A Complete Survey on Automatically Diagnosing COVID-19 In the field of Computer Vision and A Collection of Medical Images

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Abstract: As COVID-19 is the source of millions of deaths throughout the world, it turned obligatory to fight against the COVID-19 pandemic. Due to the need for expensive equipment, experienced radiologists, and the time-consuming in Reverse Transcription Polymerase Chain Reaction (RT-PCR) test, researchers find out the necessity to embrace X-ray images and Computed Tomography (CT) images based diagnosing. Wreak havoc of COVID-19 instigated me to review current emerging Artificial Intelligence(AI) based automatic diagnosing models through the statistical survey that will pave out the way of research. In this paper, I study different available research resources at the time span from April 2020 to July 2020. In order to help researchers in further research, I presented a statistical survey so that researchers can pick a preeminent diagnosing model. I took a look at 74 papers from April to July and specified preprocessing techniques, feature extraction, classification method, interpretability method, and experimental result. Moreover, I analyze training,testing and validation split ratio, as well as look into the dataset's availability publicly. Some researchers are able to gain noticeable performance by adopting their own local model. On the contrary, some researchers adopt an existing pre-trained model and achieve the utmost result. Some models need to feed huge data and some models outperform despite having small data. In the following sections, all of the criteria will be illustrated briefly.

Keywords: COVID-19 . Dataset Source . CT Images . X-ray Images . Feature Extraction

1 Introduction

COVID-19 is the disease which is caused by severe acute respiratory syndrome coronavirus 2(SARS-CoV-2) that creates a worldwide pandemic of respiratory illness that emerged in Wuhan City, China in December 2019. The first recorded case of COVID-19 outside of China was on 13 January 2020. Within 17 days on 30 January, the World Health Organization(WHO) reported 7818 total confirmed cases worldwide among them China was in majority.WHO made the assessment that COVID-19 is a worldwide pandemic on 11 March 2020. From now on the number of affected persons and death is increasing day by day as it spreads from person to person.

Till now COVID-19 affected 213 countries[1] and the number of affected people reached 21,511,064 the number of deaths is 766,394 up to 15 August 2020 globally. The globally recovered people's rate is 14,254,024. Currently, Infected Patients are 6,490,646 among them 99% is in mild condition and 1% is in critical condition.

In these circumstances diagnosing COVID-19 is inevitable otherwise the death toll will go on.RT-PCR is accepted as a standard diagnosing method widely but it only focuses on virus detection that can mislead to detect the people who have recovered from the virus. Moreover, it requires adequate expertise to collect viral RNA which is typically extracted from the nasopharyngeal of patients additionally RT-PCR is also time-consuming. To reach better model researchers focus on diagnosing based on scanning images(X-ray, CT-Scan). Researchers are paying more attention to Artificial Intelligence(AI) based diagnosing models as it requires less time, effort as well they focus on accuracy. RT-PCR test requires expensive equipment whereas image scanning based diagnosing is less expensive and doesn't need the

[1] https://www.worldometers.info/coronavirus/

expertise to test. To make more accurate and precise results many researchers developed Domain Extension Transfer Learning CNN, transfer learning, attention mechanism, and Gradient-weighted Class Activation Mapping (Grad-CAM).

In this survey, many research papers will be reviewed; most of them are in pre-print format because diagnosing COVID-19 is beyond description. The motive behind this survey is to disclose numerous approaches that have been proposed and developed by researchers to create new probability and add a new direction to the research in AI-based diagnosing systems to combat against COVID-19.
Contribution of the survey is furnished as the following :

I successively reviewed and analyzed 74 papers that pay attention to COVID-19 diagnosing models from the perspective of preprocessing, feature extraction, classification, and evaluation among them 50 was X-ray image based diagnosing and 26 was CT-Scan based diagnosing, and 2 papers used both. These models are proposed from 1 April to 29 July [2] 2020. Based on the discussion of the existing model's feature extraction, I pointed out that model performance as well as point their classification methods and interpretability methods.

2 Dataset Description:

To get precise and accurate results more data is mandatory to feed the model. Relevant, accurate, and adequate training data is considered as the backbone of any diagnosing model. The more we will train our model the more accurate result it will produce. Based on different available research resources two types of datasets are found: computed tomography (CT) images and chest X-ray dataset.

Both of the chest X-ray and CT image datasets can be used to evaluate different feature extraction methods and their accuracy. In contrast to other types of pneumonia, it is asserted that both chest X-ray and CT image can help to point out the property of COVID-19, thus datasets can play a pivotal role in detecting COVID-19 and predicting survival rate from the disease. Due to the expense, shortage of training kits, inaccurate true positive rate, and time cost in RT-PCR test (X-ray image and CT image) based diagnosing is widely adopted to detect COVID-19 by the researchers that are based on the Artificial Intelligence(AI) system.

2.1 CT images

Computed tomography (CT) imaging is claimed as a substitute for the RT-PCR test. A precise image of the patient's chest is found from chest CT-Scan. An effective way to monitor the condition of the lung is Computed Tomography (CT) [8].COVID-19 CT segmentation dataset is evaluated in eight papers. Two papers evaluate their system using the COVID-CT dataset[29],[60]. Average 89% accuracy is gained by the researchers using this dataset. Particular details of the CT image data source are indicated in Table 1. Prediction comparison between COVID-19 and non-COVID is shown in Fig. 1 that demonstrates two chest CT images including COVID-19 affected and non-affected patients CT image.

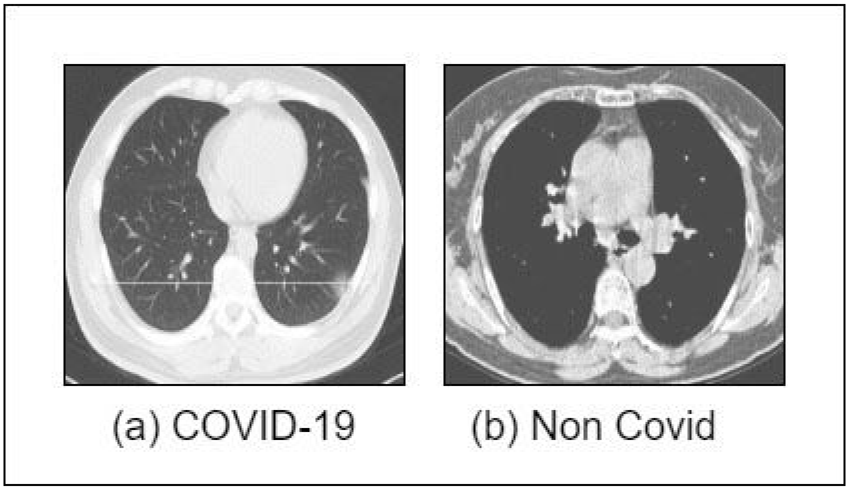

Figure 1: Sample Chest CT Images[2]

Table 1 presents the available data sources that researchers used in their research to find out the promising model for detecting COVID-19 that requires less time as well as less effort. In addition Table 1 represents papers that make use of datasets along with a number of the papers.Besides, some papers utilized CT images datasource[4],[21],[42],[49],[58] that are not publicly available.Further in this section frequency of papers that used a specific dataset of CT images are illustrated in Fig. 2.

Table 1: Publicly available Dataset for CT Images

Dataset Title	Available Source	Papers	Number of Papers
COVID-19 CT segmentation dataset	http://medicalsegmentation.com/covid19/	[2],[5],[8],[11],[50], [63], [65], [39]	8
SIRM	https://www.sirm.org/	[46],[69]	2
COVID-CT	https://github.com/UCSD-AI4H/COVID-CT	[60],[29]	2
University Hospitals of Geneva (HUG)	www.ChainZ.cn, El-Camino Hospital (CA), Zhejiang Province, China University Hospitals of Geneva (HUG)	[45]	1
Lung Segmentation and Candidate Points Generation	https://www.kaggle.com/arturscussel/lung-segmentation-and-candidate-points-generation	[49]	1
LIDC	https://doi.org/10.1118/1.3528204	[12]	1
CC-19	https://github.com/abdkhanstd/COVID-19	[9]	1

