

Title: A Review on Detection Techniques of COVID-19 using Deep Learning on Chest X-Ray Images

Khushbu Mushtaq^{1*}, Mir Aman Sheheryar², A.M. Wani³

^{1}Corresponding Author, Research Scholar, Central University of Kashmir, School of Engineering and Technology, Department of Information Technology, Ganderbal, Jammu & Kashmir, 191201, India.*

+91 7889382790

sheikh.khushbu13@gmail.com

²Assistant Professor, Central University of Kashmir, School of Engineering and Technology, Department of Information Technology, Ganderbal, Jammu & Kashmir, 19120, India.

+91 9906669334

aman.sheheryar11@gmail.com

³Professor, Central University of Kashmir, School of Engineering and Technology, Department of Information Technology, Ganderbal, Jammu & Kashmir, 19120, India.

+91 9419089786

amwani011@yahoo.co.uk

Abstract

The novel coronavirus 2019 (COVID-19) is an ongoing pandemic and is caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). Coronavirus-2019 (COVID-19) has caused a significant outbreak worldwide. The first COVID-19 case appeared in December 2019 in Hubei Province of Wuhan, China. In just a matter of weeks, it took over the whole world and was declared a pandemic by the World Health Organization (W.H.O.) in March 2020. The virus can lead to an increased risk of long term health problems and is easily transmitted. The pandemic has resulted in global, social and economic disruption leading to a worldwide recession severely impacting people's health and lives worldwide. With the recent developments in Deep Learning, machine learning algorithms can assist the medical fraternity in the initial screening and diagnosis of COVID-19.

Herein in this paper, we presented a review of different Deep Learning techniques used in analyzing the chest radiograph X-Ray images for initial screening and diagnosis of COVID-19. Deep neural networks are used to detect COVID positive cases from COVID negative patients in a quick, non-contact, low cost and efficient manner, which will benefit healthcare workers and in resource planning.

Keywords- COVID-19, Respiratory syndrome, Deep Learning, CNN, X-Ray

1 Introduction

COVID -19 is a contagious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS -CoV -2). The COVID -19 virus first appeared in the city of Wuhan, China, in December 2019. It took over the world quickly, leading to a drastic

loss of human life worldwide and caused substantial economic and social disruption. As of November 2021, more than 251 million cases and more than 5.07 million deaths have been confirmed due to COVID -19 [1]. Millions of people worldwide have lost their livelihood and have been forced into unemployment, poverty and undernourishment. Millions don't have access to quality healthcare, reliable income and food supplies. The pandemic has hit everyone hard, especially the marginalized communities who already suffer from crises like lack of food security, public health, safety, and employment and labour issues. Lockdowns have led to mental frustration, burnouts and the increased insecurity of income and future wellbeing.

Coronavirus (COVID -19) comes from a Coronaviridae family in Nidovirales order. The virus surface contains crown-like spikes; therefore, it was named coronavirus. The size of coronavirus ranges from 26- 32 kilobase containing a single-stranded Ribonucleic Acid (RNA) [2]. Coronavirus was believed to infect only animals, especially those who had infrequent contact with humans [3] until in 2003, Severe Acute Respiratory Syndrome (SARS -CoV or SARS -CoV -1) broke out in Guangdong province of China. It produced pneumonia-like symptoms and spread around the globe, infecting more than 8000 individuals across 29 countries and lead to 776 deceased individuals [4]. Then after a decade in 2012, a new type of coronavirus broke out known as the Middle East Respiratory Syndrome Coronavirus (MERS -CoV) or camel flu. MERS -CoV was believed to have been originated from bats. But humans were infected from camels, and therefore World Health Organization (W. H. O.) issued precautions while dealing with camels. Symptoms included fever, cough, diarrhoea and shortness of breath. It infected more than 2428 people and led to 838 deaths [5]. There are currently no vaccines for SARS -CoV and MERS -CoV. Some treatments do seem to improve the outcomes, but there is no specific vaccine to date.

