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# A Survey of COVID-19 Detection From Chest X-Rays Using Deep Learning Methods

Bhargavinath Dornadula, Vellore Institute of Technology, Chennai, India

S. Geetha, Vellore Institute of Technology, Chennai, India

L. Jani Anbarasi, Vellore Institute of Technology, Chennai, India

Seifedine Kadry, Department of Applied Data Science, Noroff University College, Kristiansand, Norway & Artificial Intelligence Research Center (AIRC), College of Engineering and Information Technology, Ajman University, Ajman, UAE & Department of Electrical and Computer Engineering, Lebanese American University, Byblos, Lebanon*

https://orcid.org/0000-0002-1939-4842

## ABSTRACT

The coronavirus (COVID-19) outbreak has opened an alarming situation for the whole world and has been marked as one of the most severe and acute medical conditions in the last hundred years. Various medical imaging modalities including computer tomography (CT) and chest x-rays are employed for diagnosis. This paper presents an overview of the recently developed COVID-19 detection systems from chest x-ray images using deep learning approaches. This review explores and analyses the data sets, feature engineering techniques, image pre-processing methods, and experimental results of various works carried out in the literature. It also highlights the transfer learning techniques and different performance metrics used by researchers in this field. This information is helpful to point out the future research direction in the domain of automatic diagnosis of COVID-19 using deep learning techniques.

## KEYWORDS

Chest X-Rays, COVID-19 Detection, Deep Learning, Survey, Transfer Learning

## INTRODUCTION

Corona Virus disease 2019 (COVID-19) is caused by Severe Acute Respiratory Syndrome Corona Virus 2 (SARS-CoV-2) is the COVID-19 pandemic. Wuhan the city of China, where the disease was first detected in December 2019, led to a significant effect on human lives and their health. 188,620,082 total cases and 4,065,876 deaths worldwide were recorded by the mid of July 2021. India is now in second place after the USA, with maximum cases recorded being involved. To classify the virus in the human body, a special procedure called Real-Time Reverse Transcription–Polymerase Chain Reaction (RT- PCR) Test is used. In general, the COVID-19 virus collects in the throat or within a person's nose. The diagnostic method of the RT-PCR test begins with the collection of samples by

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*Corresponding Author

swab from the specified parts of the body. By treating them with various chemical solutions, the cells and nucleus are lysed. Lastly, the sample contains deoxyribonucleic acid (DNA) and RNA only. It is a mixture of the individual's residual genetic material and the virus's RNA. Using a particular enzyme via reverse transcription, the RNA is then converted to DNA. To build a mixture, short fragments of DNA are also added. If the sample contains a virus, then the very less parts of the DNA match the output parts of the viral DNA. Then the hybrid input is put into an RT-PCR unit. By cycling through temperatures to ignite chemical reactions, the RT-PCR machine heats and cools the mixture. The target parts of viral DNA get their new identical copies through this process.

Repeated cycles are carried out with the sample by the RT-PCR COVID-19 Test Unit. This helps to copy the viral DNA target pieces. The number of copies of viral DNA would double at the end of each cycle. As a result, at the final stage of the scenario, approximately 35 billion new duplicates of the viral DNA parts from each variety of the virus are produced. Usually, this entire process of RT-PCR takes 3-4 days and if the person is suffering from COVID-19 the chances of spread from that person to multiple people are very high before one can check their result and as the cases are increasing rapidly lack of testing kits have become a major problem throughout the world. Taking this as a major problem, alternative methods are under research for finding out disease at a very early stage that is by using Chest X-ray to find out the virus in human's lungs.

When using CT scans or X-rays images, the identification of COVID-19 symptoms in the lower portions of the lungs is more reliable than when using RT-PCR. Scans and chest X-ray tests may be replaced with RT-PCR tests in some situations. However, because of the comparatively lesser count of radiologists concerning current residents and the high amount of reappraisal of affected people who want to know the advancement of their disease, they cannot fix the issue exclusively. Increase in the pace of the procedure to resolve the difficulties of CT scans and X-rays and to support radiologists. This can be done through the design of advanced diagnostic systems using instruments of Artificial Intelligence (AI). The main goal is to bring down the time and effort needed to conduct COVID-19-positive patients' CT scans and X-rays and to assess the rate of progression of the disease. Radiological imaging is considered an effective screening technique for the diagnosis of COVID-19, and several authors have shown that the radiological history of COVID-19-related pneumonia is compatible with the clinical existence of the disease.

Almost all coronavirus patients, when tested by CT scans, displayed similar characteristics, including early-stage ground-glass opacities and later-stage pulmonary consolidation. The morphology and peripheral distribution of the lungs may, in fact, be rounded. AI can be seen as an alternative option to conventional approaches that are time-consuming and labor-intensive to initially test a COVID-19 patient. For a specific category, a class activation map shows the discriminatory area that Convolutional Neural Network (CNN) uses to classify the category. Figure 1 and Figure 2 show the sample chest X ray of normal and infected persons.