[2] http://medicalsegmentation.com/covid19/

Dataset			

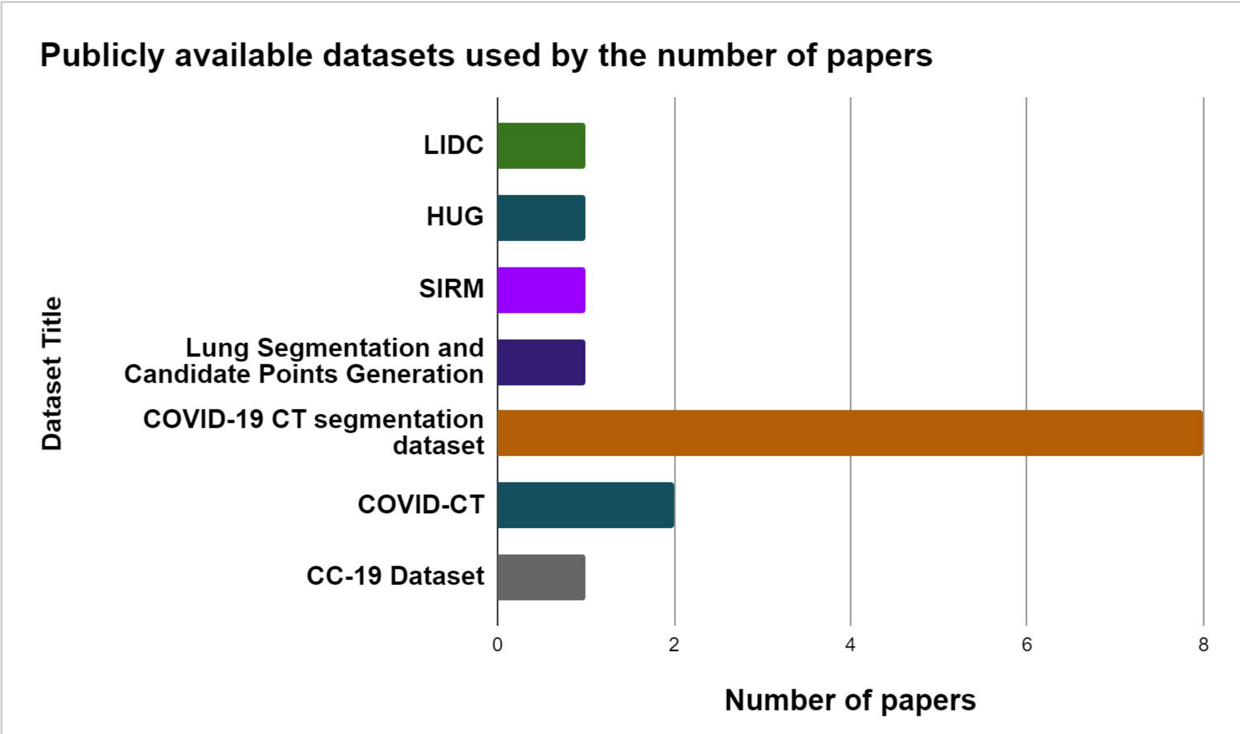

Figure 2: Frequency of papers that used a specific dataset of CT images

2.2 X-ray images

Due to the low sensitivity, a high false-negative rate of RT-PCR test, diagnosing using X-ray image gained high popularity because of its low expense, less time requirement, sufficient inexpensive equipment, high sensitivity. Twenty-five papers make use of COVID-Chest X-ray-dataset[3]. Chest X-ray Images (Pneumonia) dataset is evaluated by six papers. Evaluating COVID-19 Chest X-ray Dataset Initiative[36] in their system researcher gained accuracy 93%. On the other hand, 97.3% accuracy is obtained using OCT and Chest X-ray images dataset in their model[10]. Precise details of available X-ray image data sources are presented in Table 2.Prediction comparison between COVID-19, normal, and viral pneumonia is shown in Fig. 3 that demonstrate three X-ray images.

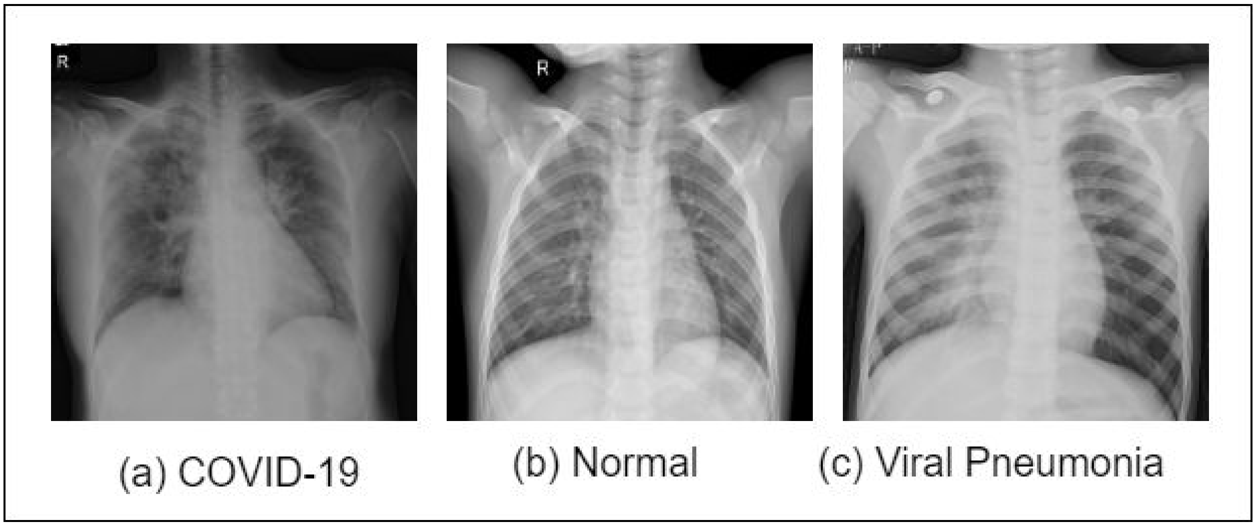

Figure 3: Sample Chest X-ray Images[3]

Table 2 presents the available data sources that researchers used in their research to find out the promising model for detecting COVID-19 that requires less time as well as less effort. In addition Table 2 represents papers that make use of datasets along with a number of the papers.Besides, some papers utilized X-ray images datasource[41],[47],[49],[51],[52] that are not publicly available.Further in this section frequency of papers that used a specific dataset of X-ray images are illustrated in Fig. 4.

Table 2: Publicly available Dataset for X-ray Images

Dataset Title	Available Source	Papers	Number of papers
Covid-chestxray-dataset	https://github.com/ieee8023/covid-chestxray-dataset	[1],[3],[7],[10],[15],[17],[18],[20],[22],[23],[25],[31],[32],[40],[48], [49], [51], [54], [61], [66], [67],[70],[71],[72],[73]	25
Chest X-ray Images (Pneumonia)	https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia	[7],[18],[37],[54],[67],[76],	6
Radiopedia	https://radiopaedia.org/articles/normal-chest-imaging-examples?lang=gb	[17],[30],[33][51],[70]	5
COVID-19 Radiography Database	https://www.kaggle.com/tawsifurrahman/covid19-radiography-database	[6],[24],[25],[36]	4
COVID-19 Chest X-ray Dataset Initiative	https://github.com/agchung/Figure1-COVID-chestxray-dataset	[36]	1

[3] https://github.com/drkhan107/CoroNet/blob/master/dataset

ActualMed COVID-19 Chest X-ray Dataset Initiative	https://github.com/agchung/Actualmed-COVID-chestxray-dataset	[36]	1
COVID-19 Image Data Collection	https://arxiv.org/abs/2003.11597	[36],[43]	2
COVID-19 database	https://www.sirm.org/category/senza-categoria/covid-19/	[1],[[24],43],[51],[70]	7
Labeled Optical Coherence Tomography (OCT) and Chest X-ray Images for Classification	https://data.mendeley.com/datasets/rscbjbr9sj/2.	[10],[15], [23], [44]	3
COVID-19 X-ray dataset (COVID-CAPS)	https://github.com/ShahinSHH/COVID-CAPS	[57]	1
Kaggle RSNA Pneumonia Detection Dataset	https://www.kaggle.com/c/rsna-pneumonia-detection-challenge	[17],[22],[36],[61], [66], [72], [73],	7
NIH Chest X-ray Dataset	https://www.kaggle.com/nih-chest-xrays/data	[16], [70]	2
Pneumonia Classification	https://drive.google.com/open?id=1J9I-pPtPfLRGHJ42or4pKO2QASHzLkkj	[33]	1
COVID-19	https://github.com/muhammedtalo/COVID-19	[16]	1
COVIDGR-1.0	https://github.com/ari-dasci/covidgr	[13]	1
pulmonary-chest-x-ray	https://www.kaggle.com/kmader/pulmonary-chest-xray-abnormalities?select=ChinaSet_AllFiles	[7]	1
OCT and Chest X-ray images	https://data.mendeley.com/datasets/rscbjbr9sj/2.	[10]	1

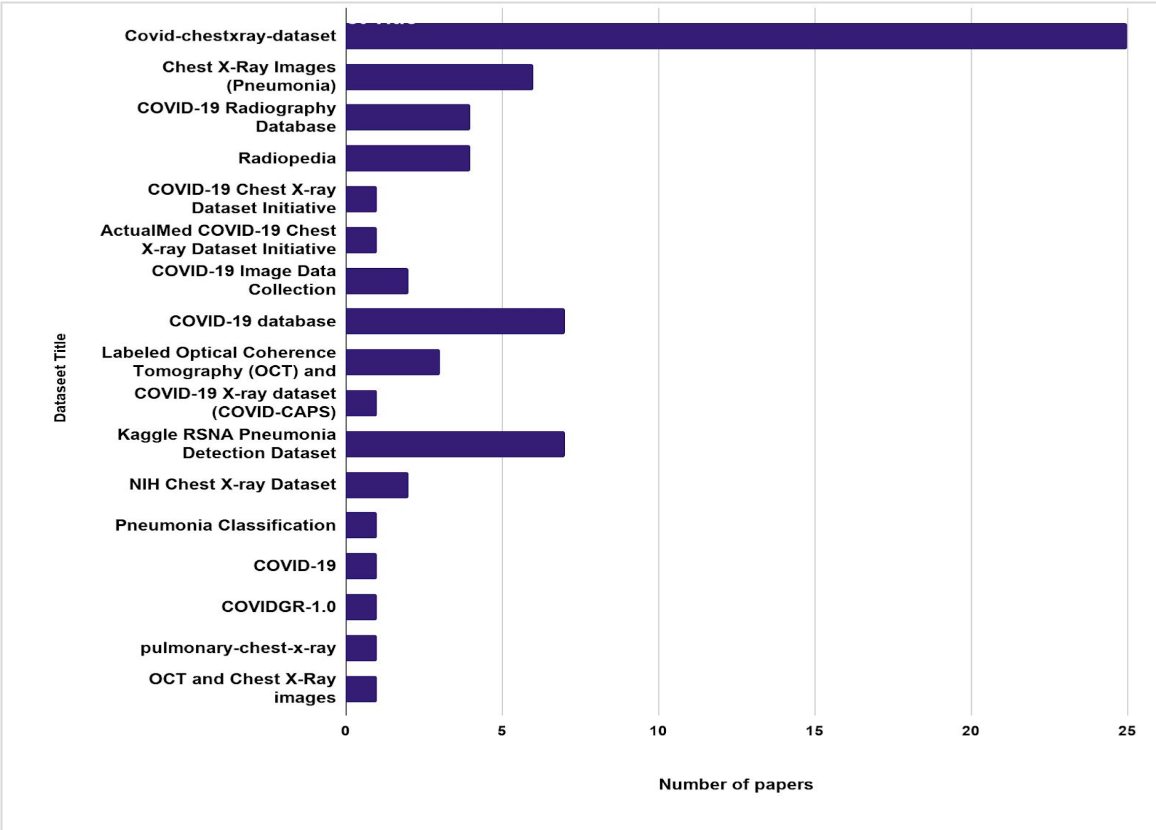

Figure 4: Frequency of papers that used a specific dataset of CT images

3 Dataset Preprocessing :

Data preprocessing regards as a strategy that converts raw data into prepared data. By data preprocessing methods researchers develop their data set as a clean and organized dataset. Thus, the performance of the diagnosing model also enhanced adopting various dataset preprocessing techniques. Data preprocessing is considered obligatory for diagnosing as it fills missing values, smooth noisy data indicates outliers, and sorts out inconsistencies. When researchers face difficulties because of the shortage of sample datasets, preprocessing can be a great help to the researchers by generating images. By dataset preprocessing before feature extraction diagnosing models can be generalized. In this section, adopted preprocessing methods are reviewed that is considered as the first step in diagnosing the model. Different types of preprocessing techniques like 224 x 224 resizing, brightness adjustment, Generative Adversarial Network(GAN), and Vertical flip are depicted in Fig.5, and from that figure clear visualization of various preprocessing techniques can be apprehended