On 12th December 2019, Coronavirus 2019 (COVID -19), a contagious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS -CoV -2), broke out in Wuhan, China. It is said to have been originated from Huanan Seafood Wholesale Market, a local fresh seafood market in Wuhan that sold live animals [6]. Some studies suggest that the coronavirus originated in bats as COVID -19 is 96 % identical to the whole genome level of a bat coronavirus [7]. Other viruses like Ebola, SARS in 2003 and MERS in 2012 also seem to have been originated in bats. Studies show that bats have a unique immune system called "innate immunity". Their body can maintain high body temperatures and a higher level of interferon, which enables it to tolerate and harbour so many viruses [8]. Bats have a general ecological separation from humans, thus requiring other mammalian species as intermediate or amplifying hosts where SARS -CoV -2 mutated for efficient human transmission. In SARS, civets played the role of the intermediate host, and in MERS -CoV, camels played the role of intermediate hosts. In COVID -19, Malayan pangolins (*Manis Javanica*) were illegally imported into southern China and became intermediate hosts, where the SARS -CoV mutated and emerged into the human species [7]. It started slowly by infecting a few people in Wuhan after coming in contact with the virus. But as the virus is easily transmittable, it surged the entire planet just within a span of few weeks. And soon after, it took the whole world and broke as a pandemic resulting in severe complications and deaths worldwide. After the epidemic spread globally, the World Health Organization (W. H. O.) declared a pandemic in March 2020. When a human body contracts the virus, the coronavirus COVID -19 moves along the respiratory tract and attacks the lungs. Symptoms include fever, cough and headache. Patients can also experience fatigue and breathing difficulties. It can also lead to loss of smell and taste. The occurrence of the symptoms differs from person to person. Almost 81 % develop mild symptoms, 14 % develop severe symptoms, and 5 % suffer acute symptoms [6]. Older people are at higher risk due to low immunity. Symptoms may take one to fourteen days to show up. Recovery time can be two weeks or greater, depending on the severity of the virus. Sometimes it may take months for some symptoms to go away,

also known as "Long Covid". The mortality rate of COVID -19 is 3.4 %. COVID -19 has a high transmissibility rate where droplets and tiny airborne particles can transmit it.

The global virus pandemic hit millions across the world in 2019 and continues to spread and infect. The pandemic has a profound impact on the entire humanity. The pandemic has resulted in global, social and economic disruption. The pandemic has led to a worldwide recession, severely impacting the health and lives of people worldwide, leading to a tragic loss of life and damage to human health and communities. There is a massive demand for medical supplies that are not being fulfilled. Hospitals are not equipped with the necessary and enough resources as required in a worldwide pandemic. Intensive treatments like mechanical ventilators are not working consistently in some locations and are present in lesser numbers [9].

Vaccination has been developed but doesn't prove to be fully effective yet against the virus. Different companies have produced other vaccinations with different effective rates. Currently, 21 vaccines are being rolled out in different countries worldwide. A vaccine candidate first goes through various trials or phases for testing before being rolled out in the market for public use. Firstly pre-clinical trials are conducted, where the vaccine is developed and tested using lab experiments. Then after passing the pre-clinical trials, vaccines enter phase 1 of the vaccine development process. In phase 1, the safety, dosage and side effects of the vaccine are tested. This trial is done on a smaller group of people. After passing this phase, the safety and efficiency of the vaccine are explored in phase 2. This phase is done on larger groups of people. After passing phase 2, very few vaccines make it to phase 3. In phase 3, the vaccine is extensively tested on thousands of people where the effectiveness of the vaccine is tested. Rare side effects also show up when the vaccine is being tested on large groups. After phase 3, the final step is performed. But some regulators of some countries approve vaccines for public use even before phase 3 trials end, like Russia and China. In phase 4, the national regulatory approves and monitors the population in clinical trials for a long time frame before finally approving it for public use [10]. Currently, W. H. O. has approved 194 vaccines in pre-clinical trials which are being explored in lab experiments. The number of vaccines in clinical trials is 123. 36 vaccines are in phase 1, where the safety tests are performed on healthy young individuals. In phase 2, 41 vaccines are tested on broader groups of people. In phase 3, 36 vaccines are in large trials globally where the impact of COVID -19 is being tested. 21 vaccines are currently in use and offered to the general public. There are 8 vaccines in phase 4, where these vaccines are monitored in a wider population [11].