**Figure 1. Chest X-ray of a normal person, Pneumonia infected person, and COVID-19, the infected patient**

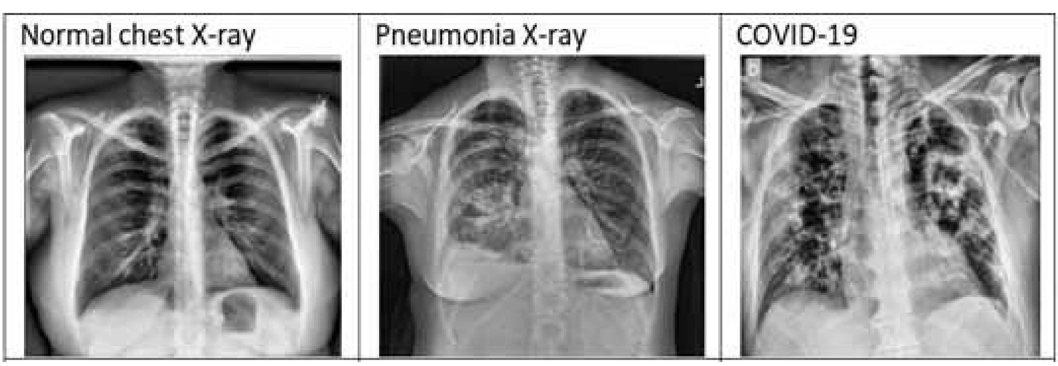
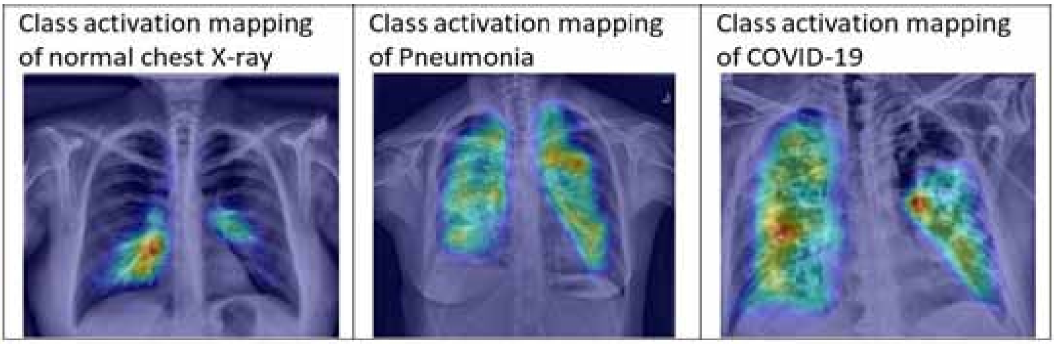


**Figure 2. Class activation mapping of normal, pneumonia, and coronavirus patient**




To work on these medical images, especially Chest X-Ray images, detection of COVID-19, as per conventional image processing methods, need feature extraction and selection steps. The selected features will be fed to a machine learning model, which is trained to detect the COVID-19 presence/absence in the images. However comprehensive the selected features are, the machine learning models could not achieve a superior detection performance of above 90% accuracy. Hence, the upcoming deep learning models are found to be the most suitable, since they have the feature engineering phase as a part of the core functionality. Among the AI-based methods, deep learning offers a promising direction that provides a superior detection performance for the COVID-19 traces from the Chest X-Ray images. The possibilities of transfer learning over the pre-trained convolutional neural networks offer domain customization ability to the CNN model, thereby allowing the researchers to develop an efficient deep learning model exhibiting high performance. Initially, few works were reporting the use of CNNs on Chest X-Ray image-based COVID-19 detection. Nevertheless, in the gradual course of time, many advanced and improved architectures for the diagnosis of COVID-19 are reported in the literature. In this paper, we have attempted to review these new methods which are specifically using Chest X-ray images for COVID-19 detection using deep learning approaches.

Artificial Intelligence (AI) strategies for recognizing cases of infection and their radiological features from medical imaging such as chest X-rays and CT scans are effective for accurate diagnosis. COVID-19 detection can be approached in a variety of ways using Machine Learning and Deep Learning. Medical imaging analysis guided by AI has a lot of potential as the main diagnostic for COVID-19 diagnosis. The initial stage in the diagnosis is to acquire deep features that can catch COVID-19 radiological patterns in chest X-rays. Machine Learning algorithms are explored for COVID-19 classification in many researchers. As a result, algorithms like Support Vector Machine (SVM), Classification and Regression Tree (CART), and Random Forests result in better infection prediction and diagnosis. These automated systems can help to relieve the burden on the healthcare system. Early detection of illness can help you save time and money. Treatment is to be given in the early stages of infection to avoid risky effects. Due to the enormous velocity and scale of information, automated systems where cleaning and processing becomes a major challenge, especially when high-resolution images need to be processed. To support and enhance the process CNN is used for enhancing the classification and prediction of COVID-19 from X-ray images.

The highlights of the proposed work include:

- To analyze the most recent developments in the use of CNN algorithms to detect COVID-19 in X-ray images.
- To compare and analyze the results of recent COVID-19 detection research and to identify areas for improvement.
- To identify the drawbacks of the reviewed research works as well as the possibilities for future research.

The central aim of this paper is to methodically summarize the workflow of the existing research, accumulate all the different sources of datasets of Chest X-Ray images, sum up the frequently used methods to diagnose COVID-19 automatically using these medical images so that a researcher can analyze all these previous works based on many parameters and find an optimal solution. The paper is oriented in the following manner:

1. Firstly, various works reported in the literature highlighting their approach and performance are discussed in Section II.
2. Secondly, the Dataset source and different types of images used in the papers are listed in Section III.
3. Thirdly, different CNNs employed, transfer learning, various performance metrics used in the works are presented in Section IV.
4. Finally, a discussion summarizing the limitations and areas of improvement is presented to help the new researchers to contribute solutions for detecting COVID-19 overcoming the limitations.

## MACHINE LEARNING AND DEEP LEARNING APPROACHES

The diagnosis process of whether the chest X-ray image is pneumonia infected or COVID infected or not infected at all, has been executed using various machine learning and deep learning approaches. The machine learning approaches employed hand crafted features extracted from the chest X-Ray images and developed the machine learning models, classifying with commendable accuracies. However, there was some scope for improvement in terms of feature efficiency and in cases where only few image samples were available. Hence several approaches using deep learning have been proposed. Deep learning models provided superior performance since they did feature engineering as a part of the training phase. The best features providing clues to the classifier about the pneumonia/COVID presence have been extracted. In the initial stage, standard deep learning models like Inception, ResNet, DenseNet, etc., were employed. Later stages, transfer learning is imparted, and the accuracy improved. Recently many custom-built deep learning models are proposed and shared in the literature, which are very specifically built to operate on these chest X-Ray images. These models exhibited a highly commendable performance. The automation process has reached to a comfortable and stable state so that, the scientific findings are resourceful in early detection and treatment to the infected patients. The following sub sections discuss the various approaches made under these categories.

