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Chapter 5

Non-contact measurement system for COVID-19 vital signs to aid mass screening—An alternate approach

Vijay Jeyakumar, K. Nirmala and Sachin G. Sarate

Department of Biomedical Engineering, Sri Sivasubramaniya Nadar College of Engineering, Chennai, India

5.1 Introduction

The world is seeing an outbreak of a big pandemic. The record of events that lead to the available information about this disease goes like this. A sudden appearance of a large number of cases with lower respiratory tract infections with an unknown disease was detected in Wuhan city. This was reported to the World Health Organization (WHO) country office in China. Wuhan is the largest metropolitan area in China's Hubei province. The beginning of symptomatic individuals of this disease can be traced through published literature to the start of December 2019. The earlier cases were classified as "pneumonia of unknown etiology" because the causative agent was unidentified. The number of cases was 29. The Chinese Centers for Disease Control and Prevention (CDC) and the local CDCs ran a program to investigate this event. They attributed the etiology of this disease to a new coronavirus. The Director-General of WHO announced on February 11, 2020, that the disease caused by this new virus was coronavirus disease 2019 and an acronym COVID-19 was coined. Severe Acute RAR Respiratory Syndrome Coronavirus (SARS-CoV) and Middle East Respiratory Syndrome Coronavirus (MERS-CoV) are the two other CoV epidemics that have occurred in the past 20 years. The former one had a fatality rate of 9.6% with about 8000 cases and 800 deaths and the later one began in Saudi Arabia, which had a fatality rate of 35% with about 2500 cases and 800 deaths.

The virus has spread globally in a very short period as it is very contagious. The WHO declared it as Public Health Emergency of International Concern as it had disseminated to 18 countries. Out of these 18, four countries had reported human to human transmission. This declaration was done on January 30, 2020. On February 26, 2020, the first case of disease, which was not related to China, was recorded in the United States.

The name given to the virus was 2019-nCoV in the initial stage. The International Committee on Taxonomy of Viruses gave a new name to it—the SARS-CoV-2 virus. This was done because the virus is similar to the one that caused the SARS outbreak (SARS-CoVs).

This virus belongs to a large family of viruses that have a single-stranded RNA. They can be isolated from a varied number of animal species. This family of viruses has become the dominant pathogen of looming respiratory disease epidemics. These viruses can shift between species and can cause diseases like mild common cold to more harsh diseases. The dynamics of SARS Cov-2 are not known exactly and it is being speculated that it also has an animal origin like SARS-CoV, which came from Himalayan palm civet and MERS-CoV, which came from camels to humans.

The introduction to COVID-19 is discussed in section 5.1 followed by the global scenarios of COVID-19 in section 5.2 of this chapter. The various measurement tools and testing protocols are briefed in section 5.3. The non-contact approach to physiological measurement, the proposed methodology and its experimental results are discussed in section 5.4.

5.2 COVID-19 global scenarios

On February 28, 2020, the WHO raised the threat to the COVID-19 epidemic to "very high." On March 11, 2020, the disease was declared as pandemic because the number of cases outside China had increased 13 times. Around 114 countries were involved, and the number of cases crossed 118,000.

It has been estimated that strict shutdowns at the beginning of the disease would have saved 3 million lives across 11 European countries. All over the world, governments are working hard to establish measures to stop the effects. To reduce the impact of the threat, health organizations are streamlining the flow of information and issuing directives and guidelines. Scientists all over the world are working hard to know the mechanism of transmission, the clinical picture, new ways to diagnose the disease, its prevention, and are building new treatment protocols. It is still uncertain as to when this pandemic will reach its peak.

5.2.1 Infections, recovery and mortality rate

Even until now, the treatment methods are only of supportive form. The best weapon is prevention with a motive to reduce human to human transmission in the community. It was seen that the cause of the reduction in cases in China was the implementation of aggressive measures to isolate individuals. The disease had spread to Europe from China. The disease spread in Italy, started in the northern region and then throughout the country. It was a testing time for the health system in Italy. Humongous efforts were taken by political and health authorities.

The disease then spread to the United States very quickly. Afterward, the COVID-19 quickly crossed the ocean and as of August 15, 2020, about 21,487,828 cases (with 766,027 deaths) have been recorded in the United States, whereas Brazil with more than 3,282,101 cases and about 106,608 deaths is the most affected state in South America and the second in the world after the United States. India has become the third most affected country with 2,587,461 cases and 50,080 death cases. Across the globe, the total number of COVID-19 affected (21,487,282), recovered (14,243,436), and death (766,027) cases are increasing on an hourly basis.

