COVID-19 Detection with Non-Contact Sensing

Subjects: Others
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COVID-19 disease, caused by SARS-CoV-2, has resulted in a global pandemic recently. With no approved vaccination or treatment, governments around the world have issued guidance to their citizens to remain at home in efforts to control the spread of the disease. The goal of controlling the spread of the virus is to prevent strain on hospitals. Non-invasive methods can be used to detect the COVID-19 and assist healthcare workers in caring for COVID-19 patients. Early detection of the COVID-19 virus can allow for early isolation to prevent further spread.

Keywords: COVID-19 ; Population Health ; Sars-Cov-2 ; AI ; ML ; Disease diagnostics ; Sensing

1. Introduction

Non-contact sensing is the ability to detect information without direct contact with a subject. In terms of healthcare, non-contact can be used monitor the human body without devices physically touching the body. Non-contact techniques are considered highly valuable in dealing with a highly infectious disease such as COVID-19, as contact may contribute to the spread of disease. This is because healthcare workers will not need to make physical contact with patients to enable the monitoring of the patient. Using wearable devices can cause risks to healthcare workers as they will need to have physical contact with patients to attach the device. Despite precautions being undertaken such as wearing gloves and face masks, there will be lower risk if contact with patients can be successfully removed completely. Healthcare sensing technologies aim to collect information from a person which can be processed by Artificial Intelligence (AI) to provide decision support or directly analyzed by a clinician to diagnose a disease or monitor existing conditions.

The use of AI can help to relieve pressure on hospital staff while they work hard to manage resources during the global pandemic. Non-contact remote sensing technology can sense such healthcare markers without introducing anything to the body (e.g., wearable devices). Wearable devices can be uncomfortable for some which will entice users to remove the device and results in misplacement or damage [1]. The non-contact techniques can assist in the detection of COVID-19 and the care of patients suffering from COVID-19. This will allow for quick diagnosis and allow for healthcare professionals to make clearer judgements on the treatment of the patient and allow for quarantine action to be undertaken. Vital-sign monitoring can provide great assistance in the fight against COVID-19 for several reasons. These reasons include detection of irregular breathing patterns, which is a major symptom of COVID-19, but it can also monitor the health conditions of patients suffering with COVID-19. Although COVID-19 affects the respiratory system [2][3], it has also been shown to take effect on the cardiovascular system [4]. These non-contact methods can also monitor heartbeats and therefore provide a monitoring system of the patient cardiovascular system. It can be concluded that non-contact sensing that monitors these vital signs can be used to aid in the detection and treatment of COVID-19. Examples of non-contact techniques described in this paper include computed tomography (CT) scans, X-rays, Camera Technology, Ultrasound Technology, Radar Technology, Radio Frequency (RF) signal sensing Thermography and Terahertz. Table 1 details the advantages and disadvantages of each technique. These methods can be used with AI to help give diagnosis. Currently testing for COVID-19 is done by doing a swab test. The results of these tests are currently returned the next day, but may be delayed by up to 72 h [5].

Table 1. Summary of Non-Invasive Techniques.

Method	Accuracy	Cost	Time for Measurement	Time for Results	Harm to Body	Skills of Operators	Possibility of AI
CT	**High**	**High**	**Moderate**	**Fast**	**Low**	**High**	**Yes**
X-Ray	**High**	**High**	**Moderate**	**Fast**	**Low**	**High**	**Yes**
Camera	**High**	**Medium**	**Real Time**	**Real Time**	**None**	**Medium**	**Yes**
Ultrasound	**High**	**Medium/High**	**Moderate**	**Medium**	**Low**	**High**	**Yes**

Method	Accuracy	Cost	Time for Measurement	Time for Results	Harm to Body	Skills of Operators	Possibility of AI
Radar	High	High	Real Time	Real Time	None	Medium	Yes
RF	High	Low	Real Time	Real Time	None	Low	Yes
IR Thermo	High	Medium	Fast	Fast	None	High	Yes
THz	High	Medium	Fast	Fast	None	High	Yes

2. Main Non-Invasive Techniques.

2.1. CT Scanning

An example of a non-invasive technique to detect COVID-19 is using computed tomography (CT) scans [47]. This process involves taking several X-ray images of a person's chest to create a 3D image of the lungs. The images can be reviewed by professionals to look for abnormalities in the lungs. The professionals are trained to review the images and they can tell from the captured image what is normal tissue of the lungs and which part of the lungs look to be infected. Infection can lead to inflammation of the tissue which will be present in the CT images. This method has been used to look for pneumonia which is an infection of the lungs which can affect the lungs similarly to how COVID-19 has an effect on the lungs of a patient. The activity of COVID-19 in the lungs is more prominent in the later stages of infection; however, ultimately, research has shown that CT scans showed a sensitivity of 86–98% [6].

