Artificial Intelligence based Multi-sensor COVID-19 Screening Framework

Inteligencia artificial para el marco de detección COVID-19 multisensorial

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Keywords

Convolutional Neural Network; COVID-19 detection; Deep Learning; Multi-sensor.

Abstract

Many countries are struggling for COVID-19 screening resources which arises the need for automatic and low-cost diagnosis systems which can help to diagnose and a large number of tests can be conducted rapidly. Instead of relying on one single method, artificial intelligence and multiple sensors based approaches can be used to decide the prediction of the health condition of the patient. Temperature, oxygen saturation level, chest X-ray and cough sound can be analyzed for the rapid screening. The multi-sensor approach is more reliable and a person can be analyzed in multiple feature dimensions. Deep learning models can be trained with multiple chest x-ray images belonging to different categories to different health conditions i.e. healthy, COVID-19 positive, pneumonia, tuberculosis, etc. The deep learning model will extract the features from the input images and based on that test images will be classified into different categories. Similarly, cough sound and short talk can be trained on a convolutional neural network and after proper training, input voice samples can be differentiated into different categories. Artificial based approaches can help to develop a system to work efficiently at a low cost.

Palabras clave

Red neuronal convolucional; detección COVID-19; aprendizaje profundo; sensor múltiple.

Resumen

Muchos países están luchando por los recursos de detección de COVID-19, lo que plantea la necesidad de sistemas de diagnóstico automáticos y de bajo costo que puedan ayudar a diagnosticar y que se pueda realizar una gran cantidad de pruebas rápidamente. En lugar de depender de un solo método, se pueden utilizar la inteligencia artificial y enfoques basados en múltiples sensores para decidir la predicción del estado de salud del paciente. La temperatura, el nivel de saturación de oxígeno, la radiografía de tórax y el sonido de la tos se pueden analizar para la detección rápida. El enfoque de múltiples sensores es más confiable y una persona puede ser analizada en múltiples dimensiones de características. Los modelos de aprendizaje profundo se pueden entrenar con múltiples imágenes de rayos X de tórax que pertenecen a diferentes categorías para diferentes condiciones de salud, es decir, saludable, COVID-19 positivo, neumonía, tuberculosis, etc. El modelo de aprendizaje profundo extraerá las características de las imágenes de entrada y en base a eso, las imágenes de prueba se clasificarán en diferentes categorías. De manera similar, el sonido de la tos y la conversación corta se pueden entrenar en una red neuronal convolucional y, después de un entrenamiento adecuado, las muestras de voz de entrada se pueden diferenciar en diferentes categorías. Los enfoques basados en materiales artificiales pueden ayudar a desarrollar un sistema que funcione de manera eficiente a bajo costo.

Introduction

Coronavirus Disease 2019 commonly known as COVID-19 is a respiratory disease mainly caused due to the SARS-COV-2 coronavirus. This virus is a kind of contagious spherical positive-sense single-stranded RNA virus, which affects the respiratory system of the body. Spikes of the protein emerging out of the surface and construct a crown-like structure can be seen with the help of an electron microscope. Fever, cough, breathlessness, and tiredness are some of the common symptoms among the patients of COVID-19. The severity level can be range from mild to severe having chances of multi-organ failure, pneumonia, cardiovascular complications, and death in some cases. These issues arise the concern due to this pandemic due to viral infection. COVID-19 disease emerged as a major health issue this year and the number of COVID-19 affected patients are significantly increasing day by day which arises the need for countermeasures to control the spread and rapid diagnostic systems are to be developed. Thus, suitable approaches should be determined in the direction of solutions for COVID-19 related problems and extract the proper information from the large volume of data gathered associated with this.

As on 22 July, more than 14 million confirmed cases of COVID-19 cases are reported from 216 countries and other territories [1]. COVID-19 caused more 0.6 million deaths worldwide. Lots of work is going on to develop the vaccine to fight with this pandemic, but still, no specific vaccine or treatment is available. In parallel, COVID-19 cases are increasing day by day. Many attempts have been made to develop a rapid and accurate detection method to diagnose infected patients in their early stages of infection. Thus, artificial intelligence can play an important role in that direction.