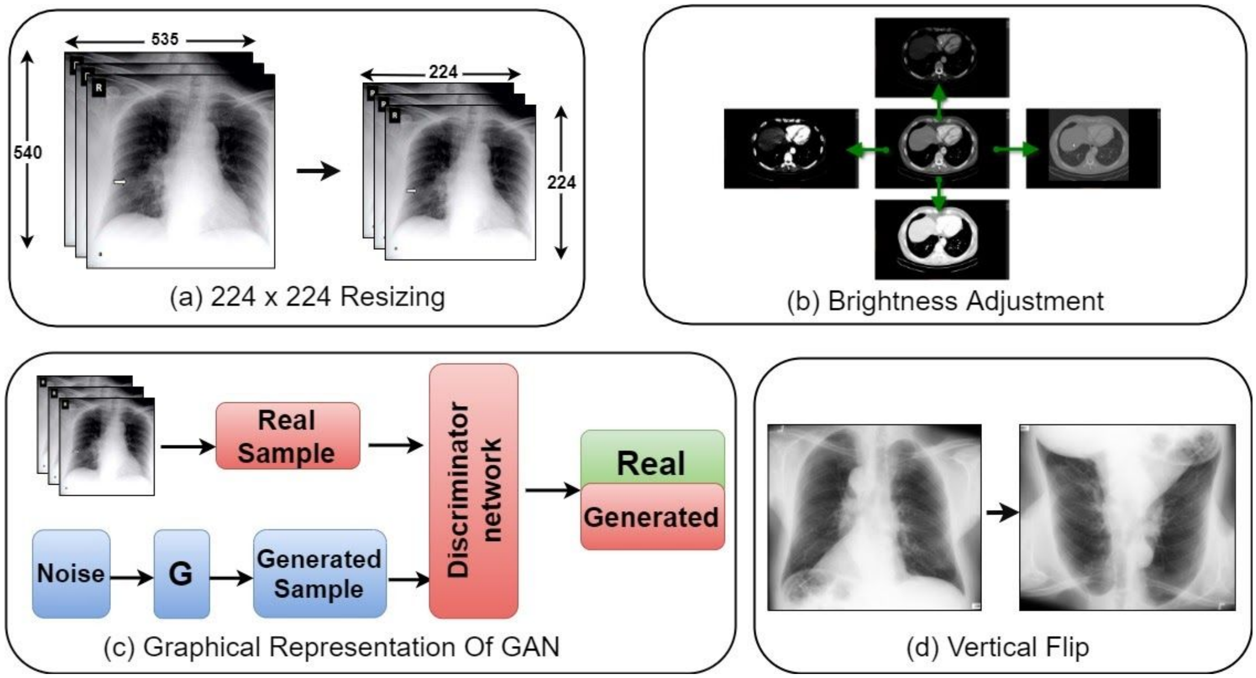

Figure 5: Different Types of Preprocessing Methods

Resizing is necessary to sustain images in the same estimate because the images are not always within the same size. All the samples in a dataset must be in the same size otherwise it postulates issues while diagnosing. Image resizing is done on different scales, sometimes at 352 x 352 [8] pixels and sometimes at Image size 237 x 237 pixels [10].

Flipping or Rotating performs image enhancement in datasets. Vertically or horizontally image pixels can be reversed. Additionally, images can be rotated at different angles for instance: 90, 180, or 270 degrees.

Cropping or Scaling is performed by resampling the image thus the size of the whole image changes. Scaling can enlarge or lessen an image in size. Cropping reduces redundancy and shrinks unwanted areas on the various scales. Researchers many times use random cropping in various scales [21],[55].

Brightness or Intensity adjusting increases or reduces the brightness of an image by substituting pixel values with a constant. Brightness can be increased or reduced by subtraction or addition.

Generative Adversarial Network(GAN): Due to the scarcity of Chest X-ray and CT image dataset GAN is widely adopted in several datasets to generate images at the same time it demises overfitting. Sometimes interference caused by image enhancement using GAN, to demise interference researchers performed histogram equalization [47] on the datasets. However, histogram equalization may impact on image details and show unexpected noise to resolve the problem Contrast Limited Adaptive Histogram Equalization (CLAHE) was proposed in paper [41].

In this section, I review preprocessing methods that are depicted in Table 3 used by researchers in their paper including resizing, flipping or rotating, scaling or cropping, contrast adjusting, brightness, or intensity adjusting, GAN, and so on. Resize a common feature of data preprocessing used in 31 papers. Next to it, Flipping is used in 29 papers. Along with that scaling or cropping, Contrast adjusting, Brightness or Intensity adjusting, and GAN is used in 20,14,7,4 papers respectively. The author used both resizing, flipping or rotating, and scaling or cropping in paper [2], and in paper [21] author used four preprocessing methods respectively Flipping or Rotating, Scaling or Cropping, Contrast adjusting, and Brightness or Intensity adjusting. Like this many authors used more than one preprocessing method in their research. Oppositely some authors used only one preprocessing method as an example in paper[9] author used scaling, in paper [11] the author used resizing 352 x 352, in paper [16] author used rotation, and so on. Moreover, some researchers also use an adaptive winner filter for noise reduction [59], Affine Transformation [31] in their research.

Table 3: Different types of preprocessing methods used by the papers

Preprocessing Methods	Papers	Number of Papers
Resize	[1],[2],[5],[6],[8],[10][11],[16],[18],[19],[20],[22],[23][24],[[26],[28],[30],[32],[37],43],[45],[46],[48],[50],[53],[54],[56],[60],[61],[63],[67]	31
Flipping or Rotating	[1],[2][15],[16],[21],[22],[24],[25],[27],[35],[36],[37],[38],[42],[43],[46],[47],[48],[50],[51],[53],[55],[57],[61],[62],[65],[71],[74]	29
Scaling or Cropping	[2],[9],[18],[19],[21],[22],[25],[36],[46],[48], [50],[53],[55],[56],[57],[60],[61],[65],[71],[74]	20
Contrast adjusting	[6],[21], [24],[28], [30],[35], [38], [41],[43],[48], [52], [53], [59], [68]	14
Brightness or Intensity adjusting	[21][36][46],[48],[52],[71],[74]	7
GAN	[13] [39],[44], [60]	4

The ratio of preprocessing techniques are exhibited In Fig. 6. Resize contains the highest percentage and GAN at least percentage respectively 29.50%,3.80%. Percentage of resize, flipping or rotating, scaling or cropping, contrast adjusting, brightness or intensity adjusting, and GAN is represented in Fig. 6 utilizing data of Table 3.

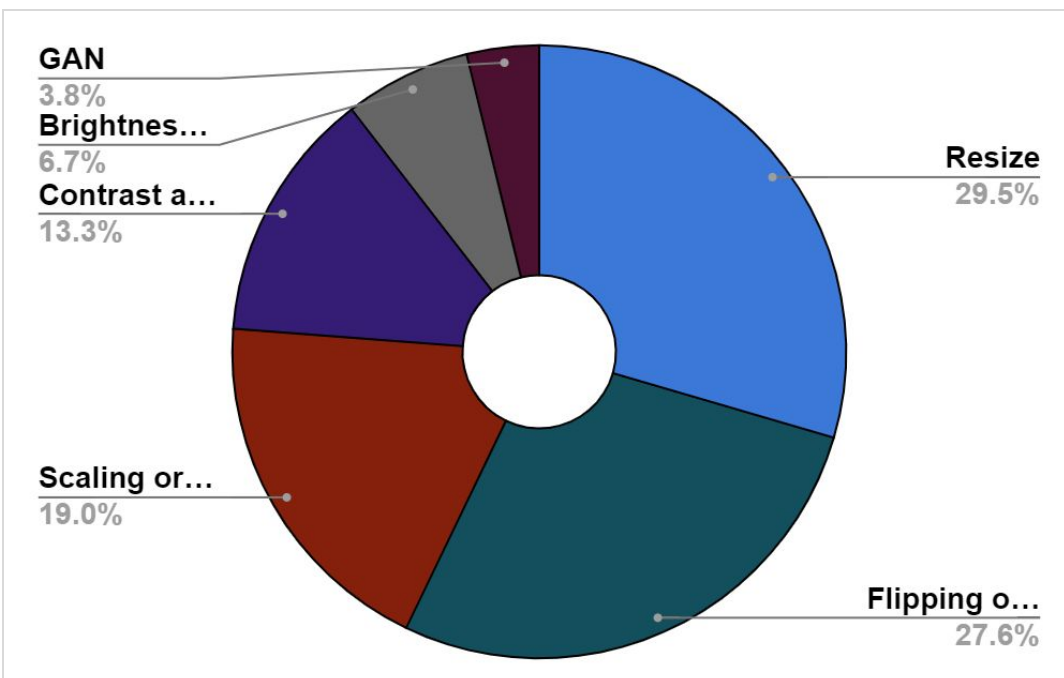

Figure 6: Ratio of Different preprocessing methods

4 Image Feature Extraction:

Feature extraction is a procedure that classifies and recognizes features of images. Several images preprocessing techniques like resizing, normalization, scaling, etc are needed to apply on the sampled image before getting features using the extraction method. Feature extraction is beneficial for reducing the number of resources required for processing without dropping important or admissible information as well as Feature extraction can also lessen the amount of dispensable data. Convolutional Neural Network(CNN) is used for both feature extraction and classification. Pertaining convolutional and pooling layer Feature extraction is carried out. A CNN architecture is instantiated in Fig. 7 has the following layers: Convolution, Pooling, Fully Connected layer. Except for CNN other pre-trained models as example ResNet, VGG, Inception and so on researchers also applied in their literature.

