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Coronavirus Spread Limitation using Detective Smart System

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Abstract: Given the circumstances the world is going through due to the novel coronavirus (Covid-19); this paper proposes a new smart system that aims to reduce the spread of the virus. The proposed Covid-19 containment system is designed to be installed outside hospitals and medical centers. Additionally, it works at night as well as at daylight. The system is based on Deep Learning applied to pedestrian temperature data sets that are collected using thermal cameras. The data set is primarily of temperature of pedestrians around medical centers. The thermal cameras are paired with conventional cameras for image capturing and cross referencing the target pedestrian with an existing central database (Big Data). If target is positive, the system sends a text message to the potentially infected person's cell phone upon recognition. The advisory sent text may contain useful information such as the nearest testing or isolation facility. This proposed system is assumed to be linked with the bigger network of the country's Covid-19 response efforts. The simulation results reveal that the system can achieve an average precision of 90% fever detection among pedestrians.

Keywords: Covid-19; Thermal camera; pedestrian detection and Deep Learning.

1. Introduction

Corona virus is a family of viruses (SARS) that had caused major global health concerns. They manifest a range of symptoms ranging from a harmless cold to life threatening Pneumonia. Corona pneumonia viruses may cause viral pneumonia complicated with bacterial pneumonia. It may also cause bronchitis, whether viral bronchitis complicated with bacterial bronchitis. Alarming spread of Corona virus to the human population has triggered a lot of researches on detection and mitigation [1]-[10].

When Covid-19 went Pandemic, countries engaged strict traffic controls in their ports (Air and Sea). Automated Covid-19 detection at these ports is imperative [11], [12].

Video based monitoring systems are now a common fixture in ports. Originally designed for security, these camera systems have also been used for medical purposes in the past [13]. These systems are now ubiquitous, from high security facilities down to the humble corner convenient store. Furthermore, the technology has advanced significantly. These cameras are now capable of recording beyond the visual light spectrum i.e., infrared and ultraviolet [14], [15].

Earlier cameras were low resolution and are limited to the visual spectrum (from Red to Violet). Advancement in technology made Infrared and Ultraviolet detection a common place. Infrared emitted by a body is actually directly proportionate to its temperature. Thus, detecting the Infrared emission of the body is a good way of detecting body temperature (same technology used in Night Vision). Thermal cameras are sensitive to any environmental temperature variations. Hence, it can provide more details than the conventional camera. Unlike conventional cameras, the thermal camera is robust enough against harmful weather conditions and wider light spectral variations e.g., harmful UV. Coupled with sophisticated algorithms such as Deep Learning, these cameras can function as image recognition systems [16].

The proponents cannot stress enough the need to use all possible technology advancements in mitigating social problems such as pandemics and security threats. Camera or video technology is one of them. The ever-broadening spectrum and ubiquity of camera technology should also broaden its purpose of use. They should be used from managing a local village's night time security to containing the spread of a new virus. To support this point, in [17]-[21] the authors prove that the thermal face recognition system is more optimal than the conventional video-based security systems.

In this paper, an automated, deep learning based, mass pedestrian fever detection is proposed. The proposed system uses deep learning on pedestrian thermal data sets collected using thermal detection capable camera systems. Since Infrared is the target spectrum, this system can be used at night as well as daytime. Furthermore, a conventional camera is utilized to determine the target's identity. Identity is established doing cross-reference thermal and conventional camera data and existing Big Data. From simulation results, the proposed system can achieve promising performance in mass fever detection.

This paper is organized as follows: Section 2 introduces the thermal spectrum and the pedestrian detection based on neural networks; the proposed system architecture and its operation are described in Section 3; section 4 is where a statistical model is developed on patients at different detection probabilities; the simulation results are explained in Section 5 and finally, Section 6 concludes the paper.

