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Detection of COVID-19 in Computed Tomography Images Using Deep Learning: A Literature Review

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ABSTRACT

Several diagnostic imaging methods are being studied with the development of the COVID-19 disease. One of them is computed tomography (CT), which has the best level of detail among medical imaging exams. CT generates a repetitive and tiring workload, in addition to requiring a team familiar with the findings that indicate pneumonia caused by COVID-19. Several studies were carried out using deep learning techniques to reduce manual work and collaborate with teams and experts. Thus, this study presents a review of the literature regarding the detection of COVID-19 in CT that uses deep learning. We present here the main techniques used, such as pre-processing, segmentation, and the main models for classification. We also present several image bases that are publicly available. All this contributes to a theoretical basis for future work.

CCS Concepts

· **Computing methodologies → Computer vision problems;**

Keywords

Deep Learning; COVID-19; Computed Tomography.

1. INTRODUCTION

COVID-19 is a disease caused by the SARS-COV-2 virus, and as of August 2021, it has killed a total of 4.4 million people and has a total confirmed case of 211 million [27]. Symptoms of the disease range from mild cases and rapid recovery to severe states causing pneumonia and shortness of breath, and some cases can lead to critical illness, including respiratory failure [24].

Early diagnosis is essential and it is used the examination of the polymerase chain reaction with the possibility of real-time reversal (RT-CPR) [36]. However, the availability of these tests is limited, so other diagnostic methods have been widely studied, such as radiography and computed tomography (CT). Among these, radiography is the most commonly available. However, for COVID-19, radiography has limited performance due to its low sensitivity and specificity [13]. As a result, CT has been considered a more effective and reliable means due to its level of detail. Still, the manual process used to analyze chest CT images makes this work tiring and requires a team familiar with the findings in the images. That is suggestive of COVID-19-compatible viral pneumonia.

The present work presents a bibliographic review of studies that use deep learning techniques to classify these findings on CT images. Such techniques aim to reduce the manual process of analyzing these images and reduce the need for a team familiar with the findings in the images. The main objectives of this work are: 1) To identify the main bases of public images. 2) To identify the deep learning architectures that achieved the best results. 3) To survey data augmentation, fine-tuning, image segmentation, and pre-processing techniques. All this information contributes to a theoretical basis that may help develop computer systems and applications that contribute to the aid of the diagnosis of COVID-19 in CT images.

The rest of the article is organized as follows. Section 2 presents the theoretical foundation. Section 3 describes the methodology addressed. Section 4 presents the summarized results. Section 5 describes the research challenges and directions. Section 6 presents the article's conclusions.

2. THEORETICAL FOUNDATION

2.1 Computed Tomography

CT consists of an X-ray source driven in circular motions, emitting fan-shaped X-ray beams. On the opposite side of this source are detectors that transform the radiation into electrical signals and later digital images [19]. Thus, CT can assist in diagnosing various diseases, making it possible to detect and monitor diseases, being extremely useful in cases of COVID-19 to check its evolution and complications.

A chest CT exam is recommended for cases of COVID-19. The images generated from these exams can be treated in a 2D or 3D. Each exam generates multiple 2D images for the same patient. These images together form a 3D representation. In Figure 1, we can see some images generated by CT of the chest. Each exam can contain dozens or hundreds of images. In Figure 2, we see the union of these images forming a single volume, where it can be analyzed from other angles, helping to have a better diagnosis.

Figure 1: Representation of images returned from chest CT scan.

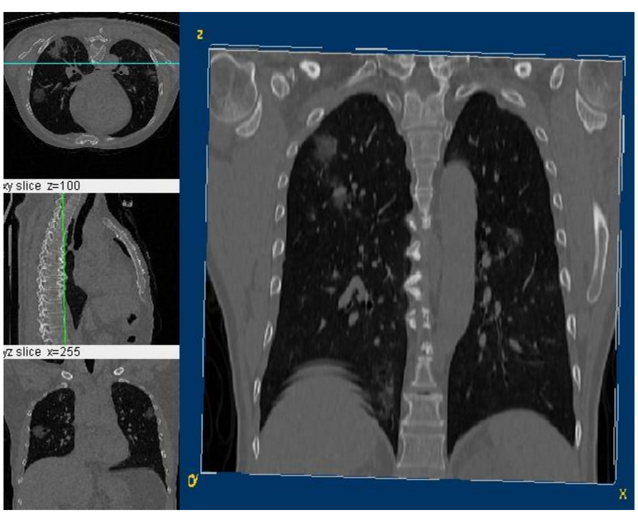

Figure 2: Representation of a complete volume of the CT scan of the chest.

