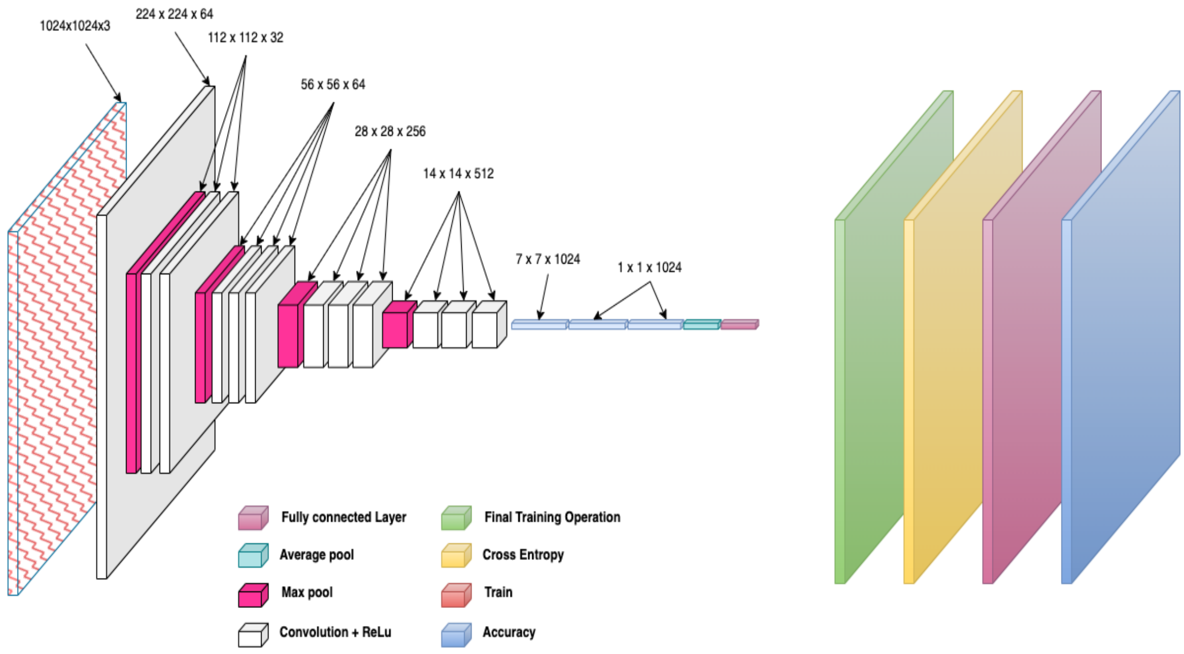

Figure 8. MobileNet V1 architecture.

- EfficientNet[8]: EfficientNet is a CNN design that uses a set of scaling coefficients to consistently scale the depth, breadth, and resolution dimensions, ensuring balanced optimisation in all network dimensions. EfficientNet is shown in **Figure 9**.

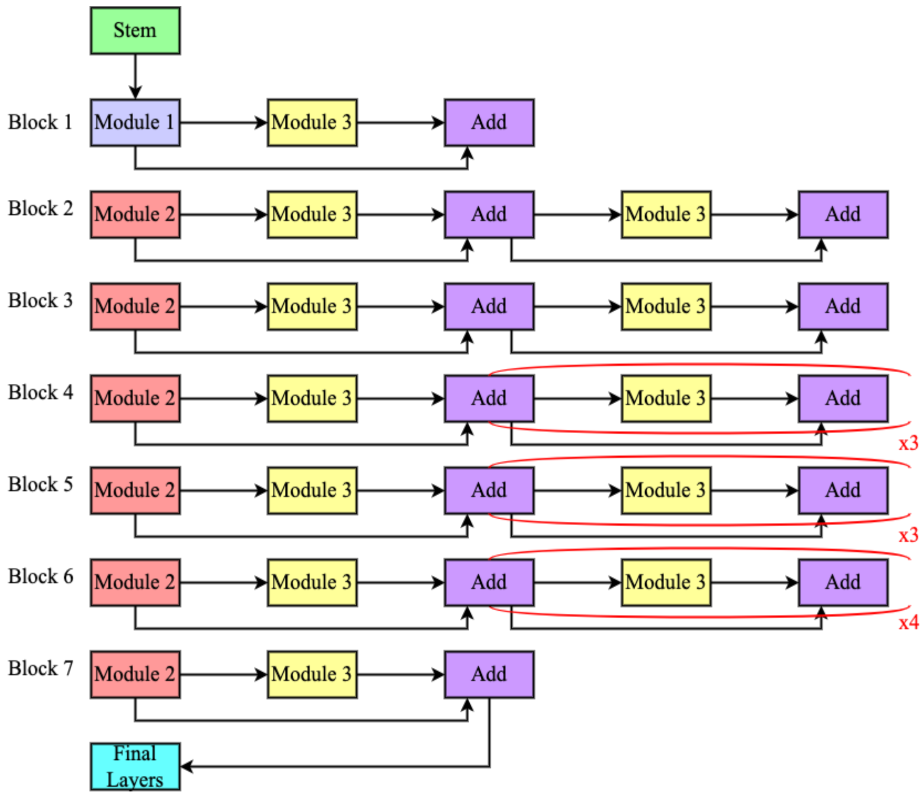

Figure 9. Efficient Net architecture.