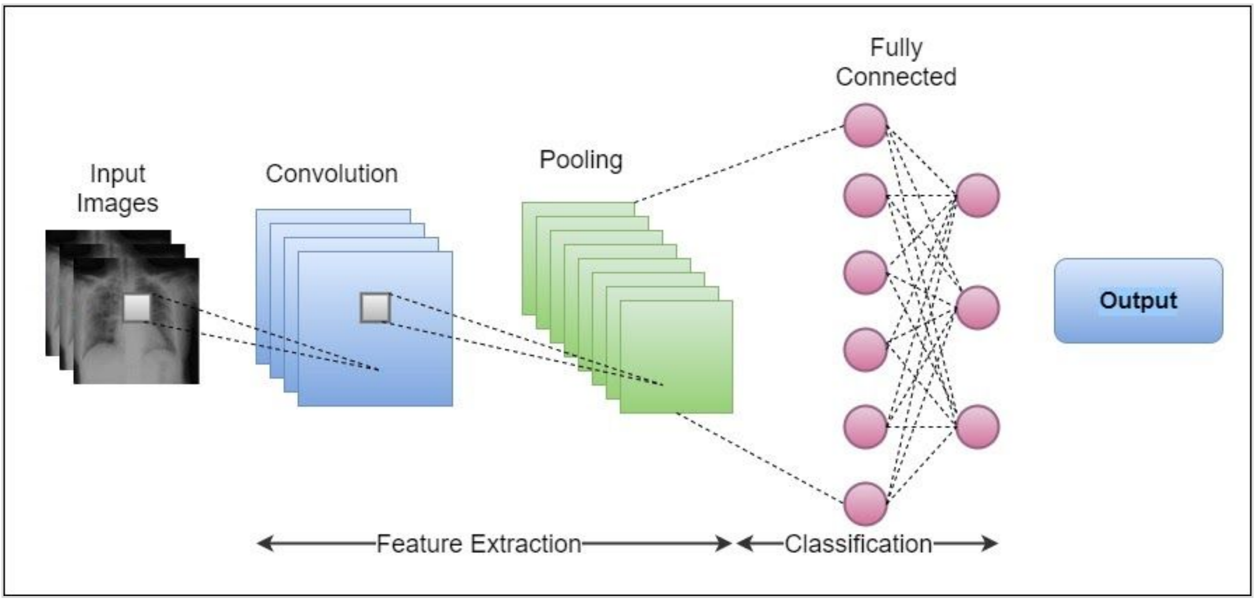

Figure 7: Basic Pre-trained CNN architecture

4.1 Feature Extraction methods for CT

To recognize patterns from the CT images between COVID-19 patients and nonaffected persons, various pertained models(ResNet, VGG, DenseNet, etc) availed the researchers nowadays. A few pre-trained models mostly used by researchers are delimited in Table 4, among all ResNet is used largely then VGG, DenseNET, and others.

Researchers use ResNet as a pre-trained model [42] for binary classification of CT scan images that is 71 layers deep and requires an input image size of 224x224x3. As an extension of CNN researchers uses DenseNet [29] to boost computational efficiency reducing image dimension and obtain 90.61% accuracy.As a feature extraction method researchers employ a modified version of inception V3 (IV3*) then train the extracted features using layers of the capsule network [9] that achieved the highest sensitivity and lowest specificity compared to other pre-trained models. Researchers use eight different Deep Learning Models in the paper [4] and found NasNet and MobileNet performed better than the other six models.

Table 4: Feature Extraction methods for CT images used by the papers

CNN	Paper	Number of Papers
ResNet	[4],[9],[12],[21],[29][39],[42],[45],[46],[55],[58]	11
VGG	[4],[8],[9],[11],[46],[55],[58]	7

DenseNet	[4],[9],[21],[29],[58]	5
Mobilenet	[4],[9],[29]	3
SqueezeNet	[42],[69]	2
Inception	[29],[68]	2
CrNet	[58]	1
EfficientNet	[58]	1
GoogLeNet	[46]	1
InceptionResNet	[4]	1
NasNetMobile	[4]	1
FCN8	[8]	1
U-Net	[5]	1
Alex-Net	[9]	1

Excluding those feature extraction methods researchers also use Conditional Generative Adversarial Network(cGAN)-based COVID-19 CT image synthesis method [2], Visualizes features via t-SNE, Least Absolute Shrinkage and Selection Algorithm (LASSO) [12] were used to find the most discriminative 12 features in distinguishing COVID-19 from other pneumonia (Three additional features were also extracted for the attentional regions, distance feature, 2D margin fractal dimension, and 3D grayscale mesh fractal dimension).In one more study researchers use Handcrafted features[34] Volume features, Infected lesion number, Histogram distribution, Radiomics features - Adaptive Feature: (Random forest + feature selection)*2 in their research. Additionally, I observe the use of Inception Recurrent Residual Neural Network(IRRCNN) [49] in another research, and attention mechanism-resdil block, and deep supervision [63]. Researchers trained their model with a linear activation for the output and a mean squared error for the loss function (loss1) and accuracy[64].

4.2 Feature Extraction Methods for X-ray

In this section several pertained models(ResNet,VGG,DenseNet etc) to detect COVID-19 from X-ray images are reviewed.A few pre-trained models mostly used by researchers are delimited in Table 5, among all ResNet is used largely then DenseNET, VGG, Inception, Xception, and others.

Researchers use 14 individual state-of-the-art pre-trained networks [7] in order to extract the deep features from the pre-trained networks and achieve the highest accuracy in ResNet as well as estimate time for feature extraction where ResNet requires less time for deep feature extraction among all 14 models. Convolution Neural Networks were trained using the supervised learning process for instance: Xception ResNet and VGG-16 [10] to minimize the loss function and obtain accuracy above 97% through VGG. Using 8 different Deep Learning Model [4] researchers found NasNet and MobileNet outperformed all the models and they used both CT image and X-ray images to evaluate their system.DenseNets concatenates output features rather than sum the output feature maps of the layer with the incoming feature maps.DenseNet outperformed than other models [18] having 85% sensitivity.In the following section, some other feature extraction methods adopted by the researchers are discussed elaborately.

Table 5: Feature Extraction methods for X-ray images used by the papers

CNN	Papers	Number of Papers
ResNet	[1],[4],[7],[10],[13],[14],[18],[20],[22],[27],[28],[31],[32],[38],[40],[41],[44],[47],[51],[61],[62],[66],[67],[71],[73],[74]	26
DenseNet	[1],[4],[7],[14],[18][22],[23],[28],[30],[31],[41],[47],[48],[52],[56],[66],[67],[72],[74]	19
VGG	[1],[4],[7],[10],[16],[19],[27],[28],[30],[37],[40],[47],[51],[56],[66],[67],[71]	17
Inception	[1],[14],[18],[24],[32],[41],[56],[66],[67]	9
Xception	[7],[10],[15],[30],[54],[56],[61],[66],[67]	9
InceptionResNet	[4],[7],[18],[22],[30],[56],[66],[67],	8
NASnet	[4],[7],[22],[23],[30],[67],	6
AlexNet	[7],[44],[66],[17],[27],[28]	6
GoogLeNet	[7],[27],[40],[44],[66],	5
SqueezeNet	[41],[44],[52],[62],	4
ShuffleNet	[7],[52],[66]	3
Mobilenet	[4],[7],[30]	3
EfficientNet	[71]	1

Excluding those feature extraction methods researchers also use Parallel-Dilated COVIDNet (PDCOVIDNet) [1] to detect COVID-19 from chest X-ray images that can encapsulate and propagate important features in parallel over the network which boosts detection accuracy significantly. A multiple loss based deep neural network labeled as CovMUNET that is also proposed by researchers [3] to learn better feature maps and with the help of learning categorize the CXR images more precisely. In one more study, researchers use Fast Deep Learning Computer-Aided Diagnosis(CAD) System [25] against the Novel COVID-19 pandemic from Digital Chest X-ray Images that is based on YOLO Predictor. Additionally, I observe the use of Self Supervised Super Sample Decomposition for Transfer learning (4S-DT) [27], Gravitational Search Algorithm (GSA) based model [48], Inception Recurrent Residual Neural Network(IRRCNN) [49], and a Capsule Network-based Framework (COVID-CAPS) [57].

Except for the pre-trained CNN models that are already presented in Table 4 and Table 5, several specialized diagnosing models using those pre-trained models researchers adopt nowadays to enlarge accuracy. I represent the researchers' proposed feature extraction method based on both CT images and X-ray images in Table 6.