In a study [13], chest CT shows a sensitivity of 97% in detecting COVID-19. This demonstrates that chest CT performs close to RT-PCR for COVID-19, proving an effective and reliable means. All this shows that CT has a great power to detect and evaluate the lesions caused by COVID-19, so this research focused on the search for works that used CT images to solve the problem of detecting COVID-19 in medical imaging.

2.2 Deep Learning

Deep Learning is a sub-area of artificial intelligence, which offers ways to analyze audio, text, visual content such as videos and images [28]. With the evolution of technology, several studies and works show excellent results for identifying diseases in medical images. It is possible to help a specialist or even suggest a diagnosis. As an example, the work of [9] uses convolutional neural networks to detect cancer in histopathological images, where its approach can automatically detect breast cancer with a prediction accuracy of 99.86%, as well as this work, several others show that deep learning techniques can help in the detection of diseases in medical images. It is also possible to verify the evolution of the disease automatically, reducing the manual workload.

The main deep learning technique for chest CT examination is Convolutional Neural Networks (CNNs). These networks have a deep and hierarchical architecture, capable of extracting characteristics from the input data and representing them as information, from the representations from the simplest to the most complex, and classifying them. CNNs are composed of three types of layers: convolution, *pooling* and fully connected. In the convolutions layers, we have feature extraction. After that, the characteristics pass to the *pooling* layers that are responsible for simplifying this information, reducing the data dimension, and accelerating the processing for the next layer. Finally, the fully connected layers interpret the features generated in the previous layers to classify them. In Figure 3 we have a simple representation of the structure of a CNN.

This technique plays a fundamental role in several studies, proving a robust technique with excellent results. Hence, we focused on the search for works where authors use CNN to classify CT images of the chest or to segment the regions where they contain lesions caused. By COVID-19.

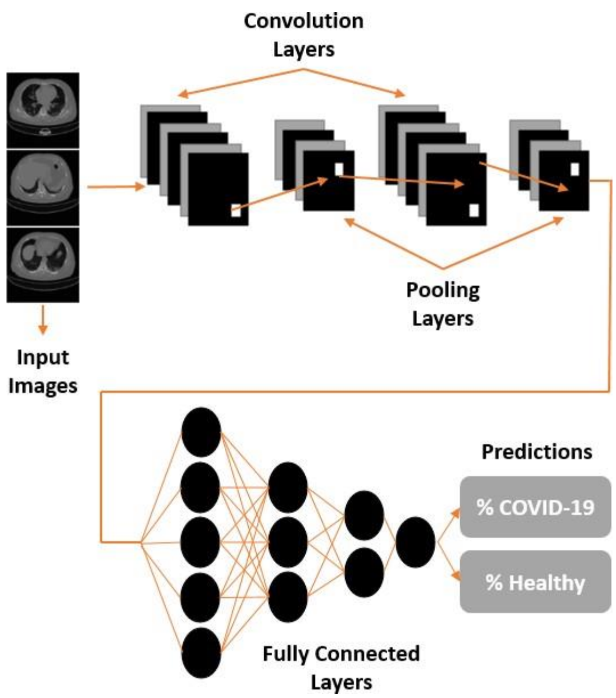

Figure 3: Representation of the basic structure of a CNN.

3. METHODOLOGY

In this literature review, the steps proposed by Kitchenham [21] were used, namely: planning, conduction, and data extraction. For planning, we started with the following questions: “Which medical imaging bases are the authors using?”, “What are the main deep learning techniques being used?”, “Which of the CNNs used have the best performance?”. We have defined the following criteria for Inclusion (I) and Exclusion (E) of works: (I) Whether the article employs computer vision or digital processing techniques on CT images related to COVID-19; (I) Whether the article performs a detection of pneumonia caused by COVID-19, using deep learning on CT images; (I) Studies from 2020 onwards; (E) If you speak a language other than English; (E) If you do not have a methodology for solving the problem. In the driving stage, we submit the search string (“deep learning” OR “convolutional neural network”) AND (COVID-19 OR SARS-COV-2 OR coronavirus) AND (CT OR computed tomography) in the IEEE Xplorer, Scielo, Science Direct, and PubMed databases, resulting in 189 articles, these articles went through the exclusion and inclusion stages, thus serving as filters to select only works of interest and focus; at the end of all stages, a total of 30 articles were selected in the last stage. These returned articles had their main information extracted, with the main objective of detailing what state-of-the-art authors are using to solve this problem. In Figure 4 we present all the stages and the filters used during the conduction stage. The information extracted from the selected works is presented in Section 4.