3. Discussion and results

Studies evaluating COVID-19 detection and diagnosis used the concept of artificial intelligence. The specificity as well as sensitivity of radiographic X-ray images can be improved through Deep Learning algorithms, based on an analysis of various studies, as compared to a radiologist's diagnosis. More than 90% of patients with COVID-19 disease can be accurately diagnosed using the X-ray technique. As multiple different bacterial and viral pneumonias share the same symptoms[12] as COVID-19, diagnosing this sickness is very difficult. Many study articles were analysed, and it was shown that practically all the studies utilised CNN algorithms. Here, **Figure 10** illustrates the percentage rate of using different deep learning models in analysis of various research papers. It was found that the Resnet model is used in large number of papers with precision F1 score accuracy in the range of 84.4%[13], 91.41%[14], 92.07%[15] & 97.87%[16] respectively.

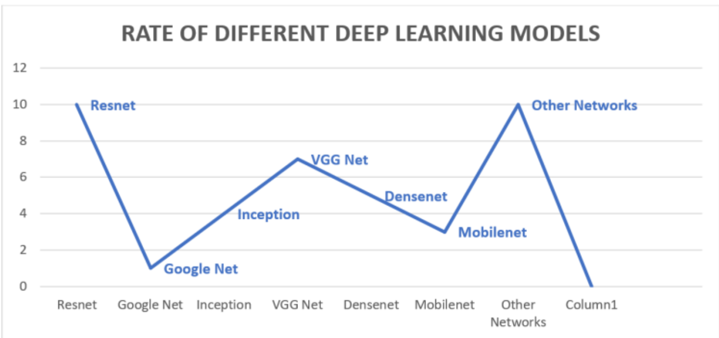

Figure 10. Percentage rate of different deep learning models used in different research paper.

Furthermore, **Figure 11** shows the rate of detection and diagnosis performed in different research papers, and it was obtained that most of the papers deal with the detection of COVID-19 in comparison to the diagnosis of this disease, which is better for the further spread of the disease. As detection at an early stage will save a lot of time and decrease the danger to the person and society from this disease.

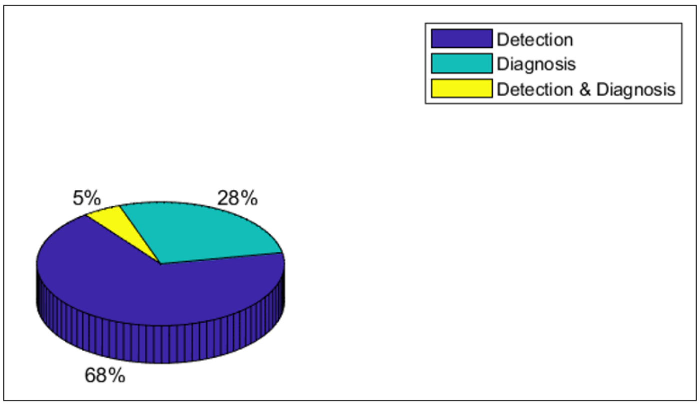

Figure 11. Ratio of detection and diagnosis of radiology modality in different research papers.

Moreover, **Figure 12** shows the flowchart of classification of input image datasets using pre trained deep learning models. As deep learning CNN models require to train according to input dataset therefore the input image dataset is split into Training data, testing data and validation data. After this using the weights learned from pre trained CNN models training of models is done using training data which is followed by testing and validation process in order to classify the input image dataset as COVID, viral/bacterial pneumonia and healthy individuals.