### Machine Learning Approaches

Turker et al (Tuncer et al., 2020) presented an AI-based computer vision approach to automatically diagnose the Coronavirus using chest X-ray scans of infected victims with help of ML models such as SVM, DT, Linear Discriminant (LD), Subspace Discriminant (SD), and K Nearest Neighbor (kNN). Residual Exemplar Local Binary Pattern (ResExLBP) and Iterative ReliefF (IRF) technique were used for feature generation and selection. This work achieved 100% accuracy using the SVM classifier.

Sousa et al (Sousa et al., 2013) implemented an ML model to diagnose Pneumonia in infants with help of radiographic images. The most popular ML algorithms such as Naive Bayes, KNN, and SVM are used for image classification and the SVM classifier gave the best results than the others.

F. Rustam et al (Chachlakis, 2019) made use of 4 different regression models for Coronavirus for future prediction of Linear Regression, Least Absolute Shrinkage and Selection Operator (LASSO) Regression, SVM, Exponential Smoothing SPP (Spatial Pyramid Pooling) is an identification network that has categorized an X-ray picture into three groups, they are COVID-19 active, healthy, and other viral pneumonia types.

Khan et al. (Khan et al., 2021) took weights related to each neuron in similarity with different inputs from the dataset belonging to the cluster represented by the neuron in a fully trained organized self-function map. An estimation of the mean of the neuron weights in a cluster can be given in the data set for the corresponding mean of the cluster. In addition, the variance of the corresponding cluster in the dataset was calculated by measuring the variance of the cluster's neuron weights. The X-ray image pixels were viewed as separate, and for each pixel, an independent normal distribution was modeled, allowing regions to be independently analyzed. Ekta Gambhir (Singh et al., 2020) did a regression analysis of COVID-19 was developed using ML algorithms using a new form of algorithm called the Polynomial Regression Algorithm, which gives a better rate than the SVM algorithm when compared.

Shome et al. (Shome et al., 2021) mentioned four different variations were measured: Corona Virus pneumonia, non-Corona Virus pneumonia, general pneumonia, and non-affected lungs, respectively. They suggested an Artificial Intelligence system that was split into 2 levels. Phase 1 categorizes the chest X-ray levels into normal pneumonia and non-affected pneumonia. If the X-ray is considered as the pneumonic class, stage 2 receives input from phase 1 and later classifies it into positive and negative Corona Virus and Corona Virus.

## Standard Deep Learning Approaches

Ardakani et al. (Ardakani et al., 2020) suggested an efficient AI technique for distinguishing 108 COVID-19 infected and 86 with further typical and pneumonia illness by taking 1020 CT scans. The top 10 CNN models such as AlexNet, Visual Geometry Group (VGG) - VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101, and Xception have been used for classification. Among them, ResNet- 101 and Xception have achieved the best performance.

Brunese et al. (Brunese, 2020) suggested a three-fold architecture to counter Coronavirus from chest X-ray. The initial model identifies X-rays of infected victims from normal ones and the second model will classify the infected one's X-ray scans as COVID-19 or Pneumonia. The third model provides a visualization of Coronavirus infected images. A deep CNN named VGG-16 is used to build the first and second model and achieved an accuracy of 92.7%.

Pathak et al. (Pathak et al., 2022) has proposed a Deep Transfer Learning method to categorize Coronavirus victims with the help of CT scans. The important attributes from the scans are extracted with the help of ResNet-50 architecture. CNN is used for chest CT scan image classification and the proposed model achieved two accuracies i.e., 96.22% and 93.01% on training and test datasets. Automated detection of COVID-19 victims with help of a Deep Transfer Learning-based approach is suggested by Gupta et al. (Gupta et al., 2021) using chest X-rays. A modified Inception model is used in the proposed model. The model efficiency is evaluated using performance metrics and compared with various existing competitive models like VGGNet, ResNet, AlexNet, GoogleNet, and InceptionNet. The proposed model is better than all other competitive models and achieved an accuracy of 99.52%.

Ahmad et al. (Ahmad et al., 2022) proposed AI-based 2D and 3D Deep Learning models to automatically recognize Coronavirus disease from thoracic CT scan images and obtained a sensitivity of 98.2% and specificity of 92.2%. Ojala et al. (Ojala et al., 2002) used TensorFlow and VGG-16 for highly sophisticated numerical calculations for model construction and training. Their analysis was made using the K-fold cross-validation model and with the Leave-one-out cross-validation method. It is observable that an average accuracy of 87.36 percent was given by the established model.

Barnett and Preisendorfer (Barnett and Preisendorfer, 1987) estimated the weights of every neuron that takes the arrangement of different inputs in the dataset that belongs to the group which is represented by the neuron in a fully trained self-organizing function map. For every attribute in each cluster, firstly means will be calculated and then the variance is calculated then for every cluster which allowed them to find a match for the Normal Distribution model. Using small training datasets, Hsu et al. (Hsu et al., 20008) have used the classification network which is to differentiate the chest X-ray photos concerning the types of disease. For two reasons, they choose the simple related ResNet-18 as the main aspect of their algorithm for classification. The priority is to avoid overfitting because it is understood by utilizing an excessively complicated model for a limited amount of data, overfitting will occur. Secondly, to compensate for the tiny training data collection, they decided to pass learning with ImageNet pre-trained weights. With 86.9 percent sensitivity, it was possible to differentiate between regular and abnormal images.