Bases	1	2	3	4	Taxa de Aceite
IEEE Xplorer	75	1	34	17	23 %
PubMed	50	2	18	3	6 %
Scielo	1	0	0	0	0,0 %
Science Direct	63	0	31	10	16 %

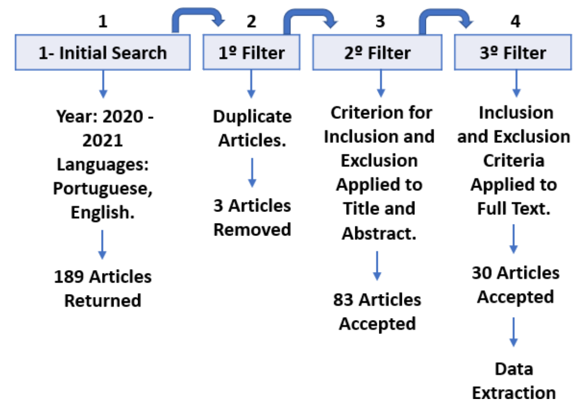

Figure 4: Bibliographic review filtering steps.

4. RESULTS

Deep learning techniques can offer viable ways to solve problems in a real environment. Thus, we present the main works found using such techniques in CT images. In addition, we also present the main publicly available image bases.

4.1 Own Models

In this section, we present the main results of the authors who used techniques and methodologies to create new customized models based on others already existing in the literature to solve this problem.

The authors [22] propose a lesion detection and classification approach. The method includes segmentation, lesion detection, and disease classification. In work, the authors illustrate the processes of the network called NCIP. The complete NCIP-Net includes three-stage, stage 1: Lung Segmentation. The purpose of this process was to limit lesion detection in a sub-region to reduce computation time and avoid false positives (FPs). Stage 2: Injury Detection and finally stage 3: Classification of the disease.

In [31], the authors bring a proposal for a new model whose metrics surpass more known models. In the methods, the actors bring a pre-processing of images to the dataset used to adapt the images to the patterns of convolutional neural networks. The authors [40] present a proposal for a model called 7L-CNN-CD combined with a method for pre-processing the images. The 7L-CNN-CD approach uses a seven-layer convolutional neural network as a background and integration of data augmentation and stochastic clustering methods. The authors' pre-processing used a transformation to shades of gray, after which the histogram equalization, margin clippings, and finally a resizing of the images to 256x256x1 were used. The approach of [37], a model is proposed to predict the probability of COVID-19 infection and find lesions on chest CT. The method constitutes a 3D deep convolutional neural network to detect COVID-19 (DeCoV-Net) from CT volumes. DeCoVNet took a CT volume and its 3D lung mask as input. A pre-trained UNet generated the 3D lung mask.

In the work proposed in [7], he presents a pre-processing image approach and also brings an optimized model called ADECO-CNN. The authors use publicly available datasets; in this work, the authors present four pre-processing steps. The original images pass through an edge detection filter, after which a BGR image is converted to YUV. An intensity equalization is applied, and finally, the images return from YUV to BGR. The work by [17] presents the LeNet-5 model, together with the data augmentation technique and a pre-processing of the images. The authors used a public database, together with the use of data augmentation technique and pre-processing of images; in the pre-processing, the images were converted to grayscale, and the pixels of the images were normalized to a scale from 0 to 1.

In [15], a new model (COVIDNet-CT) is presented. This model was previously trained on the ImageNet dataset, then using transfer learning, the model was trained on the CT image set. The authors bring a set of public images together with data augmentation. In addition, methods were applied to remove the visual indicators of the images that could interfere in the classification work. In the authors' work [29], a new network-based on ResNet50V2 in attribute pyramid is proposed. The authors present a new architecture to improve classification accuracy, and this feature pyramid-shaped architecture can investigate images at different image resolutions without losing small region data. The set of images used is publicly available. In addition, the authors also bring a methodology for selecting images in TIFF files.

In the study of [16], the authors employ a new model with self-adaptive auxiliary loss (DSN-SAAL) for the classification of COVID-19 on CT images. Self-adaptive auxiliary loss considers data overlap between CT slices and possible noisy labels during data collection to classify unbalanced data. The authors also present a new set of public images. In [11], a Vertex of Uncertainty (UVHL) Hypergraph Learning method for identifying COVID-19 is presented. This method alleviates the influence of noisy data on CT images.

