SURVEY ON INTELLIGENT COVID-19 DETECTION FROM CHEST X-RAYS

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Abstract - *A novel strain of coronavirus disease was first identified in Wuhan, China. The COVID-19 pandemic caused the death of an outsized number of individuals. Since the disease is highly contagious, there is an urge to identify the positive cases as soon as possible. Applying AI techniques besides radiology imaging will be useful for precise identification of coronavirus disease. It will be beneficial to overcome the problem of shortage of medical kits and specialized physicians. The latest literature on using CXR images to detect COVID-19 is reviewed in this paper. Following a summary of the subject, the analysis examines the efficacy, influences and computational complexities of the algorithms proposed by various researchers. It also addresses the consistency, volume and usefulness of the available datasets.*

Key Words: Covid-19, X-ray, Convolution Neural Networks (CNN), medical imaging, Deep Learning, Detection.

1. INTRODUCTION

Coronavirus disease 2019 (COVID-19) is a contagion caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [8]. In December 2019, the primary case was identified in Wuhan, China. People suffering from COVID-19 will experience respiratory illness.

As reported by the World Health Organization on 3 January 2021, it has affected around 222 countries and territories with around 83,322,449 confirmed cases of COVID-19, including 1,831,412 deaths [9]. The virus spreads through infected secretions like respiratory secretions or droplets and saliva. Since the disease is highly contagious, accurate and timely diagnosis is extremely important to scale back further spreading.
There are many medical terms for detecting coronavirus disease, including RT-PCR test, rapid antibody test, antigen test, TrueNat test, and others. Among this the RT-PCR test is the most commonly used one.

The COVID-19 patient's upper and lower respiratory specimens, such as swabs, sputum, nasopharyngeal, and others, are tested using the Reverse Transcription-Polymerase Chain Reaction (RT-PCR). Under the supervision of medical practitioners, the throat or nasal swabs of the individual are collected. This test allows for the identification of particular genetic material in pathogens such as viruses or bacteria. For the identification of targeted genetic materials, this method employs radioactive isotope markers. Problem with RT-PCR is that it has high false positive and false negative rates. There have been reports of cases where the test result is negative, implying that the person does not have the disease or disorder when, in fact, the person does. On the other hand, there have been several instances where people have had positive test results but later discovered that they did not have the disease. This results in huge complications for the patients as well as those around them. Furthermore, due to the rapid rise in the number of cases, RT-PCR test kits are in short supply across many countries. Moreover, RT-PCR consumes time and it is very expensive. It is also worth noting that proper training is required to collect samples for the test. Given the limitations, Computer Tomography (CT) and X-ray images could be the next best substitute for detecting COVID-19.

Chest radiography (CXR) is an economical, time consuming, most available and easy-to-use medical imaging and diagnostic technique compared to other radiological tests like CT scans. Chest radiography has an important role in diagnosing lung diseases. Even though this method has a lot of advantages, accurate interpretation of information was always a major challenge for the doctors. However, using computer aided diagnosis (CAD), doctors can now diagnose lung diseases including Pneumonia from a chest x-ray more rapidly and reliably. So following the similar method, integrating CAD methods into radiologist diagnosis systems to detect COVID-19 greatly reduces the workload of medical practitioners and increases the reliability and quantitative analysis.

Technology enhancements have a rapid effect on every field be it medical field or the other field. Use of machine learning and deep learning techniques are increasing because of the flexibility to cope with numerous dataset exceeding human potential within the field of medical services. Researchers have proposed various machine learning and deep learning techniques to detect COVID-19 from chest X-Rays and CT images and have obtained promising results. To increase the accuracy of the results, many researchers have used transfer learning and ensemble learning methods. As time flies by researchers are finding new and improved models to detect the coronavirus disease. We attempted to review some of the models.

