A Survey on how computer vision can response to urgent need to contribute in COVID-19 pandemics

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Abstract—**The coronavirus first outbreak in Wuhan city of China by December 2019. Due to its highly contagious power, they spread promptly in the four continents. Moreover, it devastating our daily lives and cause huge economic damage. Therefore, it is urgent to detect the positive cases at the earliest and put then under isolation. Automatic virus detection using Machine Learning will be a valuable contribution to prevent the spread of this epidemic. The purpose of this paper is to present short reviews on the coronavirus detection. In reviewing the existing works, we summarized and compared some related works performed on a collection of CT and X-ray images provided from infected patients. We conclude the paper with some discussions on how computer vision can response to urgent need to contribute in pandemics and to investigate many aspects of new viral replication and pathogenesis.**

Keywords—Computer vision, COVID-19, deep learning, coronavirus detection, CT image, X-ray image, CNN.

I. INTRODUCTION

COVID-19 is the fifth pandemic since the flu pandemic in 1918 (figure 1). At first, the disease was called Wuhan pneumonia by the press because of the pneumonia symptoms [1]. The COVID-19 is an infectious disease caused by SARS-CoV-2 virus, firstly detected in December 2019 in China. The World Health Organization recognized it as global pandemic on 11 March 2020, after that it widely spread around the world killing Thousands of People. The five pandemics since 1918 have a main characteristic that are highly contagious. The most important measure to take is social distancing and quarantine measures work. The European Centre for Disease Prevention and Control reported that the number of confirmed cases in the period between 31 December 2019 and 07 May 2020 risen to 3 713 796 cases of COVID-19 including 263 288 deaths [2]. Scientific community has an obligation to provide prompt responses to the urgent need to the fight against this huge threat and mitigate its spread. Computer vision and Artificial Intelligence (AI) researchers immediately involved in the fight against this pandemic. Much attention has been given to areas of research that tackle some of COVID 19 prevention, detection and understanding the transmission of the pandemic. The computer vision and IA researchers are devoting a considerable effort to topics related to (1) Unmanned Aerial Vehicle (UAV) applications. An UAV is fitted with different types of cameras (HD cameras, thermal and infrared camera and can operate over a wide area and computer vision systems allows to develop different focuses of interest and applications: typical examples are crowded scene analytics, body temperature measure and as more recent applications, measures the distances between individuals in the crowd. The computer vision and IA systems allows understanding if there is suspicious situation in the scene demanding to broadcast advices related to lockdown measures. (2) The highly response and efficient diagnosis COVID-19 Pneumonia applications. In this context, X-Ray and CT Images have been commonly used in COVD- 19 detection stage. However, to the best of our knowledge, almost all the approaches are using a deep model for COVID19 detection. A wide range of variant CNN model were proposed using confirmed COVID-19 images and non-confirmed COVID-19 images. The proposed approaches based on CNN model achieved acceptable percentages for almost all classes.

The rapid spread of COVID-19 and the vast demand for efficient diagnosis leads us to focus on comparing different proposed architectures to researcher's valuable tools, future trends and public databases since this problematics are new.

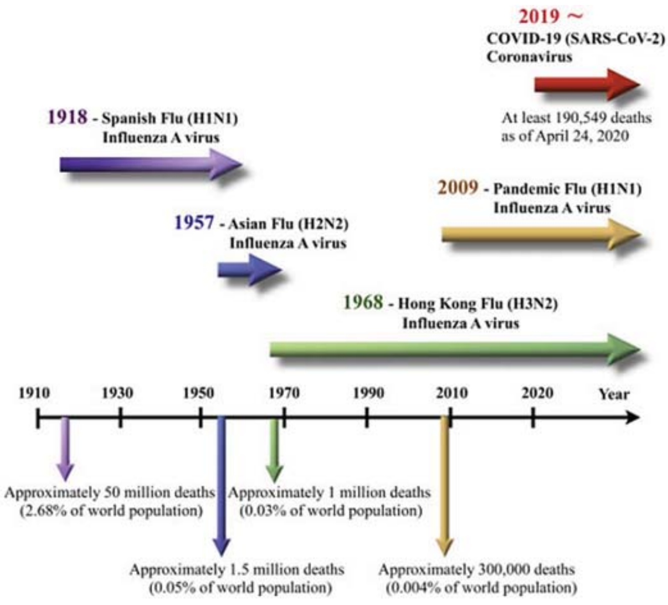

Fig. 1. A timeline of five pandemics since 1918 [1].