Table 6: Summary of specially designed architectures for COVID-19 detection

Feature extraction method	Papers	Interpretability method	Dataset Type	Classification	Experimental Result(%)
Parallel-Dilated COVIDNet (PDCOVIDNet)	[1]	Grad-Cam	X-ray	Mult- class	Accuracy:96.58
CovMUNET	[3]	Not used	X-ray	Mult- class	Accuracy:99.41
COVID TV-UNet	[5]	Not used	CT	Mult- class	Dice Score:86%
COVID-SDNet	[13]	Grad-cam	X-ray	Binary	Accuracy:97.37
COVID-Net	[36]	Grad-cam	X-ray	Multi-class	Accuracy:93.30
CovXNet	[26]	Grad-cam	X-ray	Multi-class	Accuracy:97.40
CheXNet	[35]	Not used	X-ray	Binary	Accuracy:95.90
CoroNet	[54]	Not used	X-ray	Binary	Accuracy:89.60
COVID-CAPS	[57]	Not used	X-ray	Binary	Accuracy:95.50
Decapse(Capsule)	[60]	Not used	CT	Binary	Accuracy:87.60

PDCOVIDNet detects COVID-19 from chest X-ray images. The proposed PDCOVIDNet differentiates the dilation rate in a parallel stack of convolution layers on CNN, thus reflecting more distinguishable features. In paper [1] authors use a 2,905 chest X-ray image for diagnosing, from that 2,324 images are used for the training datasets.

CovMUNET is a multiple loss based deep neural network procedure that detects COVID-19 cases from X-ray images. In paper [3] using CovMUNET for 2 class classification (COVID vs non-COVID) researchers gained noticeable accuracy than 3- class classification (COVID-19 vs normal vs pneumonia) 99.41% CovMUNET contains two branches namely Reconstruction Branch and 'Classification Branch' that calculate two different losses. In this study, the author utilizes 5-fold cross-validation and the dataset size is 6594.

COVID TV-UNet is a deep learning-based framework for detecting pathologic COVID-19 regions or associated tissues in pulmonary CT images tissue areas from clinical CT images. In this study [5], the author uses a total of 929 images from publicly available COVID-19 segmentation datasets. among which 473 are labeled as COVID-19.

COVID Smart Data based Network (COVID-SDNet) is a CNN based classifier that incorporates segmentation, data-augmentation, and data transformations along with an eligible Convolutional Neural Network (CNN) for inference. The author introduces us with a high clinical quality dataset [13] named COVIDGR1.0 which comprises 754 images among which 377 is labeled as COVID-19. For a transfer learning approach, ResNet-50 is adopted by the researchers that are initialized with ImageNet weights.

COVID-Net specifically proposes a neural network to detect COVID-19 using chest X-ray images. Based on the advantages of CXR imaging for the rapid outcome of COVID-19 screening, tangibility, mobility, the author makes predictions through the COVIDNet interpretability method. The author makes use of projection-expansion-projection design patterns in COVID-Net architecture [36]. The proposed COVID-Net was pre-trained on the ImageNet dataset and then assigned to the COVIDx dataset and achieved accuracy about 93.3% on the COVIDx dataset.

CovXNet is a multi-dilation convolutional neural network which detects COVID-19 and other pneumonia automatically using chest X-ray images that utilize depthwise convolution for efficiently extracting diversified features. In the paper[26] author uses a total of 6161 datasets among which the first dataset consists of 5856 images (1583 normal X-rays, 1493 non-COVID viral pneumonia X-rays, and 2780 bacterial pneumonia X-rays) and the 2nd dataset comprises 305 images.

ChexNet is basically a DenseNet-121 type of deep network trained on the ChestX-ray14 dataset. They used the Softmax activation function To classify COVID-19 the Softmax activation function is used(Normal, Viral Pneumonia, and Bacterial Pneumonia). The number of trainable parameters in this model is 6,955,906. Before the classification layer, the author used pre-trained CheXNet to extract 1024-D feature vectors by taking the output after global pooling in paper [35]. The sensitivity achieved by ChexNet is noticeable. In this paper, the author utilizes the largest Covid-19 dataset named QaTa-Cov19 that constitutes 6286 images among them 5028 is used to train the dataset.

CoroNet is a Deep Convolutional Neural Network model that is based on Xception architecture. In paper [54] authors collect two different datasets that are publicly available then create their own dataset to detect COVID-19 infection automatically using chest X-ray images. In the paper the author also uses softmax to predict and it is inspected from that CoroNet has 33,969,964 parameters in total out of which 33,969,964 trainable and 54528 are non-trainable parameters. Author achieves promising results through CoroNet in spite of using a small dataset(COVID-19 284, Normal 310).

COVID-CAPS is a Capsule Network-based Framework that identifies COVID-19 cases from X-ray Images which consists of 4 convolutional layers and 3 Capsule layers. It is noticeable COVID-CAPS shows higher performance dealing with a small dataset [57]. The number of trainable parameters using COVID-CAPS without pre-training and with pre-training is 295,488.

Detail-Oriented Capsule Networks (DECAPS) combine Capsule Networks (CapsNets) that is basically based on ResNet to identify discriminative image features to detect COVID-19 patients using CT images. In paper [60] the author gained accuracy 87.60% using DECAPS model which comprises a smallest amount of dataset. Because of the scarcity of sample image authors applied conditional adversarial network and also adopted other preprocessing techniques for instance Rescaling(286X286), Cropping(256X256). Among the total dataset 391 images are labeled as COVID-19 and 339 images are labeled as Normal. ResNet has three residual blocks and, outcome 1024 feature maps, with a 1 × 1 convolutional layer. It contains a ReLU non-linear layer. Author also shows using Peekaboo with DECAPS accuracy of the diagnosing model increased.

5 Classification

The classification process took place in the softmax layer, and a fully connected layer whereas the Convolutional layer proceeds as a feature extractor in a pre-trained CNN. Some researchers proposed improvements based on pre-trained CNN along with a Support Vector Machine(SVM) classifier [46], [66]. The SVM classifier uses deep features that are extracted from each CNN network for detection. Researchers combine CNN with KNN and a support estimator network [14] that requires huge data to train. In paper [6] researchers use a COV-ELM classifier that classifies COVID-19 cases from the chest x-ray images using an extreme learning machine (ELM) and lessens training time with the least interventions required to tune the networks.

Researchers developed an end to end web-based detection system with a Bagging trees classifier to replicate a digital clinical pipeline and ease the screening of suspicious cases [67]. Researchers achieved satisfactory performance despite the limited number of image samples using the Bagging trees classifier. In [34], researchers proposed Adaptive Feature Selection Guided Deep Forest(AFS-DF) as a classification method in the meanwhile they compared AFS-DF with Logistic Regression (LR), Random Forests (RF), Neural Networks (NN), SVM classifiers and AFS-DF attain higher accuracy.
It is obvious from Table 7 Binary class is mostly used by researchers than Multi-class. However, Binary classification may create ambiguity while detecting COVID-19 as it can not distinguish between other Viral Pneumonia and COVID-19.

Table 7: Classification Methods

Classification Methods	Papers	Total
Binary	[4],[9],[11,][13],[14],[15],[18][19],[21],[22],[23],[25],[27],[28],[29],[30],[32],[34] ,[35],[37],[42],[44], [46],[48],[49],[51], [52],[53], [54],[55], [57],[58],[60],[62],[64], [66], [67],[68], [69], [72]	40
Multi-class	[1],[2],[3],[5], [6],[7],[10],[12],[16],[17], [22], [24],[31],[33], [36],[38], [40],[41], [42], [43],[45], [47], [49], [50],[56],[58],[61], [64],[70], [71], [73], [74]	32

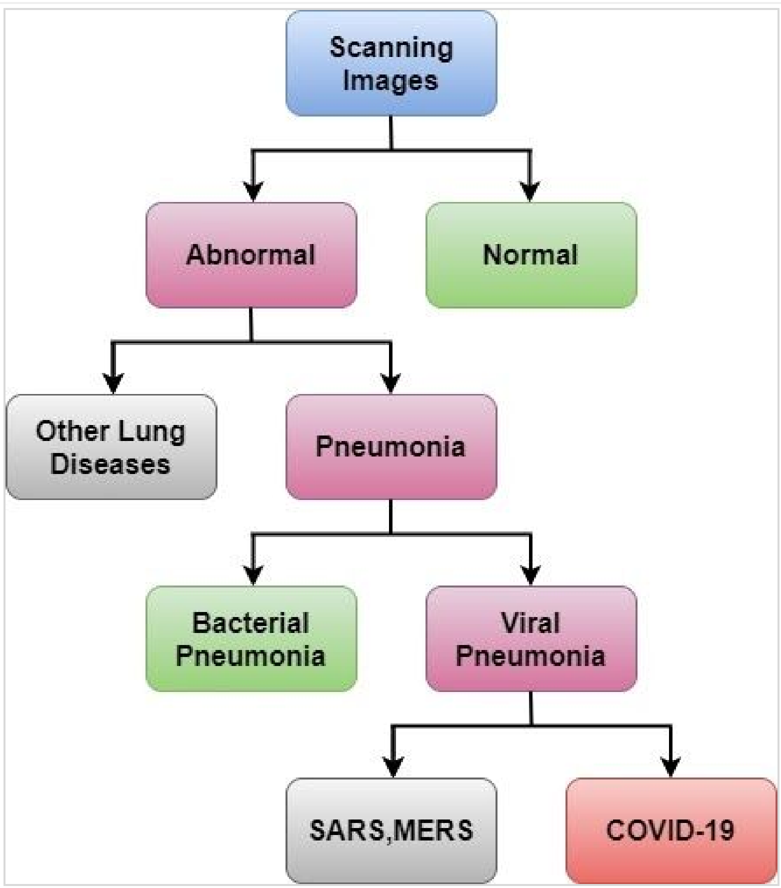

Figure 8: A relationship of Lung Diseases

A straightforward way of COVID-19 diagnosing system tasks is binary classifying the scanning images into COVID-19 class and normal class, and that is adopted by many papers[21].[19],[23].As shown in Fig. 8., test images of other groups of abnormal Lung Diseases can be miscategorized as COVID-19.
Lung diseases belonging to the same subclass share similar patterns in diagnosing using X-ray image or CT images and contain a higher probability to be miscategorized to resolve this dilemma researchers adopt multi-class classification in many papers [7],[12],[17].