In [42], a model called EDL-COVID is presented; this model was used for the detection of COVID-19 in CT images. The authors used transfer parenthesis to train three CNN models to achieve this model, and the overall performance showed that EDL-COVID was better than a single classifier. The authors use public image bases, and these images have been pre-processed to obtain high-quality images.

4.2 Pre-trained models

Following the authors mentioned above, in this section, we have the authors who used pre-trained models with some other techniques, such as fine-tuning.

The authors [10], who bring a new training procedure, called Adversarial Graph Learning (AGL), being evaluated in two CNNs. The chosen models were used for training in the set of public images. The AGL framework helps the network to learn more distinctive features. The work done by the authors [1] presents a methodology for the pre-processing of CT images, and the VGG16 architecture is used to receive a fine adjustment. The database used is publicly available; the pre-processing steps consisted of transforming image intensities in the Hounsfield unit, extracting the lung part through image processing techniques, histogram equalization, and stretching the contrast of the images. Already the authors in [38] present a redesign of COVID-Net, originally developed for x-ray imaging; this approach was able to overcome COVID-Net. The authors used a publicly available image database. In [4], models with transfer learning, data augmentation, and fine-tuning are used. The authors used an image resizing to 224x224 pixels. The models were trained on imageNet and then fitted on the CT image set.

In the study done by the authors [12], it uses Inception V3, with the transfer of learning, data augmentation, fine-tuning and hyper-parameter tuning. The authors use a publicly available set of images. The authors [6] apply a simplified version of the LeNet-5 network to extract the characteristics of the images and XGBoost for classification. The authors used a publicly available database. The study proposed by [20] contains a methodology for pre-processing the images. The VGG-19 model with learning transfer and fine-tuning is used for image classification. Each image is converted from gray to binary scale, after which the noise removal is applied using the Median Blur filter. Finally, a crop is made to exclude all unnecessary images and keep only the areas of interest.

In [8], and [25], transfer learning techniques with data augmentation and a combined CNN are employed. The dataset used is publicly available. Pre-processing is used to adapt the images to the specific parameters of the models. In the work by [18], he employs a modified ResNet architecture for classification of CT images. This modification is designed to solve the vanishing gradient problem and improve classification performance by dynamically combining features at different network layers. The work carried out by [35] presents a method in Multiple Kernels-ELM (MKs-ELM-DNN) for the detection of COVID-19 through chest CT images using the DenseNet201 network; for this, the authors use a public database.

In the research work [23], the authors use a named model of CheXNet, based on the transfer of learning that aims to identify COVID-19 in chest CT images. The authors used a database of public images. The authors also evaluated several pre-trained networks through training experiments in several pre-defined structures until reaching the proposed model. In work by [3], the authors use Super Resolution (SR) in image preprocessing with data augmentation and transfer learning techniques. It was possible to observe that SR improved the results of models such as MobileNet; for this research, the authors use a public database.

4.3 Model Review

Finally, in this section, we present the authors who used existing models in the literature to comparatively evaluate the performance of these models.

The authors [33] present an evaluation of different pre-trained CNNs, highlighting ResNet18 and DenseNet121 between the models with and without segmentation, respectively. In [5] a study of three types of ResNet is carried out, where ResNet-18 obtained the best results. To evaluate the results, the authors used six machine learning indicators and used Grad-CAM as a visualization technique to intuitively understand where the models are focusing. The authors in [39] present a study on three popular models of CNN using transfer learning, where VGG16 and VGG19 obtained similar and better results than Xception. The authors use a public dataset. In the pre-processing of the images, resized to 224x224 pixels is used, and the images were normalized by dividing each pixel by 255.

In the work [32] the authors aimed to distinguish COVID-19 from other infections. Among the CNNs used, ResNet-50 stood out; for all cases, it obtained the best results. As preprocessing of the images, the authors use a resizing to 224x224x3. The authors in [2] and [14] present a study with ten and fifteen CNNs, respectively, where Resnet-101, Xception, EfficientNet, and InceptionV3 stood out. Both use publicly available image banks.

4.4 Image Datasets

The lack of data is the greatest difficulty in developing research with CNN in the context of the new coronavirus in CT images. Due to this problem, several image bases are being made available. Thus, we present here some of these bases found during this review, being the SARS-COV-2 CT-Scan [1] database available on Kaggle by the authors [34]. This database has 2482 CT scans, with 1252 CT scans positive for an infection and 1230 CT scans for uninfected patients. The authors [41] bring a dataset [2] that contains 349 positive CT images for covid-19 and 463 CT images for non-covid-19. Another data source that it was possible to identify is the Radiopaedia website with a session of covid-19 with some cases.