2. Pedestrians Detection Using Deep Learning Based on Thermal Imaging

As shown in Fig. 1, the infrared spectrum of the human body heat emission is divided into four sub-bands according to the wavelengths, which are;

- Near IR (NIR; wavelength 0.75: 1.4 μm),
- Short Wave IR (SWIR; wavelength 1.4: 3 μm),
- Medium Wave IR (MWIR; wavelength 3: 8 μm), and
- Long Wave IR (LWIR; wavelength 8: 15 μm).

Fig. 1. The heat emission spectrum by the human body [17].

The images in the NIR and the SWIR are affected by the daylight (noise band). Therefore, these bands are used for indoor applications. While MWIR and the LWIR bands, are mostly used in outdoor facial recognition applications. This is evidently because the latter two bands are

significantly higher than the noise band (daylight band). However, the images detected in these bands are highly affected by any environmental temperature variation. Additionally, eyeglasses distort this IR spectrum [18]. Consequently, faces with eyeglasses will be veiled. To overcome these challenges, thermal and conventional cameras imaging fusion techniques are used [19], [20].

Many approach to thermal human recognition is through convolutional neural network (CNN) architecture [21]-[25]. CNN technique has relatively higher accuracy rates than traditional techniques of image processing features extraction. The main structure of the CNN is shown in Fig. 2.

Fig. 2. The convolutional neural network (CNN) structure [21].

The used input datasets differ according to the application. Some researchers have used their own dataset. While others have utilized some benchmark datasets. Then, the features are extracted from the images using the convolutional layers associated with its activation functions. Each convolution layer is a dot product between the features filter coefficients and the input image. Hence, activation function such as Rectifier Linear Unit (ReLU) is applied to the filter output. Thereafter, pooling layer (such as Max-Pooling) is usually performed after each convolution layer has reduced the weights and the dimensions. At this stage, the important features are extracted. Finally, the features are prepared for the fully connected layers, which are basically traditional neural networks. Consequently, the output is the data used for pedestrian detection and/or classification process. It is worth mentioning that the detection problem is classified as two-class classification problem.

Different metrics can be utilized to evaluate the performance of CNN [26]. For the classification problem, the confusion matrix is the most important tool for investigating the CNN performance. Additionally, some other common metrics are available such as Accuracy, Precision, Recall,

Specificity, F_1 score, etc. The accuracy is defined as the proportion of corrected predictions over all cases as,

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}$$

Where: T_P, T_N, F_P and F_N are the true positive, the true negative, the false positive and the false negative values. The precision can be defined as the ratio of the T_P to the sum of all the positive detections as follows,

$$Precision = \frac{T_P}{T_P + F_P}$$

On the other hand, the Recall metric can be used to determine the detection rate as the percentage of the correctly classified positive class. Hence, the Recall and the Miss Rate can be written as,

$$Recall = \frac{T_P}{T_P + F_N}$$

$$Miss Rate = \frac{F_N}{T_P + F_N}$$

While, the Specificity metric is used to calculate the proportion of the correctly classified negative class. It can be written as,

$$Specificity = \frac{T_N}{T_N + F_P}$$

3. The Proposed System Architecture

Figure 3 illustrates how the proposed system works for monitoring and tracking people possibly infected with the virus. It should be noted that the system works only at the time of a pandemic for resource conservation purposes. In this system, once the conventional camera takes a picture of the person to cross-reference his identity from the Big Data system, the thermal camera takes an IR image of the same person. These cameras are to be installed in well planned strategic locations such as carpark poles, entrances etc. One recommendation is to install the cameras at poles 100 m

high in congested traffic areas and 500 *m* in low traffic ones, so that they can capture the face and the throat. The thermal images of the people are collected individually for better accuracy. All of the thermal cameras are set at certain threshold temperature. This temperature should evidently be higher than the healthy human body temperature i.e., temperature medically defined as fever.

To confirm if the person is infected, an algorithm is used to cross-reference the collected data from the Big Data for identification. A text message is sent on his cell phone to guide him to the nearest CT station in the same location. The same person goes through further test protocols and triage established for pandemic mitigation.

