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A COMPREHENSIVE SURVEY OF COVID-19 DETECTION USING MEDICAL IMAGES

DIGITAL IMAGE PROCESSING

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ABSTRACT

Around the end of 2019 started an outbreak of flu and related disease, the SARS-COV2 (severe acute respiratory syndrome coronavirus 2), which commonly came to be called the COVID-19. It effected millions of people and creating a chao, ultimately bringing the world to a standstill. It caused the death of many people and declared as a pandemic by the World Health Organization. Millions of people are infected by this virus and are still getting infected every day. As the cost and required time of conventional Reverse Transcription Polymerase Chain Reaction (RT-PCR) tests to detect COVID-19 is uneconomical and excessive, researchers are trying to use medical images like X-Ray and Computed Tomography (CT) images to detect this disease with the help of Artificial Intelligence (AI) based systems to assist in automating the scanning procedure.

KEYWORDS

COVID-19, Deep Learning, Neural networks, Medical Images, Survey, AI, Classification, SVM

INTRODUCTION

Coronavirus Disease 2019 (COVID-19) is an infectious disease that started to proliferate from Wuhan China, in December 2019 . Within a short period of time, this disease is ravaged every corner of the world and the World Health Organization declared this disease as a pandemic on 11 March 2020. This disease is caused by the strain of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). In July 2020, cases reached almost 12 million worldwide, and death due to this disease kept rising day by day, and the death toll is over 4.9lakhs just in India, and about 50 lakh deaths globally . From the data shown in Wikipedia, the total deaths and total cures is illustrated in Fig. 1 . Observing the statistics and properties of COVID-19 it can be asserted that this life-threatening virus can unfurl from individual to individual via cough, sneezing, or even close contact. As a result, it has become important to detect the affected people earlier and isolate them to stop further spreading of this virus.

RT-PCR is a procedure of assembling samples from a region of a person's body where the coronavirus is most likely to congregate, such as a person's nose or throat. Then this sample is treated with chemicals to track down the existence of the coronavirus. It is well known that results from real-time RT-PCR using primers in different genes can be affected by the variation of viral RNA sequences. Genetic diversity and rapid evolution of this novel coronavirus have been observed in different studies. False-negative results may occur by mutations in the primer and probe target regions in the SARS-CoV-2 genome. Although it was attempted to design the real-time RT-PCR assay as precisely as possible based on the conserved regions of the viral genomes, variability causing mismatches between the primers and probes and the target sequences can lead to decrease in assay performance and potential false-negative results. Furthermore, in many regions of the world RT-PCR's availability is limited. Hence, medical images like Computer Tomography (CT) and X-Ray images can be the next best alternative to detect this virus as most of the medical/hospital commonly have this apparatus to generate images. Also, CT or X-Ray images are readily available where there is no RT-PCR. Moreover, RT-PCR is expensive and consumes a considerable amount of time for the identification. Additionally, proper training is required for the health workers to collect samples for PCR whereas, it is relatively easy to handle and produce CT and X-Ray images.

To work on these medical images, deep learning methods are the most conventional and might be the only direction. Deep Learning is an emerging field that could play a significant role in the detection of COVID-19 in the future.

