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# **Medical Images Based Covid-19 Detection Survey**

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#### ABSTRACT

In December 2019, COVID-19 appeared for the first time in Wuhan (Hubei Province, China), after which it quickly spread over the entire earth. The World Health Organization quickly designated COVID-19 a pandemic because of the high number of deaths and rapid global spread of the disease. Because of this, many facets of society have been impacted, and those effects may last for years to come. Therefore, COVID-19 detection methods were the focus of numerous research projects in the past. This has led to the development of the COVID-19 AI Detector, a specialized area of artificial intelligence-based research. In this paper, we survey all significant current efforts that have taken advantage of machine learning to COVID-19 detection and prediction. We first surveyed all datasets used in relevant research, and then summarized them in a table containing the link to that data. Then, we mention all the methodologies employed to detect the presence of COVID-19 using such datasets. Later, the challenges and difficulties that facing the concerned researches are reported, while the results of all interesting related work that lay ahead in this field before concluding this paper were discussed fairly.

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#### 1. Introduction

The term COVID-19 was taken from the nomenclature: "Coronavirus disease 2019"; In December 2019, the Municipal Health Committee in Wuhan (China) submitted a report for the first time, in which it was stated that the disease arose due to severe acute respiratory syndrome 2 (SARS - COV - 2) coronavirus, which is considered one of the most deadly global epidemics in human history [1]. In March 2020, the World Health Organization (WHO) declared the COVID-19 outbreak a global pandemic. This has led to the impact on people socially, economically and medically and to the

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occurrence of global distress. The WHO indicated in many of its reports that the COVID-19 early symptoms include: chest pressure, breath difficulty, pain movement, and loss of speech. Later, the patient may develop other symptoms such as dry cough, fever, fatigue and aches, as well as conjunctivitis, sore throat, diarrhea, discoloration of the teeth or skin rash, and even the toe [1, 2]. On 10 March, 2020, WHO, UNICEF and "the International Federation of Red Cross and Red Crescent Societies" have produced guidance outlining critical considerations and practical checklists for keeping schools safe, and advice for parents, carers, children and students themselves [3].

As a trend in the scientific community, artificial intelligence (AI) has succeeded in COVID-19 detection and diagnosis [2, 4]. Machine learning (ML) and AI algorithms have been exploited to diagnosis this disease, by designing a routine that can view a large number of X-ray images taken from the patient's chest. And because the results made it possible to obtain a diagnosis of the disease faster than laboratory methods, this routine was helpful to doctors in the matter of quickly detecting the presence of coronavirus in patients and monitoring them as well, where the computer play the role of COVID-19 AI Detector (CovidAID) [5]. In urgent cases, doctors may ask a radiologist to make the diagnosis using radiological imaging methods of the lungs such as computed tomography (CT) or chest x-rays (CXRs). Then, by analyzing these images, the specialist can determine a final diagnosis. Careful medical images analysis will help to pass the RT-PCR technique limitations. Figure (1) shows that used tests for COVID-19 detection are divided into two groups, including: (1) laboratory diagnostic test, and (2) imaging modality [6, 7].



Fig. 1 - COVID-19 detection tests.

# 2. COVID-19 Medical Image Datasets

Scientific researchers are began to published a lot of papers that are interested in trying to detect the disease early, which requires collecting a set of image data for analyzing and studying the effective factors that may leads to make a fast and accurate diagnosis. Thus, imaging databases and registries were created using different imagery techniques to be an essential datasets for radiology based diagnosis, and also to develop AI tools for automated diagnosis. Table (1) provides a summary of some up-to-date COVID-19 imaging datasets [6].

Ser.	Name	Size (Patients)	Format	Country	Link
1	AlforCovid Imaging Archive	983	DICOM	Italy	https://alforcovid.radiomeca.it\
2	MosMed Covid- 19 Chest CT database	1110	NifTi	Russia	https://mosmed.ai/datasets/covid19.1110
3	Kaggle: COVID- 19 radiography	4728	PNG	Global	https://www. kaggle.com/tawsi furra hman/ covid19- radiography-database
4	Covid-19 Radiography 11	3887	JPG	Global	https://www.montreal_univ.edu/sudalairajkumar/novel- corona-virus-2019-dataset
5	Kaggle: SARS- CoV-2 CT Scan Dataset	5738	JPG	Global	https://www.kaggle.com/plameneduardo/sarsc ov2- ctscan-dataset
6	Kaggle: Chest X- Ray Images	3774	PNG	Global	https://www.kaggle.com/paultimothymooney/chest- xray-pneumonia
7	SIRM	101 patients	JPG	Global	https://radiopaedia.org/articles/covid-19-3
8	Github: UCSD COVID-CT	349 from 216 patients	PNG	Global	https://github.com/UCSD-A14H/COVID-CT
9	Github: COVID- CXR-AI	1171	JPG	Global	https://github.com/lpbaltazar/COVID-CXR-AI
10	Github: CVR-Net	3515	PNG	Global	https://github.com/kamruleee51/CVR-Net
11	GitHub: Covid- Chestxray	2541	JPG	Global	https://github.com/tawsifur/COVID-19-Chest-X-ray- Detection
12	GitHub: covid- chest x-ray	1500	PNG	Global	https://github.com/ieee8023/covid-chestxray-dataset
13	GitHub dataset	2631	JPG	Global	https://github.com/lindawangg/COVID-Net
14	ImageNet dataset	1750	JPG	Global	https://data.mende ley. com/ datas ets/ rscbjbr9sj/3
15	CT machine learning database	930 images from 461 patients	JPG, NifTi	Global	https://github.com/ieee8023/Covid-chestxray-dataset
16	NIH Chest X-Ray	60361	JPG	Global	https:// nih/covid-chestxray-dataset
17	Eurorad database	50 patients	JPG	Global	https://www.eurorad.org/advanced-search?search=COVID
18	Coronacases.org	10 patients	online	China	https://coronacases.org/
19	CT egmentation dataset 1	100 images from 40 patients	NifTi	Italy	https://medicalsegmentation.com/covid19
20	CT egmentation dataset 2	100 slices from 9	NifTi	Global	https://medicalsegmentation.com/covid19
21	CT egmentation dataset 3	20 cases	NifTi	Global	https://zenodo.org/record/3757476