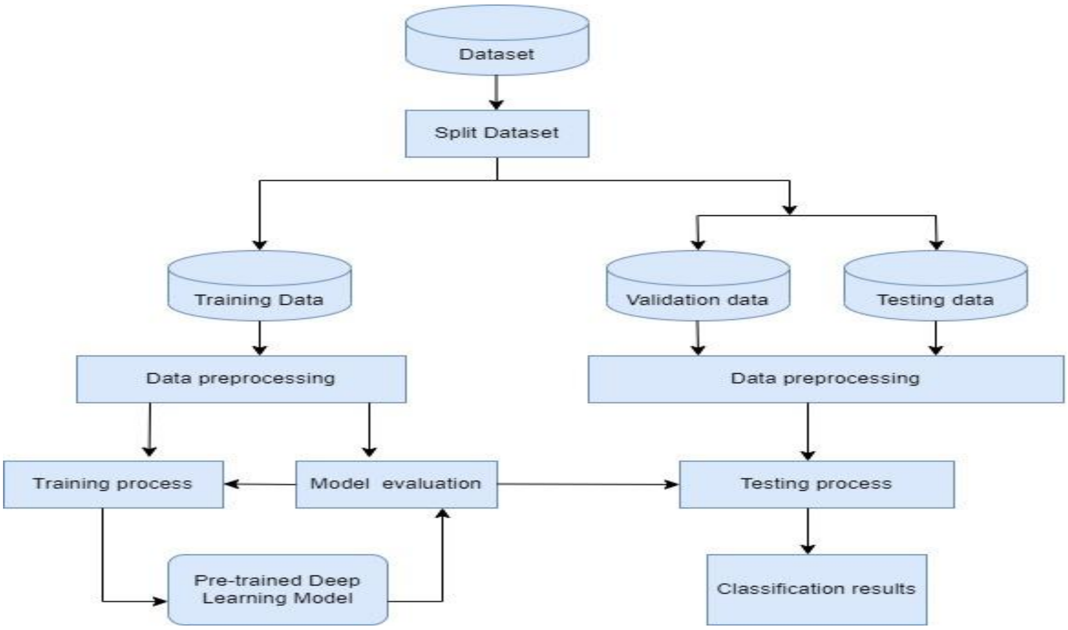

Figure 12. Flowchart of basic pre trained deep learning models for image classification.

All the publications that have been evaluated are from after 2020 due to the disease's novelty. The goal of the study was to detect COVID-19, diagnose it, or both detect and diagnose it. **Table 1** gives the detailed review of the existing works related to the detection and diagnosis of the COVID-19 disease. Also, **Table 2** sums up the publicly available datasets used by the reviewed papers. Here is the detailed description of reviewed papers for example, Arias-Londono et al.[7] discusses the detection of COVID-19 from chest X-rays and performs three experiments with different numbers of datasets taken for the VGG16 and VGG19 neural network models and observes that an accuracy of 99.06% and an F1 score of 99.06% can be achieved. Taresh M[11] discusses the concept of Transfer learning, which uses different CNN networks where CXR images are used for the analyses of different pretrained deep networks, and after analysis, the best pretrained model in terms of sensitivity, specificity, precision, and other factors was found to be Mobile Net and VGG16. Also.

Table 1. Comparison of various existing works.

Author	Aim of study	Population	Data pre-processing	ML used	Model	Type of data	Validation results
Wang S and Yang G (2022)[5]	Detection	7544 CT scan	Segmentation	Deep learning	ResNet 50 3D U Net	CT scan	Accuracy: 94.52%
Arias-Londoño JD et al. (2020)[7]	Detection	79,500 X-ray	Resizing and segmentation	CNN	COVID-Net	X-ray	Accuracy: 91.53% Recall: 87.4% BAcc: 87.6% GMR: 87.37% AUC: 0.97
Ghaffar Z et al. (2022)[8]	Detection	15,147 X ray	-	Deep learning	MobileNet VGG 19 NASNetMobile InceptionV3 EfficientNet	X-ray	Accuracy: 95% Sensitivity: 95% Specificity: 97% F1 score: 95% Precision: 95%
Karakanis S and Leontidis G[9]	Detection	275 COVID 275 Normal	Data augmentation	CNN	Resnet 8	X-ray	Accuracy: 98.7%
Hasan N et al.[10]	Detection	2482 CT image	Normalization	CNN	Dense Net 121	CT image	Accuracy: 92.0% Recall: 95.0%
Taresh M[11]	Detection	1200 CXR of COVID19, 1341 healthy individual 1345 viral pneumonia (open source)	Normalization	CNN with transfer learning	Mobilenet VGG16	X-rays	Mobilenet AUC: 0.9814 Accuracy: 98.29 Sensitivity: 97.56 Specificity: 98.74 VGG: 16 AUC: 0.9815 Accuracy: 98.29 Sensitivity: 97.57 Specificity: 98.72
Arias-Garzón D and Alzate JA[12]	Detection	Exp 1-4610 CXR Exp 2-3240 CXR Exp 3-5469 CXR	Pre-processing and segmentation	Deep learning	VGG 16 VGG 19	X-rays	Accuracy: 99.06 F1 score: 99.06 Recall: 99.06 Precision: 99.07
Oh Y et al. (2020)[13]	Detection	502 X-ray images	Data type casting, histogram equalization, gamma correction, resizing, data augmentation (using patch images)	Deep learning	Dense Net 103, Resnet-18, Patch based classification network	X-ray	Accuracy: 88.9% Precision: 83.4% Recall: 85.9% Specificity: 96.4% F1 score: 84.4%
Sethy PK and Behera SK (2020)[14]	Detection	25 X-ray	-	Deep learning	Resnet 50 with SVM	X-ray	Accuracy: 95.38% FPR: 95.52% F1 score: 91.41% Kappa and MCC: 90.76%

Table 1. (*Continued*).