CNN model is being trained on the real data and then synthetic augmentations, a boost in encourage efficiency from 85 percent to 95 percent accuracy is reported. Markopoulos et al. (Markopoulos et al., 2014) made use of 14 layers of general CNN and that has been followed with the help of batch normalization operation in addition to Leaky Rectified Linear activation Unit function (ReLU) activation function here every bias of the CNN layers cannot be activated as shown in Figure 3.

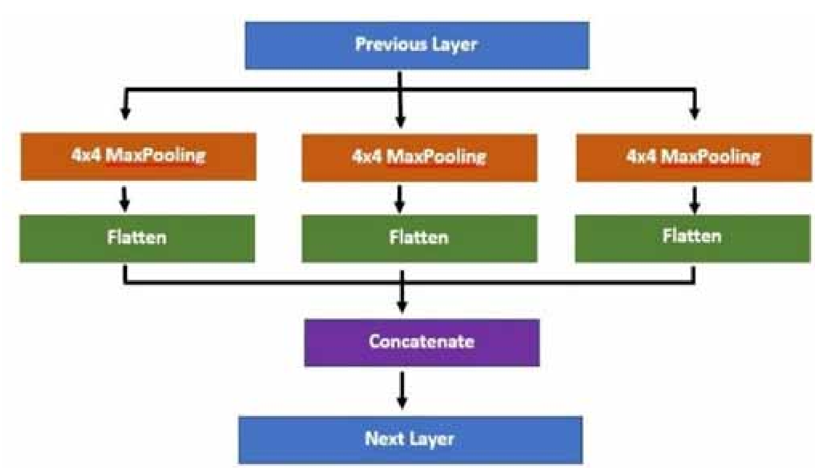
For the automated diagnosis of coronavirus disease, Apostolopoulos and Mpesiana (Apostolopoulos and Mpesiana, 2020) used the data of X-ray scans from victims who have pneumonia, reported Covid-19, and regular events. It followed the technique called Transfer Learning. 96.78 percent, 98.66 percent, and 96.46 percent are the highest precision, sensitivity and specificity collected.

Adaptive Learning Rate Method ADADELTA was used by Ke and Kanade (Ke and Kanade, 2005) to pick a high learning rate outcome and stop hitting and checking by using ResNet. On a given neural network model, a bundle of images has been trained and loss is measured. A graph has been drawn with the representation of the Y-axis as the linear value of the loss function and the X-axis indicating the learning rates of logistic scale value. The quality of the learning speed for which the least loss function is required is chosen as the learning rate.

Chowdhury et al. (Chowdhury et al., 2020) collected 6249 Chest X-Ray. At 75:25, the fraction percentage was used to split the data into testing and training sets from the dataset. The set which is used for validation was sustained at 30 percent of the training set. The implementation is conducted using the four Xception, ResNet50, MobileNet, and Inception V3 architectures of CNN, as the backend was used, using the TensorFlow Keras platform. For all four models, the uncertainty matrices were observed on the test dataset. Khan et al. (Khan et al., 2020) took four common pre- accessed models, ResNet18, ResNet50, SqueezeNet, and DenseNet-121, which were assessed for their efficiency. Detecting Corona Virus with the help of residual ConvNet-ResNet18 and ResNet50: skipping one or more layers is done by a link known as shortcut link is the core concept of ResNet. This will support the network to have a clear path to the network's very early layers, making it much simpler to change the gradient for those layers.

Shibly et al. (Shibli et al., 2020) worked with the TensorFlow library of Google and VGG-16 used for higher numerical computation performance related to model creation and training. Their

**Figure 3. Architecture of the modified module of SPP (Markopoulos et al., 2014)**



research used the K-fold cross-validation method where the K value was taken as 10 with the help of Leave-one-out cross-validation concerning the cross-validation approach.

The objective of Zhou et al. (Zhou et al., 2021) was to merge a technique related to the processing of the images for anomaly detection using supervised deep learning required for the diagnosis of Corona Virus based on chest CT imaging. In this study, Computed Tomography image anomaly detection at two levels was implemented with a matrix profile technique. CT images were simply flattened at a one-dimensional level and translated to a one-dimensional vector so that they could directly implement the matrix profile algorithm. A matrix profile was measured at the two-dimensional level in a window slide manner for each image segment. A CT-Severity Score (CT-SS) anomaly intensity score was determined, and the CT-SS difference was checked between the Corona Virus Computed Tomography and Non-Corona Virus Computed Tomography images to penalize the pixel values of each image, a calculated anomaly mask which is sparse was applied. To differentiate the Corona Virus CT from Non-Corona Virus CT images, the anomaly-weighted photos were then used for the training of DenseNet which is a standard deep learning model. For a base comparison model, a VGG19 model was used.

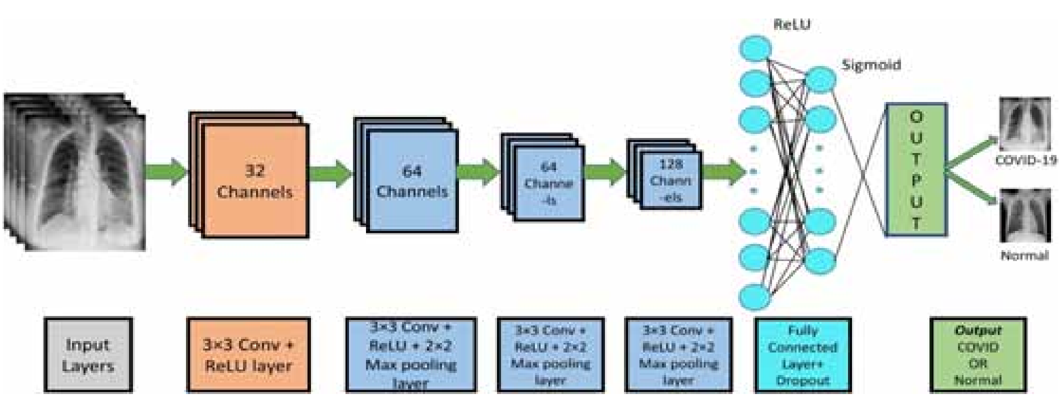
Identification of Corona Virus cases using chest Xray's of people, a Convolutional Neural Network-based model has been suggested by Haque et al. (Haque et al., 2020). This model performs at 97.56 percent and 95.34 percent respectively with precision and accuracy. In addition, the model is contrasted with two different Convolutional Neural Network models with a variety of number of layers of convolution. The study showed that the proposed models have a better score of F1 and overall performance (Model 1) than that of the other two as detailed in Figure 4.