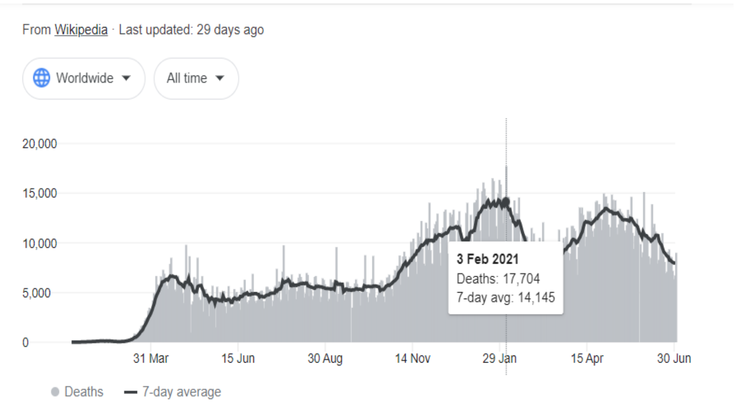


Fig. 1 Global deaths for every 45 days due to covid-19 pandemic

LITERATURE SURVEY

Till now researchers have used machine learning/deep learning models to detect COVID-19 using medical images such as X-Ray or CT images and obtained promising results. Many researchers also used transfer learning, attention mechanism and Gradient-weighted Class Activation Mapping (Grad-CAM) to make their results more accurate. Artificial intelligence (AI) technologies strengthen the power of the imaging tools and can play a vital role in medical specialists.

F Shi et al. [1] in his research paper, "Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation, and Diagnosis for COVID-19" has implemented AI-empowered image acquisition to significantly help automate the scanning procedure and also reshape the workflow with minimal contact to patients, providing the best protection to the imaging technicians. Also, AI can improve work efficiency by accurate delineation of infections in X-ray and CT images, facilitating subsequent quantification. The paper mainly discusses the integration of AI with X-ray and CT, both of which are widely used in the frontline hospitals.

Ulhaq A et al. [3] reviewed some papers that worked on diagnosis, prevention, control, treatment, and clinical management of COVID- 19. However, as time goes by researchers are finding advanced and improved architectures for the diagnosis of COVID-19. In this paper, we have tried to review these new methods alongside with the basic structures of the earlier COVID-19 classification models. This survey will cover the research papers that are published or in pre-print format. Although it is not the most favorable approach due to the likelihood of below standard and research without peer-review, we intend to share all proposals and information in a single place while giving importance to the automatic diagnosis of COVID-19 in X-Ray and CT images of lungs.

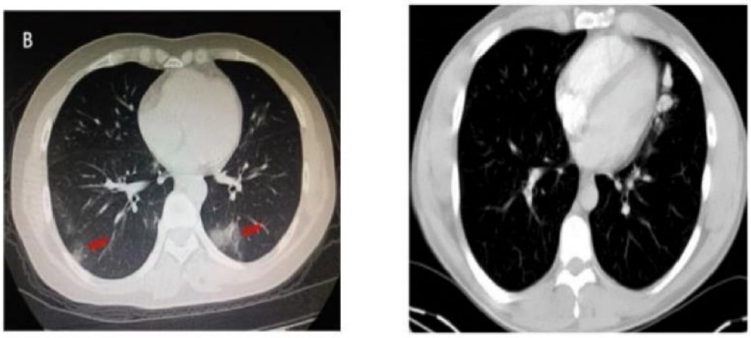
The fundamental aim of this paper is to systematically summarize the workflow of the existing research, accumulate all the different sources of datasets of lung CT and X-Ray images, to sum up the frequently used methods to automatically diagnose COVID-19 using medical images so that a novice researcher can analyse previous works and find a better solution. We oriented our paper as follows:

- Dataset source and different types of images used in the papers are described in section2.
- The methodology where data pre-processing and augmentation techniques, feature extraction methods, classification, segmentation, and evaluation that researchers obtained are characterized and discussed.

METHODOLOGY

COVID-19 DATASET AND RESOURCE DESCRIPTION

The diagnosis of any disease is like the light at the end of the tunnel. In the case of the COVID-19 pandemic, the importance of earlier diagnosis and detecting the disease is beyond measure. The initial focus must be on the data by which we need to efficiently train a model. This data will help Machine Learning (ML) or Deep Learning (DL) algorithms to diagnose COVID-19 cases. Due to the disadvantages of RT-PCR, researchers adopted an alternative method which is the use of Artificial Intelligence on chest CT or X-Ray images to diagnose COVID-19. Fundamentally, a chest CT image is an image taken using the computed tomography (CT) scan procedure where X-Ray images are captured from different angles and compiled to form a single image. A depiction of the CT images (COVID-19 infected and Normal) is illustrated in Fig. 2.



(a) (b)

Fig. 2: CT images (a) COVID-19 (b) Normal.