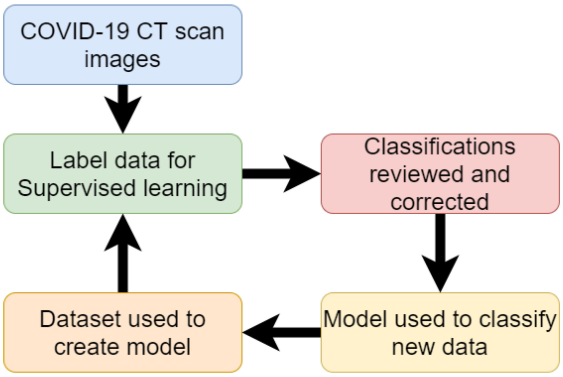

Figure 1. Flow chart of work for detection of COVID-19 from CT scan (Reproduced from [7]).

2.2. X-Ray Imaging

X-ray images can provide an analysis of the health of the lungs and are used frequently to diagnose pneumonia [8]. The same strategy is used with X-ray images of the lungs to display the visual indicators of COVID-19 [9][10]. This is due to the similarities between COVID-19 and pneumonia as diseases that take an effect on the respiratory system. Similar to CT scans, X-ray equipment is also expensive and requires professionals to analyze the X-ray image.

The paper entitled "Automatic detection of coronavirus disease (COVID-19) using x-ray images and deep convolutional neural networks" used X-ray images taken of COVID-19-infected lungs and patients with lungs that were non-infected with COVID-19 to create a data set of x-ray images which was then used to predict COVID-19 automatically in patients. The X-ray images are passed into a ResNet-50 Convolutional Neural Network (CNN) which successfully obtained results of 98% accuracy in the differentiating between COVID-19 infected X-ray images and the non-infected x-ray images [11].

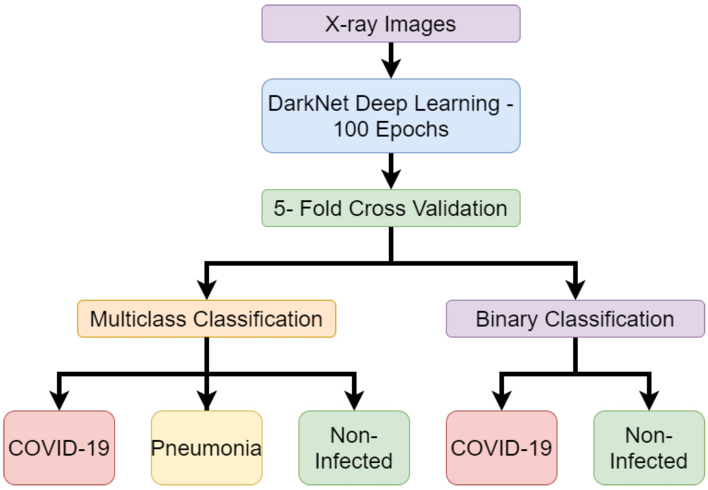

Figure 4. Flow chart of work for detection of COVID-19 from X-ray images (Reproduced from [12]).

2.3. Camera Technology

Camera technology can be used to provide non-contact sensing by observing the chest movements of an individual [13] [14]. This can be achieved by capturing video footage of movements of the chest or, in the case of depth cameras, they are able to calculate depth by using two sensors with a known range [14]. The information captured using camera technology can be used provide assistance in the detection of COVID-19 as one of the symptoms of the disease includes an increase in the breathing rate of patients.