Ozturk et al. (Ozturk et al., 2020) recommended a model that offered detailed binary and multi-class classification. 87.02 accuracy is achieved for binary instances, for multi-class instances, the model provided a classification accuracy of 98.08%. The DarkNet paradigm is used for the real-time object detection method YOLO as a classifier. 17 convolutional layers on each sheet, along with multiple filtering techniques.

## Specially Built Deep Learning Approaches

Togacar et al. (Togacar et al., 2020) have proposed a deep learning model with a dataset that contains X-ray scans of Coronavirus and Pneumonia victims and normal ones. The dataset in this paper has been preprocessed using the fuzzy color technique and then by combining and classifying efficient features with the help of SVM. The proposed model is then trained using deep learning techniques like MobileNetV2 and SqueezeNet and obtained a classification accuracy of 99.27%. A fast and alternative screening approach using an effective Deep Learning-based CNN named nCOVnet was modeled by Panwar et al. (Panwar et al., 2020) for identifying the COVID-19 infected patients with

**Figure 4. CNN model workflow proposed diagram for Corona Virus detection (Haque, 2020)**



a dataset containing X-ray images of infected ones. The proposed model used a CNN for feature extraction and categorization of scans and achieved a 97.62% true positive rate.

Mahmud et al. (Mahmud et al., 2020) designed an automated COVID-19 and other Pneumonia related disease identification methods using images of infected patients' X-rays. A deep CNN method called CovXNet was used for extracting the important features from the X-ray images and classifying them accordingly. Many forms of CovXNet architecture were used for training different datasets and obtained a very satisfactory accuracy rate for all the classifications. CoroNet, a deep CNN model proposed by Khan et al. (Khan et al., 2020) uses chest X-ray images to diagnose coronavirus disease. The popular Xception architecture is used as a base and the ImageNet dataset is used for pre-training the model and then trained with two publicly available datasets containing scans of COVID-19 and Pneumonia infected patients. The proposed model obtained an accuracy of 89.6%.

Manoj Kumar et al. (Manoj Kumar et al., 2022) developed a new classification model called CovStacknet and, based on the features extracted from given X-ray images, it was based on using StackNet metamodeling techniques combined with a deep CNN. An accuracy score of 98% has been obtained by the proposed model. A Multi-Scale Discriminative network (MSD-Net) for segmentation of multi-class of Corona Virus lung infection on CT was proposed by Zheng et al. (Zheng et al., 2020). A new paradigm has been suggested in the MSD-Net: Pyramid Convolution Block (PCB), Channel Concentration Block (CCB), and Residual Refining Block (RRB). By using different numbers and different sizes of kernels the receptive field can be increased by PCB, which has increased the ability to segment polluted areas of various sizes. CCB has been used to integrate feedback from two processes and focus features on the area to be segmented. The task of RRB was to refine the maps of the roles.

COVID-Net, a Deep CNN is designed to diagnose COVID-19 with help of X-ray scans, was introduced by Wang and Wong (Wang and Wong, 2020). The earliest open-source network architecture to detect COVID-19 from x-ray scans at the time of initial release is COVID-Net. A dataset composed of 13,975 X-ray scans is used from five open access data sources through 13,870 patient events. By using the deep function, SVM differentiates the COVID-19 affected X-ray from others scans. Sethy et al. (Sethy et al., 2020) indicated that the resnet50 plus SVM classification model achieved precision, 95.38 percent, 95.52 percent, 91.41 percent, and 90.76 percent respectively for COVID-19 identification, FPR, F1 ranking, MCC, and Kappa. Compared to other classification methods, the classification model ResNet50 plus SVM is superior.

COVIDX-Net model which involves 7 separate Deep CNN model architectures, such as the updated VGG19 and modified version of Google MobileNet, was discovered by Hemdan et al. (Hemdan et al., 2020). To distinguish whether the victim is affected with COVID-19 or not, each Deep Neural Network model can evaluate the normalized intensities of the X-ray picture. CNN-based pre-trained models such as ResNet50, ResNet101, ResNet152, InceptionV3, and Inception-ResNetV2, were used by Narin et al. (Narin et al., 2021) to diagnose contaminated patients with coronavirus pneumonia with help of chest X-ray images. Three separate four-class binary classifications (COVID-19, safe, pneumonia) were adopted with help of cross-validation of 5- fold.

### Generative Adversarial Network Approaches

Limited image set is a critical issue in chest X-Ray image classification. Using generative adversarial network (GAN), an attempt has been made to add more images which look realistic. Markopoulos et al. (Markopoulos et al., 2017) used CovidGAN along with the CNN architecture, they have combined synthetic Chest X-Ray (CXR) images with real CXR images. This is a significant approach, since the limitation due to inadequate clinical images could be overcome with this approach.

## COVID-19 DATASETS AND RESOURCES

Various datasets have been collected from various locations such as "Chest X-ray Images (pneumonia)". The Kaggle CT Images registry is a very popular archive of normal, viral, and bacterial pneumonia, with 5247 chest X-ray pictures ranging between 400p to 2000p resolution. 5247 chest X-ray images are taken from 3906 photos of various subjects are affected with pneumonia (pneumonia which contains bacteria has 2561 images and pneumonia which is viral has 1341 images) and 1341 scans are taken from ordinary subjects. To invent a new database, chest X-rays were used from this collection for normal and viral pneumonia. Table 1 shows the various datasets used by different researchers' papers and their source of datasets.