6 Experimental results

Several pre-trained models are proposed by the researchers; perhaps specific methods are enough qualified to gain the highest accuracy depending on its total dataset size, classifier, number of convolutional layers in a CNN, and so on. Experimental results are measured in terms of accuracy in this survey, when researchers don't state accuracy as an alternative sensitivity, Area Under Curve (AUC) or specificity is picked up that illustrates how precisely and accurately that model can predict the result.

6.1 Experimental results for CT images

Abbreviated evaluation of COVID-19 diagnosing models using CT images presented in Table 8. I also mentioned the size of the train, test, and validation set. Some authors in their papers [11],[53],[59] did not apparently provide the size of train, test, and validation set, I compute them with corresponding train, test, and validation split ratio. On the contrary, some papers apparently stated the size of the train-test-validation data of COVID-19 images [5],[68],[69] and for those papers, I computed the ratio according to the split that was provided. Even so, for some papers, the distribution of the dataset [50],[55],[34] was not clearly mentioned. Moreover, some papers apparently mentioned the use of data for validation[5],[8],[11] along with some papers do not state exact data instead provide a comparison based on 10-fold cross-validation[50], 5-fold cross-validation [53] for performance assessment. Along with the best experimental results using CT images feature extraction methods corresponding to the accuracy and total dataset(COVID-19 patients, non affected patients, and other pneumonia diseases) also reviewed in Table 8. In terms of sensitivity, accuracy, and AUC VGG, IRRCNN, ResNet scores higher 97%, 99.56% and99.40% respectively.

Table 8: Summary of experimental result along with the extraction method using CT images

Paper no	Date	Total images	Train Test Val Ratio(%)	Train	Test	Validation	Result(%)	Feature Extraction for best result
4	27 July 2020	400	Train :80 Test:20	329	80	Not specified	Accuracy: 95.2%	NasNetMobile
5	27 July 2020	929	Train :70 Test:22 Val:8	650	204	75	Dice score:86	TV-UNet
8	7 July 2020	829	Train:45 Test:50 Val:5	373	414	42	Dice score:90	Region based active learning
9	10 July 2020	34006	not clear	Not specified	Not specified	Not specified	Sensitivity: 96.7	Inception
2	29 July 2020	829	Train:36 Test:8	300	73	Not specified	Specificity: 99.97	cGAN

11	7 July 2020	829	Test:45 Test:50 Val:5	373	414	42	Sensitivity: 97	VGG
12	2 June 2020	10250	Not specified	Not specified	Not specified	Not specified	Sensitivity: 90.19	ResNet
21	17 June 2020	812	Train:42 Test:40 Val:18	341	325	146	Accuracy: 79.50	DenseNet
29	24 June 2020	746	Train: 52 Test: 25 Val: 14	425	203	118	Accuracy: 90.61	DenseNet
34	7 May 2020	2522	Not specified				Accuracy: 97.79	AFS-DF
39	21 May 2020	100	Train:45 Test:50 Val:5	45	50	5	Sensitivity: 72.50	ResNet
42	28 May 2020	746	Train:55 Test:22 Val:23	410	164	172	Accuracy: 99.40	ResNet
45	6 April 2020	Dataset 1:1865	Random split	1725	270 320	Not specified	AUC: 99.40	ResNet
46	7 April 2020	6000, 6000	Train:75 Test:25	4500	1500		Accuracy: 98.27	Fusing and ranking deep features
49	10 April 2020	420	Train:45 Test:10 Val:45	189	42	189	Accuracy: 99.56	Inception Recurrent Residual Neural Network (IRRCNN)
50	12 April 2020	110.	Val:10 fold cross				Accuracy: 89.00	U-Net
53	14 April 2020	360	Train:80 Test:10 Val:10	288	36	36	Accuracy: 89.20	VGG
55	15 April 2020	3,855	Not specified				Sensitivity: 95.00	ResNet
58	17 April 2020	746	Train:57 Test:28 Val:15	425	208	119	Accuracy: 83.00	DenseNet
59	17 April 2020	470	Train:60 Test:40	282	188	Not specified	Accuracy: 93.65	FFT-Gabor scheme
60	17 April 2020	746	Train:85 Test:15	634	112	Not specified	Accuracy: 87.60	Decapse
63	21 April 2020	829	Train:80 Test:20	663	166	Not specified	Sensitivity: 86.70	U-Net

64	21 April 2020	1044	Train:80 Test:10 Val:10	835	105	104	Accuracy: 86.00	U-Net
65	21 April 2020	100	Train:60 Test:40	60	40	Not specified	Accuracy: 83.62	MiniSeg
68	24 April 2020	1065	Train:31 Test:27 Val:N/A	330	287	Not specified	Accuracy: 89.50	Inception
69	24 April 2020	783	Train:56 Test:18 Val:26	438	145	203	Accuracy: 83.00	SqueezeNet

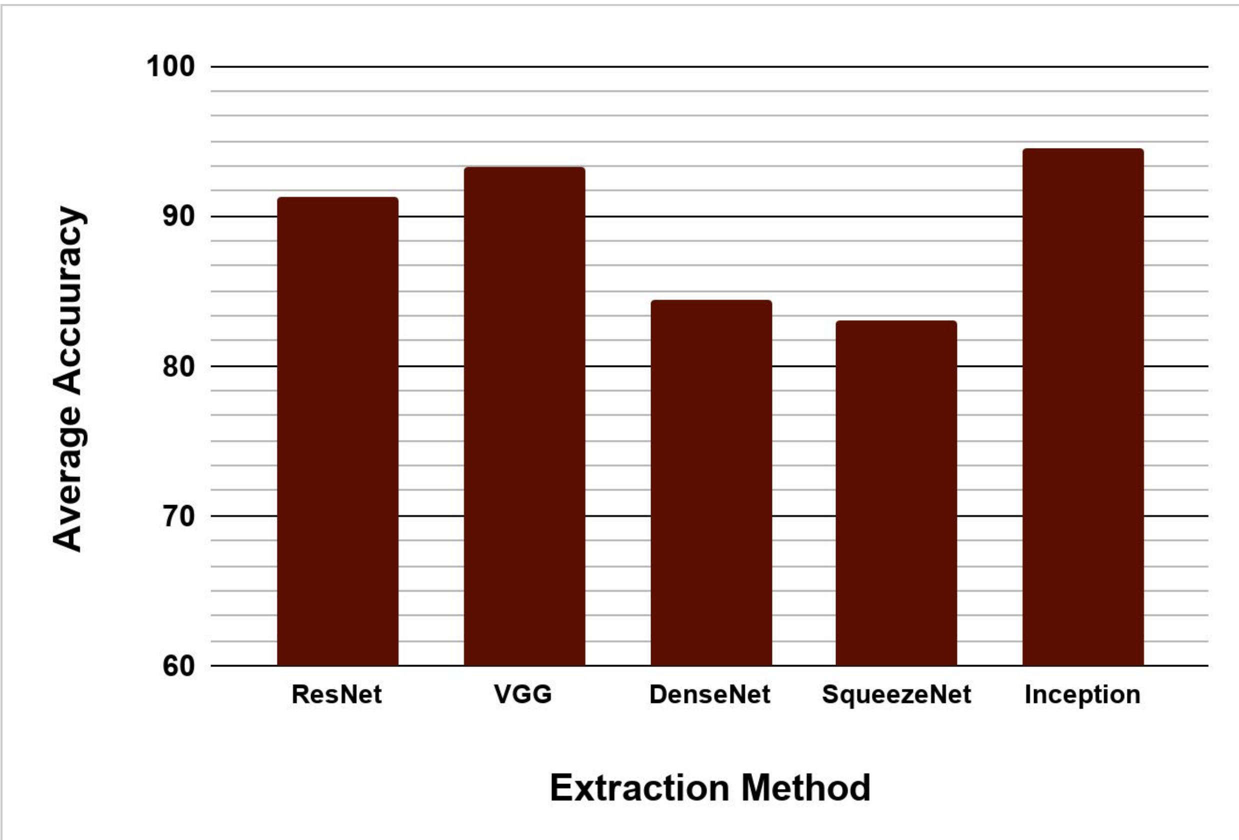

Figure 9: Average accuracy

In this section, the average result is reviewed over the extraction method. It is sharply clear from Fig. 9 that the average accuracy of Inception is far exceeding above 90% than the other 4 models and the average accuracy of SqueezeNet is not up to the mark.

6.2 Experimental results for X-ray images

Abbreviated evaluation of COVID-19 diagnosing models using X-ray images presented in Table 9.I also stated the size of the train, test, and validation set. Some authors in their papers [19],[18] did not apparently provide the size of the train, test, and validation set, I compute them with corresponding train, test, and validation split ratio. On the contrary, some papers apparently stated the size of the train-test-validation data of COVID-19 images [16],[20],[22] and for those papers, I computed the ratio according to the split that was provided. Even so, for some papers, the distribution of the dataset [7],[10],[26] was not clearly mentioned. Moreover, some papers apparently mentioned the use of data for validation[1],[16],[25],[30] along with some papers do not state exact data instead provide a comparison based on 10-fold cross-validation[6], 5-fold cross-validation [3,[18] for performance assessment.

Along with the best experimental results using X-ray images feature extraction methods corresponding to the accuracy or other metrics and total dataset(COVID-19 patients, non affected patients, and other pneumonia diseases) also reviewed in Table 9.In terms of accuracy and AUC [14],[72] performance of DenseNet is up to the mark 99.49%,88.04% respectively whereas NasNetLarge scores 100% sensitivity [23], f1 score of FFT is 95%. Additionally in respect of accuracy Xception+ResNet [61] is significantly the highest scorer 99.56%.