However, the lethality rate of this disease has been seen to be significantly less than the other two Co-V diseases. But the spread of the SARS-CoV-2 virus across the continents is much faster than any other viruses before. Due to previous underlying conditions like diabetes and hypertension, the estimate says that about one in five individuals could be at risk worldwide.

5.2.2 Economy and environmental impacts

Migrant workers are involved in jobs that are avoided by urban natives. Due to poverty, migrant workers are vulnerable to measures like a sudden lockdown. During the lockdown in India, it was observed that because of being excluded in urban society, migrant workers did not have access to social security programs and healthcare. The sudden lockdown imposed upon the country made many migrant workers to be stranded in different cities and those who were traveling became grounded at stations or state and district borders.

A large number of these workers had to walk to reach their home villages due to lack of public transport. Even after reaching home, they were seen as a risk by the locals reported by R.B. Bhagat, Reshmi, Sahoo, Roy, and Govil (2020). A study made on the effect of COVID-19 on freight market dynamics in Germany used correlation and regression analysis and found out that the growth of transport volume was influenced by COVID-19, depending on the number of new cases and the number of deaths per day as observed by Dominic Loske (2020).

A review by Nicolaa et al. (2020) studied the impact of COVID-19 on various sectors like agriculture, petroleum and oil, manufacturing and industry, education, finance, healthcare and pharmaceutical, hospitality, real estate and housing, sports, information technology, media, research, and development as well as food sector. They also speculated on the response given by Europe, the United Kingdom, the United States, China, and Japan. They observed that unemployment was caused because of measures taken by various countries like social distancing, self-isolation, and restriction of travel. The demand for commodities and manufactured products has been reduced a lot. However, there is a significant increase in the need for medical supplies. Because of the panic buying and stockpiling of food products, the food sector is also facing an increase in demand.

One study demonstrated the use of a linear input – output model to make an estimate of unemployment caused in India due to COVID-19. This study observed that the Indian economy will lose a significant amount of its GDP, around 10%-31%. It was also observed in this study that the daily supply of power from coal-fired power plants reduced by 26% and the CO₂ emissions were also reduced correspondingly to about 15–65 MtCO₂. The emission requirements imposed on coal-fired power plants will further harm the sector, suggests the analysis.

5.3 Measurement and testing protocols of COVID-19

The advent of a new virus means there is only a poor knowledge of transmission mechanisms, immunity, seriousness, clinical manifestations, and comorbidity for infection. To address the new virus, the WHO has launched a global initiative to allow any country in any resource setting to collect rapidly robust data on key epidemiological parameters to identify, respond to, and monitor the COVID-19 pandemic. These protocols are designed to collect and share data quickly and systematically in a manner that enables the collection, tabulation, and analysis across various global settings. WHO also developed several standardized investigation protocols in collaboration with technical partners, called the World Health Organization (WHO), 2020 WHO Unity Studies that includes a mixture of serological and molecular tests. The widespread adoption of Unity protocols in more than 90 countries illustrates their effectiveness in improving decision-making across countries to implement or lift effective public health and social strategy to prevent and manage COVID-19 infection.

The testing protocols framed by the WHO are

- **1.** Population-based age-stratified seroepidemiological investigation for the general population.
- **2.** The first few COVID-19 X cases and contacts transmission investigation protocol (FFX).
- 3. Household transmission of COVID-19.
- 4. Assessment of COVID-19 risk factors among health workers.
- 5. Protocol for a case study control.
- **6.** Schools and other educational institutions transmission investigation protocol for COVID-19.
- 7. Surface sampling of COVID-19 virus.