## CONVOLUTIONAL NEURAL NETWORK (CNN) GENERAL APPROACH

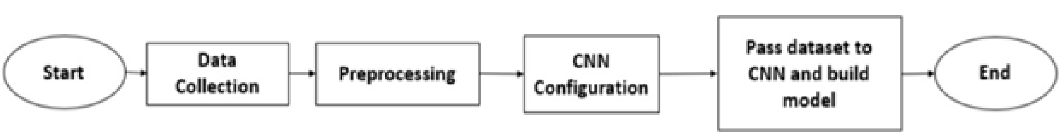
Firstly, the images of the chest X-ray dataset are collected as many websites are available from where different types of datasets related to Coronavirus, general chest X-ray, or Pneumonia images can be collected. Few are listed in Table 1. The images derived by visual sensors include a little amount of noise and distortions. Some noise levels and inconsistencies are included in the pictures taken by visual sensors. In specific, these raw X-rays are ineffective for computer vision and image recognition applications to remove appropriate functionality. Significant pre-processing is necessary to avoid disturbances and noise.

A CNN model consists of different Convolution layers, Polling layers, and fully connected layers as shown in Figure 5. We add filters while we process the image, each of which produces an output that we call a function map. If a k-feature map is created, we have k-depth feature maps.

**Table 1. Dataset and its sources with total images count**

| Ref.No | Modality | Source | Size |
|---|---|---|---|
| Markopoulos et al., 2014 | X-ray | https://www.kaggle.co m/tawsifurrahman/covid19-radiography-database | 219 Covid-19,1341 Normal, 1345 Other viral pneumonia |
| Manoj Kumar et al., 2022 | X-ray | https://www.kaggle.co m/bachrr/covid-chest-xray/ | 4273 Pneumonia, 1583 Normal |
| Zhou et al., 2021 | CT | https://arxiv.org/abs/200 3.13865 | 275 Covid-19, 195 Non-Covid-19<br>4001 Covid-19, 9979 Non-Covid-19 |
| Narin et al., 2021 | X-ray | https://github.com/ieee8023/covid-chestxray- dataset | 314 Covid-19, 2800 Normal,1493 Viral Pneumonia, 2772 Bacterial Pneumonia |
| Ozturk et al., 2020 | X-ray | https://github.com/ieee8023/covid-chestxray- dataset | 165 Covid-19, 41 Normal |
| Khan et al., 2020 | X-ray/CT | https://github.com/ieee8023/covid-chestxray- dataset | 290 lung CT images, 270 coronavirus<br>1579 Normal,1485 Covid-1,<br>3906 pneumonia, 1341 normal |
| Ke and Kanade, 2005 | X-ray | https://sirm.org/covid-19/ | 374 Covid-19<br>374 Pneumonia<br>374 Normal |
| Apostolopoulos & Mpesiana, 2020 | X-ray | https://www.kaggle.co m/andrewmvd/convid1 9-X-rays | 224 Covid-19, 700 Bacterial Pneumonia, 504 Normal<br>504 Normal |
| Markopoulos etal., 2017 | X-ray | https://www.kaggle.co m/tawsifurrahman/covi d19-radiography-database | |

**Figure 5. Flow Diagram for processing the dataset using CNN**



A suitable method has been used and operations are being performed and then accuracy has been calculated. Methods like ResNet, Inception V3, SqueezeNet, MobileNet, CovXNet (Mahmud et al., 2020), DenseNet (Zhou et al, 2021), VGG-16 (Brunese et al., 2020) are being used under the deep learning models and some models under deep learning are Naive Bayes, KNN, and SVM (Sousa et al., 2013), Linear Regression, LASSO Regression, Support Vector Machine (Chachlakis et al., 2019) etc. are being used.

- **Inception V3:** Hsu et al. (Hsu et al., 2008) presented Inception's architecture in 2014. The initial architecture has been deemed to be GoogleLeNet. Both of the following versions are called Inception Vnn. As an update to Inception, V1 batch normalization was added to Inception V2. In InceptionV3, concept factorization techniques were introduced as an enhancement over V2.
- **ResNet50:** In 2015, He et al released ResNet - The Residual Networks Architecture. It has 50 Coevolutionary layers with skipped relations that help improve the learning precision of the model. Also, it includes global average pooling rather than entirely similar layers, by decreasing the size of the model.
- **MobileNet:** In the year 2017, a different CNN design, called MobileNet, was suggested by Howard et al. In the separable convolution, they have arranged in detail and implemented the operation on the convolutional layer individually across each color channel rather than taking them as a whole. Due to this the computation in this architecture is reduced.
- **Xception:** In 2017, François Chollet developed Xception. This model can be interpreted as an improvised variant of Inception, as components of Inception have been supplemented with deeply separable convolutions. This new and reliable model scores on speed and accuracy.
- **Support Vector Machine:** SVM is a supervised ML algorithm that can be referred to for both regression and classification (Chachlakis et al., 2019). Being a non-parametric method, SVM regression relies on several functions related to calculations. The series of kernel functions convert the data inputs into the desired form. Using a linear function, SVM solves the regression problems, so it maps the input vector(x) to n-dimensional space called a feature space when dealing with non-linear regression problems (z).
- **LASSO:** It is a regression model that is part of the shrinkage-using linear regression process. In this case, shrinkage points to the reduction of a data sample's extreme values into core values. The mechanism of shrinkage thus strengthens and stabilizes LASSO and decreases the error. For multicollinearity situations, LASSO is seen as a more fitting model. Since L1 regularization is done by the model, the penalty applied in this case is proportional to the coefficient magnitude. So, LASSO simplifies the regression in terms of the number of characteristics it uses. It uses a form of regularization to penalize the extra characteristics automatically. That is, it is possible to set the characteristics that do not support the regression outcomes enough to a very small value that is theoretically zero.
- **Exponential Smoothing (ES):** Prediction is performed based on data from past cycles of exponential family smoothing processes. When they get older, the strength of previous data calculations is decaying exponentially. The value attached to several lag values is also linearly reduced. ES is an effective time series forecasting tool that is very simple, particularly for univariate performance output.