In most of the clinical screening COVID-19 patients, Reverse Transcription Polymerase chain reaction (RT-PCR) is considered as a reference method and prominently used based on the analysis of respiratory samples [2]. These medical and pathological ways to detect the COVID-19 take longer time and testing facility is limited, laborious, and has high cost as well. Hence, it causes a delay in the disease prevention measures and various countries are facing difficulties with delay in test results which sometimes results in the wrong number of COVID-19 positive cases.

A lot of research is undergoing to control the spread of COVID-19 and develop screening devices. A hybrid COVID-19 detection neural network is developed where improved marine predator algorithm for segmentation of chest X-ray image [3]. Built-in smartphone sensor-based application is prepared for abnormality detection in CT scan images. An unsupervised pleural line localization and detection method from a lung ultrasound image is proposed in [4]. Support vector machines, Viterbi algorithm, and Hidden Markov model were used for evaluation of the health condition of the person.

Different machine learning methods were also analyzed for prediction of the COVID-19 affected population [5]. Exponential smoothing works best among those four machine learning models for the statistical dataset [6] of COVID-19 affected population. A contactless patient positioning system using different components such as automated positioning, calibration, and view synthesis routines is developed and robust dynamic fusion algorithm to develop 3-D model of the patient's body [7]. A secured fog-based communication architecture was designed for the timely monitoring of the patients [8]. Similarly, COVID-19 spreaders identification method is presented using the economic and socio-cultural characteristics relating to number of death and infections [9].

The main contribution of this paper is that the multisensory COVID-19 detection framework is proposed. The multi-sensor analysis consists of four steps of testing-temperature, oxygen saturation, chest X-ray, and cough sound. Different chest X-ray and cough sounds of different persons are collected having different health conditions. Two deep learning models will be trained with chest X-ray and cough sound each. The trained model after a certain number of iterations and the moment when validation loss will be lower and validation accuracy will be higher, training will be halted. The trained models will be tested on different parameters to get the actual performance of the model. Once performance outcomes reach a satisfactory level, it will be deployed to test new images or sounds. The proposed artificial intelligence based framework can be used to separate potentially COVID-19 infected patients.

Section II will discuss the methodology of different sensors and their working to implement the COVID-19 detection framework. Section III is the conclusion and future scope is discussed.

Proposed Methodology

Relying on a single method for screening of COVID-19 cannot be the perfect solution. Some are accurate but are time-consuming at the same time also. At this time of pandemic where there is need of large-scale and fast screening, a screening framework is required which can assure the confidence in screening procedures using a multi-dimensional approach. Artificial intelligence integrated with the multiple sensors can help to deal with this problem of COVID-19 pandemic. The proposed methodology is composed of four steps, which is represented by the block diagram as shown in Fig. 1