The main aim of this paper is to systematically summarize, analyse and compare the datasets and techniques proposed by researchers to detect coronavirus disease using chest X-

Rays. We have oriented our paper as follows. Section two describes our research method. Section three elaborates the various datasets and pre-processing techniques used by various researchers. Section four focuses on the data mining techniques proposed by various researchers. A brief comparison review is presented in section five. The sixth section wraps up the discussion and draws a conclusion.

2. RESEARCH METHODS

We have performed a Systematic Literature Review. We have used a research method that has got to be neutral and guarantees perfection to gauge research associated with the corresponding field.

2.1 Data Source

Table -1: Data Sources

DATABASES	URL
IEEE Xplore	https://ieeexplore.ieee.org/
Research Gate	https://www.researchgate.net/
Springer Link	https://link.springer.com/
MDPI	https://www.mdpi.com/
Hindawi	https://www.hindawi.com/
SAGE journals	https://journals.sagepub.com/

We looked for similar studies using six research databases as primary data sources and we have taken significant papers from the chosen databases. Table 1 lists the research databases utilized in our research process.

2.2Search Terms

The below are the key words which were used as search terms for our research method.

- COVID-19 detection or COVID-19 or coronavirus disease or COVID-19 pandemic.
- Chest radiography or Chest X-rays or Detecting corona using medical images or COVID detection using X-Rays.
- ResNeXt or Deep-Learning or CNN or InspectionNet.
- Pneumonia or X-Ray or Convolution Neural Networks.
- Search terms for automated search includes, diseases or chest or COVID-19 or lung disease or x-ray

2.3 Study Selection Process

2.3.1 Criteria of Inclusion and Exclusion

In order to make an accurate comparison between different solutions offered by researchers, the inclusion and exclusion criteria mentioned below are used to draw similar studies from various sources of data.

2.3.1.1 Inclusions

- Studies on identification COVID-19 with medical images.
- Studies on detecting COVID-19 with X-rays.
- Studies not related to COVID but that solves the problem.
- Studies in English language.
- Studies that were published in conferences and journals.

2.3.1.2 Exclusions

- Studies with no affirmation of proposed methods.
- Studies in languages other than English.
- Articles, Reviews, Posters, Wikipedia, Surveys, Reports and Editorials.

3. DATASET GENERATION AND PRE-PROCESSING

Ravneet et al. [1] presented a dataset named covid19-dataset. The CXR (Chest X-Ray) images of coronavirus affected ones were obtained through online hosted data by European Health Care [19] and Italian research organization [11]. It also included the Pneumonia X-Ray images collected from the open source dataset [12]. The noisy data were removed and a dataset with 1122 images were presented. COVID-19, Pneumonia, and Normal were the three labels assigned to them. Each label consisted of 374 images. To eliminate the problem of class imbalance, the number of images under each label was made equal. To improve the prediction quality, data augmentation techniques were applied on the extracted data. All the images were rotated to 45 degrees, zoomed to 30%. Height of the images was shifted with the factor of 0.2 and were resized to 224 x 224. The dataset was further divided into training and test dataset. Among 374 images from each label, 35 images were taken for test dataset and the remaining were added for training dataset.

Rachna et al. [2] collected a dataset from Kaggle Repository which has not only the Chest X-ray scans that were Covid-19 affected but also Pneumonia and normal scans. The aim of the dataset was to investigate various ways of effectively detecting Covid virus infections using Computer Vision methodologies, rather than to prove the diagnostic ability of Deep Learning techniques. This dataset included 6432 chest X-Ray images in total. The dataset is a combination of 5467 training images and 965 test images of normal, pneumonia and covid. The training set had 1345 normal, 490 covid and 3632 pneumonia samples, while the testing set had 238 normal, 86 covid and 641 pneumonia samples. There were a total of 576 Covid-19 scans of Posterior-Anterior (PA) views in this dataset. These PA views were consistent with the dataset. The scans were scaled down to 128x128 for fast model training.