Although a CT scan consumes less time to demonstrate, it is expensive. As a result, many researchers adopted X-Ray images instead of CT images to develop a COVID-19 detection model. A chest X-Ray is a procedure of using X-Rays to generate images of the chest. It is relatively economical and convenient to maintain. X-Ray images of different people with COVID-19, viral pneumonia, bacterial pneumonia, and a person without any disease (normal) are shown in Fig. 3. Further in this section, an overview of the dataset sources used in the existing papers is characterized and datasets of both CT and X-Ray images are illustrated and covered in this section.

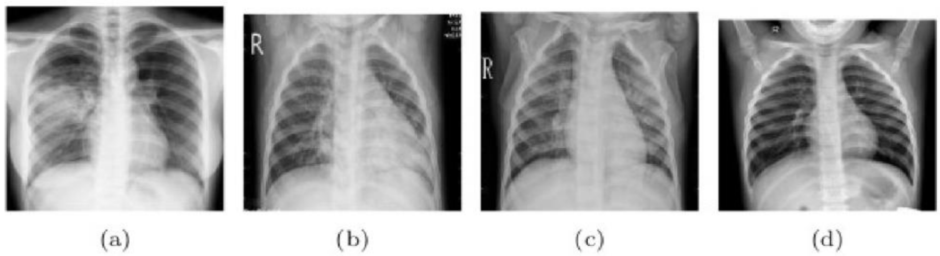


Fig. 3: X-Ray images (a) COVID-19 (b) Viral Pneumonia (c) Bacterial Pneumonia (d) Normal from COVID19-XRay-Dataset

Dataset

Nowadays, the exchange of information between researchers and physicians creates difficulties due to the lockdown phase. Hence, massive COVID-19 data are out of reach or difficult to find for many researchers. As a deep learning architecture needs a considerable number of images to learn a model appropriately and efficiently, the existing COVID-19 automation research are still in preliminary stages. However, some COVID-19 datasets are proposed and employed by the researchers which show exceptional results in detecting the COVID-19 affected lungs. To corroborate a beginner researcher, we have accumulated the abstract information of the datasets.

Image Sources

As CT images are said to be detailed than X-Ray images, the diagnosis of COVID-19 and developing a model becomes more convenient by employing the CT-scan images. For CT images-based works, four papers used the COVID-19 CT segmentation dataset to develop a classification architecture. This dataset contains hundred axial CT images from forty patients, Chen X et al. [14] and Qiu Y et al. [16] achieved 89% and 83.62% accuracy respectively using this dataset. Furthermore, two authors adopted the Lung Image Database Consortium (LIDC) dataset and accomplished an accuracy above 90%. Besides these, some authors used Societa Italiana di,Radiologia Medica e Interventistica to generate datasets , Lung Segmentation, and Candidate Points Generation and HUG dataset for their purpose.

A representation of these dataset sources is characterized in Table 1 and depicted in Fig. 4 (based on months). From the table, we can infer that the COVID-19 CT segmentation dataset was used mostly in the early months of 2020. Some researchers also used other lung disease images apart from these mostly used datasets. Nevertheless, they collected CT images from different hospitals to build these datasets.

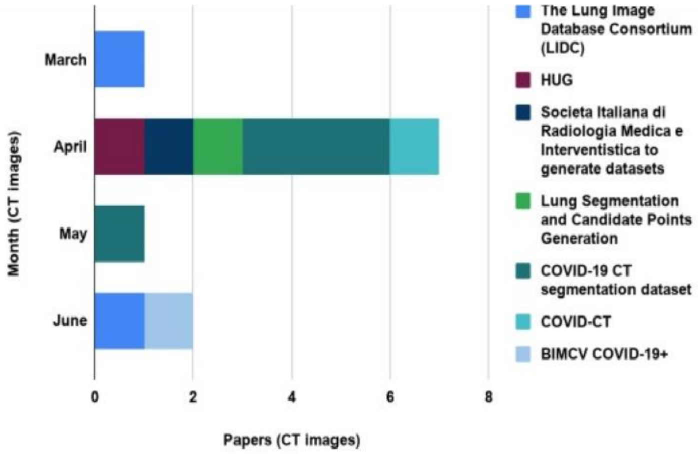


Fig. 4: A bar chart showing seven publicly available CT datasets used from March, 2020 to June, 2020.