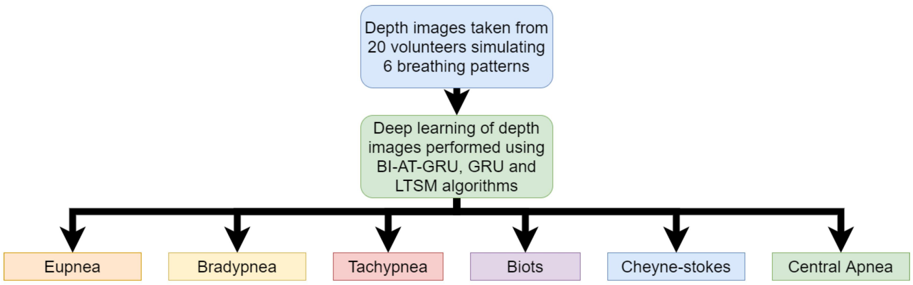

Figure 5. Flow chart of work for detection of COVID-19 from Depth Camera Image (Reproduced from [15]).

2.4. Ultrasound Technology

Ultrasound technology can be applied to detect respiratory failure of the lungs. An ultrasound machine is a device that uses high-frequency sound waves to image body movements [16]. The sound waves bounce off different parts of the body which create echoes that are detected by the probe and used to create a moving image. Lung ultrasounds have seen great development in recent years [17]. The use of ultrasound technology can be used in the detection of COVID-19 in a non-contact method where the risk of healthcare professionals becoming infected from patients can be decreased [18][19]. Ultrasound technology becomes contactless by using an ultrasound transmitter and receiver. Respiratory movement can then take place between the transmitter and receiver and creates a Doppler affect. This can then be used to create a contactless breathing monitor [20][21][22]. Ultrasound technology can be performed using smartphones for the signal and processing of ultrasound images in a portable setting [23]. The disadvantage of ultrasound technology is that patients must prepare themselves before an ultrasound can effectively create an image of the body [24]. This preparation can include not eating for a few hours before.

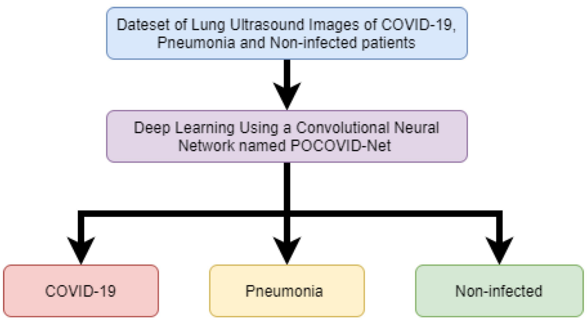

Figure 6. Flow chart of work for detection of COVID-19 from Ultrasound Technology (Reproduced from [25]).

2.5. Radar Technology

Radar technology can be used to monitor the respiratory system within a home environment and provide a quick response if abnormalities are found, which suggests COVID-19 being present. Radar systems use frequency-modulated continuous wave (FMCW) to observe the Doppler effect when a person moves [26][27][28][29]. This can be used to monitor the fine movements associated with breathing. This is achieved by using the images captured by the radar systems then applying AI to classify the images. AI models can be used to give real-time classification on new images [30][31][32]. Research done shows that radar technology can achieve 94% accuracy for the detection of breathing rates and 80% accuracy for heart-rate detection [3][33][34]. The Israeli military force has made use of radar systems for monitoring the vital signs of COVID-19 patients. The goal of using this method is to prevent medical staff from becoming infected while caring for patients [35][36]. Tachypnea is a symptom of COVID-19 and can be detected in a patient by using radar sensing technology [21][27][37]. Using radar technology to monitor vital signs can provide non-interference monitoring; however the disadvantage of radar systems is that it has high power requirements and the technology comes at a high cost [38].

3. Conclusions

The works listed have shown that COVID-19 can be detected using contactless techniques. Techniques such as CT scans and X-ray imaging provide high accuracy and high image resolution, but the cost of the equipment is high and not portable. Thermal and depth camera technology has been used to detect breathing patterns, which is associated with COVID-19 symptoms. However, these cameras are expensive and need to be operated by a professional. Radar technology is also able to detect breathing patterns but carries disadvantages of high operating expenses and capital expenditures. RF signals provide low cost and high accuracy as compared with other non-invasive technologies. The technologies can work on AI which can allow for skilled professionals to be available to assist in other areas of healthcare during the pandemic. The non-contact methods also protect healthcare workers from contracting the disease. The future direction of non-contact detection should look at the use of RF systems as the cost is cheap and it is easier to implement within a home environment in comparison to other methods. This gives the advantage of allowing the users to remain within isolation.

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