Al plays an important role in COVID-19 detection when suitable images are available for research, this enable researcher to identify COVID-19 by symptoms analysis with the help of X-rays such as difficulty breathing, cold sweats, and sore throat. It was clear that a number of these researches relied on the different data types; therefore, the research carried out to solve this problem can be classified based on data type or depending on the type of methods used. It was noticed that some of researches were depending on the sounds emanating from the patient, such as coughing and breathing, which an audio based efforts. Whereas, other researches were depending on images of lung, or other infected parts of human body, which is regarded as an image based efforts. In both cases of data types: audio and image, and machine learning principles were used for solving the problem of diagnosing COVID-19 disease, While some advanced research relied on deep learning methods in a step aimed to increase the precision of resulted classification. In the following, we provide a state-of-the-art survey of present around implemented researches of employing the AI for solving the problem of detecting and predicting COVID-19 within total published research:

# 3.1. Machine Learning Methods

Mustafa Abdul Salam et al. studied the effectiveness of federated learning versus conventional learning by evolving two models of ML: conventional ML and federated learning (FL) using federated Tensor Flow and Keras. Chest X-ray (CXR) images and descriptive dataset were used from COVID-19 patients. This study compares the accuracy, performance, and loss of the proposed models [8]. Sudip Mandal et al. focus on how Artificial Neural Network (ANN) and decision tree can detect whether any person is COVID positive, based on eight input parameters. The dataset has been collected from a website concerned with human health, in which all the data are available publicly for further analysis. The ANN and decision tree models have been trained and tested in this study to validate the proposed methodology. It has been observed that the ANN's performance is superior to the decision tree regarding classification accuracy for cross-validation and testing new cases. However, the decision tree's runtime is very small compared to ANN [9]. Rachael Harkness et al. introduced widely used models trained on open source data, and tested on a hospital dataset and an external test set to classify chest X-ray images into three categories: pneumonia, non-COVID pneumonia, and COVID-19. ROC curves were used to evaluate the classification outcomes of the models examined and then standard classification scales and confusion matrices were applied to confirm the validity of the results. The effect of the most important image features on the classification results was evaluated fairly. [10]. Ruyi Qu et al. solved the problem of detection the abnormality and classification of lung images using ML technique The Kaggle platform provided the dataset, and YOLOv5 was chosen as a model. Mean average precision (MAP) was chosen as an experiment's metric. The higher MAP indicates good performance of the model. The descriptive characteristics of the lung images for both healthy and sick cases were extracted and entered into the classifier based on ML, and the results of the experiment were very successful [11].

## 3.2. Deep Learning Methods

Lei Rigi Baltazar et al. used a COVID-19 pneumonia detection models based on AI, and in order to increase the data set collected from external sources, a retrospective clinical study data was adopted. Five deep learning models were developed to process the data distribution. The classification results of the five models were quantitatively compared to evaluate the diagnostic performance and robustness. Where it was found that adjusting the hyperparameter affects the performance of the discovery model without depending on the amount of data. The performance of the InceptionV3 classifier in discriminating pneumonia from normal CXR by specificity (Sp), sensitivity (Sn), and positive predictive value (PPV) was evaluated at 96% [12]. Md. Kamrul Hasan et al investigated potential overfitting and biases in studies that used DL-based AI tools for automated COVID-19 detection by general data constraints with different settings and focus on the challenges of how to develop deep learning methods. DL architecture is designed to function as a hybrid COVID-19 classifier between ResNet and Xception, which is available for conducting challenges identification experiments. The results of DL indicated that there may be an overestimation of performance due to adaptation to the training data set and experimental design bias. The proposed design of the DL model gave the best performance when the best settings were available [13]. Gökalp CINARER et al. used deep CNN to chest radiography to detect COVID-19. Two models were used: SqueezeNet and DenseNet. The x-ray images were scaled down to 224×224 for all images of infected and non-infected cases, then features were extracted from the image set and divided into 80% for training purpose and 20% for testing purpose. Some horizontal and vertical shifts, brightness changes, as well as angular changes have been made to the images in order to increase the data count. The classification results showed an acceptable performance of the classifier, as the experimental results were very convincing. [14]. Shashank Mishra et al. suggested the use of chest X-rays to allow patients to choose priority for RT-PCR testing. AI methods were used to detect cases of COVID-19 that used the X-ray imaging method in order to provide the possibility of diagnosis in areas where doctors are not available, where Covid-AID: COVID -19 was created, a detection device that relies on AI techniques to help diagnose disease patients by a model based on a DL neural network (NN). The results showed that the performance of the model was efficient in making the appropriate