Table 2 shows the consolidation of different classification works performed using CNN, transfer learning models, feature selection, SVM, machine learning models, GAN and its results are detailed. Although only a few strategies produce the best outcomes, the variation in performance measures between methodologies is minimal. In terms of accuracy, experiments on optimization algorithms and CNN transfer learning, have produced similar findings. As a result, a statistical significance test is required to determine which sets of algorithms are superior to the others. Furthermore, while

**Table 2. Comprehensive view of methods and their accuracy**

| Works | Model Used | Accuracy |
|---|---|---|
| Tuncer et al., 2020 | Residual Exemplar Local Binary Pattern (ResExLBP), Iterative ReliefF (IRF). | 100% accuracy using the SVM classifier. |
| Sousa et al., 2013 | Naive Bayes, KNN and SVM | 92.3% |
| Barnett et al., 1987 | Clustering(K-Means), SOFM Algorithm | 91.2% |
| Chachlakis et al., 2019 | Linear Regression, LASSO Regression, Support Vector Machine | 90.1% |
| Markopoulos et al., 2014 | batch normalization operation and Leaky ReLU | 95.8% |
| Singh et al., 2020 | Polynomial Regression Algorithm, Support Vector Machine | 89.2% |
| Haque et al., 2020 | ReLU | 97.5% |
| Wang and Wong, 2020 | Covid-Net | 92.4% |
| Hemdan et al., 2020 | COVIDX-NET | 90.0% |
| Ozturk et al., 2020 | DarkCovidNet | 98.08% |
| Khan et al., 2021 | ResNet18, ResNet 50, SqueezeNet, DenseNet 121 | 92.3% |
| Shibly et al., 2020 | VGG-16 | 91.4% |
| Zhou et al., 2021 | DenseNet, VGG19 | 92.3% |
| Manoj Kumar et al., 2022 | CovStackNet | 98% |
| Shome et al., 2021 | 2D Convolutional Layer | 96.5% |
| Zheng et al., 2020 | MSD-Net | 93.4% |
| Apostolopoulos & Mpesiana, 2020 | VGG-16 | 93.48% |
| Sethy et al., 2020 | ResNet50 | 95.3% |
| Narin et al., 2021 | ResNet50, Deep CNN | 98% |

transfer learning-based work is most of the time, concepts like attention and hybrid may gain better results. In recent works, CNN has gained a lot of attention.

## ISSUES AND CHALLENGES IN THE STUDY

The data management and analysis are constrained by the data volume, which can be minimized at the cost of a penalty for any resolution (Barnett and Preisendorfer, 1987). By adding more labeled data, which improves the learning process of GAN, the performance of the synthetic observations produced in this study could be enhanced (Markopoulos et al., 2017). The lack of data consistency (Ke and Kanade, 2005) is one of the greatest disadvantages of our research. Further research on a broader range of efficiently marked COVID-19 images is needed for a much more comprehensive measurement of the output of these models, owing to the small number of publicly available COVID-19 data to date (Khan et al., 2021). Positive case identification of COVID-19 from radiological images using a deep learning approach from the medical expert's research community (Shibly et al., 2020) was not acknowledged. It is also reflected from our survey that there is a deficit of annotated

COVID-19 medical images/datasets. The process requires image quality enhancement, segmentation as preprocessing, and domain adaptation in transfer learning for a model, which may improve the deep learning classification performance.

### Insufficient Dataset

COVID-19 image databases are being updated regularly with clinical data received from hospitals and testing labs. But they are not enough benchmarked large-scale datasets to reliably validate the performance of the research approaches. Many studies have reported results relying on insufficient samples, which may or may not generalize to real-world data. Furthermore, a great number of researchers have used privately acquired data, making it impossible to compare. Augmentation strategies have been presented in the literature to address this fewer data. However, annotated datasets are essential for developing effective learning algorithms and establishing standards. Furthermore, to prevent bias in the training, the huge heterogeneous data obtained from multiple scanners must be normalized.

### Challenges in Deep Learning Models

COVID-19 detection built by modifying individual layers and performing intense hyperparameter optimization, standard CNN architectures must be performed for achieving good results. While only a few research have applied such optimizations, whereas others used regular deep learning models directly. Similarly, to achieve the best results for medical imaging transfer learning models must be created from scratch. Due to the limited quantity of data model overfitting is also possible. Capsule-net, require huge time for training and prediction since they demand complex computational hardware resources.

Future Trends to be performed:

- COVID-19 identification, classification, and segmentation for clinical diagnosis requires large innovations. Recently, clinical investigations have been performed in X-ray and CT images for various types of lung defects. Because the COVID-19 is so new, it lacks human-level assessments. Micro-level hidden patterns specific to COVID-19 must be identified for further investigation.
- Using artificial intelligence-based pattern mining, the physicians should be able to generate criteria for interpreting the image for determining prognosis to trace the manifestations over time, so that the patient's medical status and the data from the radiograph can be connected to draw clear conclusions in medical investigations.
- Future research will mostly focus on using explainable AI to directly assist doctors with medication.

## CONCLUSION

An automated system that detects COVID infection accurately and faster has become the most inevitable objective to fight against this pandemic. In this article, we have presented a comprehensive survey of deep learning-based COVID-19 detection methods which use Chest X-Ray medical images. The main intention of this survey paper is to epitomize the recent advancements in this domain so that the researchers get an understanding, and they could build an efficient model which can accurately detect COVID-19 disease with economic and time advantage.

