Technical Note

A Novel Design For A COVID-19 Diagnosis System Using Machine Learning And Drone Technology (COVIDRONE-20)

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Abstract: Tracking and early identification of suspected cases are essential to control and prevent potential COVID-19 outbreaks. One of the most popular techniques used to track this disease is the use of Infrared cameras to identify individuals with elevated body temperatures. However, they are limited by their inability to be implemented in open public settings such as public parks or even outdoor recreational centers. This limits their ability to effectively track possible COVID-19 patients as open public recreational places such as parks, concert venues and other public venues are hotspots for the spreading of the virus. Other technological solutions such as thermal scanners require an individual to perform the actual testing as they are not individual standalone technologies. This method of testing can potentially cause the transmission of the virus between the tester and the individual getting tested. As can be seen, an alternative solution is essential to solving this issue. In this study, we aim to present the system, design and potential scope of a non-invasive system that can diagnose and identify potential COVID-19 patients using thermal and optical images of the individual using drone technology. The proposed system (COVIDRONE) combines multi-modal machine intelligence, computer vision and real-time monitoring to enable scalable monitoring. The system will also involve the use of machine learning algorithms for better and more accurate diagnosis. We envisage that development of such technologies may help in developing technological solutions to combat infectious disease threats in the future pandemics.

Keywords: UAV Technology; Information Processing; Machine Learning; IR Technology; Covid-19; Multimodal machine learning; Machine vision; Computer vision

1. Introduction

Coronavirus is one of the major pathogens that primarily targets the human respiratory system. Currently, six human coronaviruses (HCoVs) have been identified, namely, HCoV-229E, HCoV-HKU1, HCoV-OC43, HCoV-NL63, severe acute respiratory syndrome coronavirus (SARS-CoV), and Middle East respiratory syndrome coronavirus (MERS-CoV) [11]. Previous outbreaks of coronaviruses (CoVs) include the severe acute respiratory syndrome (SARS)-CoV and the Middle East respiratory syndrome (MERS)-CoV which have been previously characterized as pandemics that posed a great threat to public health [12]. This novel Coronavirus was discovered in the Hubei province of China in December 2019 and has spread globally and continues to grow at a staggering rate. SARS-CoV-2 can be transmitted from human to human. The current hypothesis is that the first transmission occurred between bats and another intermediate host animal, however, this intermediate host animal is still unknown. It is estimated that a SARS-

CoV-2 patient will infect approximately three new people (the reproductive number is averaged to be 3.28). The symptoms can vary, with some patients remaining asymptomatic, while others present with fever, cough, fatigue, and many other symptoms [13].

Past experiences with similar respiratory syndromes like severe acute respiratory distress syndrome (SARS) have shown that early identification of suspected cases and rapid implementation of measures are critical to preventing or containing outbreaks, especially in a public setting such as airports or hospitals[14]. Historically, temperature has been proved to be a very good indicator of health. Since 400 BC temperature has been used for clinical diagnosis. Humans, being homeotherms, are capable of maintaining a constant temperature of the body, which may be different from the surrounding temperature. The body of homeotherms can be divided into two parts, the inner core, and the outer periphery. The core temperature is preserved within a narrow limit of 36.5 - 37.5 °C. This regulation of inner core temperature is essential for the normal performance of the human body. Change of core temperature by a few degrees is considered a clear indication of probable illness [15]. By now, infrared thermography (IRT) has become a matured and widely accepted condition monitoring tool where the temperature is measured in real-time in a non-contact manner. With the advent of newer generations of infrared cameras, IRT is becoming a more accurate, reliable, and cost-effective technique and as a result, has become one of the most popular early identification methods for the novel coronavirus[16]. Using IOT systems IRT has now been incorporated into more complicated systems for more efficient and widespread tracking or diagnosis. The IoT system in medicine is now in an advanced setup that contains so many varieties of mechanisms like smart sensors, medical equipment, big data, cloud computing, telemedicine, clinical information system, and many more. IoT technique is categorized into; remote monitoring of patients, remote tracking and monitoring of health, sensor-based devices for hand wash monitoring, and monitoring of interactive RFID activities [17, 18]. Using IOT, this study aims to create a system that can more efficiently and more accurately (compared to traditional thermal cameras and IOT currently available) detect or identify individuals with the novel coronavirus using IRT and drone technology. Furthermore, to improve accuracy over current IOT and IRT technology this system will also involve the use of machine learning algorithms on the thermal images and optical images to allow for better accuracy in both the diagnosis of the diseases and identification of the patient.