Amit et al. [3] gathers the CXR images from various open sources [10], [11], [12], [13], [14], [15], [16] which contained CXR images of Covid-19 positive patients, pneumonia patients and other information that were collected from European countries. From the collected images, the lateral images were discarded. The images were divided into class 0 (COVID-19 POSITIVE) and class 1 (COVID-19 NEGATIVE). Class 0 contained 538 images and class 1 contained 468 images. Then the images were normalized, resized into size of 224 X 224, shuffled and split into training and test (20%) dataset. Thus, the training dataset had 771 images that included 438 class 0 images and 333 class 1 [3] images. The testing dataset had 235 images that included 100 class 0 images and 135 class 1 images.

Boran et al. [4] collected 255 COVID-19 chest X-Ray images from [18] and a total of 5875 normal and pneumonia CXR images from [20] which had 1583 normal and 4292 pneumonia images. There were 131 male and 64 female patients with an average age of 58.8±14.9 years in the Covid-19 chest X-Ray dataset. All of these images were resized to 640 x 480 because they were of various sizes. To boost the appearance of the distorted X-Ray images, a Laplacian filter was used to sharpen them. Since each image is of different resolutions, APPN methodology was applied to all the images where the average pixel per node is found and all the images were transformed accordingly. After the preprocessing stage, the images were reduced to 30 x 20.

A study by Irfan et al. [5] consisted of 1863 images of x-ray which were taken from four different data sets. The primary data set by Cohen [31] consisted of 660 images, which included both CT-Scan and Chest X-rays. Images labeled with pneumonia and Non - covid X-ray were removed and only Covid Positive images (390) were taken for the experiment. The second data set by [32] included 30 images but only 25 images were selected. The third data set was from [23], which incorporated 237 scans but it had been narrowed down to 180 scans of covid positive alone. Finally, the fourth data set from [24] consisted of 1057 images of Covid19, Normal and Pneumonia. Out of 1057, 195 images of Covid19 and 862 images of the normal category were considered. The training set had 630 Covid19 and 642 Normal samples, while the testing phase had 100 covid19 and 100 normal samples and therefore the validation phase had 100 samples for both Covid19 and Normal categories. Due to the high risk of over-fitting, additional images were also generated using data augmentation. Images were resized to 224 x 224 x 3 in dimensions followed by a random horizontal flip to extend the efficiency, and eventually, some images were rotated 15 degrees to boost the process.

Arun Sharma et al. [6] gathered images of Covid-19, Non-Covid-19, Pneumonia, Tuberculosis, and regular chest X-Rays from three separate sources to train and improve the AI-based model. Related types of chest X-Rays, chest X-Ray images of patients under the age of 19, images other than Posterior-Anterior view, and other CT images were manually removed from the dataset after the images were collected. A total of 352 chest X-Ray images were used for further processing after the filtering. In the dataset, there were 51 Covid-19 images, 21 Non Covid-19 images, 160 Pneumonia images, 54 Tuberculosis images, and 66 regular images. 90% of the dataset (317) was used for training, while 10% (35) of the images were used for external validation. Since the number of images was limited, they were augmented using the CLoDSA augmentation tool. 27 datasets were created using this process, one containing the original images, 25 datasets containing single augmented images, and another dataset containing the combination of the above 26 datasets. They were divided into training dataset I and external validation dataset II. These 27 datasets were used to train 29 AI-based classification models.

4. DATA MINING TECHNIQUES

4.1 Transfer learning

Ravneet et al. [1] made use of a transfer learning architecture for Coronavirus detection. It included two pre-trained models, ResNet-34 and ResNet-50 that were primarily trained for image classification on the ImageNet dataset, which contained 3.2 million images. The ResNet-34 model had 5 stages with convolution and identity blocks linked in a feed forward fashion with the skip connections, with each stage having two convolution layers in itself. Similarly, the ResNet-50 model had five stages with each stage having three convolution layers. On using ResNet-34, the accuracy and error rate were 66.67% and 33.33% respectively. On using ResNet-50, the accuracy and error rate were 72.38% and 27.62% respectively. The ResNet-50 model outperformed the other pre-trained network in terms of accuracy.