Pfizer BioNTech, developed by Pfizer on 11th December 2020, with two dosages 21 days apart, has an effective rate of 95 %. Moderna vaccine was authorised for use almost after a week from Pfizer with two dosages 28 days apart and seems to have an effective rate of 94 %. Johnson & Johnson's vaccine was authorised in February 2021, with only a single shot has an efficiency of 66 % at preventing COVID -19 with symptoms and 85 % effective at preventing COVID -19 virus with severe illness [12]. Oxford AstraZeneca, with two, does, 4 -12 weeks apart, has an effective rate of 63 %. Novavax with two doses three weeks apart has an effective rate of 93 % [13]. Covishield by Oxford AstraZeneca and manufactured by Serum Institute of India with two 4 doses, 12 -16 weeks apart, has an effective rate of 90 %. Covaxin developed by Bharat Biotech in association with the Indian Council of Medical Research (I. C. M. R.) and the National Institute of Virology (N. I. V.) with two doses 4 -6 weeks apart has an effective rate of 81 % [14]. There is also a shortage of vaccinations worldwide, and there needs to be a high manufacturing rate.

W. H. O.'s mandate summarised the process of dealing with the virus COVID -19 into Detection, Testing, Treating, Isolation, Tracing and Mobilising. As detection is the first step of dealing with COVID -19 according to W. H. O.'s mandate, we focus on detection methods of COVID -19. The standard test for the diagnosis of COVID -19 RT- PCR (real-time reverse transcription-polymerase chain reaction) is time consuming, complex, costly and non-portable to geographical locations [15]. It is less sensitive to identify viruses at the initial stage due to fewer anti-bodies present. It doesn't show the extent of the spread of the virus in the lungs and contains many false negatives. It isn't available to a particular population due to high prices and non-availability. It hasn't been able to measure up to the scale of testing for the large population. Antigen Testing is fast and but has a higher false-negative rate, leading to the increase in the transmit rate of the virus, thus spreading faster. Computed Tomography Scan (C. T.) scans produce high quality, detailed images but are pretty expensive and non-accessible to small clinics or rural hospitals. In addition, patients need to be physically present and meet up with the doctor to analyse their results. This adds to the transmissibility of the virus. Hence alternate diagnostic tests which are more robust, fast and accurate are adapted for early detection.

Therefore, an early, fast and more socially distant detection of COVID -19 is required. An alternate method is by detecting COVID -19 using Artificial Intelligence (A. I.). Sustainable development of healthcare systems for future generations can be achieved by working hand in hand with digital technology. In the current pandemic, Artificial Intelligence is used conjointly with healthcare systems for better predictions and detections, e.g. COVID -19 prediction using personal handheld smartphones [16], COVID -19 contact tracing [17] and many more. Deep Learning is integrated with radiology in the alternate method by applying Deep Learning networks on Chest image X -Rays of patients and the algorithms analyze the images into COVID -19 positive and COVID -19 negative classes. Initially, a dataset is created containing the chest image X -Rays of COVID -19 positive and COVID -19 negative patients. The COVID -19 negative patients may be healthy patients or patients suffering from other diseases. Then deep neural network models are trained and tested on this dataset, and the images are classified into different classes. The performance of the model will vary according to the dataset taken from various sources, the number of dataset entries, the metadata, the different algorithms, the system and its settings, and its hardware.

This method can lead to early diagnosis of the virus, leading to early medication. A better classifier and a better detector will lead to an early and quicker screening. People can take necessary precautions to reduce the chance of spreading the virus further at an early stage. This approach can also lead to a decrease in the mortality rate and lower the pandemic curve. It will be more physically distant and will provide a low-cost screening method for a particular population. It will be readily available for clinical and portable systems, hospitals, and different geographical locations where RT- PCR is not available. Also, it will help in resource planning and resource management of the hospitals and will be hugely beneficial to the healthcare workers. It will also improve population management to give insights into the population's risk level and security. It will also give rise to individualized care based on risk depending on age and health [18].

Therefore, different algorithms whose models run on chest image X -Rays for the detection of COVID -19 are analyzed. In this study, the performances of these detection techniques are compared.