diagnosis of the studied cases. [15]. Md. Kawsher Mahbub et al. employed hierarchical RegNet was adopting CXI in DL as a method for diagnosing positive and negative COVID-19 cases. The improved RegNet architecture is designed with a small set of parameters and epochs. By evaluating the performance, it was found that the model could reach an accuracy of 98.08% after passing five periods. Two datasets were used to test the model. The first set of COVID-19 CXRs contains 1,341 negative and 1,200 positive CXRs, while the second set of COVID-19 CXRs contains 2,000 negatives and 195 positives. The results give an acceptable performance for the optimized RegNet architecture used [16]. Malak Mohamed et al. investigating the creation of a mobile application that analyzes chest x-ray images of suspected individuals and obtains immediate and accurate results based on AI and DL algorithms. This application provides the user with the ability to download the test result. A public open data set containing 1341 negative-score images and 1500 positive-score images was used. The results of the classification of these data were compared and the results of the classification were evaluated, which showed a good performance of the classifier. As a result, the user receives a message on the mobile phone telling him the case diagnosis of the scanned image if he is infected with Covid-19, infected with SARS-CoV-2, or healthy [17]. Sikandar Ali et al. developed a CNN structure for classifying COVID-19 X-ray imagery that is related to the CNN Compression Density (DCSCNN). This workbook can also diagnose cases of lung opacity and pneumonia. Various sources were used to collect data and then pre-processing was used to improve the images. Furthermore, LIME and Grad-CAM were used to identify regions of attention that inform classifier decisions. DCSCNN combines Squeeze with the power of Dense Networks. Seven types of classifiers were tested, of which six were binary classifications: lung opacity vs. COVID, normal vs. COVID, pneumonia vs. COVID, pulmonary opacity vs. normal, pneumonia vs. lung opacity, and pneumonia vs. pneumonia. There is one classifier that is applied to the different categories: COVID vs. Opacity vs. Normal vs. Pneumonia, the acceptable results gave a good indication about the validity of used method [18]. Vandit Gupta used real-time techniques to detect whether a patient was suffering from covid-19. The techniques are: Convolutional Neural Networks (CNN), and image augmentation. Two different datasets were used for Covid-19 Detection namely: normal images, Covid positive images. Based on the review performed, the classification model based on DL is designed to give acceptable classification results. [19]. Ju Luo et al. developed a DL model in the detection of COVID-19 pneumonia in order to provide assistance to radiologists. The number of studied cases was 437, and the training dataset contains, 2468 CAP, 26477 images, and 8104 COVID-19. While the validation data set contains 1,028 CAPs, 14,076 images for Norma patients, and 3,376 for COVID-19 cases, Also, the test set contains 51, 28, and 51 uninfected cases, COVID-19 patients, and CAP patients, respectively. The DL model was designed to recognize normal patients, CAP, and COVID-19, and was trained on U-Net and ResNet-50 structures. The results of the comparison of the DL model's diagnoses with radiologists' were fair [20]. Shubham Mahajan et al. presented a controlled study to analyse different models for COVID-19 detection. They provided a comparison between the VGG16, VGG19, Residual Network, Dark-Net as the foundational network with the Single Shot MultiBox Detector (SSD) for predictions. The Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied on data set before training operations. The results of the experiment confirmed that DenseNet is the best classifier compared to the SSD512 classifier [21]. E. Sankar, et al. used multiple CNN models: InceptionV3, VGG16, ResNet-50, and Xception models for trying to classify Covid-19 patients based on CT scans and X-rays of their chests. The models were trained on approximately 750 CT images and 1,000 chest X-rays over 500 epochs. The model used gave good classification results. [22]. Divyadharshini Karthikeyan et al. used the transfer learning (TL) approach, which service learning with the least number of samples and make the acquired learning transferred into greater data set. They were considering TL by three models were previously training on labelled images taken by ImageNet. These three used models are: VGG19, ResNet101, and VGG16. Different categories of images were collected to create the dataset, and results that were found to be acceptable were discussed [23]. Dandi Yang et al. used four powerful pretrained CNN models, they are: DenseNet121, VGG16, ResNet152, and ResNet50 for CT-scan classification of COVID-19. The use of Fast.AI ResNet was proposed to be used for finding the preprocessing automatically, parameters of models training, and best architecture. The results were somewhat satisfactory [24]. Edward H. Lee et al. used a DL of CNN using chest CT magnitude to foresee COVID-19 (COVID+) from non-COVID-19 (COVID-) automatically. They discussed the strategies of training and performance deviation between 8 countries and 13 international institutions. There was homogeneity in used images quality, which gave a potential for the adopted model to show distinct results [25]. Ferhat Ozgur Catak et al. proposed to use the GitHub repository to train CNN models by quantitative estimation of enhanced uncertainty for the prediction of COVID-19. They used 278 X-ray images of COVID 19 positive and 66 negative in the training process, while in the testing process they used 39 positive images and 30 negative images. The researchers used pre-trained deep CNN models: VGG19 and VGG16, DenseNet, ResNet and Inception V3 to understand the complexity nature of the images that require a DL model. The evaluation of the results showed that there is an indication of a certain accuracy that DL methods cannot overcome [26]. Nillmani et al used sixteen types of classification-based models by DL for accurate and fast automatic COVID detection. Dual networks of DL-based segmentation were used: UNet+ and UNet, in addition to eight models of classification: Resnet50, VGG19, InceptionV3, VGG16, NASNetMobile, Xception, MobileNet, and Densenet201. All of them are implemented for finding the superior