Expectedly, in a pandemic, a large number of suspected infections will be detected and collected. The proposed system is part of a bigger pandemic mitigation system such that suspected infections are automatically scheduled for isolation and assignment to a CT station. Upon confirmation of positive Covid-19 case, the system automatically arranges proper pandemic transportation at the patient's location. A mobile app with data and Bluetooth capability will provide the patient some information and protocol on how the treatment and isolation will proceed. The system is constantly updating the provided transportation the exact location of the patient or suspected infection. In rare cases where the patient has no access to the app, the CT station personnel are also informed and advised to orient the patient on the isolation and treatment protocol. A basic illustration on how the system work is seen in Fig. 4.

Fig. 3. Suggested smart system architecture

Fig. 4. System operation scenario

4. The Mathematical Model

The mathematical model for the proposed system based on three main factors:

- a) The announced daily number of infected people by WHO in a certain country. This will be expressed as the function, $y(x)$ as x is the number of patients per day.
- b) Since $y(x)$ is not exact and cannot predict the number of infected people in the country under consideration, another factor will be introduced to consider the variability in the number of infected people - $f(x)$. This function represents the probable number of infected people as a Gaussian distribution, which is most likely to the studied case. This distribution depends on its mean, μ and variance, σ_x^2 . These two parameters will be estimated using $y(x)$ especially at the beginning of virus spread.

$$f(x) = \frac{1}{\sqrt{2\pi\sigma_x^2}} e^{-\frac{(x-\mu)^2}{2\sigma_x^2}} \quad (1)$$

- c) The probability of detection, P_d which represents the percentage of detection of the proposed system over its coverage area. This percentage depends on the distribution of the smart devices over this area, the technical specifications of these devices, weather conditions..., etc. [27] – [31].

In order to estimate the mean, μ and variance, σ_x^2 of the given Gaussian distribution in (1), let us consider the function $y(x)$ as a sample represents the population of the actual patients, consider also that m is the Median, a is the minimum value, b is the maximum value and n is the size of this sample [32] - [36]. The sample elements will be assorted in an ascending way and then can be expressed as:

$$(a = x_1) \leq x_2 \leq x_3 \leq \dots \leq x_{M-1} \leq (x_M = m) \leq x_{M+1} \leq \dots \leq x_{n-1} \leq (x_n = b) \quad (2)$$

where the Median is the M^{th} number, then

$m = x_M$ if n is odd, where $M = \frac{n+1}{2}$, and

$$m = \frac{1}{2}(x_M + x_{M+1}) \text{ if } n \text{ is even, where } M = \frac{n}{2} \quad (3)$$

To estimate the mean μ , the following inequalities can be used. First, for the data set, $\{x_1, x_2, \dots, x_M\}$

$$\left. \begin{array}{l} a \leq x_1 = a \leq a \\ a \leq x_2 \leq m \\ a \leq x_3 \leq m \\ \vdots \\ a \leq x_{M-1} \leq m \end{array} \right\} (M-2)$$

$$m \leq x_M = m \leq m, \quad (4)$$

Second, for the next data set, $\{x_{M+1}, x_{M+2}, \dots, x_n\}$

$$\left. \begin{array}{l} m \leq x_{M+1} \leq b \\ m \leq x_{M+2} \leq b \\ \vdots \\ m \leq x_{n-1} \leq b \end{array} \right\} (M-2)$$

$$b \leq x_n = b \leq b$$

The sample mean, μ is the middle column after adding up and diving by n . Also, for all the three columns, adding up and diving by n can drive the following inequality:

$$\frac{(M-1)a + (M-1)m + b}{n} \leq \mu \leq \frac{a + (M-1)m + (M-1)b}{n} \quad (5)$$

substituting (2) in (5) therefore, the lower and upper bounds of the mean can be defined as:

$$\text{The lower Bound} = \frac{a+m}{2} + \frac{b - \frac{a+m}{2}}{n} \quad (6)$$

$$\text{The upper Bound} = \frac{b+m}{2} + \frac{a - \frac{b+m}{2}}{n} \quad (7)$$