Computer vision is involved in the fight against COVID-19 pandemic. A valuable contribution was made range among three axes: diagnosis, prevention and treatment (figure2).

In this paper, we are mainly interested in the contribution of Machine learning and computer vision on diagnosis level contributions to detect coronavirus pneumonia.

The manuscript is organized as follows: we first present literature survey for diagnosis COVID-19 using X-Ray and CT images in Section 2. Then section 3 is dedicated to discussing some new trends in this domain. In Section 4, we describe metric evaluation and some available public databases. Conclusion and future directions can be found in Section 5.

II. LITERATURE SURVEY

This section summarize and compare some related works in COVID-19 detection. Table 1 synthesizes a set of selected approaches in the state of the overview; almost all approaches are based on deep learning architecture except [4].

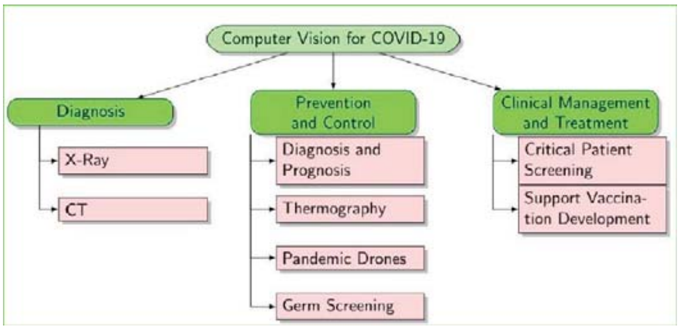

Fig. 2. A classification Computer Vision Approaches for COVUD-19 Control [3]

TABLE I. A SELECTION WORKS ON COVID-19 DETECTION

Ref.	Database	Classes	Approach	Performance
[5]	1,065 computed tomography images : 325 images pathogen-confirmed COVID-19 cases, 740 images viral pneumonia	2 classes : COVID-19 and typical viral pneumonia	Transfer learning neural network based on the Inception network used to distinguish between COVID-19 and other typical viral pneumonia	-total accuracy: 89.5% -specificity: 0.88 -sensitivity: 0.8
[8]	X-ray images: 53 confirmed COVID-19 5526 no-confirmed COVID-19 8066 Healthy	3 classes: COVID-19, No- confirmed, Healthy	Deep learning COVID-Net architecture made by : - combination of 1×1 convolutions, - depth-wise convolution, - residual modules	Accuracy 92.4%
[6]	123 frontal view X-rays [19] and to avoid the unbalanced problem they add 500 no-findings and 500 pneumonia class frontal chest X-ray images randomly from ChestX-ray8 database	- 2 classes: COVID-19 and No- confirmed -3 classes: COVID-19, No- confirmed, Pneumonia	DarkCovidNet architecture inspired by the DarkNet architecture (available at https://github.com/muhammedtalo/COVID-19)	accuracy: - 98.08% (2 classes) - 87.02% (3 classes)
[9]	X-ray images: 25 confirmed COVID-19 25 no-confirmed COVID-19	2 classes: COVID-19 and No- confirmed	ResNet50 plus SVM	Accuracy 95.38%
[10]	X-ray images: 50 confirmed COVID-19 50 no-confirmed	2 classes: COVID-19 and No- confirmed	Deep CNN ResNet-50	Accuracy 98%
[7]	170 X-ray images And 361 CT images of COVID-19 disease collected from 5 different datasets	2 classes: COVID-19 and No- confirmed	A simple CNN architecture and a modified AlexNet	Accuracy 94%
[11]	50 X-ray images 25 normal cases and 25 positive COVID-19 images	2 classes: normal cases and positive COVID-19 images	VGG19, DenseNet201, ResNetV2, InceptionV3, InceptionResNetV2, Xception and MobileNetV2	best accuracy 90.00% provided by VGG19 and DenseNet201
[4]	150 CT images belong the 53 infected cases [12] Image were patches with different sizes 16×16, 32×32, 48×48, 64×64	2 classes: normal cases and positive COVID-19 images	hand-crafted features fed an SVM classifier, hand-crafted features are: GLCM: Grey Level Co-occurrence Matrix), LDP: Local Directional Pattern , GLRLM: Grey Level Run Length Matrix, GLSZM: GreyLevel Size Zone Matrix, DWT Discrete Wavelet Transform	best accuracy 98.77% was provided by GLSZM features