networks in the detection results. System performance was evaluated using the cross-entropy loss function by laccard and Dice, area under the curve (AUC), receiver operating characteristics (ROC), then results were further validated using Grad-CAM in an interpretable AI framework. This method gave a great possibility to determine the area of injury and raise the level of classification [27]. Cheng Jin et al. proposed AI model to quickly diagnose COVID-19. Initially, a statistical analysis of CT images of infected people was done based on the AI model. The method used was developed and its work evaluated by examining a large dataset containing more than 10 thousand CT of community-acquired nonviral pneumonia, influenza A/B and COVID-19 (CAP) images. The results of the network-based deep CNN model gave remarkable results by realizing AUC, which is a very important result when studying such a problematic multiclass diagnostic task [28]. Feng Pan et al. presented a new DL-based quantitative estimation for a study comparing semi-quantitative conventional CT scores for serial CT scans of chest for COVID-19, 465 serial chest CT scans were taken from 95 patients with COVID-19, of which 34 were severe cases and 61 moderate cases. In order to achieve two main goals: to explore dynamical patterns by such two estimates of both severe groups and the moderate, and the correlation of such estimates. DL-based quantification and conventional CT scores were taken for all chest CT examinations. The used model showed acceptable results in terms of accuracy and response speed [29]. Shruti Jadon aimed to overcome the problem of scarcity of data, known DL solutions have been tried to detect cases of COVID-19 disease. These include data overload, few-shot learning, TL, and unsupervised learning. A few-shot scenario was used to detect COVID-19 by adopting Siamese nets; The results showed that prior knowledge made the classifier able to diagnose the disease with acceptable accuracy [30]. Michael J Horry et al. proved that detecting COVID-19 using X-ray images can be easy using pre-trained DL models. An autologous image processing model that makes a reliable image dataset is proposed for testing DL models. The goals of this scenario are to process X-ray images to reduce unwanted noise, so DL networks were employed to diagnosis diseases using effective features of them [31].

# 3.3. Further Related Work

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The following sections present more details about papers conducted with other methodologies for analyzing COVID-19 behavior in order to find other ways to diagnose this disease, as well as to understand how the disease can be transmitted between people in order to fight its spread and expansion between peoples, the most interesting ones are given in the following:

Adwait Patil in [32] used a one-dimensional CNN that handles metadata and audio. The Coughvid dataset consisting of 27,000 audio files with attached metadata was used for the same number of patients. The audio files are presented as tar format files. The research aims to design a model that works on calculating the probability of having Covid-19 disease. The results showed that the CNN technique had reached a satisfactory diagnostic accuracy of 72%. It was observed that the training loss was slightly less than the validation loss, and the training accuracy was slightly more than the validation accuracy. This may be attributed to the low number of people with Covid disease in the data set used, which greatly affected the diagnostic results. Khalid Mahmoud et al. in [33] used a systematic approach to study three different classification models: the classical linear model (MLR), the adaptive fuzzy inference system (ANFIS), and artificial neural networks (ANN) to infer the relationship of environmental factors with the extent of the spread of COVID-19. These factors included: humidity, wind, and temperature. Study data from COVID patients in Wuhan, China in 2020 was extracted by the publications: Haghshenas, Piro, Haghshenas, Pirouz. The classification results were evaluated by three performance indicators: the determination coefficient (R2), coefficient of correlation (R), and the root mean square error (RMSE). The diagnostic results indicated that ANFIS and ANN are two more important methods than the conventional MLR with R values (0.90) in the validation and calibration stages. The classification results also showed that the performance of ANFIS was better than both ANN and MLR. The final results describe the reliability and ability to simulate COVID-19 by exploiting the influence of environmental factors. Dasaradharami Reddy Kandati et al. in [34] proposed a new hybrid algorithm called Genetic CFL (Genetic Clustered FL), this algorithm relied on highly tuned parameters to cluster edge devices constructively, this method was applied to the dataset in the Kaggle repository, the parameters were clustered genetically modified. The results of experiments indicated that the behavior of genetic algorithm (GA) used CFL was better than using traditional AI, with an accuracy of 91.26% for the diagnosis of the disease.

