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A Survey of Deep Learning Techniques Based on Computed Tomography Images for Detection of Pneumonia †

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Abstract: A cluster of cases caused by the virus SARS-CoV-2 was detected in Wuhan, China, in December 2019. The disease derived from that virus was named Coronavirus (COVID-19), which was officially recognized as a pandemic by the World Health Organization in March 2020. Since COVID-19 can cause serious pneumonia, early diagnosis is crucial for adequate treatment and for reducing health system overload. Therefore, deep learning algorithms to detect pneumonia have been developed using computed tomography (CT) scans, as they provide more detailed information about the disease because of their three-dimensionality and good visibility. This information analyzed by specialists could support the confirmation of pneumonia. To find out the accuracy levels of various classifiers, we evaluated the baseline models utilized by researchers. The findings we drew were that the majority of CT classification algorithms have strong accuracy values in comparison to other algorithms performed using CT, but have not reached above 98%. According to the systematic literature survey, low accuracy levels resulting from the performance of the models were attributed to the incongruous dealing of medical images. These images instead of having common formats such as png or jpg, use more complex formats such as DICOM and NIFTI, in order to save more information about the disease and the patient. Moreover, some studies found that the influence of environmental conditions and lung movement could affect the quality of the image. This unclear pneumonia area may also result in a decrease in the efficiency of deep-learning algorithms for detecting pneumonia. Therefore, the objective of this survey is to identify, gather data and build a catalog of deep-learning techniques for detecting pneumonia abnormalities and annotating CT images from the literature review, reflecting a better understanding of the classification of pneumonia using CT images.

Keywords: COVID-19; pneumonia; computed tomography (CT); deep learning

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1. Introduction

Coronavirus disease (COVID-19) is a respiratory illness caused by a virus called SARS-CoV-2, which was declared a public health emergency of international concern by the World Health Organization on 11 March 2020. Two years later, in 2022, several studies continue to be conducted as the effects of COVID-19 on lung tissues are still notorious. This is because not only were the appearances of new respiratory diseases promoted, but so were the resurgence of other diseases, such as pneumonia [1]. In response to this, several subsequent investigations were oriented towards the search for digital techniques or methods [2] that could favor the detection of pneumonia caused by COVID-19. This is because an increasing number of studies on medical images were registered in academic repositories together with epidemiological, clinical, and laboratory data for decision-making. Moreover, some studies showed that computed tomography (CT) had become one of the preferred digital imaging modalities to detect COVID-19 cases in the initial stages of diagnosis, even more so when the symptoms are not particular [3]. This is due to the fact that CT can offer more detailed information related to the pathology studied [4]. Therefore, the detailed information provided by CT scans, when analyzed by doctors, could allow for the confirmation of pneumonia [5].

Nonetheless, a lack of consensus regarding the best classification model using CT is still present. This stems from the fact that deep learning classification models using CT tend not to reach above 98% accuracy [6] on average. On the one hand, the systematic review of the literature suggested that less intricate architectures, such as DenseNet and core CNN, had values around 90% to 98%, for the accuracy metric. On the other hand, some studies revealed that NASnet and VGG-16 networks obtained strong values between 83% and 98% for the accuracy metric [7]. Therefore, this study aims to identify, collect, and build a catalog of deep-learning techniques for the detection of pneumonia and similar diseases in a wider spectrum of data than precedent survey papers.

2. Methodology

To survey the literature on deep learning techniques based on CT images for the detection of pneumonia, the following keyword search strings in both the Scopus citation database: ((“CT images” OR “computed tomography” OR “computed tomography classification”) (“deep learning” OR “deep neural” OR “deep neural networks” (AND) “Convolutional Neural Network” OR “CNN” OR “ResNet”)) (AND), which retrieved 43 articles between 2019 and 2022.

Papers from *Computer Vision and Pattern Recognition* (CVPR), *International Conference of Computer Vision* (ICCV), and *European Conference of Computer Vision (ECCV)* (ECCV) were also included. The standard systematic review methods for the software engineering area were taken into account in this literature review [3]. The ultimate method was segmented into two iterations: revision and comparison. In the former, individual articles are analyzed and listed. In the latter, the studies are compared and contrasted with their properties in mind.