2 Technique

Deep learning is a subfield of Artificial Intelligence (A. I.). It is also a part of the broader family of Machine Learning based on Artificial Neural Networks (A. N. N.). Artificial Neural Networks are usually called neural networks. These neural networks are computing systems inspired by the biological neural networks in the human brain. Artificial Neural Networks simulates the way the human brain analyses and processes information. Artificial neural networks are multi-layered neural networks that are composed of artificial neurons. Each neuron takes an input and produces an output which is further sent to other neurons. Neurons are connected by a connection and these connections are assigned weights. These weights are updated constantly through the process of backpropagation. Vast amounts of data such as images and documents are sent as input and these neurons train over them. Various parameter values are set as well which affect the working of the model significantly. Artificial neural networks identify patterns in the input given and then decide the output without any human intervention. One of the Deep Learning techniques is a Convolution neural network (C. N. N.). A convolution neural network is a Deep Learning algorithm mostly applied to analyze visual imagery. Convolution neural network takes input as an image, assigns different weights and can classify objects into other classes. A convolution neural network consists of an input layer, hidden layer/ layers and an output layer. A convolution neural network contains many layers. In the first layer Convolution layer, it performs convolutions on its data. It performs the dot product of the convolution kernel matrix with the input image matrix. The convolution kernel slides over the entire input matrix while performing dot product and generates a feature map. This feature map acts as an input for the other layers. After the convolution layer, the pooling layer follows. In the pooling layer, the dimensions of the feature maps are reduced. It is then followed by a Fully Connected Layer, which connects every neuron in one layer to every neuron in the other layer. And finally, the output is given. While training, if the predicted value is not close to the actual value, then the backpropagation process takes place. Then the weights are updated and again the whole process is repeated till an optimum output is received. Various architectures of Convolution neural networks are used in multiple studies discussed in this paper.

The chest radiograph images are processed and analysed using Image processing. The model takes the input images and trains the model. It works on the pixels of the image/images. Then it extracts patterns, regularities and relevant features from the image/images. It makes predictions and classifications based on those findings. These neural network-based models detect COVID -19 from chest radiographs using markers [\[19\]](#). These markers are a frequently observed characteristic in COVID -19 chest X -Rays. They are Ground glass opacities, Broncho vascular thickening, air space consolidation and Bronchiectasis which are caused by the symptoms of COVID -19.

3 Data

3.1 Available Datasets

Data collection is the first step in creating any machine learning model. The early and fast detection of the novel COVID -19 has been made possible due to the availability of datasets. Large datasets containing chest X -Rays are available publically from the N. I. H. (Wang, 2017), Spain (Bustos, 2019), Stanford (Irvin, 2019), M.I.T. (Johnson, 2019) and Indiana University (Demner – Fushman, 2016) [\[20\]](#). At the same time, there are significantly fewer public repositories for COVID -19 image chest X -Rays currently. At the beginning of the pandemic, there was a shortage of images of chest X-Ray data of COVID -19

patients. Artificial Intelligence (A. I.) researchers searched the medical fraternity journals and publications to access a few image X -Rays to work on them. Image chest X -Rays of COVID -19 patients are still not widely publically available. One such public repository is the one provided by Dr J. P. Cohen [21], University of Montreal [22], which contains chest X-Ray images of infected patients. This data has been collected from various public sources, hospitals, physicians and publications. Data is added regularly in this repository, and so as different models and techniques are used on this growing database, it results in different Accuracies and results. Most of the studies discussed in this review paper have used COVID -19 X-Ray images from the Cohen JP repository and collected non- COVID -19 image X -Rays from other additional sources like Kaggle [23], Chexpert, Wang et al. and Kermany et al.

3.2 Model Metrics

When a model classification is performed, it is essential to evaluate the algorithm and the model used. A model may perform accurate predictions, but its overall performance, e.g. time and efficiency, might be really poor. The performance and robustness of the models are evaluated with different metrics as they have different calculating methods for other categories.

When performing classification predictions, it results in four outputs:

True -Positive: When a model classifies an observation into a class, and it belongs to that class.

True -Negatives: When a model predicts an observation does not belong to a class and does not belong to it.

False -Positives: When a model predicts an observation into a class, it does not belong to it.

False -Negatives: When a model predicts an observation does not belong to a class, and it does.

These outcomes are plotted on a confusion matrix, which visualizes rows as model predictions and columns as the actual class's ground-truth labels [24].

3.2.1 Accuracy

Accuracy is defined as the percentage of correct predictions for the test data. It determines which model best identifies the patterns and makes accurate predictions on the unseen data [25]. It measures the accurateness of the model's prediction. It is the ratio of the number of correct predictions to the number of total predictions. The accuracy is calculated as:

$$\text{Accuracy} = \frac{\text{No. of correct predictions}}{\text{Total no. of predictions}} \quad (1)$$

3.2.2 Sensitivity and Specificity

Sensitivity and Specificity are essential metrics and are primarily used in the medical and biology fields. They determine how much percentage of cases got predicted correctly (both positives and negatives). They are then used to plot Area under the R. O. C. curve (A. U. C.), which further determines the model performance [26].