Another dataset found was COVID-19 CT scans [3]; this dataset contains 20 CT scans of patients diagnosed with COVID-19 and segmentation of lungs and infections made by specialists. In [26] [4] it is possible to find several cases, being possible to extract 591 computed tomography images.

Among all the works that present public databases, we can highlight the two largest databases of publicly available images so far. COVID-CTset [29], and COVIDx-CT-2 [15]. The COVIDx CT-2 dataset comprises 194,922 CT sections from 3,745 patients, which is the largest set of images available at the moment. It is divided into 60,083 normal images, 40,291 pneumonia images, and 94,548 COVID-19 images and is available on Kaggle [5]. The COVID-CTset dataset contains 15,589 COVID-19 images (95 patients) and 48,260 normal images (282 patients) available on GitHub [6]. In Table 4.4 we illustrate these data sources as well as their respective links.

4.5 Discussions

Table 1: Base of images found and their main information.

Datasets	Images
COVIDx CT-2	194.922
COVID-CTset	63.849
COVID-19 CT scans	3.520
SARS-COV-2 CT-Scan	2.482
Radiopaedia	939
Dataset Zhao et al	812
Italian Society of Medical Radiology	519

In the Table 4.5, we present the results obtained in the researched works and the main techniques used by the authors in each work, such as: image pre-processing (PPI), transfer learning (TL), data augmentation (DA), and segmentation algorithms (S). Among the works presented, 76.66% used pre-processing algorithms, 53.33% used transfer learning, and 30% used the data augmentation technique. Only 6.66% of the works carried out segmentation. We can highlight the work of [3], with the highest accuracy (100%), precision (100%), and F1-score (100%). Another work that can be highlighted is that of the authors [16], where it was possible to reach the highest AUC (99.95%), and the authors [2] managed to reach the highest sensitivity (100

5. RESEARCH CHALLENGES

5.1 Data Base

For any type of problem using deep learning, it is necessary to use a database; working with CNNs is no different. It is necessary to use an image base to train these networks. However, this image acquisition becomes a little problematic for a recent problem due to the lack of image bases, very small image bases, or image bases with restricted access.

Some works have some difficulty regarding this image acquisition. One of the reasons is that the problem is relatively new, which makes the availability of public databases difficult. We can see that several authors use private databases, which makes it difficult for other authors to replicate their experiments or create new experiments with this data.

In this work, it was possible to identify several public databases; however, they are bases that are mostly small for the context of CNNs. It was also possible to identify two large image bases, but many authors have not yet used them in their experiments as they are relatively new bases.

Over time, new databases will appear. Those already available can receive updates with new images, facilitating the work without being dependent on small databases or private databases. In the meantime, the authors have been working with the data augmentation technique to solve the lack of data.

The increase in data played a fundamental role in most of the research presented here, and it was possible to observe that when used, the models gain greater power at the time of classification. With this, it was possible to circumvent the problems with small databases. Still, even in large databases, this technique also plays a great role, managing to increase the classification power.

In small databases, this technique can perform excellent results with an increase in processing cost; this increase in processing can be justified when we look at the increase in

[1] https://www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset
[2] https://github.com/UCSD-AI4H/COVID-CT
[3] https://www.kaggle.com/andrewmvd/covid19-ct-scans
[4] https://sirm.org/category/senza-categoria/covid-19/
[5] https://www.kaggle.com/hgunraj/covidxct
[6] https://github.com/mr7495/COVID-CTset

Table 2: Summary of works, techniques, models used and their results.