X-Ray Image Sources

X-Ray image dataset is more available than the CT images as the cost of capturing an X-ray image is considerably more economical than a CT image. Studying the existing literature, most of the authors used the COVID-chest X-ray dataset. Moreover, Kaggle RSNA Pneumonia Detection, COVID-19 database et al. [6], Chest X-Ray Images (Pneumonia) is adopted to evaluate their model. These are the most common dataset for Chest X-Ray based COVID-19 research (Table 1). However, these datasets contain a limited number of COVID-19 infected lung images which is not efficient to train a deep learning model as the model can overfit the data. For this purpose, most of the researchers utilized different pre-processing techniques to increase the dataset size, one of them is data augmentation. Furthermore, the existing works are trained on a hybrid dataset combining the COVID-19 dataset and normal lung images from another repository. For X-Ray based works, Al-antari MA et al. [8] used COVID-19 Radiography Database for alternative lung diseases. An illustration of the eighteen X-Ray dataset usage is depicted in Fig. 5. From there it can be noticed that the COVID-chest x-ray dataset was used by most of the authors followed by Kaggle's Chest X-Ray images (Pneumonia). From both Fig. 4 and Fig. 5 it can be observed that BIMCV COVID-19+ emerged in June 2020 in terms of developing a COVID-19 classification model.

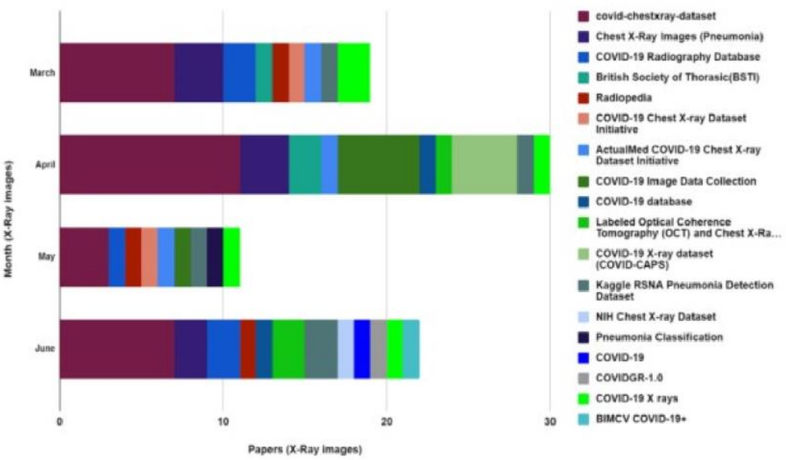


Fig. 5: A bar chart showing eighteen publicly available X-Ray datasets used from March, 2020 to June, 2020

BLOCK DIAGRAM

After data collection, several preeminent steps must be followed to diagnose COVID-19, hence this section depicts different techniques employed by different papers. Firstly, pre-processing techniques along with their characteristics and properties is described. Secondly, feature extraction methods are thoroughly discussed. After that, segmentation methods and classification techniques are reviewed. Lastly, the results obtained in the existing studied papers are briefly described. The workflow of diagnosing COVID-19 from X-Ray images demonstrated in Fig. 8.