5.3.1 Measurement methods

Diagnosis is based, as with other respiratory viruses, on two major components: clinical indications such as fever, nausea, dry cough, shortness of breath, and gastrointestinal symptoms. The procedures used for paraclinical diagnosis range from polymerase chain reaction (PCR) to computed tomography (C.T.) as reported by Longb et al. (2020) and Kumari et al. (2020). A fast and reliable diagnosis is in high demand in such a pandemic situation. There are two key populations at higher risk of acquiring a severe illness, including the elderly and those with existing chronic health problems such as diabetes mellitus, obesity, cardiorespiratory disorders, chronic liver diseases, and renal failure. A study was carried out to find the relationship between gender and transmission type in the patients by R. Kumari et al. (2020) and Bhatnagar et al. (2020). Cancer patients and those with immunosuppressive medications as well as pregnant women also have a high chance of transmitting severe illnesses when infected. Current research suggests that nausea, fatigue, cough, and productive cough were the most frequently reported symptoms in COVID-19 patients as seen by V. Singh et al. (2020) and Jieyun Zhu et al. (2020). In these patients, important physiological measurements include respiratory rate, oxygen saturation, heart rate (HR), blood pressure, temperature, level of consciousness using the Glasgow Coma Scale, pain score, and urine production. In the next section, we will discuss the diagnostic tools deployed to help manage the outbreak. Two major categories of diagnostic tools include pathophysiological tools and respiratory assessment tools.

5.3.1.1 Pathophysiological tools

In this method, suspected cases should be tested for confirming the presence of the virus with nucleic acid amplification tests (NAAT), such as reverse transcription polymerase chain reaction (RT-PCR). Infection with laboratory-confirmed SARS-CoV-2 requires real-time detection of viral nucleic acid in samples of the respiratory tract using RT-PCR assay. In the case of ambulatory patients, the samples are collected from the nasopharyngeal and oropharyngeal tract using a swab. Whereas the patient with more severe respiratory conditions sputum from the lower respiratory tract and the lavage from the endotracheal aspirate or bronchoalveolar are collected and tested. After the collection of the sample for virus detection, it should be ensured that it reaches the laboratory as soon as possible. The collected samples can be stored and transported at $2-8^{\circ}$ C.

5.3.1.1.1 Nucleic acid amplification tests

The standard detection of COVID-19 cases is focused upon NAAT that detects unique sequences of RNA viruses, as the real-time RT-PCR confirms the nucleic acid sequencing. A positive NAAT result for at least two distinct targets on the COVID-19 virus genome, of which at least one target is

ideally unique to COVID-19 virus using a reliable assay and COVID-19 virus accordingly detected by decoding part or whole of the virus genome as long as the target molecule is larger or different than the amplicon tested in the NAAT assay used. The negative result in the infected person may be due to the poor quality of the specimen, less quantity of the sample, improper handling of the sample or late collection of sample.

5.3.1.1.2 Serological testing

The evaluation of the infected patient and the magnitude of the outbreak can be investigated by the serological survey. When the NAAT assay test is negative, the validated serology test helps to diagnose the paired serum sample to confirm the presence of the virus. Serum samples were tested using the enzyme-linked immune sorbent assay. Cross-reactivity to other coronaviruses can be very difficult, but commercial and non-profit serological studies are currently being developed and evaluated.

5.3.1.2 Physiological assessment tools

The essential physiological observations to decide whether a person is infected by COVID-19, include temperature, respiratory rate, oxygen saturation, pulse rate, blood pressure, and chest imaging as reported by Carter, Aedy, and Notter (2020). Temperature measurement may be a part of the evaluation to decide whether a person has a high temperature potentially caused by an infection with COVID-19. A pulse oximeter is used to measure the blood oxygen levels in patients with preexisting respiratory conditions. In this pandemic situation, the pulse oximeter helps to measure the gradual depletion of the oxygen level in the asymptomatic individual. Because of the asymptomatic nature of most COVID-19 infections, many patients with coronavirus may suffer from significantly lower blood saturation levels without even recognizing it. The oxygen saturation of a person normally ranges from 95% to 100% (SpO₂) as evaluated by the pulse oximeter and requires immediate assistance if it begins to fall below 92.

The chest X-rays of patients infected with the novel coronavirus show characteristic pneumonia-like patterns that can help in the diagnosis. A chest X-ray can be used as an efficient, simple, fast, and inexpensive way to quickly diagnose the COVID-19 suspected individual before the confirmation from the pathophysiological test, namely the PCR test. While chest C.T. scans offer more reliable features for COVID diagnosis, they are not readily available in resource-limited environments.

5.3.2 COVID-19 innovations

COVID-19 is a fairly new disease; therefore, it is imperative to investigate all possible options to determine the most efficient way of diagnosis, treatment, and prevention. Rapidity, accessibility, and reliability may also represent important objectives for new research. Since the outbreak has already forced businesses across sectors to shut down their activities, many healthcare and technology firms are coming in to fight the pandemic.