Methods	Techniques	Model	Acc	Sens	Spec	Prec	F1	AUC
Lai et al. 2020	(S, DA)	Own Model	86.1	75.7	95.2	-	-	91.0
Sari et al. 2020	(PPI)	Own Model	97.5	-	-	98.0	98.0	-
Seum et al. 2020	(PPI, S, TL)	U-Net+ResNet18	89.9	80.4	99.5	99.5	88.9	-
Zhang et al. 2020	(PPI, DA)	Own Model	94.0	94.4	93.6	-	94.0	-
Wang et al. 2020b	(S, PPI, DA)	U-Net+Own Model	90.1	-	-	-	-	95.9
Dan-Sebastian et al. 2020	(PPI, TL)	Xception	78.4	-	-	-	-	84.69
Abdar et al. 2020	(PPI, TL)	VGG16	90.1	-	90.5	91.5	90.6	-
Cai et al. 2020	(PPI)	ResNet18	94.3	91.4	97.3	97.1	94.2	98.5
Wang et al. 2020c	(-)	COVID-Net	90.8	-	-	95.7	90.8	96.2
Castiglione et al. 2021	(PPI)	Own Model	99.9	99.9	99.9	99.9	-	-
Berrimi et al. 2021	(PPI, DA, TL)	DenseNet	95.9	-	-	-	-	-
Dutta et al. 2021	(TA, DA)	Inception V3	84.0	-	-	-	-	-
Islam and Matin 2020	(DA, PPI)	Own Model	86.0	-	-	85.0	87.0	-
Carvalho et al. 2020	(-)	LeNet5+XGBoost	95.0	-	-	94.9	95.0	95.0
Yener and Oktay 2020	(TL, PPI)	VGG16	93.0	-	-	91.0	94.0	93.0
Serte and Serener 2020	(PPI, TL)	ResNet-101	99.5	100	99.0	-	-	99.4
Kamel et al. 2021	(PPI, TL)	VGG19	98.3	-	-	95.6	97.3	-
Ardakani et al. 2020	(PPI, TL)	ResNet-101	99.5	100	99.0	-	-	99.4
Gifani et al. 2021	(PPI, TL)	Own Model	85.2	-	-	85.7	85.2	91.0
Guranj et al. 2020	(TL)	Own Model	99.1	97.3	99.9	-	-	-
Rahimzadeh et al. 2021	(PPI)	Own Model	98.4	94.9	94.7	81.2	-	-
Cruz 2021	(PPI, DA, TL)	Own Model	86.7	-	89.5	88.1	85.8	90.8
Mishra et al. 2021	(DA, TL)	Own Model	99.0	-	-	-	-	-
Jia et al. 2021	(-)	Own Model	99.3	99.2	-	-	-	-
Turkoglu 2021	(PPI, DA, TL)	DenseNet201	98.3	-	-	-	-	-
Hu et al. 2021	(PPI)	Own Model	99.4	99.3	-	99.5	99.4	99.9
Di et al. 2021	(PPI)	Own Model	89.7	93.2	84.0	-	-	-
Zhou et al. 2021	(TA, PPI)	Own Model	99.0	99.0	99.6	-	98.5	-
Li et al. 2021	(PPI, TL)	CheXNet	87.0	-	-	-	86.0	75.0
Arora et al. 2021	(PPI, DA, TL)	MobileNet	100	-	-	100	100	-

All values are in percentage.

classification power. However, this same increase in processing in a large database may not be a viable alternative since it greatly increases the training time. The gain in classification power may not be so great as to justify the increase in training time.

5.2 Feature Extraction and Classification

The classification step is one of the main steps in any automatic diagnosis of a disease. Through deep learning techniques using CNNs, we can extract the main characteristics of medical images and classify them. This automated process saves time and lessens the manual burden specialists have to manually assess medical images, an extremely tiring and repetitive job.

In research, authors mostly use pre-trained models for feature extraction and classification through the transfer of learning; these pre-trained models are adjusted to the problem in question and can perform great results.

With pre-trained models, difficulties arise in choosing the parameters that best suit the problem to be investigated; this parameter optimization takes a long time and is exhausting. We can get the best parameters on a trial and error basis, or we can search hyperparameter optimization, which takes a lot of time as the models contain a lot of parameters. In most of the researched works, the authors made the parameters used in the worked models.

Another challenge with pre-trained models is the great depth of some models, which takes a very long training time and can adjust too much to the training data, causing overfitting. Some authors review the main pre-trained models in the literature and report their performance in terms of classification and training time, which helps in choosing the best model to solve the problem in question.

In the research papers returned, we can confirm the excellent performance of transfer learning techniques and fine-tune for this problem. In all research, these techniques played a fundamental role in obtaining excellent metrics. In addition to these techniques, it was also possible to identify that the customized models created especially for the COVID-19 classification task are the ones that generally present the best performances.

5.3 Pre Processing of Images

The images from the chest CT scan usually contain noise and information that is not important to the problem at hand. These noises can disturb the classification and confuse the models. Using noisy images or information that is not part of the problem can make the models learn these characteristics instead of the main characteristics that are part of the problem. With this, the model can even perform well, but the activation regions may not be the ones that represent the problem in question.

Thus, most authors use methodologies to pre-process these images to improve their quality. In research works, several forms of pre-processing are used, such as noise removal, use of the super-resolution of images, transformations to grayscale, resizing, and cropping. All this is to improve the images and feed the models with the main features highlighted to learn what is important to solve the problem.