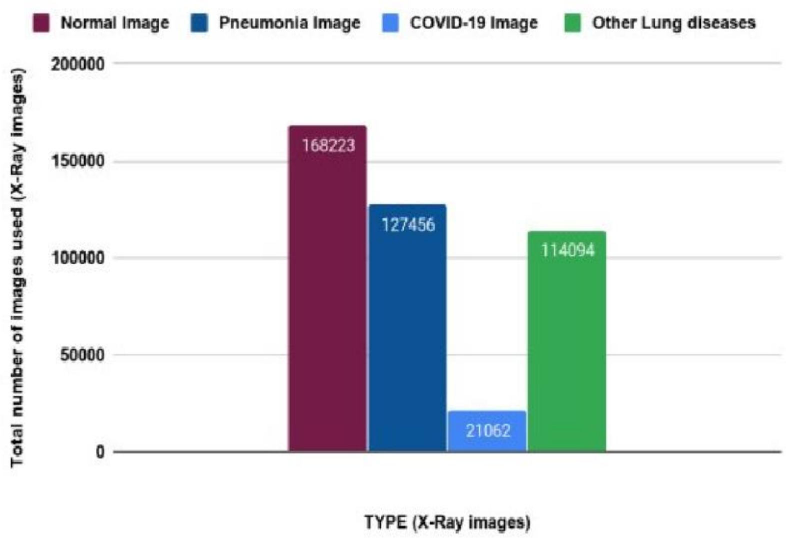


Fig. 7: The total number of X-Ray images for different disease and normal patients used from February, 2020 to June, 2020

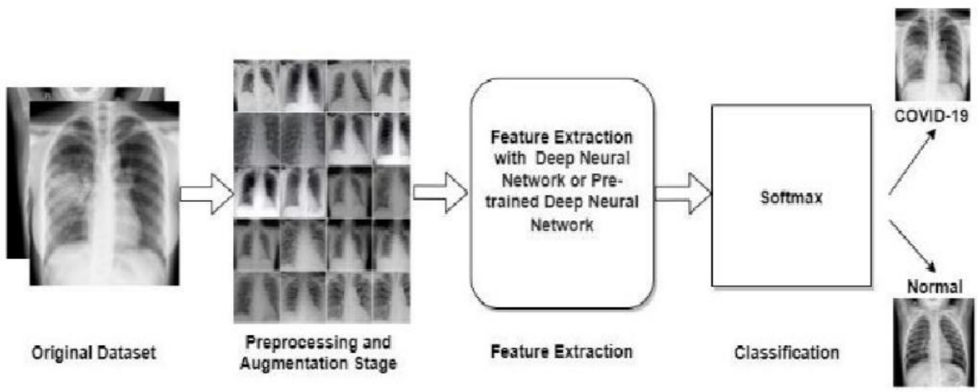


Fig. 8: Workflow of diagnosing Covid-19 from X-rays (Block diagram)

PRE-PROCESSING TECHNIQUES

There is a high chance that a COVID-19 dataset is built with some obscure, duplicate, blur, etc. images that degrade the performance of a model. Hence, itis necessary and mandatory to perform pre-processing techniques on redundant images. Various types of pre-processing techniques can be carried out based on the difficulties of the dataset. One of the major problems of deep learning is overfitting. To minimize the effect of overfitting data augmentation is used in the pre-processing stage. Resizing, scaling, cropping, flipping, rotating are the most employed data augmentation techniques. Some of these data augmentation techniques are discussed below:

- Resizing is necessary because the images are not always within the same estimate which postures an issue whereas preparing the model. To generalize the dataset all the images are resized into a fixed dimension like 224× 224 or 299 × 299.

- Flipping or Rotating is done to increase the sample size of the datasets. Mainly horizontal and vertical flipping is used to do this as depicted in Fig.9a.

- Scaling or Cropping is the next most used augmentation technique is scaling or cropping. All the portions of the images are not necessary to use. So, to reduce the redundancy researchers used the cropping method as illustrated in Fig. 9b.