Sensitivity is the metric that evaluates a model's ability to predict the true positives of each available category. It is a measure of the proportion of actual positives that were predicted as positive [26]. Sensitivity is calculated as:

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (2)$$

Specificity is the metric that evaluates a model's ability to predict each available category's true negatives. It is the proportion of actual negatives which got predicted as a negative. Specificity is calculated as:

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}} \quad (3)$$

These metrics are used to determine the performance of any categorical model, binary or multi-class. We need to evaluate these metrics for the models used, as different models are used for various purposes. A model used for predicting one category can be highly terrible for others, resulting in extremely poor performance.

This study found that all the authors used the dataset of COVID -19 X-Ray images from Cohen J. P. and used additional datasets of non- findings from various other sources. The studies have used different numbers of positive case images over the year 2020 as the repository was growing continuously with time. All the studies use different algorithms with different methodologies for the diagnosis of COVID -19. The comparison of the Sensitivities and Accuracies of various studies is presented in Fig 1 and Table 1 below.

Boran et al. (May 2020) [27] proposed a C. N. N. model to diagnose COVID -19. This study contained the highest number of dataset images. The total number of chest X-Ray images was 6100, containing 225 COVID -19 positive images. They achieved the highest Accuracy of 98.50 %, mean Sensitivity of 93.4 %, mean Specificity of 99.18 %, and mean receiver area of 96.51 % in binary classification. They were also capable of detecting a three-class classification (COVID -19, Pneumonia, normal) with an F1 score of 94.10 %. This paper had two limitations, availability of a limited dataset and missing metadata of the dataset available. Shervin et al. (April 2020) [28] submitted a paper using a combination of algorithms containing Res -Net -18, Res -Net -50, Squeeze -Net and Dense -Net -121. It had the second-highest number of dataset images. The number of chest X-Ray images was 5000, which also included 250 COVID -19 positive images. It achieved the second-highest Sensitivity rate of 98 % and Specificity of 90 %. It had the limitation of limited COVID -19 datasets. The highest Sensitivity percentage was acquired by Ioannis et al. (April 2020) [29], who used C. N. N. over the fourth-highest dataset of 1427 chest X-Ray images which contained 224 COVID -19 positive cases. It achieved the highest Sensitivity of 98.66 %, the third-highest Accuracy of 96.78 % and Specificity of 96.46 %. It also had limitations. The authors had access to a limited dataset and had small sample cases of COVID -19. Also, old pneumonia images were used as new pneumonia images with COVID -19 symptoms were not present, and many had metadata and clinical conditions missing. Ozturk et al. (April 2020) [30] proposed a Dark -Net algorithm to diagnose COVID -19 using an 1125 chest X-Ray image dataset that contained 127 COVID -19 positive cases. They achieved the second-highest Accuracy of 98.08 % for binary classification and 87.02 % for multi-class classification. The limitation was again the availability of a limited dataset of COVID -19 images. M K Pandit et al. (June 2020) [19] used a VGG -16 algorithm to detect COVID -19 over 1428 chest X-Ray images containing 224 COVID -19 positives, 700 pneumonia and 504 healthy chest X -Rays images. They achieved an accuracy of 96 % for the two-output class and 92.5 % for the three-output class. The Sensitivity and Specificity for a two-output class is 92.64 % and 97.27 % and for

three output class is 86.7 % and 95.1 %. The limitation this study had was the limited availability of the dataset. Zulfaezal et al. (April 2020) [31] used Res -Net -101 over 154 COVID -19 positive and 5828 no -findings to detect COVID -19. The algorithm's performance resulted in 77.3 % Sensitivity, 71.8 % Specificity, 71.9 % Accuracy and A. U. C. of 0.82. The limitation of this study was again the availability of a limited dataset. Prabira et al. [32] used C. N. N. and S. V. M. over a chest X-Ray dataset containing 127 COVID -19 cases, 127 COVID -19 negative cases and 127 healthy cases. They received an Accuracy of 95.33 % and a Sensitivity of 95.33 %. The limitation of this study is that if the patient is in a highly critical situation and is unable to attend for an X-Ray scan, then detection of COVID -19 through this method is not possible, and other measures need to be taken. Linda Wang et al. (May 2020) [33] created an algorithm COVID -Net over a chest X-Ray dataset collected from various resources and achieved an accuracy of 93.3 %. The limitations can be improved by collecting additional data and improve the training methodology of the model.