In all the works that made use of image pre-processing, it was shown that this technique improves the results and improves the performance of the models in finding the main features and reducing the training time of the models. The pre-processing techniques help obtain a better representation of the images, so this technique is necessary to obtain robust results with activation regions that are part of the problem and classify the images correctly with high precision.

In Figure 5, we have an illustration of some techniques that help to highlight the regions of interest in the image, and we can see in this illustration the benefit of pre-processing to remove features that are not part of the problem. For example, characteristics that are typical of chest CT exams.

5.4 Segmentation

Segmentation aims to facilitate the analysis of images to isolate regions of interest. With segmentation, it is possible to highlight regions to help an expert analyze the images. For COVID-19, segmentation can be a great ally for visualizing the lesions caused by this disease to assess the status of a patient and monitor the evolution. With this, it is possible to help the specialists reduce the tedious work of manual analysis of these images.

In the research works returned, the authors use two approaches, the first being the use of segmentation in the images to highlight the lung region, where the main characteristics of the problem are concentrated. This segmentation serves as a means of pre-processing. Everything that is not part of the buffer is excluded, returning an image only of the buffer, where the classification by the model is performed. This classification made only in lung segmentation offers excellent results.

In Figure 6, we demonstrate the most used and simple segmentation techniques. K-means and thresholding techniques have great power to segment regions quickly and easily and have very similar results between them. These techniques present excellent results without a high computational cost, unlike the segmentations that use models to segment.

The second approach focuses on the segmentation of lesions caused by COVID-19; in addition to automatically classifying the images, it is also possible to mark the regions where they contain lesions. These markings provide a view to following the evolution of the patient's clinical condition by observing the marks; with this, it is possible to help a specialist observe the evolution of the disease automatically.

In Figure 7, we can see the second approach, where we have the U-Net [30] model, one of the models most used by authors to segment the images of this problem. This model is trained with images and masks containing the regions of interest. In the figure, it is possible to observe that after the model is trained, we can pass an image of the problem, and the model will generate a mask of the region of interest, and with this, mask models do segmentations.

Regardless of the segmentation approach, we can observe excellent results. For segmentation of the lung region, some authors use thresholding techniques and models for segmentation, such as U-Net [30], a model that is widely used for segmentation. In the segmentation approach of the regions injured by COVID-19, the authors use models for segmentation, such as the U-Net.

5.5 Challenges of using Deep Learning

In the works presented, the study of COVID-19 faces problems such as small databases, which contain few samples that may not be enough to create robust models for classi-

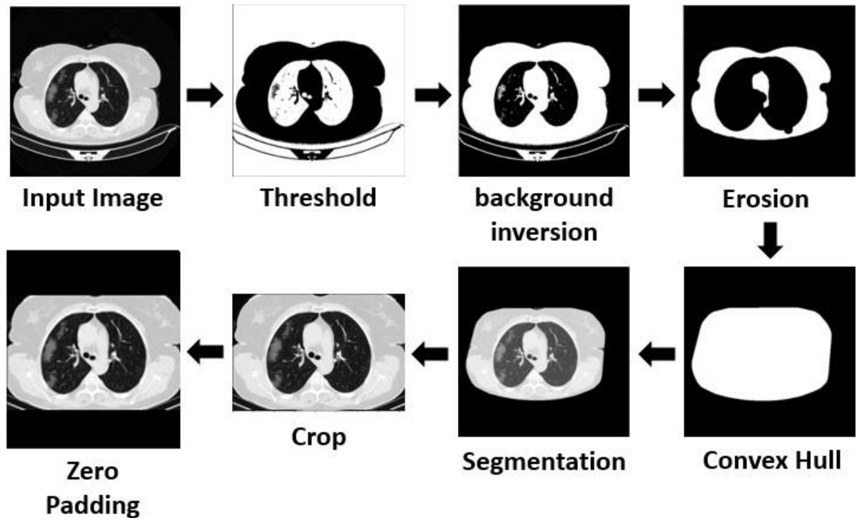

Figure 5: Some techniques for pre-processing images are also possible to use filters to improve images.