Irfan et al. [5] suggested a transfer learning model - A fully automated diagnosis method to detect Covid-19 infection. Four pre-trained models like VGG16, VGG19 [27], DenseNet121 [25] andResNet50 [26] were used. The ImageNet dataset was used to pre-train the models, and the X-Ray dataset was used to further train the models. The number of epochs for each model was set to 30, and neutron feature extraction range was expanded using the activation function: ReLU. Based on the comparative analysis and the experimental results of the four models, Both VGG16 and VGG19 [27] outperformed the DenseNet121 [25] and

ResNet50 [26VGG19 [27] had the best accuracy (99.33%) and the lowest loss. Moreover, VGG19 [27] had a higher sensitivity than VGG16.The model [5] outperformed the benchmark studies.

Arun Sharma et al. [6] trained and validated the 29 AI-based models using Transfer Learning approach. The models were trained and validated using Python, and the source code is available at [22]. To train the models, hyper-parameters were used. It included internal validation size, number of filters (for 3 convolution layers), filter Size, number of epochs, image size, batch size, fully connected layers and number of Iterations. Among the 29 models, first dataset was used to train one model, datasets 2-26 were used by the next 25 models and the 27th dataset was used by the remaining three models which used 24, 49, and 101 epochs respectively. The first 26 models, as well as the hyper parameter values, were trained over 24 epochs. The number of epochs used was reduced to avoid over-fitting the models. Best performing models were selected based on the highest accuracy model on external validation datasets. The original image-based AI model gave 100% accuracy on training dataset and 75% accuracy on internal validation datasets. Single augmentation-based models gave 100% and 62% accuracies on training and internal validation datasets. On the training and internal validation datasets, the combined dataset model (original images and augmented images) with 101 epochs gave 100% and 93.8% accuracy. Thus, the combined dataset model using 101 epochs had the best performance.

4.2 Ensemble Learning

Amit et al. [3] created a GUI framework focused on Ensemble learning and Covid-19 detection using convolutional neural networks. They proposed an ensemble method that was based on weighted average and it comprises of CNN models which were pre-trained, InceptionV3, ResNet50V2 and DenseNet201. The key idea was that if one of the three pre-trained models outperforms the other two (by getting a lower validation error), it would be given a higher weight and thus have a greater contribution in determining the class. Adam optimizer was used for all the three models for faster convergence. The ensemble learning model's validation precision, sensitivity, and F1-score were 95.7%, 98%, and 96.2%, respectively.

4.3 Deep Learning

Rachna et al. [2] applied augmentations to the dataset including rotation, zoom and sharing of images and also shuffled to generalize the model thereby reducing data over-fitting. Three different models such as: Inception net V3, A network based on CNN that decreases the quantity of parameters used thereby increasing the training speed during classification; Xception net, a variant of the previous model in which the inception modules are supplemented by depth-wise separable convolutions.; ResNeXt where the split-transform-merge technique used in previous models has been replaced by the standard remaining blocks. All the three models were implemented and the model with highest accuracy was chosen. The LeakyReLu activation function had been employed in the models to quicken the training and also to avoid the dead neurons problem which occurred within the normal ReLu function. Inception net V3 model had training and testing accuracies of 99% and 96% respectively. Xception Net model had training and testing accuracies of 100% and 97% respectively. ResNeXt model had training and testing accuracies of 98% and 93% respectively. Therefore, the Xception Net model proved to be the accurate model among the three models.

4.4 Experimentation Learning

Boran et al. [4] compared the performance of ConvNet models with other models using three experiments which were categorized as: ConvNet, Statistical measurement and Transfer Learning experiments. These experiments included three subcategories like: Covid-19/normal/pneumonia, Covid-19/pneumonia and Covid-19/normal.