Author	Aim of study	Population	Data pre-processing	ML used	Model	Type of data	Validation results
Elasnaoui E and Chawki Y (2021)[15]	Detection	6087 images	Channel identification, intensity normalization, CLAHE	Deep learning	Inception_Resnet_V2, Densenet201	CT scan and X-rays	Accuracy (%) Inception_Resnet_V2:92.18 Densenet201:88.09 Sensitivity (%) Inception_Resnet_V2:92.11 Densenet201:87.99 Specificity (%) Inception_Resnet_V2:96.06 Densenet201:94.00 Precision (%) Inception_Resnet_V2:92.38 Densenet201:88.52 F1 score (%) Inception_Resnet_V2:92.07 Densenet201:87.91
Kumar R et al. (2022)[16]	Detection	Chest X-ray images	-	Deep Learning and Machine Learning	Resnet152, GoogleLeNet	Chest X-ray	Accuracy: 97.87% Sensitivity: 97.87% Specificity: 98.93% F1 score: 97.87%
Signoroni A et al.[17]	Detection and development of Brixia severity score system for lung compromise	5000 CXR	Pre-processing and segmentation	Deep learning	BSNet (Ensemble)	X-rays	MAE: 0.441
Hammoudi K et al.[18]	Detection and diagnosis	5863 chest X-ray	-	Tailored CNN with deep learning	DenseNet 169	X-rays	Accuracy: 95.72
Shyni HM and Chitra E (2022)[19]	Detection	-	Image resizing Image segmentation Image enhancement	CNN	-	X-ray images CT scan images	-
Shah PM et al. (2021)[20]	Detection	424 X-ray	Resizing and normalization	CNN	GRU-CNN	X-ray	Precision: 0.96 Recall: 0.96 F1 score: 0.95

Table 1. (*Continued*).

Author	Aim of study	Population	Data pre-processing	ML used	Model	Type of data	Validation results
Mondal AK et al. (2021)[21]	Detection	194,922 CT images 8214 X-ray	Resizing and augmentation (rotation, scaling etc.)	CNN	xViTCOS	X-ray CT scan images	CT images Accuracy: 0.981 Precision: 0.976 Recall: 0.978 Specificity: 0.991 F1 score: 0.977 X-ray images Accuracy: 0.96 Precision: 0.965 Recall: 0.959 Specificity: 0.977 F1 score: 0.961
Ahsan MM et al. (2021)[22]	Detection	1845 X-ray	-	CNN	VGG 16 InceptionResNet V2 MobileNetV2 VGG19	X-ray	Accuracy (VGG16): 97.6%–99.7% InceptionResNet V2: 97.6%–99.7% MobileNetV2: 97.6%–99.7% VGG19: 95.2%–98.6%
Lee Y et al. (2022)[23]	Detection	5810 patients	-	Deep Learning	LSTM based on RNN	X-ray	Sensitivity: 93.33%
Agrawal T and Choudhary P (2021)[24]	Detection	2488 X-ray images	Resizing and normalization	Deep Learning and CNN	Focus Covid	X-ray	Accuracy: 95.20% Precision: 95.60% Sensitivity: 95.20% F1 score: 95.20%
Bacellar GC et al. (2021)[25]	Detection	Chest X-ray images	Resizing, Gaussian Blur, Rotation, Flip, Random Resize crop	CNN	DLH_COVID	Chest X-rays	Accuracy: 95% Precision: 95% Recall: 92% F1 score: 93%
Mousavi Z et al. (2022)[26]	Detection	8912	Resizing and normalization	CNN	CNN-LSTM	X-ray	Accuracy: 99.4% Specificity: 99.4% Sensitivity: 99.4%
Khan AI et al. (2020)[27]	Detection and diagnosis	1300	Resizing	Xception	CoroNet	X-ray	Accuracy: 89.6% Specificity: 96.4% F measure: 89.8% Recall: 89.92% Precision: 90.0%
Khuzani1A Z et al. (2021)[28]	Diagnosis	420	-	CNN	COVID-classifier	X-ray	Sensitivity: 100% Precision: 96% F-score: 0.98
Elaziz MA et al. (2020)[29]	Diagnosis	1891	-	MRFODE based feature selector	KNN classifier	X-ray	Accuracy: 0.9809 Precision: 0.9891 Recall: 0.9891

Table 1. (*Continued*).