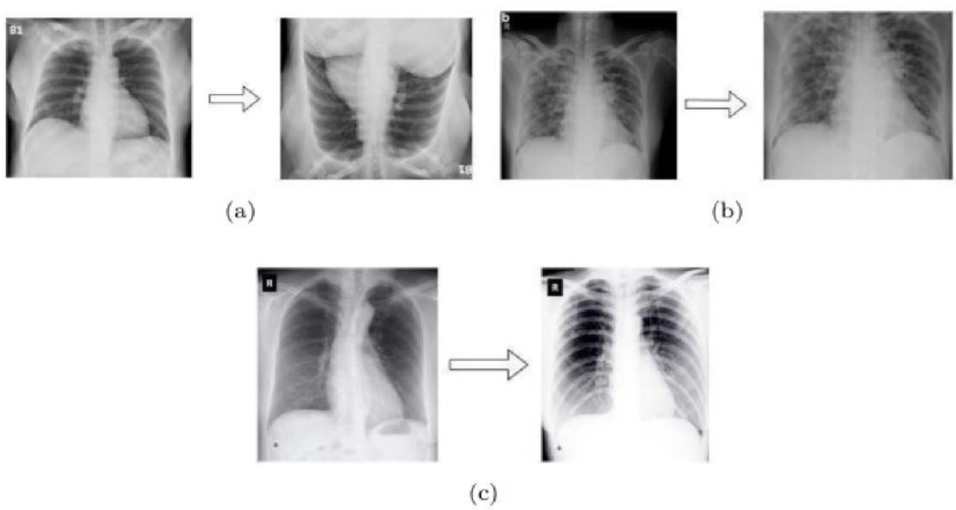


Fig. 9: Some examples of applying Pre-processing Techniques [(a) flipping by 180 degree, (b) Cropping, and (c) adjusting brightness]

- Brightness or Intensity adjusting is mandatory to increase or reduce the brightness of the images.
- An example is shown in Fig. 9c. As the COVID-19 dataset is built with an insufficient number of COVID infected images, Generative Adversarial Networks (GAN) can be employed to generate COVID affected lung images which can be a path to avoid overfitting or data insufficiency.

GAN is an unsupervised learning process structured on generative modelling embedded with deep learning architectures. It finds the patterns, similarities in the input datasets and generates new data which is like the input dataset. GAN [90] increases the sample size in the dataset but the quality of the samples is not guaranteed.

A representation of the papers applying augmentation techniques on their model is characterized in Table 4 and the percentage usage of these augmentation techniques is depicted in Fig. 10. From there it can be seen that resize and flipping has the highest percentage of 27.9% and 27.0% respectively. Scaling or Cropping, Contrast Adjusting, Brightness Adjusting, and GAN is 22.1%,12.3%, 7.4%, and 3.3% respectively. Besides these techniques, some authors used various traditional image pre-processing techniques such as Histogram Equalization, Adaptive Winner Filter, Affine Transformation, Histogram Enhancement, Colour Jittering and so on.

FEATURE EXTRACTION METHODS

Feature extraction is an essential step for classification as the extracted features provide useful characteristics of the images. For image feature extraction, Deep Neural Networks (DNN) have extraordinary capabilities to extract the important features from a large-scale dataset. As a result, these are used extensively in computer vision algorithms and Convolutional Neural Network (CNN) which is also known as ConvNet. In the following, the feature extraction model is briefly described.

Convolutional Neural Network (CNN)

In visual imagery fields, CNN architectures are mostly employed and adopted methods [92]. A CNN architecture is built with various types of network layer, pooling layer, convolutional layer, flatten, etc. corroborating the development and performance of a model. Convolution layer is the core building block of a CNN. The layer's parameters are made up of a set of discoverable kernels or filters which have a little responsive field but enlarge through the full input volume. Non-linear layer is the layer where the change of the output is not proportional to the change of the input. This layer uses activation functions to convey non-linearity to data by adding after each convolution layer. Used activation functions can be Rectified Linear Unit (ReLU) [93], Tanh, etc. Pooling layer is another important part of CNN architecture where it is used to downsize the matrix. Pooling can be done in several methods: Max Pooling, Min Pooling, Average Pooling, and Mean Pooling. Fully connected layer is the layer where every Neuron of a layer is connected with every other neuron of another layer. Traditional Multilayer Perceptron neural networks (MLP) and this layer have common principles.

Interpretability

Fundamentally, a learning model consists of algorithms that try to learn patterns and relationships from the data source. To make the results obtained from machines interpretable, researchers use different techniques such as Class Activation Mapping (CAM), Gradient-weighted Class Activation Mapping (Grad-CAM) based on a heatmap. CAM is a method that creates heatmaps to show the important portions from the images, especially which regions are essential in terms of the Neural Network. CAM has various versions such as Score CAM and Grad-CAM. The heatmap generated by CAM is a visualization that can be interpreted as where in the image the neural net is searching to make its decision. This is very important in image classification and object localization problems.