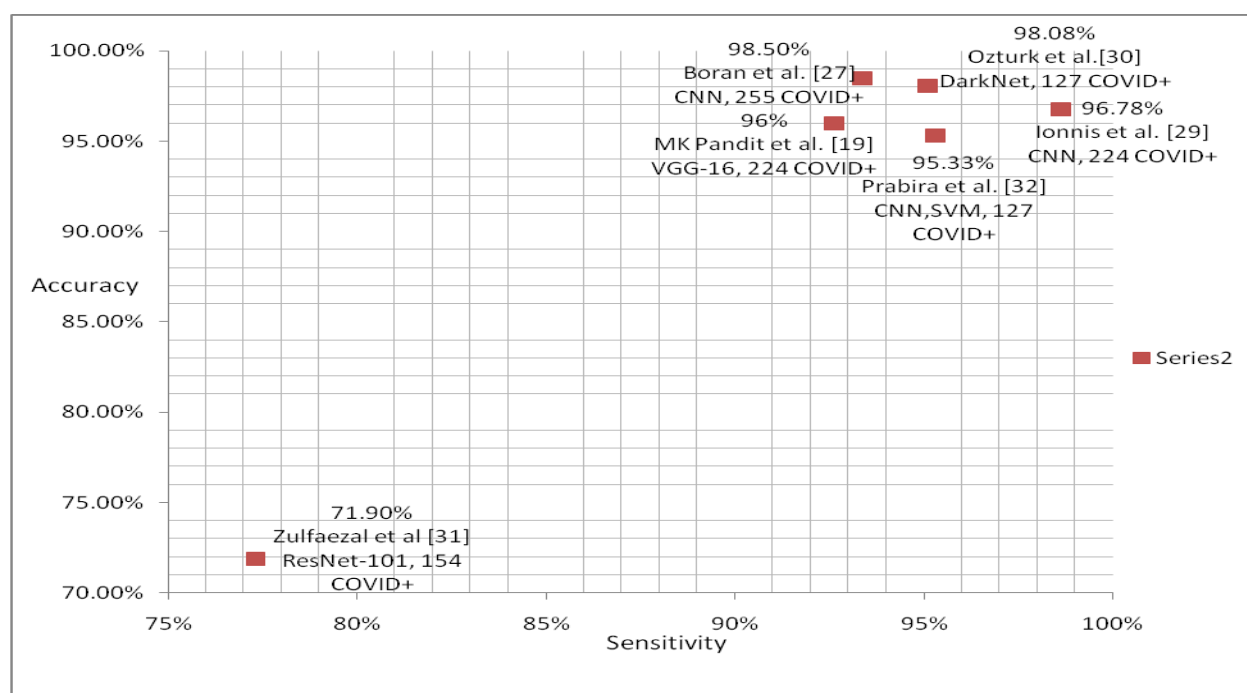


Figure 1. Accuracy vs Sensitivity Graph of different studies

The dataset is imbalanced due to fewer COVID -19 X-Ray images in the public domain, leading to a disproportionate ratio. In that case, the Specificity and Sensitivity of the model are crucial. An increase in Sensitivity increases the true- positive predictions of the model and reduces the false negatives. An increase in Specificity increases the true- negative predictions and hence reduces the false positives. Therefore, the gap between a good model's Specificity and Sensitivity measures must be as small as possible [34]. With the increasing dataset image X -Rays in the repository and the increasing number of algorithms used, the Sensitivity rate increases, which is a measure of true positives. This denotes that the model has good classification Accuracy. A model's Accuracy also depends on different factors like different datasets used for COVID -19 negative images, algorithms used, software, hardware specifications and the environment variables.

It is difficult to compare the papers mentioned in this study as there is a variation in different metric measurements of the different studies with the unbalanced size of the dataset, the algorithms used and many other factors. It is not possible to

determine the most efficient model as there are various varying factors involved. There is a lower and uneven percentage of COVID -19 positive patients in the datasets, and this limitation needs to be eliminated.