# 4. Experimental Results Overview

Many successes have been achieved in research related to diagnosing Covid-19 disease, and this may be due to the frequent use of DL systems in order to obtain accurate results, which was included in the urgent need at that time. In the following, a detailed mention of the results obtained in the field of interest is explained:

# 4.1. Machine Learning Experimental Results

Mustafa Abdul Salam et al. showed that there is good resulted accuracy and less loss in the performance of the unified ML model by the amount of execution time that is longer than the time required to implement the traditional ML model [8]. Sudip Mandal et al. discored an advantage of using a decision tree for classification problems. It is possible to achieve satisfactory classification accuracy for both models, although other advanced AI models or algorithms may be applied to improve the performance in the future [9]. Cheng Jin1 et al. The multi-way classifier was used to diagnose COVID on a set of 3199 images, which include two datasets, CC-CCII and MosMedData, respectively. Five radiologists were read. The results prove that the performance of the approved AI system has outperformed all radiologists, especially in images that contain a real challenge. The classification results were within the limits of 97.81%, 92.99% and 93.25%, and when a comparison was made between the performances of the proposed method's diagnosis with that of expert doctors; it was found that the consumed time for achieving results of COVID-19 diagnosis was less than half of the results of the doctors' diagnosis. Therefore, a detailed interpretation of the performance of the deep network was required to correlate the CT displays with the outputs of the system [28]. Feng Pan et al. used two estimation methods for Spearman's correlation coefficient, which was found to be around 0.920 (p < 0.001) to detect cases of COVID-19 at two levels; moderate and severe. The method of work was based on DL-based quantification studying the proportion of lung lesions computed and computed tomography score. With increasing amounts of estimation, the severe infestations studied reached the highest peak on the twenty-third day of the onset of symptoms, while the group of moderate infections reached its peak on the eighteenth day (18) with a faster absorption of pests. The results showed a potential benefit in estimating the severity of the disease and that there is a good relationship with the conventional CT score [29]. Ruyi Qu et al. proved the better result achieved with the AI models, in which MAP is 0.5 of chosen YOLOv5s at 0.623, 0.157, and 0.101 higher than Faster RCNN and EfficientDet, respectively [11].