Different Convolutional Neural Networks (CNN) models were experienced and provided a good identification. They achieved a recognition rates greater than 90% with two classes (confirmed and no-confirmed COVID-19) or three classes: confirmed COVID-19, No-confirmed and Healthy. However, when we add a typical viral pneumonia class the recognition rate drops significantly. This possibility is due to the similarities between confirmed COVID-19 a typical viral pneumonia both of which have close similar radiologic physiognomies [5, 6]. Compared to performance achieved by machine learning, two skilled radiologists achieved the accuracy of 55.8% in this context [5].

In Maghdid et al. [7], Authors proposed an approach based on deep learning and transfer learning for diagnosing COVID-19 pneumonia. They used to combine CNN architecture and a modified AlexNet. The best accuracy of 94 % was obtained using X-rays and CT scan images dataset.

In a study conducted by Barstugan et al. [4] provided an SVM classifier fed by hand-crafted features for COVID-19 classification. Experiments were performed using 150 CT images. Hand-crafted structural and global features were used such as Grey Level Co-occurrence Matrix, Local Directional Pattern, Grey Level Run Length Matrix, GreyLevel Size Zone Matrix, and Discrete Wavelet Transform. The best accuracy of 98.77% was obtained using GLSZM features.

III. NEW TRENDS

The COVID-19 pandemics proposed new challenges to the research community, (1) the rapid spread of COVID-19 require to find immediately a rapid solution. Mainly in new pandemics in which we do not have enough data to train a Machine learning system but we dispose a trained system in close syndrome: i.e. Pneumonia in COVID-19 and other typical viral pneumonia are different but shared some common characteristics [5]. At this level it is judicious to investigate how to use "stored back knowledge" gained while dealing with typical viral pneumonia and try to transfer the knowledge learned from the source domain whose examples are generic toward learning a classifier in the target domain containing few data as and almost different to target domain [13, 14]. In addition, transfer learning in COVID-19 remain interesting research trend because the SARS-CoV-2 virus is mutating during the pandemic and our trained system need to adapt the learned knowledge to this evolution (table II).

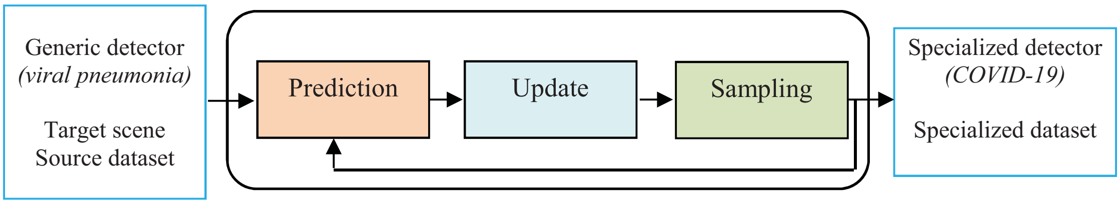

Fig. 3. Transfer learning system proposed by [13] based on SMC specialization approach

(2) Because the virus is extremely contagious, it spreads and continuously evolves in population. Urgently needs have been taken including social distancing and keeping population across the country in lockdown. In this context, governments across the world implemented regulations social distancing during the spread phase of pandemics. Computer vision systems can been deployed in these situation to ensure safety and prevent contamination due to short distancing. A valuable contribution at prevention level is to measure the distance between pedestrians in public places since many datasets are already available [14,15]. Moreover, a mask-wearing verification system can represent another interesting contribution since there is an available dataset. This dataset includes 1376 RGB facial images among them 690 are with mask on this link https://github.com/prajnasb/observations/tree/master/experiements/data.