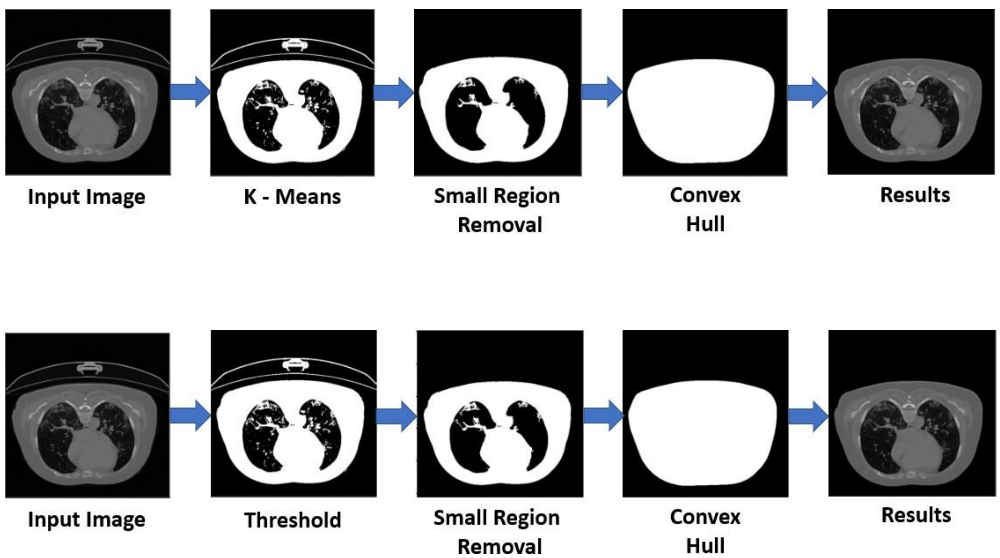

Figure 6: Segmentation scheme using thresholding and K-Means.

fication. Another problem is using very large databases, as this generates a very long training time. It is necessary to acquire expensive hardware to carry out the training of the models in an optimal time.

This problem should not be treated as a serious disease as a simple classification. All stages must be well defined, such as customized models and approaches made especially for this problem. We can highlight the segmentation of injuries, which can offer automatic markings for the specialist. That way, the specialist will have a quick and automatic second opinion.

From the survey of deep learning techniques used in the researched works, it is possible to observe that the set of techniques used together present promising results for detecting COVID-19 in CT images.

6. CONCLUSION

In this work, we carried out a survey of research that uses deep learning to detect pneumonia caused by the new coronavirus. We conclude that regardless of the modality and approaches of the authors in images from CT scans of the chest, the techniques obtained significant results in different metrics. When used with some pre-processing in the images to improve the representation of these images and obtain the regions of interest, CNNs gain greater ranking power. In addition, it was possible to identify two sets of data that solve the challenge of the amount of data inherent in the training of CNNs.

Despite the excellent results, the authors suffer from using relatively small databases, and these authors try to circumvent this problem using the data augmentation technique. This technique proves to be indispensable for this problem,

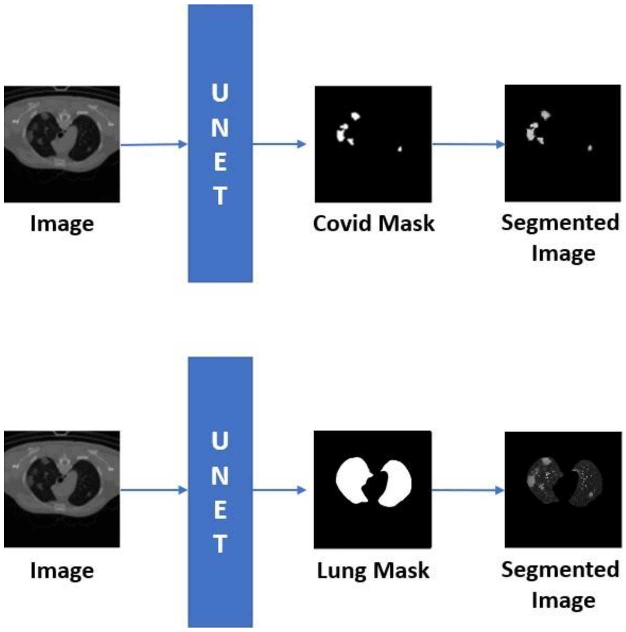

Figure 7: Segmentation scheme using models such as U-Net.

where the works show an optimal gain in performance. As it is a recent problem, the databases have been constantly made available and updated, and we bring in this work several image bases that are publicly available.

As future work, we intend to investigate the performance of the models found during this work in datasets with many different samples and classes, in addition to testing new image pre-processing methods. We also intend to optimize the hyper-parameters in the best-researched networks and automatically use image segmentation methods to detect and mark lesion regions.

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