#### 4.2. Deep Learning Experimental Results

Lei Rigi Baltazar et al. achieved higher general performance of 94-98% Sp. 90-96% PPV and 91-96% Sn in three classes in comparison with four scenarios of detection classes. It was found that InceptionV3 showed good performance of average F1-score of 96% in scenario of detecting COVID-19 pneumonia, the highest performances were: AUC of 0.99, 86% Sn, 91% PPV and 99% Sp for the purpose of distinguishing normal CXR from pneumonia. The ability to distinguish between normal pneumonia and COVID-19 pneumonia was 0.98 AUC, an exact mean of 0.99 for the other categories [12]. Md. Kamrul Hasan et al made an emphasis on interpreting and comparing the results of different DL algorithms and their challenges. Results of DL-based methods applied to chest images have shown to be useful in triaging COVID-19 patients and enriching clinical management. Their experiences indicated that expanding the image database may be necessary to improve application performance in real-world clinical settings that imposes less bias [13]. When using the SqueezeNet and DenseNet classifiers, the results showed high accuracy values of 97.7% and 99.09% after applying them to 30 epochs. These results indicated the possibility of AI methods in detecting COVID-19 patients, which gave high-accuracy results when applied to chest X-ray images [14]. Shashank Mishra et al. The accuracy of diagnosing COVID-19 was obtained by 90.5% with a sensitivity of 100% when applied to a set of chest X-ray images [15]. Md. Kawsher Mahbub et al. They found that the proposed approach can be used for comprehensive screening, the classification accuracy results were 97.13% and 99.02% when using the previously mentioned data set [16]. Malak Mohamed et al. The results include a high accuracy of 97.8%, a high F1 score of 0.986, a high sensitivity of 99.5%, and a high specificity of 97.57%. This confirms that the project of exploiting AI in detecting Covid 19 disease has met the design requirements after converting it into an easy-to-use mobile application [17]. Sikandar Ali et al. obtained a precision about 98.8% to classify normal vs. COVID-19 based on proposed DCSCNN model, then lung opacity examined with COVID-19 with to give 98.2%, normal examined with lung opacity to give 97.2%, pneumonia examined with COVID-19 to give 96.4%, lung opacity examined with pneumonia to give 95.8%, normal examined with pneumonia to give 97.4%, and finally the four classes: pneumonia vs. COVID vs. normal vs. lung opacity examined with each other to give total precision of 94.7% with excellent diagnosing behavior that helps doctors practically [18]. Vandit Gupta concluded that there is a huge scope for ML algorithms in disease prediction especially in the case of lung diseases due to the abundance of available data and extensive research done in this field and CNN's are quite powerful to detect COVID-19 patients from their X-Rays [19]. Ju Luo et al. tested the DL model in order to examine the system for detecting normal cases that were not infected with Covid disease, the results were CAP detection with limits of 92.15%, 89.28%, 98.03% respectively, while the results of applying the DL model reached a detection accuracy disease 93.84%. The accuracy of disease detection for the validation group was 92.86% compared to two junior doctors 87.75% and 86.73%, and almost equivalent to two experienced doctors 93.88% and 94.90%. Overall, the AI model performed better than the radiologists in terms of time: 35 minutes versus 75, 93, 82, 79 minutes. [20]. Shubham Mahajan et al. demonstrated the employed the field of medical imaging (computer vision) based on DL techniques. A high level of recovery and accuracy was achieved by the SSD512+DenseNet201 model with values of 94.98 and 93.01. And so a call was made to all AI researchers in the world for searching and modifying models in the stage of rapidly stabilizing increase of infection cases of this very rampant epidemic [21]. E. Sankar, et al. showed that the best performance can be achieved by using the Xception model, where precision of using IncptionV3, VGG16. ResNet50, and Xception when using Chest X-Ray dataset were 96%, 94%, 83%, and 92% frequently, and the precision of them when using CT Scan dataset were 93%, 93%, 80%, and 95%, which a regarded results refers to the ability of deep learning model to detect Covid-19 in accurate manner [22]. Divyadharshini Karthikeyan et al. noted the DL based models were well performed. The most suitable training models gave precisions as follows: VGG19 at 95.32%, VGG16 at 96.47% and ResNet101 at 97.46% frequently [23]. Dandi Yang1 et al. showed the results of the diagnosis of COVID-19 achieved with accuracy and the F1 score are above 96% using CT chest images. The classification results were evaluated by the multiclass and binary classification of X-ray images by the optimized VGG16-DL structure. The use of the improved VGG16 model applied to pneumonia and COVID-19 X-rays gave a high accuracy about 99%, and achieved best precision with COVID-19 pneumonia X-rays with the VGG16 model was up to 99% [24]. Edward H. Lee et al. significantly improved classifier performance was achieved by achieving a high detection score 0.8, AUCs was noted in most of the test sites when the training set included images of non-Chinese sites [25]. Ferhat Ozgur Catak et al. found results were demonstrating that there is a possibility to recognize between cases of detection of COVID-19 from cases of non-COVID-19 by using the pre-trained VGG16 network, the performance of this DL network achieved excellence (75%) compared to other models. The used dataset includes CT images and chest X-ray for some diseases in lungs, including the types of : suspected positive and positive of COVID-19, besides bacteria diseases (ARDS, SARS, MERS and) [26]. Rachael Harkness et al. evaluated the model performance and pre analysis of the data set of the test results 88% accuracy, are thus overstated and that this open source COVIDx data does not contain the real clinical problem. Open source data can negatively affect the performance of the classification model and make it vulnerable to confounding variables and bias. This makes it necessary to conduct a rigorous analysis that seeks to improve useful clinically applicable AI tools for the purpose of an effective method in the diagnosis of COVID-19 by chest X-ray imaging [10]. Nillmani et al showed that the results of the UNet network gave the best performance, the AUC, jacquard, dice, loss, and accuracy were 0.99 (p-value < 0.0001), 94.88%, 90.38%, 0.15%, and 96.35% respectively. UNet+ was found to be the best performing classifier. Whereas, the Xception network gave AUC, F1 score, and recall accuracy equal to 0.998 (p-value < 0.0001), 97.45%, 97.43%, 97.46%, and 97.45% respectively. It was found that the system based on current methods is much better than classification models based on segmentation. The mean accuracy of the Xception UNet+ enhanced system was 8.27% for all remaining studies. This confirms that the applicability of the segmentation-based classification system was possible because the assumption (rate of error less than 5%) is valid and can be adapted clinically [27]. Shruti Jadon showed the experimental results for diagnosing COVID-19 is possible with adopting an accurate and effective DL network even with little data by adopting low-shot learning approaches. A performance accuracy of 96.4% was reached, which is better than the performance of the basic models, which gave an accuracy of 83%. [30]. Michael [Horry et al. achieved findings were focused on the used models suitability using currently used dataset, it is found that the simpler network models (e.g., VGG19) can operate the diagnostic tasks well with a performance ratio of 83% [31].

## 5. Experimental Results Comparison and Discussion

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During an extensive round of research and investigation on all the researches that were issued under the title of facilitating procedures for detecting the diagnosis of Covid-19 disease, we found that there are the largest number of them that have taken advantage of the tools of DL systems. This may be due to the fact that the general situation at that time required the use of disease detection systems quickly and with high accuracy, and that the pandemic invading countries and peoples was vast, and researchers did not have the opportunity to deliberate and choose the best ways to detect the disease using the computer, but rather the situation was more like a state of war against the disease, Which led researchers to use fast and guaranteed methods to obtain outstanding results, which is the use of DL principles that only require the availability of a huge data set, and this is what is actually available on the ground. Table (2) lists a detailed explanation related to the published papers of detecting and predicting Covid-19.

It is noted that most of the research that has been carried out has used a dataset of chest x-ray images. Where, it can be considered that this type of imaging is available in most health centers and gives almost a good indication of the effects of the disease, but the most important thing is the speed of obtaining such images. Although the x-ray images are regarded as descriptively poor because they are mostly dark and do not give a clear distinction to the organs of the human body, the large number of them may give the classifier good ability to discriminate between healthy and infected cases. Accordingly, a number of websites that containing such datasets of X-ray images of infected and healthy people became available. While research institutions have prepared datasets in useful numbers available to researchers to performs this purpose, such as the website of Kaggle, Github, Italian Society of Medical Radiology, and Radiological Society of North America RSNA. Whereas, some researchers used a local dataset, or a dataset that they collected from health centers by themselves.