ConvNet Experiments: [4] Four different networks with different numbers of convolutions and fully connected layers followed by basic preprocessing methods were employed for all the three classes during this experiment. Seventeen experiments were conducted in the Covid-19/normal class. Here Laplacian filters were implemented to sharpen the X-Rays pictures, APPN methods for averaging the pixels and in some experiments; original images were used with various dimensions. The foremost effective mean and sensitivity score obtained were 96.51% and 93.84% respectively. In Covid-19/Pneumonia, similar experiments were conducted and also the foremost effective sensitivity and mean obtained were 92.88% and 96.33% respectively. In both these groups, unprocessed images gave the foremost effective result. Therefore, unprocessed images were used for the Covid-19/normal/pneumonia class. Four ConvNet architectures were built and also the second architecture (ConvNet#2) had the foremost effective macro-averaged F1 score of 94.10%.

Statistical Measurement Experiments: [4] Five Machine Learning classifiers such as: Support Vector Machine (SVM), Linear Regression (LR), Naive Bayes (NB), Decision Tree (DT) and K Nearest Neighbor (KNN) were implemented. SVM produced the foremost effective mean accuracy of 96.57% in Covid-19/Normal class and both NB and SVM produced the foremost effective mean accuracy of 97.85%, each.

Transfer Learning Experiments: [4] Since the unprocessed images gave the foremost effective results within the ConvNet experiments, preprocessed images were not utilized. Various architectures utilized during this experiment were: VGG16, ResNet50, Inception V3, MobileNet-V2 and DenseNet121. DenseNet121 and Inception V3 had the foremost effective mean score of 95.95% and 94.71% respectively in both Covid-19/Pneumonia class and Covid-19/Normal class. However, DenseNet121 had the highest effective mean score of 93.85% in the Covid-19/normal/pneumonia class.

Upon comparing the results of all the three experiments and also considering their optimality, ConvNet#2 architecture had the foremost effective average F1 score of 94.10% and also gave optimal results followed by DenseNet121 with 93.85%.

5. COMPARATIVE ANALYSIS AND DISCUSSIONS

We will review and compare the relevant dataset as well as the techniques proposed by various researchers for detecting Covid-19 in this section. We will gauge these methods based on the quality, volume, robustness and usefulness.

As mentioned in the table 2, there are various data sources available to perform this work. Among these, the most famous and the most widely used dataset is Covid-19 database [11] and the CXR images (pneumonia) [12].Most of the mentioned datasets in Table 2 contain a very few Covid cases and so the authors have used a mixture of two or more datasets in most of the works discussed in this literature.

Table – 2: Comparison of datasets

DATASET	VOLUME	RELEVANCE	PAPERS
Chest X-ray (Covid-19 & Pneumonia) [17]	6432 images	Relevant but only 576 Covid-19 cases	[2]
Chest X-Ray Images (Pneumonia) [12]	5863 images	No Covid-19 cases	[1], [3]
Covid-19 Database [11]	115 images	All Covid-19 cases	[1], [3]
Figure1 COVID-19 Chest X-ray Dataset Initiative [13]	48 images	All Covid-19 cases	[3]
COVID-19 CXR [10]	30 images	All Covid-19 cases	[3]
COVID-19 image data collection [16]	127 images (constantly updating)	Relevant	[3]
Normal and Pneumonia chest x-ray images [20]	5875 images	No Covid-19 cases	[4]
COVID-19 images [7]	51 images (Constantly updating)	All Covid-19 cases	[6]
Non-Covid-19 images [28]	21 images (Constantly updating)	No Covid-19 cases	[6]
COVID-19 Image Data Collection [18]	255 images	All Covid-19 cases	[4]
Pneumonia images [29]	160 images (Constantly updating)	No Covid-19 cases	[6]
Tuberculosis images [30]	54 images (Constantly updating)	No Covid-19 images	[6]
Normal images [21]	66 images (Constantly updating)	No Covid-19 images	[6]
Covid-19 image data collection [31]	660 images	Relevant but had only 390 Covid-19 images	[5]
COVID-19 chest x-ray dataset initiative [32]	32 images	Relevant	[5]
Actualmed COVID chest x-ray dataset[23]	237 images	Relevant but had only 180 Covid positive images	[5]
COVID-19 Radiography database[24]	1057 images	Relevant	[5]