Author	Aim of study	Population	Data pre-processing	ML used	Model	Type of data	Validation results
Kaya ANC and Pamuk Z (2021)[30]	Detection	3141-dataset1 1834-dataset2 3113-dataset3	Resizing and augmentation	CNN and transfer learning	ResNet 50	X-ray	Accuracy: 96.1% (dataset 1) Accuracy: 99.5% (dataset 2) Accuracy: 99.7% (dataset 3)
Hemdan EE et al. (2020)[31]	Diagnosis	50 X-ray images	Scaling and one hot encoding	Deep learning	VGG 19, DenseNet121, COVIDX-Net	X-ray	Accuracy: 90.0% Precision: 0.83 Recall: 1.00 F1 score: 0.91
Ozturk T et al. (2020)[32]	Diagnosis	127 X-ray images	-	Deep learning and CNN	DarkCovidNet	X-ray1	Accuracy: 87.02% Sensitivity: 85.35% Specificity: 92.18% Precision: 89.96% F1 score: 87.37%
Civit Mascot JC et al. (2020)[33]	Diagnosis	792 X-ray	Histogram equalization	Deep learning	VGG 16	X ray	AUC: 0.9 Accuracy: 100%
Punn NS and Agarwal S (2021)[34]	Diagnosis	1214 X-ray	Filtering and denoising	Deep learning and transfer learning	NASNetLarge	X-ray	Accuracy: 0.98 Precision: 0.87 Recall: 0.90 AUC: 0.99 Specificity: 0.98
Dansana D et al. (2020)[35]	Diagnosis	360 images	Converted into grey scale format	CNN with deep learning	VGG 19 Inception_V2 Decision tree model	X-ray and CT scan	Accuracy: 91% Precision: 100% Recall: 94% F1 score: 97%
Farooq M and Hafeez A (2020)[36]	Detection	5941 chest radiograph	Scaling and normalization	CNN with transfer learning	COVID Resnet	X-ray	Accuracy: 96.23% Sensitivity: 100%(COVID) PPV: 100% F1 score: 100%
Kadam S and Vaidya VG (2022)[37]	Diagnosis	5840 X-ray images	-	Deep transfer learning	Generative FSL	X-ray	Accuracy: 98.35% Sensitivity: 93.0% Specificity: 98.53% F1 score: 78.48%
Thuseethan S et al. (2022)[38]	Detection	1638 X-ray	-	Deep learning	EfficientNetB7 ResNet101 ResNet152	X-ray	Accuracy:95.54% Accuracy (ResNet variants): >90%
Giełczyk et al. (2022)[39]	Detection	6939 X-ray	Preprocessing with histogram, adaptive masking, Gaussian blur, Histogram equalization	CNN	Adaptive masking + Gausssian blur + hist. eq.	X-ray	Accuracy: 98.31% Precision: 97.47% Recall: 97.46% F1 score: 97.47%

Table 1. (*Continued*).

Author	Aim of study	Population	Data pre-processing	ML used	Model	Type of data	Validation results
Amouzegar F et al. (2022)[40]	Diagnosis	2482 CT images	-	CNN	ResNet18 GoogleNet ShuffleNet	CT scan	Accuracy: 96.77% Precision: 96.2% AUC: 96.84% Recall: 97.64% F1 score: 96.51%
Umer M et al. (2021)[41]	Detection	10,000 Kaggle (open source)	Segmentation and augmentation	CNN	Customised CNN	X-ray	Sensitivity: 0.989 Specificity: 0.921 AUC: 0.594
Chandra TB et al. (2021)[42]	Detection	Phase I) COVID: 696 Pneumonia: 696 Normal: 696 Phase II) COVID: 86 Pneumonia: 86 Normal: 86	Image enhancement and segmentation	CNN	ACoS system	X-ray	Phase I) Accuracy: 98.062% AUC: 0.956 Phase II) Accuracy: 91.329% AUC: 0.831s
Apostolopoulos I et al. (2020)[43]	Detection	1427 chest X-ray	-	Transfer learning with CNN	MobileNet V2	X-ray	Accuracy: 96.78% Sensitivity: 98.66% Specificity: 96.46%
Chandra R et al. (2022)[44]	Forecasting	Time series data	-	Deep learning via LSTM	Univariate LSTM, BD-LSTM, ED-LSTM	State space vector for deep learning models	General decline in cases for two months ahead (From January 2022 onwards)

Table 2. Publicly available datasets used by the reviewed papers.