Classification

Almost all of the COVID-19 diagnosis models use Convolutional Neural Network [96] as a feature extractor and as a classifier, it uses SoftMax or sigmoid. Some authors also attempted to amplify CNN with a sigmoid layer. The authors have merged CNN with the SoftMax layer along with the SVM classifier. Some also used CNN with SoftMax layer along a decision tree, random forest, XGBoost, AdaBoost, Bagging Classifier and LightGBM. Furthermore, some of them also merged CNN with KNN, support estimator network, and SVM classifier. Nonetheless, these models need a large amount of data for training which is in shortage of COVID-19 images.

Essentially there are two ways of classifying COVID-19 images, Binary Classification, and Multiclass classification. In Binary Classification authors tried to separate COVID-19 and non-COVID-19 patients, but this technique is very inaccurate as other types of lung diseases (viral pneumonia, viral pneumonia, bacterial pneumonia, and Community Acquired Pneumonia) can be classified as COVID-19. For that reason, many authors differentiate COVID-19, viral pneumonia, bacterial pneumonia, community-Acquired Pneumonia, and normal images by classifying them using a SoftMax classifier. In terms of accuracy of detecting COVID-19 images, multiclass classifiers performed better than binary classifiers.

SUPPORT VECTOR MACHINES

Classification is the process of predicting the class of given data points. A classifier utilizes some training data to understand how given input variables relate to the class. Classification belongs to the category of supervised learning where the targets also provided with the input data.

SVM is a supervised machine learning algorithm which can be used for classification or regression problems. It uses a technique called the kernel trick to transform data and then based on these transformations it finds an optimal boundary between the possible outputs. SVM finds the optimal linear decision surface based on the concept of structural risk minimization. The decision surface is a weighted combination of elements of the training set. These elements are called support vectors and characterize the boundary between the two classes. SVM classifies data based on the plane that maximizes the margin. The SVM decision boundary is straight and is a good algorithm for image classification.

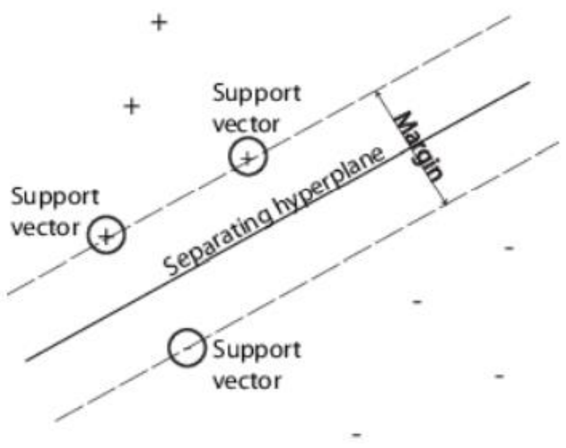


Fig 10. Illustration of SVM

Now we have at each pixel, a feature vector and we simply want to classify the feature vector as being a face or not a face. A very efficient way of doing this would be by using decision boundaries, and that is exactly what support vector machines do. They compute the best decision boundary to be used. Support vector machines are widely used not just in face recognition, but also in several other fields including computer vision, text-based applications, bioinformatics, cancer detection and control chaotic dynamics etc.

Linear decision boundary: Let's consider feature vectors is of dimensionality 2. A Linear Decision boundary in 2-D space is 1-D line that divides the space, so that every new feature that has to be classified, if it happens to be present on the left side of the line, then we say it is a face, else if it lies on the right side of the line, then it is considered as a non-face. So this decision boundary can be written using the equation, $W^T f + b = 0$, where w is the coefficient vector, f is the feature vector, b is a scalar corresponding to the intercept.