Table 1. Accuracy v/s Sensitivity of different models

Studies	Accuracy	Sensitivity
Ozturk et al. [30] (DarkNet, 127 COVID -19 +)	98.08 %	95.13 %
Prabira et al. [32](CNN,SVM, 127 COVID -19 +)	95.33 %	95.33 %
Zulfaezal et al. [31] (ResNet -101, 154 COVID -19 +)	71.90 %	77.30 %
MK Pandit et al. [19] (VGG -16, 224 COVID -19 +)	96 %	92.64 %
Ionnis et al. [29] (CNN, 224 COVID -19 +)	96.78 %	98.66 %
Boran et al. [27] (CNN, 255 COVID -19 +)	98.50 %	93.40 %
Shervin et al. [28] (ResNet18, ResNet50, SqueezeNet, DenseNet-121, 250 COVID -19 +)	-	98 %

4 Comparison

In this review, the models' various variables, which impact their performance and robustness, are analyzed. The comparison and analyses of the different models using different algorithms, techniques and datasets is carried out. Most of the publications included in this study have deduced the performance of their models in terms of Accuracy, Sensitivity and Specificity. The comparison of these metrics is represented in the following table in Table 2.

Table 2. Comparison of various parameters of reviewed papers

<u>Paper</u>	<u>Authors</u>	<u>Dataset</u>	<u>Deep learning model</u>	<u>Results</u>
Detection of Coronavirus Disease (COVID -19) Based on Deep Features and Support Vector Machine [32]	Sethy et al., 2020	C.X.R. dataset COVID -19(127) - Cohen JP,Kaggle Pneumonia(127) - Kermany et al. Healthy(127)	Deep features of 13 CNN models and SVM	Accuracy: 95.33 % Sensitivity: 95.33 %
COVID -19: automatic detection from X-Ray images utilizing transfer learning with convolutional neural networks [29]	Ioannis et al., 2020	C.X.R. dataset 1427 Xrays 224-COVID -19+ JP Cohen 700- Pneumonia Kermany 504-Normal Kaggle	CNN	Accuracy: 96.78 % Sensitivity: 98.66 % Specificity: 96.46 %

Automated detection of COVID -19 cases using deep neural networks with X-Ray images [30]	Ozturk et al., 2020	C.X.R. dataset Cohen JP (127 COVID -19 +) [7] Wang et al (normal and pneumonia).	DarkNet	Accuracy: Binary classification: 98.08 % Multi-class: 87.02 % Sensitivity: 95.13 % Specificity: 95.3 % Precision: 98.03 %
COVID -19 Deep Learning Prediction Model Using Publicly Available Radiologist—adjusted Chest X-Ray Images as Training Data [31]	Zulfaezal et al., 2020	C.X.R. dataset Cohen JP -154 COVID19+ , 5828 no findings	ResNet-101	Area under receiver operating curve: 0.82 Sensitivity: 77.3 % Specificity: 71.8 % Accuracy: 71.9 %
Deep-COVID: Predicting COVID -19 from chest X-Ray images using deep transfer learning [28]	Shervin et al., 2020	C.X.R. dataset Cohen JP - 250 COVID19+ ChexPert - 2000 non COVID19(no-finding, Edema, Pneumonia, etc)	ResNet18, ResNet50, SqueezeNet, DenseNet-121	Sensitivity rate: 98 % Specificity rate: 92.9 %
Detection of COVID -19 from Chest X-Ray Images Using Convolutional Neural Networks [27]	Boran et al., 2020	CXR dataset Cohen JP - 255 COVID19+ , 1583 healthy , 4292 pneumonia .	CNN	Mean Sensitivity: 93.4 % Mean Specificity: 99.18 % Mean Accuracy: 98.50 % Mean receiver area: 96.51 %
COVID-Net: A Tailored Deep Convolutional NeuralNetwork Design for Detection of COVID -19 Cases from Chest X-Ray Images [33]	Wang &Wong et al., 2020	C.X.R. dataset COVIDx : 1. Cohen JP 2. Chung Dataset [35] 3.ActualMed COVID -19 dataset [36] 4. RSNA Pneumonia detection dataset [37] 5.COVID-19 database [38]	COVID-Net	Accuracy: 93.3 %
Paper	Authors	Dataset	Deep learning model	Results
Automatic detection of COVID -19 from chest radiographs using deep learning [19]	M K Pandit et al., 2020	C.X.R. dataset Cohen JP -224 COVID -19 + and COVID -19 - Kagglechest X-Ray dataset 1428 radiographs- 224 COVID19+, 700 pneumonia, 504 healthy	VGG-16	Accuracy: Two-output class: 96 % Three output classes: 92.5 % Sensitivity: Two-output class: 92.64 % Three output classes: 86.7 % Specificity: Two-output class: 97.27 % Three output classes: 95.1 %