(3) The other interesting trend is person identification in challenging situation when he is wearing a mask: bottom occlusions made by a mask can significantly change the appearance of a face and a trained face detector will fail to detect such faces [16].

IV. DATABASES

Since the outbreak of Covid-19 virus, researchers and Societies of Radiology are still working on the collection of CT and X-ray images from infected patients. Almost all available datasets are small and containing a limited number of X-ray or/and CT images.

Since in training phase require a large number of examples to learn intra classes variability. Almost all authors are used to collect images from different available small datasets to construct larger one.

This measure sound very interesting because the coronavirus is mutating and we identified distinctive genomes from different countries [17]. Therefore, the collection of images from different countries and sources is important to take into account the intravariability of its effects.

TABLE II. LIST OF GENOMES SEQUENCED BY DIFFERENT COUNTRIES [17]

Accession Number	Strain/Origin
MN988668	2019-nCoV WHU01
NC_045512	Wuhan-Hu-1
MN938384.1	2019-nCoV_HKU-SZ-002a_2020
MN975262.1	2019-nCoV_HKU-SZ-005b_2020
MN988713.1	2019-nCoV/USA-IL1/2020
MN994467.1	2019-nCoV/USA-CA1/2020
MN994468.1	2019-nCoV/USA-CA2/2020
MN997409.1	2019-nCoV/USA-AZ1/2020
MN985325.1	2019-nCoV/USA-WA1/2020
MT072688	SARS0CoV-2/61-TW/human/2020/NPL
MT106054	2019/nCoV/USA-TX1/2020
MT012098.1	SARS-CoV-2/human/IND/29/2020
MT050493.1	SARS-CoV-2/human/IND/166/2020

Alqudah [18] collected augmented X-ray Images for COVID-19 datasets. This dataset a result of the merger of two online available datasets, which are (https://github.com/ieee8023/covid-chestxray-dataset and https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia). The actual version 3 of the dataset contains two folders: the first one is contained by COVID-19 augmented images while Non-COVID-19 is not augmented; however, the other folder contains augmented images for both COVID-19 and Non-COVID-19.

Authors in [7] collected images from 5 different datasets of 170 X-ray images and 361 CT images of COVID-19 disease.

The Italian Society of Medical and Interventional Radiology COVID-19 makes available x-ray referenced images related to 68 patients (SIRM) COVID-19 DATABASE, References for each image is provided in metadata, the respective classes are annotated and case review (figure 4) [12].