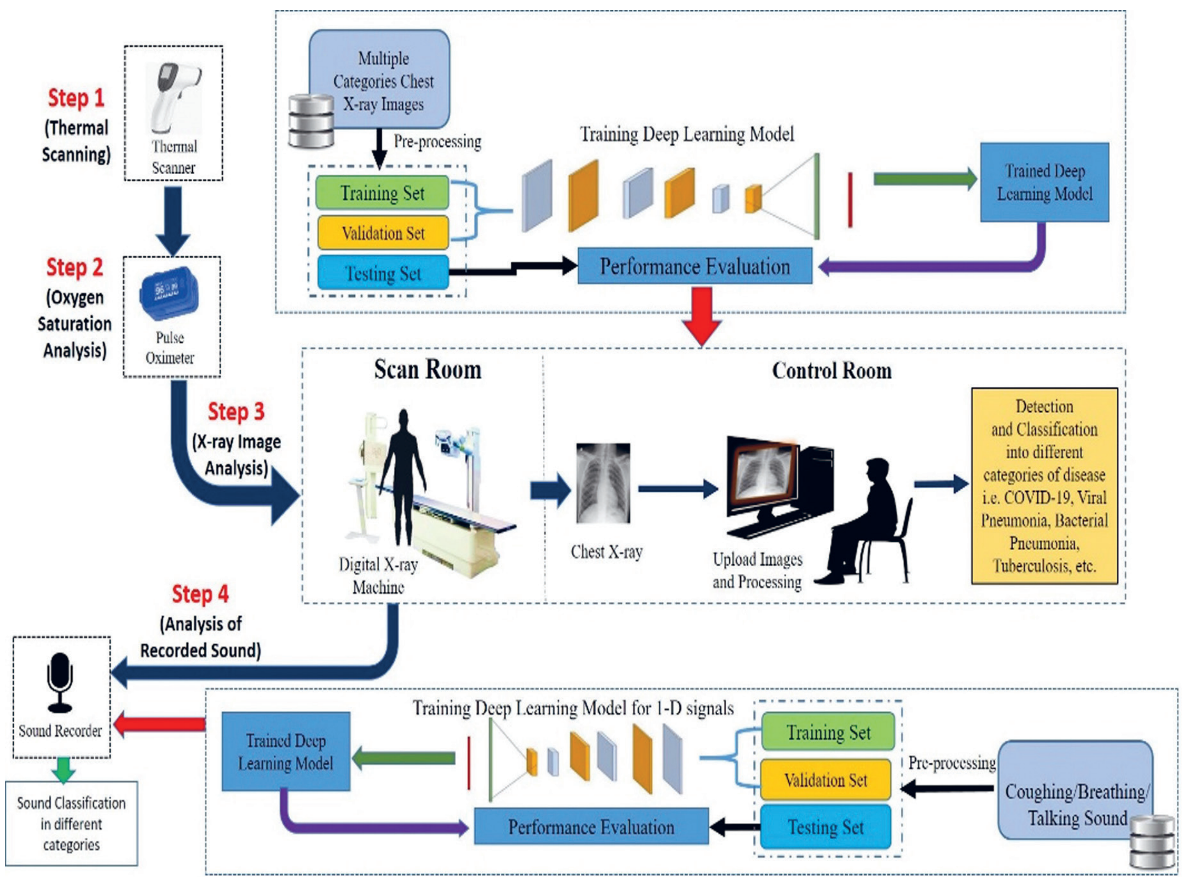

Figure 1. Proposed COVID-19 screening framework

Step-1 (Temperature Analysis)

The common symptoms of COVID-19 include the fever kind of symptoms. Therefore, to differentiate those people having abnormal temperature from normal people, a temperature scanner is to be placed at entrance of checking system. The temperature scanning can be done manually by considering proper protective measures. The alternate way is to use the automatic temperature using the face detector based positioning of the sensor, as shown in Fig. 2. The face is searched in given input frame and once face is detected, position of servo motor attached to thermal scanner is adjusted according to the obtained coordinates of forehead.

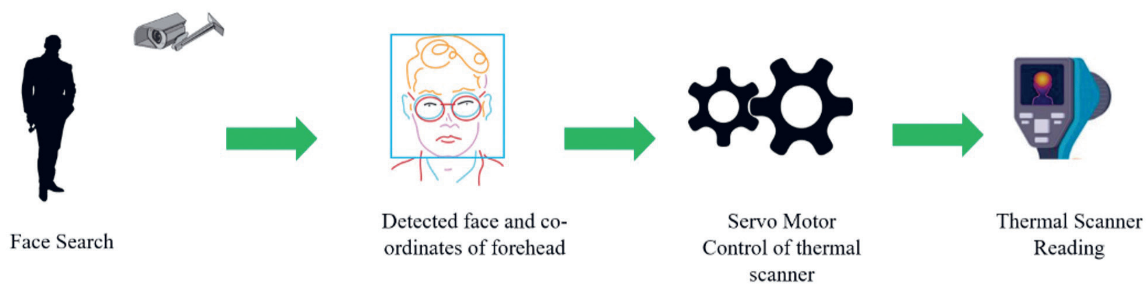

Figure 2. Face position estimation and temperature scanning.