The highest Accuracy (98.5 %) was obtained by the C. N. N. model (Boran et al. [\[22\]](#)) with 255 COVID -19 positive cases. The second highest Accuracy was obtained by Dark -Net (Ozturk et al. [\[25\]](#)) with 127 COVID -19 positive cases. The third

highest (96.78 %) was also obtained by C. N. N. (Ionnis et al. [24]) with 224 COVID -19 positive cases. The fourth highest (96 %) was obtained by VGG -16 (MK Pandit et al. [14]) with 224 COVID -19 positive cases. The fifth highest (95.33 %) is again C. N. N. in combination with S. V. M. (Prabira et al. [27]) and 127 COVID -19 positive cases. Sensitivity determines the model's ability to predict true positives. The highest Sensitivity (98.66 %) was obtained by a C. N. N. model (Ionnis et al. [24]) with 224 COVID -19 positive cases. The second highest Sensitivity (98 %) was acquired by a combination of Res -Net -18, Res -Net -50, Squeeze -Net and Dense -Net -121 (Shervin et al. [23]) with 250 COVID -19 positive cases. The third highest (95.33 %) is again C. N. N. in combination with S. V. M. (Prabira et al. [27]) and 127 COVID -19 positive cases. The fourth highest (95.13 %) was obtained by Dark -Net (Ozturk et al. [25]) with 127 COVID -19 positive cases. The fifth highest (93.40 %) is the C. N. N. model (Boran et al. [22]) with 255 COVID positive cases. The sixth-highest (92.64 %) is VGG -16 (MK Pandit et al. [14]) with 224 COVID -19 positive cases. As there are significantly fewer public repositories for COVID -19 chest X -Rays images currently, the works mentioned in this survey have used around 100 -255 COVID -19 images, mainly from a shared repository by Dr J. P. Cohen [16]. This data has been collected from various public sources and is updated regularly. Table 2 summarizes the work done by the researchers to detect the infected COVID -19 patients, using multiple machine learning algorithms, models and techniques on a growing collection of chest X-Ray image datasets, resulting in different Accuracies and results.

5 Conclusion

The novel COVID -19 has taken the whole world by storm. It has lead to a worldwide recession and has caused social and economic disruption on a global scale. As the various usual detection methods are time-consuming and have higher false positives, they have become inefficient. Furthermore, COVID -19 has led to an outbreak of additional dangerous infections like black fungus etc. Various vaccines have been developed but none of them are 100 % effective against the virus COVID -19. People who have received all the dosages of the vaccine still have the possibility of getting infected by the virus. Integrating radiology with Artificial Intelligence gives rise to a more sophisticated domain where management and resource allocation excel greatly. This survey has summed up the integrated work of different authors using different deep learning algorithms on chest radiographs X-Ray images. The performance metric Accuracy determines which model can best identify the pattern and makes correct predictions. Most of the studies used Convolution Neural Network-based algorithms and have achieved high Accuracies, but an imbalanced dataset still behaves as a limitation. With time, the size of the datasets available publically grows and the availability of datasets of different mutated variants of COVID -19 grows as well. Therefore this will give rise to better-trained models leading to better classifiers. Thus, this survey concludes that initial screening and early detection of COVID -19 will be hugely beneficial to healthcare workers and the general population in the current pandemic.

6 Future Work

Integrating Artificial Intelligence with health care is increasing continuously across various domains. Upon verification and survey using new art of technology and algorithms, it further opens up the scope for development and deployment of models becoming better detectors and better classifiers. This further leads to models with higher Accuracies making better predictions. This can lead to enhancements in the treatment plans and diagnosis of patients. It can lead to improvement of resource and

population management at hospitals. As the size of the dataset and the metadata will increase in future, better models will be trained and built-in future and will lead to better Accuracy models. This method will become a fast and cost-effective method. It is portable and a non-contact process that is the current need of the hour. It will lead to an upgrade in the process of resource planning and resource management. It can also provide a thorough understanding of the risk and security of the population, thereby enhancing population management and providing better-individualized care to particular people based on risk. As a result, optimum care will be delivered to the patients based on the scale of risk. Therefore, as the size of public, diverse and detailed datasets increases with time, it will further diminish the limitations found in this survey. This will enhance the detection process of the virus COVID -19. With the various comparisons performed, there should also be a standard established for evaluating the performance and efficiency of the training models. This standard could be developed by the regulatory bodies or organizations.

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