Table 9: Summary of experimental result along with method using X-ray images

Paper no	Date	Total images	Train Test Val Ratio(%)	Train	Test	Validation	Result(%)	Feature Extraction for best result
1	30 July 2020	2,905	Train:80 Test:10 Val:10	2324	291	291	Accuracy :96.58	PDCOVIDNet
3	29 July 2020	6,594	5 fold Val				Accuracy :99.41	ComMUNET
4	27 July 2020	400	Train:80 Test:20	320	80		Accuracy: 95.4 –100	NasNetMobile
6	16 Jul 2020	9,521	10-fold cross-Val				f1 score: 95.00	FFT
7	16 July 2020	2,186	5-fold cross-validati on				Accuracy: 98.00	ResNet
10	13 July 2020	375	Train:80 Test:10 Val:10	300	38	37	Accuracy: 97.3	VGG16
13	2 June 2020	754	Train:80 Test:20	603	150		Accuracy: 97.37	ResNet
14	7 June 2020	5824	Train:80 Test:20	4659	1165		Accuracy :99.49	DenseNet
15	8 June 2020	1419	Train:80 Test:20	1135	284		Accuracy: 98.94	Xception
16	9 June 2020	6523	Train:30 Test:30 Val:40	2000	2000	2523	Accuracy: 98.00	VGG
17	9 June 2020	1262	Train: 88 Test:12	1100	162		Sensitivity: 90.74	AlexNet
18	10 June 2020	1302	Train 60 Test40	781	521		Precision: 88.90 Sensitivity: 85.10	DenseNet

19	11 June 2020	8474	Train:90 Test:10	7626	847		Accuracy: 98.60	VGG
20	16 June 2020	15282	Train:90 Test:10	13,703	1579		Accuracy: 98.06	ResNet
22	18 june 2020	30099	Train:88 Test:11 Val:N/A	26487	3310		Accuracy: 98.00	NASNet Large
23	18 June 2020	3309	Train:80 Test:20	2647	662		Sensitivity: 100.00	NASNet Large
24	18 June 2020	35500	Train:88 Test:4 Val:8	31340	1800	2360	Accuracy: 98.00	Inception
25	19 June 2020	1312	Train:70 Test:20 Val:10	918	263	131	Accuracy: 97.40	CAD system
26	20 June 2020	6161	5-fold cross-validation				Accuracy: 97.40	CovXNet
27	23 June 2020	50,000	Train:70 Test:30	35000	15,000		Accuracy: 97.54	ResNet
28	23 June 2020	2271	Train:70 Test:30	1590	681		Accuracy: 98.9	DenseNet
30	26 June 2020	239	Train: 70 Test: 20 Val: 10	167	20	22	Accuracy: 98	Residual Att Net
31	1 May 2020	6297	Train :27 Test :26 Val :46	1591	1439	2772	Accuracy: 97.10	DenseNet
32	5 May 2020	502	Train:70 Test:20 Val: 10	399	100	3	Accuracy: 88.90	ResNet
33	6 May 2020	1144	Train:70 Test:30	801	343		F1 Score: 89.60	Inception
35	8 May 2020	6286	Train:80 Test:20	5029	1257		Accuracy: 95.90	CheXNet
36	11 May 2020	13,975	Not specified				Accuracy: 93.30	COVID-NET
37	16 May 2020	50	Not specified				Accuracy: 90-92	VGG
38	17 May 2020	1764	Train:70 Test:30	1235	530		Accuracy: 95.12	ResNet
40	21 May 2020	2239	Not specified				Accuracy :97.01	DCSL

41	23 May 2020	701	Train:80 Test:20	561	140		Accuracy: 98.22	Inception
43	1 April 2020	3905	10-fold cross validation				Accuracy: 99.18	MobileNet
44	2 April 2020	5824	Train:80 Test:20	4659	1165		Accuracy: 99.00	Resnet
47	9 April 2020	16995	5-fold cross validation				Accuracy: 94.80	DenseNet
48	9 April 2020	414	Train:70 Test:15 Val: 15	290	62	62	Accuracy: 98.00	DenseNet
49	10 April 2020	5216	Train:80 Test:10 Val:10	4172	522	522	Accuracy: 94.52	(IRRCNN) and NABLA-3
51	13 April 2020	455	10-fold cross validation				Accuracy: 91.24	(Resnet-50+VGG16+CNN)
52	13 April 2020	537	Train:70 Test:20 Val:10	376	107	54	Accuracy: 93.5	MobileNetv2
54	14 April 2020	1300	4-fold validation				Accuracy: 89.60	Xception
56	16 April 2020	16700	Train:90 Test:10	15030	1670		Accuracy: 99.01	Inception
57	16 April 2020	864	Train:90 Val:10	777		87	Accuracy: 95.70	COVID-CAPS
61	17 April 2020	15085	Train:25% val:75%	3783		11302	Accuracy: 99.56	Xception+ResNet
62	20 April 2020	5071 (5536 after augmentation)	Train:40 Test:60	2028	30426		Sensitivity :97.50	ResNet
66	22 April 2020	381	Train:60 Test:20 Val:20	228	76	76	Accuracy: 95.33	ResNet
67	22 April 2020	274	10-fold cross validation				Accuracy: 99.00	DenseNet
70	24 April 2020	109203	5-fold cross validation				Accuracy: 95.30	Domain Extension Transfer Learning CNN
71	28 April 2020	13800	Train:98 Test:2	13,525	276		Accuracy: 93.90	EfficientNet

72	30 April 2020	59937	Train:80 Test:20	47,950	11987		AUC: 88.04	DenseNet
73	30 Apr 2020	11663	Train:91 Test:9	10613	1050		Sensitivity: 88.33	ResNet
74	30 Apr 2020	15111	Train :80 Test:10 Val:10	12088	1511	1511	Accuracy: 89.40	DenseNet

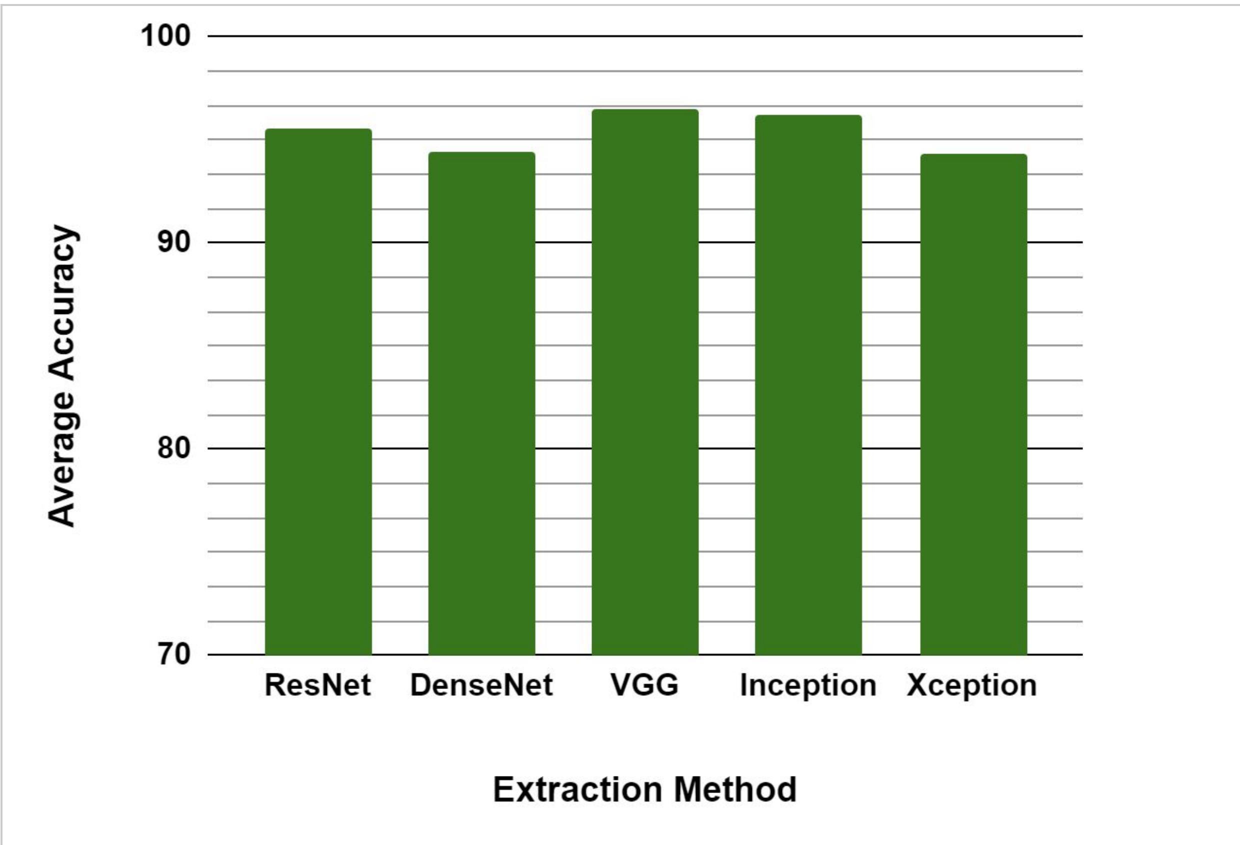

Figure 10: Average Accuracy for X-ray image

In this section, average accuracy is reviewed over the best 5 extraction methods. It is sharply clear from Fig. 10 that the average accuracy of VGG is far exceeding above 95% than the other 4 models and the average accuracy of Xception is not up to the mark. The average accuracy of VGG and Inception is immensely close 96.5%,96.3% individually. X-ray image based diagnosing is superior rather than CT image-based diagnosing clearly appreciable from Fig. 9 and Fig.10

7 Interpretability

Class activation mapping is a method to generate heatmaps of images that is a visualization and can be interpreted as telling researchers wherein the image the neural net is (metaphorically) looking to make its decision indicating a highly important area. Several variations of the method including Score-CAM and Grad-CAM (Gradient Weighted Class Activation Mapping) is accepted widely.CAM is proposed by researchers to examine overfitting occurrence even CAM is capable to classify relevant portions of the image for CNN. Actually, when the diagnosing model has significant accuracy on the training data, but unmarked accuracy on the Test dataset, CAM helps to verify whether the CNN is biased or not while predicting on the features of the images.