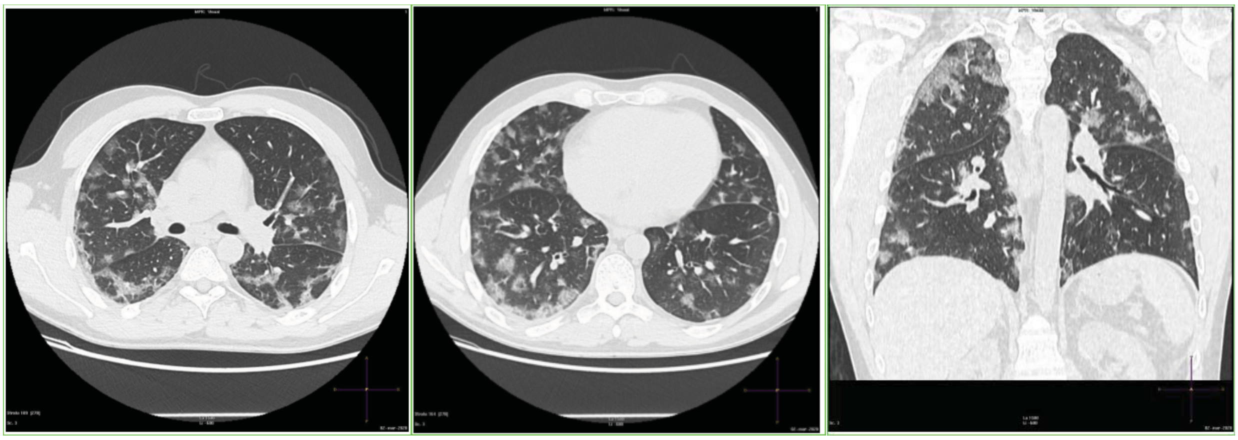

Fig. 4. A sample of COVID-19 positive images to a 45-year-old male patient with fever, cough. Respiratory failure (hypoxemia and hypocapnia). Leukopenia. Nasal swab positive for SARS-CoV-2. Case 4 from database [12].

TABLE III. TABLE I: AN OVERVIEW OF PUBLIC AVAILABLE DATA SETS

Data set	Description	Web link
[19]	123 frontal view X-rays tomography images	https://github.com/ieee8023/COVID-chestxray-dataset
[20]	219 COVID-19 positive images, 1341 normal images and 1345 viral pneumonia images.	https://www.kaggle.com/tawsifurrahman/covid19-radiography-database
[18]	69 images of lung x-ray of infected people with covid-19 and 79 lung x-ray images of a healthy person.	https://data.mendeley.com/datasets/2fxz4px6d8/4#folder-2eec69c7-9b6c-4864-b9d5-bd059e2dd24b
[12]	68 images of x-ray and CT of infected people with covid-19	https://www.sirm.org/en/category/articles/covid-19-database/
[21]	This is a dataset of 100 axial CT images from >40 patients with COVID-19	http://medicalsegmentation.com/covid19/
[22]	The COVID-CT-Dataset has 349 CT images from 216 patients	https://github.com/UCSD-AI4H/COVID-CT
[23]	CT images from 59 patients	https://www.bsti.org.uk/training-and-education/covid-19-bsti-imaging-database/

[24] Since SARS-CoV-2 virus attacks the lungs of infected people, the French Society of Radiology (SFR) announced on April 2, 2020 the creation of a French Imaging Database against Coronavirus (« FIDAC»). It indicates having recorded "6235 scanners out of 16762 (37%) chest scanners for the exploration of a possible attack by the coronavirus in one week", coming from 315 French centers already registered in the project, as well as Belgian, Swiss centers , Maghreb, Africa and others. "This project aims to quickly collect several thousand scan files made for suspected lung damage related to SARS-CoV-2". The database will be open until August 2020.

V. DISCUSSION AND CONCLUSION

This paper provides a survey of the recent advances in the literature review on the detection of outbreak Covid-19 virus. Reviewed paper is performed in the five last months. Many approaches are proposed using mainly deep architecture. I identified only one paper using handcraft features. However, there is no new contribution on machine Learning architecture almost all papers are trying to present a prompt solution to COVID-19. Researchers and Societies of Radiology are still working on the collection of CT and X-ray images from infected patients. Almost all available datasets are small and containing a limited number of X-ray or/and CT images. The overall performances shows acceptable score when dealing with binary classification or even adding a healthy class. However, when dealing with a multi-class classification including viral pneumonia images the performances drops significantly. That is mean that the COVID-19 shows the partially similar aspects of viral replication and pathogenesis with other pneumonia virus.

Future trends to how computer vision can response to urgent need to contribute in pandemics and to investigate many aspects of new viral replication and pathogenesis. First, we need to build a dataset suitable for training a Machine learning. Secondly. However, when we do not have enough data to train a Machine learning system but we dispose a trained system in close syndrome, it is judicious to investigate how to use "stored back knowledge" gained while dealing with typical viral pneumonia and try to transfer the knowledge learned from the source domain.

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