By observing the results of Covid19- detection obtained in the published research that referred to in Table (1), we find that most researchers have used deep machine learning methods, and this may be due to their actual need at that time for a rapid and efficient diagnostic system. Among the most important DL systems that were used is VGG16, which gave the best classification results in most of the research, as the detection accuracy reached 99%, while the detection rate ranged between 91-99% when using the VGG models. Secondly, we note that the CNN method has succeeded in providing high detection accuracy compared to other methods of DL. It is worth noting there are significant differences observed between the results of methods of DL and results of traditional ML, as detection accuracy of traditional ML methods did not exceed 88% average score as Table (3) shows, and in some of them it declined to reach 82%. The high classification scores achieved by using DL may be due to the large number of descriptive characteristics used by this method, which serve the process of analyzing image components towards better distinction and better detection results.

Method	Dataset	Results	References
	Github: COVID-CXR-AI	96%	[12]
	Github: CVR-Net	Acceptable accuracy	[13]
InceptionV3	ImageNet dataset	Acceptable accuracy	[22]
-	GitHub dataset	Acceptable accuracy	[26]
	NIH Chest X-Ray	68%	[31]
	Github: COVID-CXR-AI	Acceptable accuracy	[12]
Xception	DatasetResultsGithub: COVID-CXR-AI96%Github: CVR-NetAcceptable accuracyImageNet datasetAcceptable accuracyGitHub datasetAcceptable accuracyImageNet dataset95%NIH Chest X-Ray68%Github: COVID-CXR-AIAcceptable accuracyImageNet dataset95%NIH Chest X-Ray69%Github: COVID-CXR-AIAcceptable accuracyCollected Dataset93.88%ImageNet datasetAcceptable accuracyCollected Dataset93.88%ImageNet datasetAcceptable accuracyGitHub datasetAcceptable accuracyKaggle: COVID-19 RadiographyAcceptable accuracyNIH Chest X-Ray70%ImageNet dataset97.46%,Kaggle: SARS-CoV-2 CT ScanAcceptable accuracydGithub: CVR-Net79.9%Github: CVVID-CXR-AIAcceptable accuracyKaggle: covidx-cxr293.01%ImageNet datasetAcceptable accuracyKaggle: COVID-19 Radiography99%GitHub dataset75%Covid-19 Radiography 1193.3%,NIH Chest X-Ray82%Github: CVR-Net78.5%Kaggle: covidx-cxr294.98.%ImageNet dataset96.47%Github datasetAcceptable accuracyNIH Chest X-Ray83%Kaggle: Covid-19 radiography97.7%Kaggle: Covid-19 radiography97.7%Kaggle: Covid-19 radiography93.01%Kaggle: Covid-19 radiography97.7%	[22]	
-	NIH Chest X-Ray	69%	[31]
ResNetV2	Github: COVID-CXR-AI	Acceptable accuracy	[12]
	Github: CVR-Net	Acceptable accuracy	[13]
	Collected Dataset	93.88%	[20]
DecNet FO	ImageNet dataset	Results96%Acceptable accuracyAcceptable accuracy68%Acceptable accuracy95%69%Acceptable accuracy95%69%Acceptable accuracyAcceptable accuracy93.88%Acceptable accuracyAcceptable accuracyAcceptable accuracyAcceptable accuracyAcceptable accuracy70%97.46%,Acceptable accuracy79.9%Acceptable accuracy93.01%Acceptable accuracy99%75%93.3%,82%78.5%94.98.%96.47%Acceptable accuracy83%97.7%93.01%Acceptable accuracy94%Acceptable accuracy94%Acceptable accuracy94%Acceptable accuracy94%Acceptable accuracy	[22]
Resnet-50	Kaggle: COVID-19 Radiography	Acceptable accuracy	[24]
	GitHub dataset	Acceptable accuracy	[26]
	NIH Chest X-Ray	70%	[31]
ResNet-101	ImageNet dataset	97.46%,	[23]
ResNet152	Kaggle: SARS-CoV-2 CT Scan	Acceptable accuracy	[24]
CVR-Net (ResNet-50 and Xception combination)	Github: CVR-Net	79.9%	[13]
	Github: COVID-CXR-AI	Acceptable accuracy	[12]
	Kaggle: covidx-cxr2	93.01%	[21]
	Github: COVID-CXR-AI 96%   Github: CVR-Net Acceptable accuracy   ImageNet dataset Acceptable accuracy   GitHub dataset Acceptable accuracy   GitHub dataset Acceptable accuracy   NIH Chest X-Ray 68%   Github: COVID-CXR-AI Acceptable accuracy   NIH Chest X-Ray 69%   etV2 Github: COVID-CXR-AI Acceptable accuracy   Github: CVR-Net Acceptable accuracy   Github dataset Acceptable accuracy   Kaggle: COVID-19 Radiography Acceptable accuracy   Github dataset 97.46%,   et-101 ImageNet dataset 97.46%,   et152 Kaggle: SARS-CoV-2 CT Scan Acceptable accuracy   Net (ResNet-50 and Github: CVR-Net 79.9%   ion combination Github CVID-CXR-AI Acceptable accuracy   ImageNet dataset 75% Covid-1	[22]	
	ImageNet dataset	97.46%	[23]
VGG-16	Kaggle: COVID-19 Radiography	99%	[24]
	GitHub dataset	75%	[26]
	Covid-19 Radiography 11	93.3%,	[30]
	NIH Chest X-Ray	82%	[31]
	Github: CVR-Net	78.5%	[13]
Github: CVR-NetAcceptablInceptionV3ImageNet datasetAcceptablGithub: COVID-CXR-AIAcceptablNIH Chest X-Ray68%Github: COVID-CXR-AIAcceptablXceptionImageNet dataset95%NIH Chest X-Ray69%ResNetV2Github: COVID-CXR-AIAcceptablCollected Dataset93.88%ImageNet datasetAcceptablCollected Dataset93.88%ImageNet datasetAcceptablGitHub: COVID-19 RadiographyAcceptablGitHub datasetAcceptablGitHub datasetAcceptablGitHub datasetAcceptablGitHub datasetAcceptablGitHub datasetAcceptablGitHub COVID-19 RadiographyAcceptablCVR-Net (ResNet-50 and Xception combination)Github: CVR-NetVGG-16Github: COVID-CXR-AIAcceptablKaggle: covidx-cxr293.01%ImageNet dataset97.46%Kaggle: covidx-cxr293.01%ImageNet dataset97.46%VGG-19ImageNet dataset96.47%GitHub dataset75%Covid-19 Radiography 1193.3%,NIH Chest X-Ray82%GitHub dataset96.47%GitHub dataset96.47%GitHub datasetAcceptablImageNet dataset96.47%GitHub dataset96.47%GitHub datasetAcceptablImageNet dataset96.47%GitHub datasetAcceptablResNet-121Kaggle:	94.98.%	[21]	
VGG-19	ImageNet dataset	96.47%	[23]
	GitHub dataset	Acceptable accuracy	[26]
	NIH Chest X-Ray	83%	[31]
DenseNet-121	Kaggle:Covid-19 radiography	97.7%	[14]
DenseNet201	Kaggle: covidx-cxr2	93.01%	[21]
DenseNet121	Kaggle: COVID-19 Radiography	Acceptable accuracy	[24]
DenseNet	GitHub dataset	Acceptable accuracy	[26]
	GitHub: Covid-Chestxray	94%	[17]
Xception combination) VGG-16 VGG-19 DenseNet-121 DenseNet201 DenseNet121 DenseNet CNN	Kaggle: Chest X-Ray	Acceptable accuracy	[19]
	GitHub dataset	Acceptable accuracy	[10]