In response to the shortfall of intensive care ventilators, start-ups such as Nocca Robotics (incubated at Indian Institute of Technology (IIT)-Kanpur), Aerobiosys Innovations (incubated at IIT Hyderabad), and AgVa Healthcare are working to develop affordable, user-friendly, and portable ventilators that can be deployed even in rural areas of the country. Indian Institute of Science in collaboration with MIISKY Technovation Pvt. Ltd. (April 2020) introduced a device (a smartwatch) that can measure various vital parameters of individuals under isolation on a real-time basis. Linked to a smartphone via Bluetooth, the smartwatch will record the patient's blood oxygen saturation and body temperature in real-time. Experts from the Henry Ford Innovation Institute created COVID care kits filled with different tools that patients may need for disease self-management outside of the hospital. IIT Delhi has also come up with an affordable testing kit to fight against COVID-19. In the meantime, IIT Guwahati is developing robotic units to carry drugs and food to isolation wards to prevent access to healthcare personnel. PerSapien Innovations, New Delhi-based company, has ended up producing a single mask that is capable of protecting the eye, nose, mouth, and ear of COVID-19 patient healthcare providers.

5.4 Non-contact approaches to physiological measurement

Reports from the WHO suggest that one way to contain the disease outbreak is effective screening procedures, as illustrated in the section 5.3.1. This involved identifying individuals with fever, which is a possible symptom of contracting diseases such as SARS or novel coronavirus. SARS-Cov-2 disease (COVID-19) is an infectious disease caused by a coronavirus and patients infected with the virus mostly report mild to moderate respiratory symptoms like fever, tiredness, and dry cough. Some patients may have aches and pains, nasal congestion, runny nose, sore throat, or diarrhea. The main symptom of diseases such as SARS and novel coronavirus is fever onset in the affected individuals. A very common screening approach in public places to separate the coronavirus-infected person is the measurement of their body temperature. Infrared-based thermal scanners are being used to check the skin temperature of individuals in public places. Screening people for possible hyperpyrexia in crowded places such as airports, buses, train terminals, and public places is a complex classification problem. Screening of individuals in public places leads to time-consuming and misclassification when temperature alone is considered.

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During this pandemic, the primary duty of the healthcare sector is to identify an individual or group with serious illness, without admitting all symptomatic patients in hospitals or isolating them in quarantine places. Besides, it is important to identify seriously ill patients in the preliminary stage, thereby the point of deterioration where they can be extremely challenging to handle in both pre-clinical and hospital environments can be avoided. Apart from initial temperature screening, if any person is found to be affected, the present testing methods like viral tests and antibody tests are usually practiced. The CDC recommends a COVID-19 test using a nasopharyngeal swab. The technician will insert a special 6-inch cotton swab into both nostrils one by one and move it around for about 15 seconds. It will not hurt, but it might be uncomfortable. This sample is sent to the laboratory for further testing. However, these results yield uncertainties of a person to be having symptomatic or telltale signs. In a few cases, the time duration to receive the testing laboratory results is delayed. The number of COVID tests performed by the government healthcare professionals on daily basis is not proportionate for large population countries like India.

5.4.1 Need for non-contact measurement

Recently, the US Food and Drug Administration (FDA) has insisted the manufacturers of specific FDA-cleared noninvasive, vital sign-measuring devices to expand their use, so that healthcare providers can use them to monitor patients remotely. The devices include those that measure body temperature, respiratory rate, HR, and blood pressure. These are primary signs of concluding that the person is affected by the coronavirus. FDA Principal Deputy Commissioner said, allowing such devices to be used in remote places like home and office can help healthcare providers access information, thereby reducing the need for preliminary tests and also minimizes the risks of spreading the disease to others. Another practical constraint is deploying all the virtual devices like Electrocardiogram (ECG) machines, pulse oximeter, infrared thermometer, and spirometer (respiration measuring device) or multiparameter monitors in public places. That is expensive and requires trained technicians to operate. Sterilization of devices is mandatory before every examination starts, once the data are read for one individual. Considering all the above issues, a method has been proposed here to assess the COVID-19 vital signs (HR, respiratory rate, oxygen saturation (SpO₂), and temperature) from the victims face (Chen et al., 2015; Mori et al., 2016) using thermal and/or visible light scanners (Smilkstein, Buenrostro, Kenyon, Lienemann, & Larson, 2014). This type of non-contact physiological measurement setup would lead to large population screening, particularly in containment zones, airports, malls, industrial estates, educational institutions, and places where more people are permitted (Fig. 5.1).