Perhaps, because of its nonlinearity vanishing property of the classifiers nowadays Gradient Weighted Class Activation Mapping (Grad-CAM) [47] is broadly by researchers. As an interpretability method gradient-guided class activation maps (Grad-CAM++) and layerwise relevance propagation (LRP), Local Interpretable Model-Agnostic Explanations (LIME) are widely adopted by many researchers for explaining the predictions and to identify the critical regions on patient's chest besides generating class-discriminating attention maps.

However, In this survey, I oversee two interpretability methods that are Grad-Cam and CAM. Both the X-ray image based diagnosing model and CT-image based diagnosing model used Grad-Cam more in comparison to CAM. Besides in some literature [4],[22] authors also utilize LIME with the purpose of rectifying misclassification. Chest X-ray images of a patient In Fig. 11 are displayed to output heatmaps for interpretation of the ultimate result and represent an intuitive understanding of which area is the model focusing on.

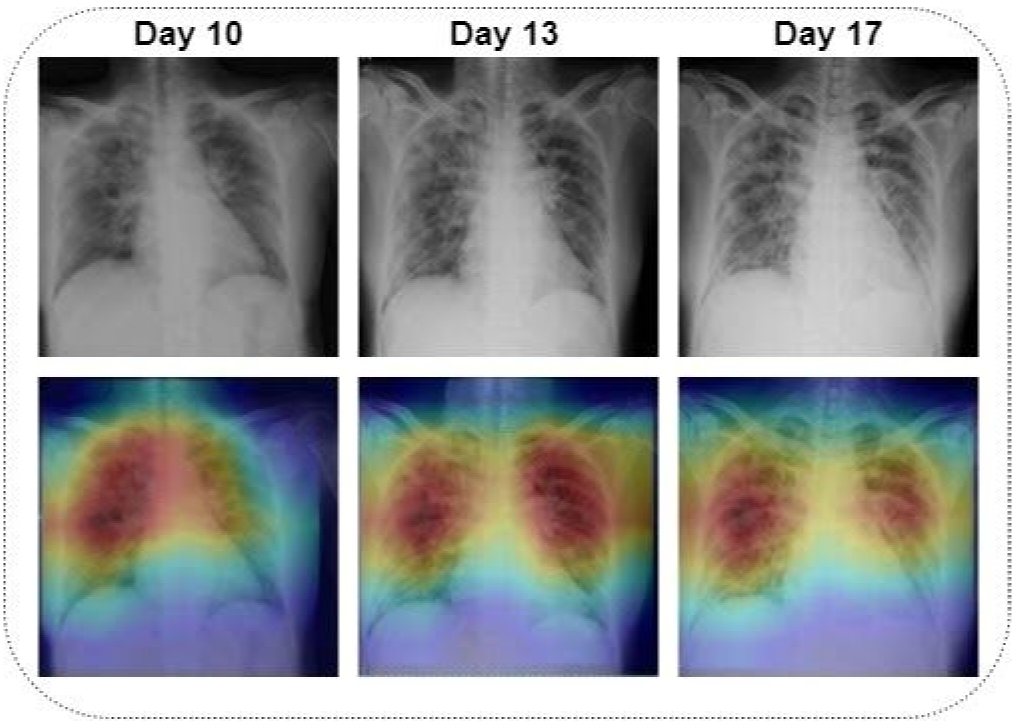

Figure 11: Chest X-ray images of a patent in three points in the upper row and in a lower row their heatmaps using Grad-Cam

In CT image-based diagnosing model researchers use Grad-Cam at 3 literature, CAM at 2 literature depicted in Table 10.

Table 10: Interpretability methods used in the CT images based works

Interpretability method	Papers	Total
Grad-Cam	[12],[45],[58]	3
Cam	[53],[69]	2

In the X-ray image-based diagnosing model researchers use Grad-Cam at 15 literature, CAM at 4 literature depicted in Table 11.

Table 11: Interpretability methods used in the X-ray images based works

Interpretability method	Papers	Total
Grad-Cam	[1],[6],[10],[13],[15],[16],[20],[26],[31],[32],[47],[52],[56],[70],[73]	15
Cam	[22],[41],[72],[74]	4

The entire use of Grad-Cam and Cam based on both CT-image and X-ray image based diagnosing systems in this survey are interpreted in Fig. 12 to deliver a sharp concept of interpretability.

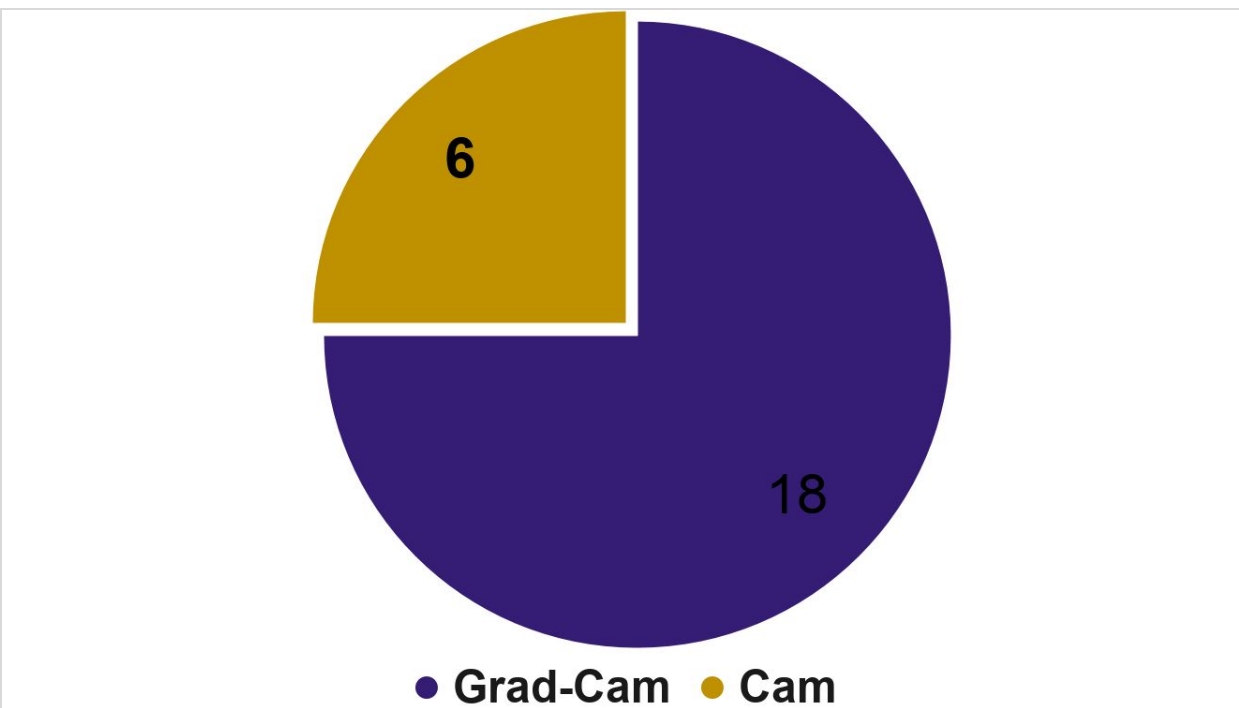

Figure 12: Total number of Grad-Cam and CAM for both CT and X-ray based works

8 Discussion

In this survey, I reviewed 74 automatic COVID-19 diagnosing models and overseen the characteristics of this diagnosing model. It is obvious from this survey, the average accuracy of X-ray image based

diagnosing is better than CT image-based diagnosing 96.5%,94.5% respectively. The reason could be a massive amount of X-ray training data than CT training data. The average training data size of the CT image-based diagnosing system is 609.9 whereas the average training data size of the X-ray image-based diagnosing model is 2857.9. But many authors don’t clarify their dataset size [10], as well as many authors, do not provide a clear indication of training dataset size in their literature [36],[40].
For transfer learning, some diagnosing models adopted pre-trained CNN model [46] even showed high performance 98.27% accuracy, while others proposed various architectures to detect COVID-19 cases from Chest X-ray images to obtain more discriminative features as in paper [3] author propose CovMUNET, which is a multiple loss deep neural network approach, in paper [25] author proposed a deep learning CAD system to simultaneously recognize the COVID-19 9 among the other eight lung diseases: Atelectasis, Infiltration, Pneumothorax, Mass, Effusion, Pneumonia, Cardiomegaly, and Nodule using chest X-ray images, in paper [53] author propose a weakly supervised deep learning strategy for detecting and classifying COVID-19 infection from CT images. The proposed model can reduce the demands of manual labeling of CT images. But still, researchers are unable to detect infection and discriminate COVID-19 from non-COVID-19 cases. To enhance the performance of the classifiers, researchers proposed[16] multi-class classification. We also abbreviated the results of diagnosing models. Some of the models report very good performance, but the size of some test sets are not sufficient [19].

Conclusion

In this survey, I provide the overview of research works that detect COVID-19 using CT image and X-ray image on the basis of feature extraction method, classification, interpretability, and model accuracy. Early quarantine is a must for an affected person in order to decrease the infection rate and to get clinical support diagnosing COVID-19 as early as possible is mandatory. AI-based diagnosing models using Chest X-ray images and CT-Scan images have a higher potentiality to support radiologists in COVID-19 detection rapidly.

The rate of death can be decreased by recognizing patients that are affected so that they can get immediate medical attention and that is possible only by adopting AI-based diagnosing systems as it can diagnose at a very limited time and precisely. It is noticeable in this survey that we analyze different research work so that researchers can pick out the best one or discover any model based on our data that we analyze considering different aspects. I hope this survey can provide valuable insight into computer vision efforts against the COVID-19 pandemic and assist the researchers in new work.

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