Temperature sensing and decision equations on the basis of temperature of forehead, $T_{forehead}$, are given by

$$\text{Normal: } T_{forehead} \leq 99^{o}F \tag{1}$$

$$\text{Mild Sympton:} 99^{o}F < T_{forehead} \leq 100^{o}F \tag{2}$$

$$\text{Severe Sympton: } T_{forehead} > 100^{o}F \tag{3}$$

If the forehead temperature, $T_{forehead} > 99°F$, it will warn it as mild symptom. In such cases, if the temperature goes below the 99°F or shows temperature-decaying pattern after few time or taking some rest, it will be treated as normal condition. Otherwise, it will give temperature related warning and advise for treatment and health checkup.

Step-2 (Oxygen Saturation Analysys)

An oximeter is a device, which is used to check the oxygen saturation level of the blood and can be checked while taking input from the fingertips. The pulse oximeter has seen significant advancement in the field of the clinical monitoring system. It is photometric technology-based non-invasive device that is used to measure the heart rate and blood oxygen saturation level (SpO2). The block diagram of oximeter and its working is given in Fig. 3. The difference in the light absorbed by the tissues for two lights of different wavelengths is used to measure the oxygen saturation level of the blood. Wavelengths of light should be chosen properly such that they can give a large difference in the extinction coefficients of oxyhemoglobin and deoxyhemoglobin. Thus, red (660 nm wavelength) and near-infrared (940 nm wavelength) light are good choice for the same. Based on the study in [10], below the 92% oxygen saturation level is considered as more likely to be admitted in the hospital in an intensive care unit.

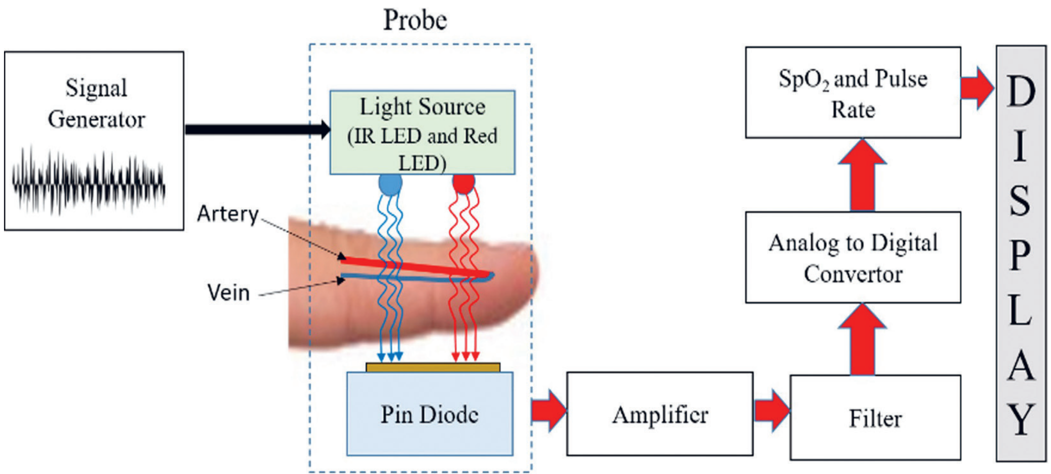

Figure 3. Pulse Oximeter components and working.

Similar to the temperature sensor, there are three condition for different oxygen saturation level, Osat as given by the equations:

$$\text{Normal: } O_{sat} > 92\% \tag{4}$$

$$\text{Mild Sympton:} 90\% < O_{sat} \leq 92\% \tag{5}$$

$$\text{Critical: } O_{sat} < 90\% \tag{6}$$

Person whose oxygen saturation is below 90% need to be admitted in the hospital immediately and to be retain in proper care.