## Table 2 - Used deep learning methods.

	ImageNet	97.81%	[28]	
	Covid-19 Radiography 11	90.2%,	[30]	
RCNN	Kaggle: Chest X-Ray	39%	[11]	
	Collected Dataset	94.90%	[20]	
U-Net	Collected Dataset	96.35%	[27]	
	Collected Dataset	96.10%	[27]	
SqueezeNet	Kaggle: Covid-19 radiography	97.7%	[14]	
Single Shot Multibox	GitHub: covid-chest x-ray	90.5%	[15]	
Detector (SSD)				
RegNet	Kaggle: COVID-19 Radiography	99.02%	[16]	
MobileNet	Github: COVID-CXR-AI	Acceptable accuracy	[12]	
Residual Network	Kaggle: covidx-cxr2	Acceptable accuracy	[21]	
Dark-Net	Kaggle: covidx-cxr2	Acceptable accuracy	[21]	
DCD	ImageNet dataset	80%	[25]	
deep learning-based	Collected Dataset	Acceptable accuracy	[29]	
quantification				
YOLOv5	Kaggle: Chest X-Ray	62.3%	[11]	
EfficientDet	Kaggle: Chest X-Ray	61.6%	[11]	

#### Table 3 - Used Machine learning methods.

Method	Dataset	Results	References
Keras and TensorFlow federation	Kaggle: chest x-ray radiography Kaggle: CoronaVirus2019	better prediction than deep learning	[8]
Grad-Cam and Lime	COVID-19 Dataset	98.8%	[18]
ANN	Collected data	84.80%	[9]
decision tree	Collected data	83.75%	[9]
Logistic Regression	Covid-19 Radiography	82.4%	[30]
K-Means Clustering, Gaussian Mixture Models Clustering	Covid-19 Radiography	94.6%	[30]

## 6. Conclusions

By looking at the most important research published during the past three years that dealing with the detection of Covid-19 disease, we conclude that the research published in 2020 was brief and did not include detailed studies on the effects of the disease on the human body that enable computers to detect it. Varying detection ratios is because not many data are available. We also found that subsequent research in the year 2022 included studies on the best classifiers that could deal with various types of Covid-19 image data, and this, of course, led to achieving very high detection rates. This indicates that there has been some relaxation in the subjects of scientific research, which led to the achievement of good results. It is obvious that researchers go to DL methods in most of the classifier models used, this is due to the urgent need to obtain high accuracy disease detection results, but some researchers have satisfied this situation by transferring learning from DL based classifier to ML classifiers. In general, the research published in this field has made important achievements in combating Covid-19 in order to serve the international community.

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