Reference	Name of dataset	Images	Resolution
[3]	CT samples	CT images	60 × 60 × 3
[7]	Covid chest X ray dataset	Chest X-ray images	256 × 256 × 3
[9]	Cohen and Kaggle	Chest X-ray images	446 × 446 × 1
[10]	SARS-CoV-2 CT-scan dataset	CT images	227 × 227
[11]	Kaggle	Chest X-ray images	224 × 224 × 3
[16]	Cohen	Chest X-ray images	224 × 224 × 3
[24]	Kaggle-1 and Kaggle-2	Chest X-ray images	1024 × 1024, 256 × 256
[28]	Cohen	Chest X-ray images	227 × 227
[30]	Cohen	Chest X-ray images	227 × 227
[36]	COVIDx dataset	Chest X-ray and CT images	128 × 128 × 3, 224 × 224 × 3, and 229 × 229 × 3

Signoroni et al.[17] discuss a method known as Brixia Score (BS Net), which gives severity scores on the basis of affected lung conditions in individuals. In this, they used pre-processing and segmentation in order to get the desired part for further processing. Hammoudi et al.[18] used Tailored CNN along with the Dense Net 169 model in order to process X-ray images and got an accuracy of 95.72% in the detection and diagnosis of pneumonia cases, i.e., viral and bacterial pneumonia. Hasan et al.[10] used the Dense Net 121 model in order to detect the presence of COVID-19 in CT scan images and got an accuracy of 92.0%. Karakanis and Leontidis[9] discussed the Lightweight deep learning model in order to classify COVID-19 versus Normal cases, which they also classified as the third class of bacterial pneumonia. For classification, they used data augmentation in order to overcome the issue of the scarcity of input data images. Mary Shyni and Chitra[19] compared the two imaging modalities, i.e., X-rays and CT images, and found that besides having better sensitivity than CT images, X-ray images are widely used and are simple and less expensive in order to detect COVID-19 in a normal case. This paper also shows that better sensitivity, specificity, precision, and accuracy are obtained by the deep learning models in the case of binary classification (COVID-19 vs. Normal) vs. multiclass classification (COVID-19, normal, and Bacterial Pneumonia). To detect COVID-19 from X-ray pictures, Shah et al.[20] suggested a GRU (Gated Recurrent Unit) CNN network. Here, GRU will serve as the classifier, while CNN will be employed for feature extraction. This model had very high precision (96%), recall (96.0%), and other metrics. This model achieved very good precision, i.e., 96%, a recall of 96.0%, etc. To screen COVID-19 using X-ray and CT images, xVITCOS[21] employs the notion of vision transformers (rather than CNN) for the screening of COVID-19. In order to deal with the problem of data scarcity, a multi-stage transfer learning technique is used in the above paper. By utilising this technique, the overall accuracy of this model by using X-ray images comes out to be 96.0%, with specificity of 97.1% and precision of 95.9%. To correct for class imbalance, Arias- Londoño et al.[7] employed COVID-Net with minor modifications to regularisation in the final two dense layers and a weighted categorical cross-entropy loss function. Three experiments were performed with different pre-processing applied to the input X-ray image data. The output of these three experiments was evaluated to observe how these pre-processing steps affect the results and improve their explanation ability. A new approach, which is based on the patch basis over the Convolutional Neural network, was proposed by OH et al.[13] In this approach, they have used a very small number of trainable parameters. The systematic collection of CXR data for the training of deep neural networks is difficult. So, this patch-based approach achieves state-of-the-art performance with sensitivity of 90.0%, 93.0%, and 100.0% in Normal, pneumonia, and COVID-19 cases, respectively. Ahsan et al.[22] tested deep learning models over three datasets and found the performance of these models over this dataset. Out of these models, VGG16 and MobileNetV2 outperformed others with an accuracy of around 100%. A deep learning model was proposed by Lee et al.[23] in order to improve the speed of the RT-PCR test for COVID-19 detection. The model at position 21 had an AUROC, sensitivity, and specificity of 84.55%, 93.33%, and 75.72%, respectively, out of all the Deep Learning models generated here thus far. Moreover, there is a 24th DL model in the same study report, with sensitivity and specificity of 91.27%, 90.00%, and 92.54%, respectively, under the receiver operating characteristic (AUROC). Agrawal and Choudhary[24] developed Focus Covid for COVID-19 detection using X-ray images. Kumar et al.[16] have reduced the feature space of the extracted features from the pre trained CNN models with the use of PCC(Pearson Correlation Coefficient) along with variance thresholding so as to achieve accuracy sensitivity, specificity, F1 score as 97.87%, 97.87%, 98.93%, 97.87% respectively. Bacellar et al.[25] developed a new model DLH_COVID to classify Chest X ray images into three classes as COVID-19, Pneumonia and normal case. They obtained Accuracy of 96% in classification of COVID-19. Mousavi et al.[26] proposed a CNN-LSTM that uses chest X-ray images to classify the X-ray images into four classes such as Bacterial, viral, healthy and COVID-19 pneumonia. This proposed method has achieved 99.0% accuracy in separating COVID-19 from a group of healthy people. Khan et al.[27] created the CoroNet model for detecting and diagnosing COVID-19 from chest X-ray images. This model is based on the Xception model architecture, and its training is done on the chest pneumonia X-ray images obtained from the datasets, which are publicly available. This model achieved an overall accuracy of 89.6%. Zargari Khuzani1 et al.[28] suggested a COVID-classifier in order to create a sophisticated machine learning classifier capable of distinguishing COVID-19 cases from non-COVID-19 cases with high accuracy and sensitivity. This method used dimensionality reduction to build a set of CXR picture optimum features. To extract features from COVID X-ray pictures, Elaziz et al.[29] developed a novel descriptor (FrMEMs) for functional multichannel exponent moments. Also, a novel feature selection technique based on enhancing Manta Ray Foraging Optimisation (MRFO) behaviour through differential evolution (DE) was created. For the first and second datasets, this method’s accuracy was