FIGURE 5.1 Use of non-contact physiological measuring device at various crowded places.

5.4.2 State of the art to prior work

Many research works are found in peer-reviewed articles for non-contact measurement of physiological signals. These inventions are available only in the written form with obtained results.

Ji-Jer Huang, Syu, Cai, and See (2018) developed a capacitive-coupled device embedded on a sofa monitor in the ECG system in a contactless environment. Such a system was able to calculate HR variability parameters. Sun et al. (2017) developed an improved thermal/red, green, and blue (RGB) imaging techniques for a touchless measuring device to estimate HR, respiratory patterns, and skin temperature using Complimentary Metal Oxide Semiconductor- Infrared (CMOS-IR) equipped camera. They experimented in a real-time environment by applying the infrared rays to observe the respiratory and temperature of the subject. The RGB images produced from the CMOS camera were used to predict the HR. Matsunaga, Izumi, Kawaguchi, and Yoshimoto (2016) proposed a microwave-based Doppler sensor to achieve better usability in measuring HR rather than any skin contact sensors or electrodes. Instantaneous HR measurement results aid an individual to manage cardiac-related symptoms and mental stress conditions. Cho et al. (2017) also proposed a webcam-based contactless HR measurement method. Such a system has an HSV + mIIR algorithm for appreciating a robust HR measurement from RGB colored facial images. Tang, Lu, and Liu (2018) presented a versatile measuring practice to monitor ECG signals in unhindered environments by considering the advantage of CNN architectures for skin detection and camera-based remote photoplethysmography method. The advantage of utilizing the CNN model enhances the robust monitoring of HR, thereby increasing the skin feature extraction in a single step rather than multiple steps like face tracking, detection, and classification.

5.4.3 Proposed approach

The main objective of this work is to identify a person with COVID-19 symptoms in a crowded place without any specialized measuring device. Thermal image scanning cameras are widely used in the measurement of temperature. The color distribution in the scanned images can provide the levels of body temperature. These cameras can only pick up "elevated skin temperatures," not measure the warmth of persons' skin. Henceforth it urges the suspecting individuals to undergo secondary screening, also makes the person a carrier to spread the disease, if the diagnosis is delayed. A high temperature or fever is just one common symptom of the virus. Others include nausea, headaches, fatigue, and loss of taste or smell. It is inferred that not every individual with the virus gets a high temperature and not everyone with a high temperature is infected with the coronavirus. Therefore IR cameras alone will miss infected people with other symptoms or no symptoms at all-known as false negatives. They will also identify people unwell with a fever for other reasons-known as false positives. Considering this, the other signs of COVID-19 are also extracted. As discussed in section 5.2, many works have been carried to measure physiological parameters (like HR, respiration rate, and SpO₂) from thermal imaging. With a walkthrough screening, it is possible to extract all the signs from facial thermal images within 30 seconds. The whole process is explained in the diagrammatic approach shown in Fig. 5.2.



FIGURE 5.2 Block diagram of the proposed approach.

5.4.4 Methodology

Fig. 5.2 shows two different lights (i.e., infrared and visible) to be illuminated on a person. The purpose of using two light sources is to make the measurement system cost-effective with greater efficiency. The images of a person are recorded for 30 seconds (1280×720 at 120 fps) under different lighting conditions. The brightness of ambient light can be measured by the lux meter. Persons with different skin colors will be considered for the experiment. Hence, two different databases consisting of thermal and visible light objects are created.

If a frame has more persons, their faces are tracked and identified using facial recognition algorithms. All these objects are converted into frames without affecting the quality. During the recording of subjects, their physiological parameters are recorded with a multiparameter monitor to verify the predicted results of our approach. The feature points related to HR, temperature, respiratory rate, and SpO₂ are located in the Region of Interest (RoI) and mostly correlated with various color spaces, RGB, the HSV (hue, saturation, and value), and the Lab (lightness, a, and b) color spaces.