3. Results

The synthesis of this research is a catalog of the determinants of the detection of pneumonia using computed tomography. Researchers can use different datasets, deep learning techniques, and metrics presented from this overview and determine the optimal approach for the topic of study. The information is pertinent to the topic at hand, as the studies reviewed were conducted between 2019 to 2023, in the timeframe of the pandemic.

Study fields: Table 1 indicates that COVID-19 pneumonia is the most frequent study field in relation to computed tomography studies. Other study fields mentioned were tumors, cancers, and hemorrhages, in that order. In addition to this, the most common study application was classification. Other applications include segmentation and synthesis.

Table 1. Computed tomography analysis in various study fields. Studies range from 2019 to 2022. The analysis summarizes information regarding the study field, type of application, author, and date of publication.

Study Field	**Application**	**Publication**	**Study Field**	**Application**	**Publication**
Tuberculosis	Classification	Lewis (2021) [8]	COVID-19	Quantification	Aquino (2022) [9]
COVID-19	Classification	Kaur (2021) [10]	COVID-19	Classification	Latif (2022) [2]
COVID-19	Classification	Kollias (2022) [1]	Brain Lesion	Classification	Buchlak (2022) [11]
Lung Tumor	Synthesis	Jin (2021) [12]	Liver Tumor	Segmentation	Ahmad (2022) [13]
Liver Tumor	Segmentation	Li (2022) [14]	Pneumonia	Classification	Lacerda (2021) [3]
Dental	Reduction	Liang (2019) [15]	Lung Nodule	Classification	Naik (2021) [16]

Table 1. *Cont.*

Study Field	Application	Publication	Study Field	Application	Publication
Lung Cancer	Classification	Kalaivani (2020) [17]	Dental	Reduction	Xu (2022) [18]
Pneumonia	Segmentation	Zhang (2020) [19]	Lung Lesion	Classification	Wibowo (2021) [20]
Pneumonia	Classification	Tan (2020) [21]	Brain Hemorrhage	Classification	Ker (2019) [22]
Pneumonia	Classification	Rathod (2021) [5]	Intracranial Hemorrhage	Segmentation	Irene (2020) [23]
Pneumonia	Classification	Hasan (2020) [4]	Head Hemorrhage	Segmentation	Inkeaw (2022) [24]

Datasets: Table 2 shows a short list of the repositories that include computer tomography images in DICOM format that were found, in contrast to CXR images. Most of those datasets applied multi-classification and may contain from 400 to 48,260 images.

Table 2. DICOM format computed tomography datasets. All data belong to public datasets. The analysis summarizes information regarding the study field, type of classification, number of images, author, and date of publication.

Study Field	Class	Images	Publishing Information	Study Field	Class	Images	Publishing Information
Fibrosis	Binary	34,000	2020 (OSIC) [25]	Breast Cancer	Multiclass	150	Calisto (2021) [26]
Lung Cancer	Binary	22,800	Mirsky (2019) [27]	Pneumonia	Multiclass	1000	Harvard (2021) [28]
Lung Cancer	Multiclass	1693	Rutherford (2021) [29]	COVID-19	Multiclass	48,260	Afshar (2021) [30]
Pneumonia	Binary	150,000	N.H.S. (2021) [31]	Pneumonia	Multiclass	6000	Iglesia (2021) [32]

Models: Table 3 displays that the CNN baseline model was used frequently for multi-classification study types, and the most studied field was COVID-19 and pneumonia. Various models were also applied, such as ResNet-50, SRGAN, X2CT-GAN, or some others for data preprocessing, which may include data augmentation or data segmentation.

Table 3. Deep learning classification models for computed tomography images. Studies are related to lung infections, such as COVID-19, pneumonia, tuberculosis, and cancer. The analysis summarizes information regarding the identified, study field, description of the model and parameters, metrics, results, author, and date of publication.