96.09% and 98.09%, respectively. Narin et al.[30] studied and proposed pre-trained convolutional networks. They used three separate binary classifications with the help of four classes (COVID-19, normal, viral pneumonia, and bacterial pneumonia). Considering performance results, it was observed that ResNet50 outperformed other models with the highest classification performance. COVIDX-Net[31] used a number of X-ray image analysis models that exist currently: VGG19, DenseNet121, InceptionV3, ResNetV2, InceptionResNetV2, Xception, and MobileNetV2. Out of these models, VGG19 and MobileNetV2 outperformed other models in terms of Precision, recall, and F1 score. Ozturk et al.[32] proposed the DarkCovidNet model for automatic detection of COVID-19 from X-ray images. Using 17 convolution layers, the suggested model achieved 87.02% accuracy for multiclass classification (COVID vs. no findings vs. Pneumonia) and 98.08% accuracy for binary image classification (COVID-19 vs. non-COVID-19). A comparative study of different deep learning models is done by El Asnaoui and Chawki[15] for the detection and classification of COVID-19. Chest X-ray images and CT scan images were used to evaluate the model's performance, and it was found that DenseNet201 and Inception_ResNet_V2 outperformed other models with 88.09% accuracy with DenseNet201 and 92.18% accuracy with Inception_ResNet_V2, respectively. Sethy et al.[14] suggested using Support Vector Machine (SVM) along with a classification model, i.e., Resnet 50. A classification accuracy of 95.38% can be achieved using this model compared to other deep learning models. Civit Mascot et al.[33] proposed to use a VGG-16-based deep learning model for the identification of pneumonia and COVID-19 using X-rays. They achieved a very high sensitivity of around 100%. Punn and Agarwal[34] utilise deep neural networks using fine-tuning techniques to automatically diagnose COVID-19 with limited chest X-ray images. They performed binary and multiclass classification and found that NASnetLarge displayed better scores in accuracy, precision, and AUC (Area Under Curve) in comparison to other models. Dansana et al.[35] used a fine-tuned version of the neural networks VGG19, Inception_V2, and the decision tree model over the Chest X-ray image dataset. They observed that VGG19 outperformed these models with 100% precision for COVID, 84% for the normal case, and around 91% accuracy. COVID Resnet[36] employed Resnet 50 and fine-tuned this network to achieve an accuracy of 96.23% with the COVID-net dataset. By pre-training a convolutional encoder model on the Kaggle chest X-ray dataset and obtaining sensitivity and specificity distributions for this model, Kadam and Vaidya[37] use the Generative Few Shots Learning technique for COVID-19 classification from chest X-ray images. A new model that combines segmentation and classification was put forth by Wang and Yang[5]. A 3D U-net segmentation model algorithm-based diagnostic model using Resnet50 The classification model achieves 94.52% accuracy in classifying the three classes of COVID, normal, and pneumonia by utilising various types of datasets. Ten Deep CNN models were compared for the purpose of detecting COVID-19 using chest X-ray pictures by Ghaffar et al.[8] MobileNet, EfficientNet, and InceptionV3 out of these models attained average accuracy of 95%, 95%, and 94%, respectively. Using a dataset of chest X-ray images, Thuseethan et al.[38] conducted a comparative examination of state-of-the-art deep neural networks for COVID-19 identification. EfficientnetB7 surpassed other deep networks with 95.54% accuracy, according to their analysis. Gielczyk et al.[39] analysed various pre-processing methods required for the processing of the input Chest X-ray dataset used in machine learning algorithms for the early detection of COVID-19. Histogram equalization and Gaussian blur, bilateral filter, adaptive masking and gaussian blur. Out of these pre-processing techniques, histogram equalisation with gaussian blurring and adaptive masking outperformed other techniques with >97% accuracy, precision, and recall. Amouzegar et al.[40] proposed a parallel combination of three pre-trained models, Resnet18, Googlenet, and Shufflenet, trained over a CT scan image dataset to achieve 97% accuracy in the diagnosis of COVID-19. To identify the characteristics of the chest X-ray pictures, Umer et al.[41] COVINet's proposal uses a convolutional network architecture. Two, three, and four classes—normal, COVID-19, viral pneumonia, and bacterial pneumonia—are considered while classifying the cases accordingly. The normal, COVID-19-infected, and suspicious patients were distinguished in the work of Chandra et al.[42], using radiomic texture descriptors that were derived from CXR images. A two-phase classification system (normal vs. abnormal and COVID-19 vs. pneumonia) is used in architecture. Here, classification is carried out using a classifier that relies on a majority vote and is composed of an ensemble of five supervised classification algorithms. Two steps are used to achieve the results: Phase I consists of 2088 CXR images in total. Phase II consists of 258 CXR images in total. Phase I accuracy is 98.06%, and Phase II accuracy is 91.32%. Apostolopoulos et al.[43] proposed a CNN architecture by using transfer learning in order to detect COVID-19 from the Chest X-ray image dataset. Here different metrics were obtained, such as sensitivity, accuracy, and specificity, with 98.66%, 96.78%, and 96.46%, respectively. Chandra et al.[44] have done a forecast of COVID-19 for the populous country of India. They have used deep learning with the concept of LSTM. By modifying LSTM into univariate, multivariate, bidirectional, it was obtained that the probability curve for COVID-19 in India shows a general decline for the new cases at that time.