This paper presents a comprehensive review of the ML and DL approaches applied on Chest X-ray images in the fight to combat COVID-19. Various machine learning models like SVM, multi-layer perceptron, random forest, XGBoost, etc. are employed and are found to be effective in classifying COVID-19 and pneumonia infections from normal people. In one case, SVM classifier applied on ResExLBP features produced even 100% accuracy. However, the reproducibility and replicability of that laboratory generated performance is a serious question. In DL-based chest X-ray image classification, there are many stages, covering tasks like image preprocessing, image segmentation, hand crafted feature extraction /feature engineering and image classification.

This review work also highlights that there are scientific findings using standard deep learning models and custom-built DL models specifically for chest x-ray image-based diagnosis of pneumonia and COVID infections. Standard DL methods such as CNN, ResNet, VGG-16, VGG-19, Inception successfully diagnosed COVID-19 when used on X-ray images. For the case of X-rays images, ResNet 18, GoogleNet and AlexNet algorithms exhibited good accuracy of above 90% when applied to a small dataset of 1000s of samples and adapted binary classification – infection vs normal. Nevertheless, on multi-classification on a dataset of 3,487 samples, maximum accuracy of 98% is achieved using StackNet. For the case of CT images, ResNet demonstrated a performance in the range of 92% to 98%, in its variants and hybrid models. VGG models showed an accuracy of 93.48% when applied to a dataset of 3000 image samples. Custom built DL models perform better than standard DL models. This is a good indication of feature understanding and more such models may be developed in future.

Practical utilization of deep learning models for chest X-ray based COVID/pneumonia diagnosis pose numerous challenges. Few critical challenges are (i) regulations to conduct the automated diagnosis, (ii) limited real time clinical images, (iii) noisy images (iv) good understanding of how AI learns to diagnose and (vi) data privacy. Additionally, the need for large database of high-quality clinical chest x-ray images is vital for DL models to succeed. Further, if the datasets could indicate different stages of COVID-19 infection levels, the diagnosis results could help the borderline patients and save their lives by providing timely and correct treatment. Though this survey discusses the work only on chest X-ray images, the reliability of the diagnosis can be enhanced when we use multiple imaging inputs, like ultrasound, CT scan, and Magnetic Resonance Imaging (MRI) images for each infected patient. The significant but subtle feature in one modality can be more apparent in another modality. Another significant possible work on images is annotating the clinical images with suitable labels after segmenting them over the infected region. There are numerous COVID-19 infected clinical images without suitable labels. Hence unsupervised learning algorithms on segmented images can prove to be resourceful. Ultimately, with the AI techniques, especially the deep learning models which can do feature engineering on their own, the early detection of infection can help save precious human lives and combat COVID-19 pandemic successfully.

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*Bhargavinath Dornadula completed her Masters in Computer Science and Engineering with a Specialisation in Big Data Analytics at Vellore Institute of Technology, Chennai, Tamil Nadu, India. Her research interests include machine learning and deep learning in the healthcare domain and building data science tools for healthcare modeling.*

*S. Geetha (Senior Member, IEEE) is currently a Professor and the Associate Dean, Research with the School of Computer Science and Engineering, Vellore Institute of Technology, Chennai Campus, India. She received the B.E. degree in Computer Science and Engineering from Madurai Kamaraj University, India, in 2000, and the M.E. degree in Computer Science and Engineering and the Ph.D. degree from Anna University, Chennai, India, in 2004 and 2011, respectively. Her research interests include steganography, steganalysis, multimedia security, intrusion detection systems, machine learning paradigms, computer vision and information forensics. She has more than 20 years of rich teaching and research experience. She has published more than 100 papers in reputed international conferences and refereed journals like IEEE, Springer, Elsevier publishers. She joins the Review Committee and the Editorial Advisory Board of reputed journals. She has given many expert lectures, keynote addresses at international and national conferences. She has organized many workshops, conferences, and FDPs. She was a recipient of the University Rank and Academic Topper Award in her B.E. and M.E. degrees, in 2000 and 2004, respectively. She was also the proud recipient of the ASDF Best Academic Researcher Award 2013, the ASDF Best Professor Award 2014, the Research Award in 2016, and the High Performer Award 2016, Best Women Researcher Award 2021.*

*L. Jani Anbarasi received B.E. degree from Manonmanium Sundaranar University in Computer Science and Engineering in 2000, M.E. Degree from Anna University in 2005 and Ph.D. degree from Anna University in the year 2015. She has around 15 years of experience in various institutions and is currently working as Assistant Professor(Sr) in School of Computer Science and Engineering, VIT Chennai. Her area of expertise includes Cryptography, Image Processing and Soft Computing Techniques. She has published around 71 technical publications in various International Journals and Conferences. Her Professional membership includes India Society for Technical Education (Life Member) and ACM. Received Best Paper award in, “International Conference on Knowledge based Computing Technologies (ICKCT ‘16)”, KCG College of Technology, Chennai. February 2017. Received Best Paper award in “IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 14 to 16 Dec 2017.*

*Seifedine Kadry, PhD, has been an Associate Professor with Beirut Arab University in Lebanon since 2017. He serves as Editor-in-Chief of the Research Journal of Mathematics and Statistics, the ARPN Journal of Systems and Software, and the International Journal of Mathematical Sciences and Computing (IJMSC). Currently, he is the department chair of Math and Statistics in the American University of the Middle East. In addition, he has published several authored and edited books in Elsevier, Springer, IGI, and Taylor and Francis publishers. He is the author of more than 100 papers on applied math, computer science, stochastic systems, and education in peer-reviewed journals. Since 2008, he is the symposium chair in ICNAAM international conference.He received PhD in computational and applied mathematics in 2007 from the Blaise Pascal University (Clermont-II) - Clermont-Ferrand in France, MS in applied mathematics in 2001 from École Polytechnique Fédérale de Lausanne (EPFL) and BS in applied mathematics in 1999 from the Lebanese University.*