Then, the estimated mean can be expressed as:

$$\mu = \frac{\text{Lower Bound} + \text{Upper Bound}}{2} = \frac{a+2m+b}{4} + \frac{a-2m+b}{4n} \quad (8)$$

Therefore, the sum of mean squares can be estimated as:

$$\mu^2 = a^2 + m^2 + b^2 + \left(\frac{n-3}{2}\right) \frac{(a+m)^2 + (m+b)^2}{4} \quad (10)$$

Using the computational formula, the sample variance can be calculated as:

$$\sigma_x^2 = \frac{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}{n(n-1)} = \frac{\sum_{i=1}^n x_i^2 - n(\frac{1}{n} \sum_{i=1}^n x_i)^2}{(n-1)} \quad (11)$$

However, we can estimate $\sum_{i=1}^n x_i^2$ and $\frac{1}{n} \sum_{i=1}^n x_i$, then using (8) and (10), the sample variance can be expressed as:

$$\sigma_x^2 = \frac{1}{n-1} \left(a^2 + m^2 + b^2 + \left(\frac{n-3}{2} \right) \frac{(a+m)^2 + (m+b)^2}{4} - n \left(\frac{a+2m+b}{4} + \frac{a-2m+b}{4n} \right)^2 \right) \quad (12)$$

Finally, the estimated number of patients can be expressed by $y_{est}(x)$ given by:

$$y_{est}(x) = P_d y(x) f(x) \quad (13)$$

5. Result and Discussion

5.1 Pedestrian and Patient Detection

In this proposed system, the thermal camera can measure pedestrian temperatures to detect fever. While a conventional camera provides information that is more detailed on the pedestrian's face features.

Pedestrian initial detection is done using the thermal camera. That is due to its ability to work in both nighttime and daytime. If the pedestrian is detected, his temperature is evaluated to determine if the target is feverish.

The used dataset for training the proposed model is collected from several available thermal camera videos for detection of pedestrians approaching or waiting at the crosswalk [16]. Samples of the video frames are shown in Fig. 5. The sample video has 29 frames/sec with frame dimension of 368×288 pixels. The corresponding pedestrian distribution with the time of the sample video is shown in Fig. 6.

Fig. 5. Samples of the thermal camera dataset.

Fig. 6. The pedestrian distribution.

The pedestrian detection is based on the aggregate channel features (ACF) algorithm [37]. It converts the channel of the extracted region into LUV color space channel. Then, the gradients magnitudes are computed for the Histogram of Gradient (HoG) calculation. Further, the features channels are aggregated and convolved to extract the feature vector. Eventually, it is arranged in a boosted tree. The pedestrian detection results of the ACF algorithm with the highest Intersection over Union (IoU) scores are presented in Fig. 7. It can be shown the high confidence scores which can be obtained that indicates the high accuracy of the detection algorithm.

Fig. 7. Samples of the pedestrian detector output.

The performance of the pedestrian detection system can be measured using the precision and the miss rate metrics as shown in Fig. 8. From results, the system can achieve 0.9 average precision and 0.3 average miss rate.

Fig. 8. The system performance evaluation.

5.2 Image Registration and Face Recognition

Image registration is an elimination process within a full motion scene. Both fixed and moving images are used in producing one coordinate domain. Fig. 9 shows an example of a successful registration. Fig. 9a displays two overlapped images before the registration process. While, Fig. 9b shows the overlapped images of the same subject after the registration. It can be shown that the image registration reduces the shifted pixels relative to both frames. This increases the signal to noise ratio of the resultant image [38].

The proposed system performs pedestrian detection and registration as described earlier. The outputs of these processes are then used to improve or train the system. Thus, fusion between both the thermal and the normal images increases the accuracy of the captured patient image. After the registration process, the face recognition technique is performed with the help of the Big Data center to recognize the patient's identity.