4. Challenges and future scope

Researchers have faced several challenges in implementing ML and DL based combination models for COVID-19 diagnosis and detection. Although significant advancements have been made in identifying suitable models, there is still a lack of comprehensive knowledge in this field. One of the primary challenges is the complexity and variability of COVID-19. The virus exhibits diverse manifestations and affects individuals differently. This variability poses challenges in accurately capturing the patterns and characteristics of the virus in imaging data. The lack of a comprehensive understanding of the disease's dynamics, especially in its early stages, delays the development of highly accurate and reliable models. Another challenge lies in the availability and quality of data. Access to large and diverse datasets plays a crucial role in training ML and DL models effectively. However, the collection and curation of such datasets, particularly those containing labelled COVID-19 imaging data, have been limited. Additionally, the quality and consistency of the available datasets can vary, which can impact the performance and generalizability of the models. Furthermore, the rapid evolution of the COVID-19 pandemic requires continuous adaptation of the models. As new variants emerge and medical knowledge expands, the models need to be regularly updated and validated to ensure their relevance and accuracy. This dynamic nature of the virus poses ongoing challenges for maintaining the efficacy of the developed models over time. Ethical considerations and privacy concerns also present challenges when accessing and sharing medical data for research purposes. The sensitive nature of patient data requires adherence to strict privacy regulations, which can limit the availability and accessibility of large-scale datasets. Balancing the need for data privacy with the perseverance to develop effective detection models is a delicate task. To address these challenges, interdisciplinary collaborations among researchers, healthcare professionals, and data scientists are essential. With these advancements, healthcare resources can be better utilised, ultimately leading to improved patient outcomes.

5. Conclusion

Artificial intelligence (AI) has demonstrated its potential as a powerful diagnostic tool in various medical domains, and now researchers are exploring its application in the diagnosis of COVID-19. The paper motive is that through this review, the researchers can get a comprehensive overview of detection models for COVID-19 using ML/DL techniques and medical images. By gaining insights from this paper, researchers can build more efficient models, which will ultimately help alleviate the burden on healthcare systems and save lives from this deadly virus. Through a systematic review and analysis, the authors conclude that a combination of DL models can lead to an adequate and useful system for COVID-19 diagnosis, achieving an impressive accuracy rate of 99.06%. The limitations of these models stem from the scarcity of available image data for COVID-19 patients.

Author contributions

Conceptualization, RD and KS; methodology, KS; software, KS; validation, KS; formal analysis, KS; investigation, KS; resources, KS; data curation, RD; writing—original draft preparation, KS; writing—review and editing, RD; visualization, RD; supervision, RD; project administration, RD; funding acquisition, KS. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interests.

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