Some of the datasets are highly imbalanced, so the researchers have followed various preprocessing and augmentation techniques which are discussed in the third section of this literature. In most of the cases, the authors have concluded their work with few images. As a result, the findings cannot be applied on a large scale. We recommend gathering massive data that is balanced and contains a large sample of Covid-19 cases.

The samples from the current dataset can be used as a temporary solution, but the combined images are only around twenty thousand, which is far too few for efficient and reliable detection.

As mentioned in the table 3, various researchers have presented substantial effort in the domain of Covid-19 identification. The findings of the majority of the proposed works are similar in precision, but they were computed on a small scale database and cannot be used on an industrial scale. By using transfer learning methods, Irfan et al. [5] have achieved 99.33% accuracy on the validation dataset. This is worth noting. Most of the researchers have used transfer learning techniques to gain high accuracy. On using Xception Net, Rachna et al. [2] achieved an accuracy of 97% which is also remarkable. Amit et al. [3] have achieved an accuracy of 95.7% by using Ensemble learning methods which is again an exceptional work. Boran et al. [4] and Arun Sharma et al. [6] have achieved 94.10% and 93.8% accuracy respectively. However, there are other works which have provided less than 90% accuracy for Covid-19 detection like Ravneet et al. [1]. Therefore, the current best performance is provided by Irfan et al. [5].

Table – 3: Comparison of Covid-19 detection strategies

CITATION	TECHNIQUE	RESULTS
Ravneet et al. [1]	Transfer learning of pre-trained ResNet-34 and ResNet-50 models	66.67% accuracy on using ResNet-34 and 72.38% on using ResNet-50
Rachna et al. [2]	Deep Learning of Inception net V3,Xception Net and ResNeXt	97% accuracy on using Xception Net.
Amit et al. [3]	Ensemble of pre-trained DenseNet201, ResNet50V2 and InceptionV3	95.7% accuracy and 98% sensitivity
Boran et al. [4]	Experimentation Learning of ConvNet, Statistical measurement and Transfer Learning Experiments	94.10% efficiency using one of ConvNet architectures.
Irfan et al. [5]	Transfer learning of pre-trained DenseNet121, ResNet50, VGG19, VGG16.	VGG19 Achieved 100% sensitivity and 99.33% accuracy
Arun Sharma et al. [6]	Transfer learning using AI-based models.	Combined dataset model which used 101 epochs achieved 93.8% accuracy

6. CONCLUSIONS

Detection of Covid-19 virus is very essential because of its rapid spread. Apart from detecting the virus, the detection has to be very accurate and also must be fast. We can achieve this by using Deep Learning and Machine Learning algorithms. Throughout this paper, we have studied various ways to detect the virus in X-Ray images thereby reducing the delay in detection and other limitations using the current method. Convolutional Neural Networks, Deep Learning, and Machine Learning algorithms are used to analyze X-Ray images. Majority of the papers that we have surveyed not only detects Covid-19 virus but also differentiates pneumonia and normal X-Rays. This diagnosis is very essential as this helps patients and doctors treat the disease if any, at an early stage. From our survey, it is deductible that since it has only been a few months after the outbreak of the pandemic, the number of datasets available is quite little. With many more X-Ray images, more accurate results can be obtained in the future. In all the papers, performance is measured based on the F1 score, mean accuracy, and other computational complexities of the models.

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