The extracted features are given as reference (or) training dataset to the deep learning (DL) model. The purpose of implementing DL for this study is for the consideration of more objects, frames, and training datasets. Machine learning algorithms such as neural networks, support vector machines, and similar kinds of approaches cannot handle high dimensional real-time data. The features are extracted from two different databases created by thermal and visible lighting conditions. All these features are given separately to the DL model. The test data will then be given to the trained model to predict the COVID-19 vital signs. All these predicted results can be statistically correlated with the actual measurements observed during the recording. These correlation results will be useful to define the overall system performance. The vital sign measurements would be the initial screening parameters before COVID-19.

5.4.5 Preliminary experimental results

Preliminary work has been carried out (Jeyakumar, 2020) to experiment on non-contact measurement of HR from subjects' facial images under the visible light spectrum. A dataset of 160 facial videos each 30 seconds long with the corresponding HR is introduced. The dataset is designed to test the robustness of HR estimation methods. 20 subjects performed four activities (normal with open eyes and closed eyes, running, listening to music) in two lighting setups as mentioned in Table 5.1.

Each activity was captured by the Apple iPhone XS Max mobile camera placed in a tripod with a pixel dimension of 1920×1080 . Simultaneously, the corresponding HR was measured using Larsen and Toubro Patient

| IABLE 5.1 Subjects selection based on skin tone and lighting condition. | | | | | | | | |
|--|-----------------|---|----|-----------------------------|-------------------------------|----------------|----------------|---|
| Subjects | | | | Facial videos (per subject) | | | | |
| Male | Pale skin | 5 | 10 | 20 | Normal with eyes open | 1 ^a | 1 ^b | 8 |
| | Dark skin | 5 | | | Normal with eyes close | 1 ^a | 1 ^b | |
| Female | Pale skin | 5 | 10 | | After listening to mild music | 1 ^a | 1 ^b | |
| | Dark skin | 5 | | | Running (50 stairs) | 1 ^a | 1 ^b | |
| ^a Natural li ^b Dim light | ghting. ing. | | | | | | | |

Monitor (Model No Star Plus-300) with a photoplethysmographic sensor. The range of age of the subjects was from 19 to 29 years, their mean HR was 110 (approx.), and the standard deviation was 25 (approx.). These videos were converted into frames before feeding into the model. The frame rate was set to 0.5 fps. Therefore, each video had been converted into 60 frames approximately, thus obtaining 10,553 images. The participants who participated in this experiment had been given informed consent forms (Fig. 5.3).

These images were fed as input to the system. Very high dimension images (1920×1080) are undesirable as they take up extra computation time. Hence all the images were resized to a dimension of 64×64 . Image resizing was done using the CV2 package in python. The analysis was made to find the correlation between facial features and HR. The following inference was made after the analysis of the correlation between facial images and HR.

- There exists a correlation between the mean intensity of the green channel and the HR.
- As the HR increases, the mean intensity of the green channel decreases.
- The wavelengths concerning green colors have maximum absorptivity, and evident that rise in blood volume leads to less absorptivity by red color (Fig. 5.4).

Face detection and region of interest selection 5.4.5.1

The face was detected from the frame by a face detector. The forehead region was isolated as the RoI from the whole frame by using the Viola – Jones algorithm (Haas-cascade classifier) (Fig. 5.5).

The proposed system consists of two parts. The videos were split into frames and were separated into three parts-training set, testing set, validation set, and



FIGURE 5.3 (A) Facial image captured under ambient lighting condition. (B) Facial image captured under dull light after running about 100 meters.



FIGURE 5.4 Graph of heart rate versus mean intensity of green channel.

annotated. In the first part, the video was split into frames that were annotated/ labeled. These frames were split into training, testing, and validation sets in the proportion of 80:15:5. These frames were fed into the proposed system as input along with the respective HRs. The output was a numerical number, which represented the HR. The correlation between the predicted HR from the system and the actual HR value was calculated to determine the system's accuracy. To feed the data into the CNN model, the pretrained models such as Alexnet and Lenet were initially considered. Due to the overfitting issue, these models provided a high misclassification rate during the testing phase. As an alternative to these issues, a smaller version of Visual Geometry Group (VGG) network with fewer weight layers was considered to make the training period less (Fig. 5.6).



FIGURE 5.5 Face detection and region of interest (RoI) selection.



FIGURE 5.6 A smaller version of VGG net.

The model built had six layers in total, not counting the max pool layers and the Softmax layer at the end. It had one input layer, five hidden layers and one output layer (Table 5.2).