Model	Study Field	Description	Metrics	Result	Publishing Information
3D CNN	Tuberculosis	Data augmentation: X2CT-GAN/multiclassification: healthy and TB/binary cross-entropy loss (BCE).	Accuracy	0.8600	Lewis (2021) [8]
NASnet	Tuberculosis	Multiclassification: granuloma, cavitation, and classification Adam optimizer.	Accuracy	0.8300	Lewis (2021) [8]
RNN	COVID-19	Data preprocessing: ResNet-50/binary classification: COVID-19 and non-COVID-19/Softmax activation.	F1 score	0.7700	Kollias (2022) [1]
Dense Net	Lung Cancer	Data preprocessing: CNN/binary classification: normal and malignant lung cancer.	Accuracy	0.9085	Kalaivani (2020) [17]
VGG-16	COVID-19	Data preprocessing: SRGAN/binary classification: COVID-19 and non-COVID-19.	Accuracy F1 Score	0.9800 0.9800	Tan (2020) [21]
LSTM	Pneumonia	Data preprocessing: CNN and Q-deformed entropy/binary classification: COVID-19, pneumonia, and healthy.	Accuracy	0.9868	Hasan (2020) [4]

Table 3. *Cont.*

Model	Study Field	Description	Metrics	Result	Publishing Information
ANN	Pneumonia	Data preprocessing: Hyperband/binary classification: COVID-19 and non-COVID-19.	Accuracy F1 Score	0.8800 0.8900	Lacerda (2021) [3]
CNN	COVID-19	Segmentation: U-net and histogram equalization/binary classification: COVID, non-COVID/Softmax layer.	Accuracy	0.9800	Mahmoudi (2022) [33]
CNN	Pneumonia	Data preprocessing: CNN/binary classification: COVID and non-COVID.	Accuracy F1 Score	0.9326 0.9331	Polat (2021) [6]
CNN	Pneumonia	Segmentation: 3D CNN/multiclassification: COVID-19, IAVP, and infection irrelevant (ITI).	Accuracy F1 Score	0.8930 0.8560	Xu (2020) [34]

Metrics: Table 3 shows that accuracy is the most used metric in the evaluation of deep Learning classification models. Its value ranges from 83% to 98%. Furthermore, the F1 score is analyzed, having 77% as its lowest value and 98% as its highest value.

4. Discussion

Regarding the results, according to Table 1, the most common study field in computed tomography is between COVID-19 and pneumonia, concerned with the study of the lung and its derivatives. Then, it is followed by cancer and tumor studies, and lastly by hemorrhage studies, in that order. In this case, the liver and brain were frequently analyzed. Most of these studies were conducted in 2021, one year after the pandemic started. Moreover, several studies have chosen classification as the type of approach; in fact, more than 50% of them. The second-most common type of application was segmentation, revealing that there is also quite some interest in this type of study. Likewise, Table 2 summarizes information regarding the public datasets found in this systematic review. In fact, it is perceived that there are more multiclass datasets than binary class datasets. Moreover, a vast majority of the study fields correspond to respiratory diseases, therefore, lung images were commonly found in those datasets. It is also identified that most of the datasets listed are from the year 2021, as in that year, the number of cases of COVID-19 infections began to increase strongly since the pandemic was declared. Additionally, Table 3 shows that the frequent metric used in deep learning classification models for computed tomography studies was accuracy. The average value of this metric is 92%, meaning that model performed in most of the studies does not reach above 95%. Along with that metric, the F1 score or also known as Dice Score was used, having 89% as an average value, which is a bit less than the accuracy average value. Moreover, most of the studies were conducted in 2021, as Table 1 has also shown. Most of these models used the datasets from Table 2, which focused mostly on the classification of lung diseases, such as pneumonia and COVID-19. Nonetheless, models that resulted in having the lowest metrics correspond to muticlassification studies and this is due to the fact that models used in those studies have to work with more variables in the experiments. On the other hand, binary classification studies that have less complex characteristics reported higher metric scores.

5. Conclusions

This work sought to provide a comprehensive literature review concerning novel deep-learning techniques for the detection of pneumonia using computed tomography (CT) images. Therefore, this paper is expected to be used to build better classification models for more accurate detection of pneumonia. A limitation of the research stems from the fact that it only examined Scopus studies and some articles from computer vision conferences, leaving aside other sources that could offer further insights into classification models.

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Abbreviations

The following abbreviations are used in this manuscript:

COVID-19	Coronavirus 2019
CNN	Convolutional neural network
CT	Computed tomography
DICOM	Digital imaging and communication in medicine

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