Fig. 9. Image registration: a) Overlapped images before registration. b) Overlapped images after registration [38].

5.3 Virus Spreading Detection

This system is primarily for detection, collection, Neural Network training and early prediction of deadly viral infection to mitigate epidemic and pandemic spread of a virus. Therefore, the proposed system will provide a learning (Neural Network) that could be deployed in the early onset of a deadly viral spread. Further, this system is capable of learning from Big Data established from previous pandemics that could be used for future pandemic mitigations. The greater the likelihood infections are detected; the less likely epidemics will occur. In these results, the effect of three values of the probability of discovering the infections was presented based on three real examples. These results were announced by the WHO from Feb., 15 to Apr. 8, 2020 [39].

Fig. 10 shows the numbers of infected people due to the spread of Corona virus in three countries of the world USA, Italy and Saudi Arabia in the mentioned periodic data according to WHO. From Feb., 22 to Mar.25, Italy ranked first globally in the number of people infected with Coronavirus, but the situation changed after that, and USA became the first in the world by a large difference in the number of infected people.

Fig. 10. Normal spreading distribution of corona patient in three different countries from Feb., 15 up to Apr. 8, 2020 as a case study

Although a country like Saudi Arabia at the end of this period is considered to have no more than 1 percent of those infected in USA. This is due to the rapid application of precautionary rules to limit the spread of infection and also the population density per square kilometer which has a very significant impact. Among these rules is the application of the curfew throughout the day or part of the day.

In Figs. from 11 to 13, the proposed system has been applied to the three countries mentioned previously, with a probability of detecting 90%, 85% and 80%. With the onset of the spread of the infection, the system is activated and compared to the normal situation. Obviously, it appears from all results that, by increasing the percentage of probability of detection, the number of infected cases increases over the number that appears in the normal case of using precautionary instructions only where the situation is controlled and the results from the use of this system are distinguished in the less-spread of infection and blockade it in less time.

Fig. 11. Normal spreading distribution of corona patient in USA versus the suggested system spreading at different detection probabilities

Fig. 12. Normal spreading distribution of corona patient in Italy versus the suggested system spreading at different detection probabilities

Fig. 13. Normal spreading distribution of corona patient in KSA versus the suggested system spreading at different detection probabilities

6. Conclusions

This article proposed a new early detection system for the Covid-19. The main purpose of this system is to limit the spread of this virus and some other diseases which work with the same mechanism. The proposed system depends on the available modern and smart technologies like thermal cameras and Big Data system. In this system, two synchronized pictures of the patient face and his body temperature are taken using a conventional and thermal camera, respectively. The data are sent to the Big Data system to establish identity. Once it shows a higher temperature than a certain threshold value (normal body temperature), the patient receives a cell phone message to have another check and confirmation in the nearest CT satiation, since fever is just a symptom. In the mathematical model of this system, the reported data from WHO is considered as training data set to train the system. Hence, its median, minimum and maximum values are used to estimate the population mean and variance. This leads to improved system performance as the system learns. The figures representing the results are related to the distribution of the smart devices over the coverage area along with their technical specification. This model was applied on the data of three countries; USA, Italy and KSA with different values of the probability of detection. In all these

examples, the system shows high efficiency and possibility for limiting the virus spread in a short period.

Declarations

According to the ethical approval of Fig. 9, it is cited form [38]. Additionally, by tracking the licensed under a Creative Commons Attribution 4.0 International License, it is indicated that, you are free to share, copy and redistribute the material in any medium or format. In this paper, the FREE FLIR Thermal Dataset is used. It can be downloaded from: <http://www.flir.com/oem/adas-dataset-form/>. Furthermore, the exactly frames for testing can be shown in: <http://www.youtube.com/watch?v=yODTcCwOcV4>. Also, we got the number of COV-19 patients from the WHO website. It is open access website and we cited this in section 5.3 in the paper by [39].

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