Consider the case, $W^T f + b > 0$ This refers to the region to the left of the line. As mentioned earlier, if the feature exists on the left hand side, it is classified as a face. Linear decision boundaries can be used irrespective of the dimensionality, in case of 3-D space, the linear decision boundaries will be in 2 dimensionality, that is, it will be a plane. Similarly, if you happen to be in an n-dimensional feature space, then there will be n-1 dimensional hyperplane as the linear decision boundary. It's a hyperplane because it's in higher dimensions. The equation of the hyperplane will be of the same form, $W^T f + b = 0$.

Evaluating a decision boundary: We do this by defining what's called a 'Margin' or a safe zone. It is this width that must be extended or the boundary has to be increased until it almost touches the features on both sides. Safe zone is defined as the width that the boundary could be increased by before it hits at least one feature point on each of the two sides, and the thickness of this band is what is called as margin. There can be different decision boundaries, meaning each different line can produce different safe zone, each one thinner or thicker than the other. If a new feature falls in a certain region, it might get classified it as a face in case of one such margin, but as a non-face in another margin. So, the only factor to be considered while choosing the right one is the decision boundary having the maximum margin.

SVM is trying to find a decision boundary which has a safe zone with the maximum margin. When we consider the maximum margin, both the face and non-face points are touching the safe zone, and these points can be seen as supporting the safe zone and hence are called as support vectors. Closest data samples or features to the boundary are called as support vectors. What's interesting with this is that, once the support vectors are computed, the points that lie on the boundary of the safe zone are determined, now all the other features can be ignored. Meaning the features on the boundary of the safe zone are all that is needed to represent the decision boundary and the other points on either side can also be ignored.

RESULTS

,Researchers use different evaluation metrics to analyse their COVID-19 model's performance. Among them, the most popular and used metrics for detecting COVID-19 are Accuracy, Precision, Recall/Sensitivity, F1 Score, Specificity, and Area Under Curve (AUC). We have given the number of COVID-19 images from the total images used for training, testing, and validation purpose. Some papers explicitly stated the train-test split of COVID-19 images and for some papers, the calculations of the split, according to the ratio would be provided in the paper. Even so, for some papers, it is not clearly stated how they distributed their dataset. Additionally, some papers explicitly stated the use of data for validation. These papers with their Accuracy, AUC, Sensitivity, and Specificity are given along with their distribution of COVID-19 images in training, testing, and validation set. It can also be observed that CT image-based models gained a minimum accuracy of 79.50% for the paper J. Zhao et al. [19] and maximum accuracy of 99.56% for the paper Uzkaya et al. [13].

CONCLUSION

As COVID-19 is spreading worldwide expeditiously, accurate and faster detection of the disease has become the most essential objective to defend this outbreak. In this paper, a comprehensive survey of AI-empowered methods that use medical images to combat this pandemic are mentioned. The fundamental purpose of this survey is to represent the current information so that researchers understand and aware of the up-to-date knowledge and build a model that can accurately detect COVID-19 disease at an economical cost and relatively faster in time. We surveyed a total of 80 COVID-19 diagnosis architectures among which 28 are using CT images, 50 are using X-Ray images and 2 are using both CT and X-Ray images. Till now none of these models are proved to be as reliable to replace RT-PCR tests, but still, researchers are always trying to improve these techniques.

From our survey, it is noticeable that the X-Ray image dataset is more widely available than the CT Image dataset, as a CT scan procedure is costlier and more time-consuming than an X-Ray. So, most of the researchers utilized Chest X-ray images for diagnosing COVID-19. After carefully analysing the existing research works in this domain, we find out that there exists a shortage of annotated medical images of COVID-19 affected people. Enriching quality annotated medical images of COVID-19 affected people can play a significant role to boost up the performance of the mentioned data hungry models. Furthermore, it must noted that using segmentation as pre-processing has an extensive impact on model performance. It is also observed that domain adoption in transfer learning is the widely used technique which gives a promising result. Furthermore, many researchers used Gradient-weighted Class Activation Mapping (Grad-CAM) with heatmap to interpret the performance of the model. Though this survey paper cannot claim to be an in-depth think about those studies, it presents a practical outlook and shows a valid comparison of the research in this field over these months which can be the conductor for the researcher to find future direction.

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