Step-3 (Chest X-ray Analysis)

As the COVID-19 is a kind of respiratory disease, many symptoms or abnormal changes can be seen in the chest X-ray of the person infected with this disease. Some asymptomatic cases where temperature and other parameters are measured as normal can be detected with the help of analysis of chest X-ray. To make such kinds of decisions and analysis expert radiologists are required. But the ratio of the expert radiologists in the larger population is very less, thus artificial intelligence-based methods made for object detection and classification such VGG-16 [11], VGG-19 [12], YOLO, Capsule Networks can be trained with the large volume of chest X-ray image data having the labels provided by the expert radiologists. The screening system can be trained with multiple classes of respiratory diseases such as viral pneumonia, bacterial pneumonia, tuberculosis and SARS for multi-classification of diseases based on chest x-ray images. In case of less availability of the labeled dataset, a chest X-ray image scan be augmented with the multiple numbers of traditional techniques such as rotation, scaling, shear, illumination variation, noise induction, etc. More accuracy can be achieved with the COVID-19 positive and negative patients, so that system can extract better features to discriminate between two classes.

The chest x-ray dataset of COVID-19 is collected from the online dataset from multiple countries [13]. 1000 number of chest X-ray images from each class of healthy and pneumonia affected people is also collected [14]. The dataset is divided in training, validation and testing set in the ration of 14:3:3 respectively, as given in Table 1.

Table 1. Dataset description of chest X-ray images.

Category	Dataset	Training Set	Validation Set	Testing Set
COVID-19	237	167	35	35
Pneumonia	1000	700	150	150
Healthy	1000	700	150	150
Total	2237	1567	335	335

The dataset is trained on two deep learning models namely, VGG-16 and VGG-19. The training parameters are as follows in Table 2.

Table 2. Training parameters for deep learning models.

Parameters	Value
Epoch	1000
Padding	'same'
Learning rate	0.001
Momentum	0.90
Batch size	32
Dropout rate	0.2-0.5

VGG-16 and VGG-19 models are trained for 1000 number of epochs and best model having lower validation loss is saved. These models are evaluated on the unseen test set of chest X-ray images. The output confusion matrix is shown in Fig. 4.

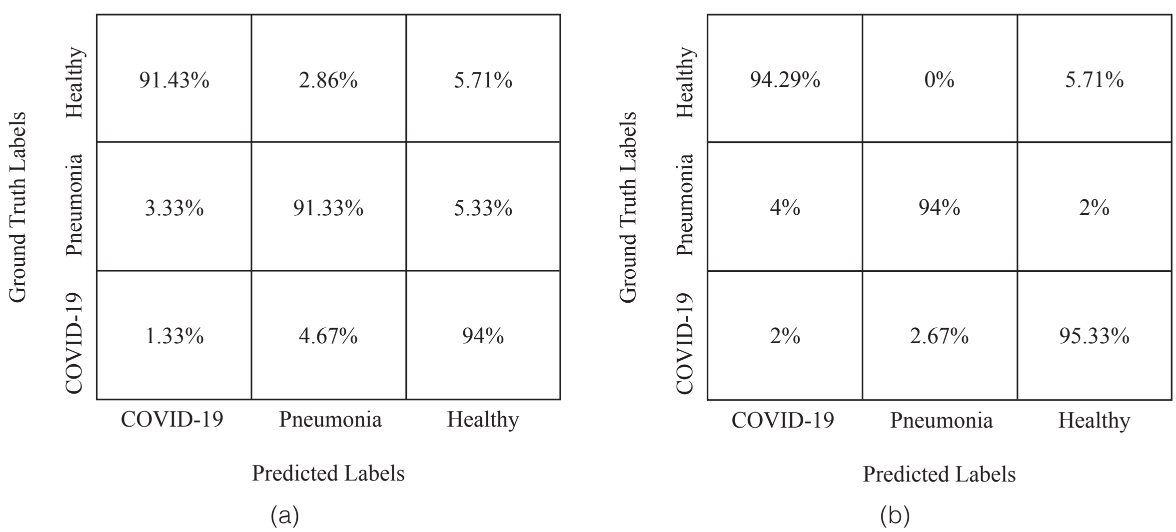

Figure 4. Confusion Matrices, (a) VGG-16, (b) VGG-19.