To optimize the parameters, Adam optimizer was used for the first and second moments of the gradient for updating the learning rate adapting to each training image. The above VGG model was trained with the training images with the hyperparameter tunable optimization function. During the training, the maximum validation accuracy of 74.66% and minimal loss of 10.1% at epoch 50 was obtained. A sample of images was given during the testing phase and the trained model provides the predicted values of the HR. The accuracy of the trained system was calculated from Eqs. 5.1 and 5.2.

$$\operatorname{Error}(\%) = \frac{(\operatorname{Obtained} \operatorname{HR} \operatorname{value} \sim \operatorname{Actual} \operatorname{HR} \operatorname{Value})}{\operatorname{Obtained} \operatorname{HR} \operatorname{value}} * 100$$
(5.1)

$$Accuracy = 100 - Error (\%)$$
(5.2)

The CNN was implemented by python with Keras package using NVIDIA GeForce GTX 1060 GPU. The predicted results of the model are shown in Fig. 5.7.

For the above test images, the accuracy rate was 97.5%, 95.96%, and 95.45%, respectively. The overall mean accuracy for the test images was

| TABLE 5.2 Hyper parameter values. | | | | | |
|-----------------------------------|------------------------|--|--|--|--|
| Number of filters | 32, 64, 128 | | | | |
| Size of filter | 3×3 | | | | |
| Max pooling shape | 2×2 | | | | |
| Stride | 1 | | | | |
| Padding | The number on the edge | | | | |
| Learning rate | 0.01 | | | | |
| Number of epochs | 50 | | | | |
| Batch size | 64 | | | | |
| Activation function | Relu, Softmax | | | | |
| Hidden layers | 5 | | | | |
| Dropout | 0.25, 0.5 | | | | |
| | | | | | |



FIGURE 5.7 HR values of A O.value—80 Bpm; A.value—82 Bpm B O.value—99 Bpm; A. value—95 Bpm C O.value—110 Bpm; A.value—105 Bpm.

92.32%. Still, there is scope to improve the system's overall efficiency by upgrading the processor and considering more data to train the model. In this preliminary study, HR alone was considered from the facial attributes. However, other vital parameters like respiration rate, SpO2, and temperature can also be measured from the approach proposed here.

5.5 Conclusion

The number of positive coronavirus cases continues to increase at an unprecedented rate globally which urges the doctors, nurses and other medical professionals to work round the clock. This affects their physical and psychological condition badly. Hence a measuring system to screen the people in a large scale is the need of the hour.

Temperature measurement is a part of the evaluation to decide whether a person has a high temperature potentially caused by an infection with COVID-19. Using various instruments for temperature measurement, such as oral thermometers, involves physical contact that can increase the risk of infection spread. Thermal imaging systems and non-contact infrared thermometers, instruments for non-contact temperature measurement are used to measure an individual's temperature. These non-contact temperature evaluation devices can quickly measure and display a reading of temperature, so that a large number of people can be individually assessed at entry points. Such instruments have many benefits but they must be used properly to get correct readings. The elevated temperature alone cannot be taken into consideration to confirm COVID-19, further assessments of other vital parameters are needed to evaluate in non-contact environment.

Certain proven studies and results are available in the literature stating that the various physiological parameters can be determined from the facial images. Most of the COVID-19 tests are being done due to a rise in body temperature alone. This culminates in most of the test results being declared as asymptomatic cases of COVID-19 if the temperature is not measured. If this approach is implemented in the current scenario, the number of true positive cases will increase. By adopting this approach, the mass screening of individuals or groups in industrial, home, and educational institutions is possible. Daily increase of positive COVID-19 cases in green containment zones is another big challenge to the healthcare department. This happens because of migrants moving from the red zone to other low case load containment zones. If this measurement system is installed at entry points such as toll gates and immigrant zones of airports and harbors, then the spread of SARS COVID-19 by the overseas travelers can be identified and the travelers can be isolated and guarantined. The systems would be beneficial to the persons who are undergoing self-quarantine at their home. Moreover, these systems would be an assistive device to assess the vital signs of a vulnerable group. These systems can be incorporated in any surveillance systems like CCTV and Drone. These would be more beneficial to healthcare professionals. Such a system is useful to find cases of infectious diseases and for the continuous health monitoring of elderly people, sportspersons, and young children, and also for remote monitoring, follow-up and communication with the patients without human contact and risk of infection to the healthcare workers.

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