Confusion matrix is showing the high discrimination capability of trained model. VGG-19 model is showing good classification results for different classes. The overall classification accuracy for VGG-16 and VGG-19 is achieved as 92.53% and 96.12%, respectively.

Generative Adversarial Networks (GAN) can also be equipped to generate similar images from a limited image dataset [15]. GAN is equipped with two neural networks that compare the results with one another to generate new synthetic images that can be used to train the deep learning along with the original images, as shown in Fig. 5.

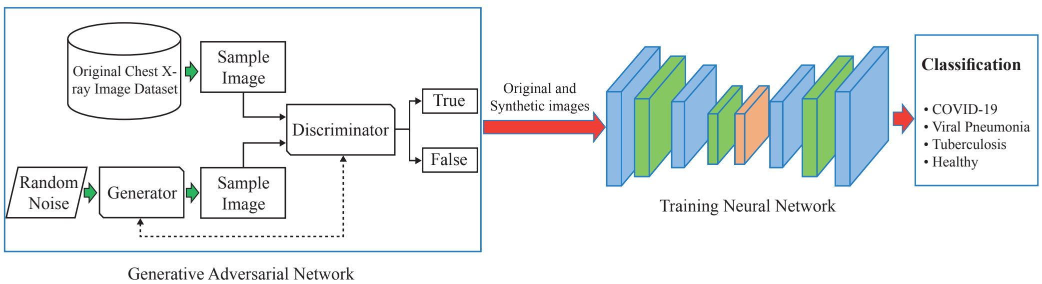

Figure 5. GAN generated trained data and training network.

Step-4 (Audio Signal Analysis)

Step 4 is an advanced step in COVID-19 screening. The main challenge is to get a proper dataset of audio samples from the people belonging to different classes i.e. healthy, tuberculosis, COVID-19, dry cough, etc. Voice or 1-D data sample will be recorded while a person is coughing, talking, breathing, etc. Anything that affects the respiratory system of the body, shows the impact in the voice of that person. These signals will be properly analyzed and the part of the signals not belonging to the required frequency range will be neglected. After having pre-processing, the signals will be used to train the convolutional neural network for multiple iterations. Training will try to extract different voice parameters and train them in different classes according to the resemblance. When the validation loss is lowered and accuracy will be intensified, training will be halted and the performance of the trained model will be analyzed based on the multiple parameters. Signal augmentation can also be applied before training of the neural network in cases where data is limited.

Conclusions

Different sensor and artificial intelligence-based framework is proposed in this paper which can be implemented for automatic and rapid screening of COVID-19. Hence, more cases can be traced easily and can be implemented anywhere at low cost with limited resources. The proposed framework test temperature, oxygen saturation level, chest X-ray, and voice samples of the person and analyzed all the samples and person having the symptoms or any abnormality can be differentiated from the healthy persons. The system is composed of four steps and all the steps analyze different parameters and all are time efficient. VGG-16 and VGG-19 models trained on chest X-ray images of different classes gives overall accuracy of 92.53% and 96.12%, respectively. The proposed framework can help to control the spread of COVID-19 by detecting the COVID-19 affected patients and verifying with multiple sensor-based methods. Portable X-ray machine is easily available but needed a space to install, thus the installation needs to deployed at the higher sensitive areas like airports, clinics etc. The artificially intelligent based framework can be helpful in getting faster result to diagnose potentially COVID-19 infected people.

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