2. System Description

COVIDRONE - 20 is a COVID - 19 diagnostic system that incorporates the use of drone and IRT technology to create a more efficient COVID - 19 diagnostic system. In its initial stages, the system will consist of a drone, a small CPU that can be equipped on a drone for data processing on the drone, and a server or very powerful local or remote computer for data collection. As the system progresses into its later phases or stages the drone will become less dependent on the server or local computer. The elevated temperature detection is carried out by using machine learning techniques. The thermal image captured by the drone is fed to the well-trained machine learning model deployed in the local host computer for classifying the image into covid-19 or normal. The machine learning part consists of steps such as data collection, data preparation, cleaning, modeling, training, testing, and deployment. The data here is thermal images of human faces from which we can identify those with elevated temperatures. Two methods for modeling and training are proposed based on the way we collected the data. For the process of binary classification of the thermal images, we need to train the model with the two classes of data. The two classes are normal thermal images and the covid-19 thermal images. So, to train such a model for binary classification, we have to collect both classes of thermal images. The normal images are collected from open-source thermal image databases and the second class, covid-19 thermal images can be collected by field data collection method. This process of binary classification data collection requires time and expert assistance. So, another model training method is also proposed in which the model is trained using the open-source, freely available normal thermal images only. Here we train the model using a single class and the process is known as the Class Classification (OCC) training, and the model learns the second class, the Covid-19 class after deployment since the proposed model is an online model. So, there are two sources to collect the data, open-source databases and the field. After collecting the data, the raw image data has to go through a series of preprocessing steps such as cleaning, resolution adjusting, labeling, etc to finally end up with well-prepared data for training the classification model. After the data preparation, we define and build the model for the classification of thermal images into normal and covid-19. The model is built using Convolutional Neural Networks (CNN)-based architecture. There are two methods for training the model as discussed above. If the data collected contains only the normal class, we go with the OCC training method and if the dataset prepared contains both the classes, then we train the model with the binary classifier training method and conventional binary cross-entropy like loss functions. After the training process completes and the model attains a good performance level, a small portion of the dataset we split for testing is given to the model and estimates the test performance evaluation metrics. Later, the model performance in training and testing are compared, and checking for the model under-fitting and overfitting are carried out. The weight values of the best-performing model are saved into an HDF (Hierarchical Data File) and later loaded into the CPU of the drone to make predictions.

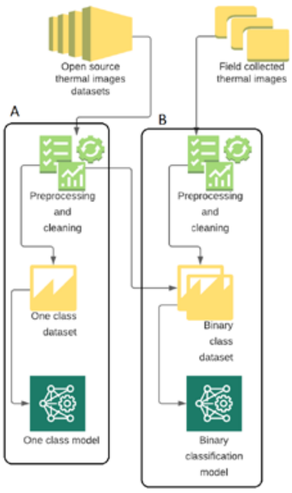

Figure1: Machine learning workflow. A: The One-Class Classification training model and B: The Binary Classification training model.

2.1 Data collection and preparation.

Thermal imaging is used to study several diseases where the skin temperature can reflect the presence of inflammation in underlying tissues or where blood flow is increased or decreased due to a clinical irregularity [4]. Currently, many physicians use thermal imaging cameras to detect several medical conditions, such as arthritis, repetitive strain injury, muscular pain, and circulatory problems [5]. The model here is a binary classification machine learning model which classifies the given thermal image into any of the two classes, namely normal (Class 0) and covid-19 (Class 1). So we need to prepare a cohort of thermal images containing both classes of images. The normal images can be collected from open-source datasets such as the L- CAS Thermal Physiological Monitoring Dataset [1], IRIS Thermal/Visible Face Database [2], Terravic Facial IR Database [3], etc. These are some easily available thermal images datasets and we consider them into the normal class which has no elevated temperature level for the diagnosis of covid-19. IRIS

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Thermal/Visible Face Database contains 4228 thermal images of resolution 320 x 240 and Terravic Facial IR Database contains thermal images of faces in different variations with 320 x 240 resolution.

Class 1, which is the covid-19 patients' thermal images can be collected from fields such as hospitals, clinics, and diagnostic centers. We need these images also to train the classifier. But this process will take time. That's why we propose another model called an OCC model which can be trained with class 0 only and later it will be learning class 1 during the deployment as an anomaly. For both of these models, we have to do some preprocessing and cleaning the data. It also helps in speeding up the training process. For thermal images data, mainly we do resolution adjustment, clearing, class imbalance, Denoising, Histogram equalization, normalization, labeling, etc. In resolution adjustment we make all the images in the same resolution, choosing a standard resolution would be better for defining the layer parameters of the model. In the case of the binary classification model, we have to make sure that both classes of images are in the same resolution. The class imbalance is the imbalance in the number of images in two classes and this is a major problem when we train the model as the model might be biased towards the class which has more images in it. This problem can be addressed using data augmentation techniques in the Keras Python library. Under-sized images are removed during the cleaning and Histogram equalization process using algorithms like CLAHE (Contrast Limited Adaptive histogram equalization) helps in increasing the visual quality of the images. After these processes, we have to do standardization and labeling. Standardization is a kind of normalization in which we convert each pixel from the image into a similar scale and of zero mean and unit variance. Initially, the pixel values might be ranging from 0 to 255, so, we scale them into 0 to 1 to get a distribution with zero mean and unit variance. The labeling process is simple since we are initially doing a binary classification model only. So, only class 0 and class 1 labels are there

2.2 Modelling and training.

The model is based on CNN which is nothing but normal ANN (Artificial Neural Network) with mathematical convolutions employed at the input side. Many models have been proposed for classification and object detection in thermal images based on CNN as it is the simplest method [7] [8] [9]. CNN's learn high-level features such as edges and boundaries of an image rather than low-level features in ANN. Mathematical convolution applies a filter/kernel on the input image to get the high-level features called feature maps. CNN reduces the image size and pooling processes such as max-pooling are further reducing image size, but the depth of the image is increased throughout the layers. This depth contains information about the high-level features extracted. ReLU (Rectified Linear Unit) is applied after convolution to give non-linearity to the data. So, here there are two layers of convolution-ReLU-Pooling after which the image feature maps are sent to the fully connected conventional ANN, and the weights are learned through backpropagation. The model is trained using the loss function "binary cross-entropy" since we are training a binary classification model.

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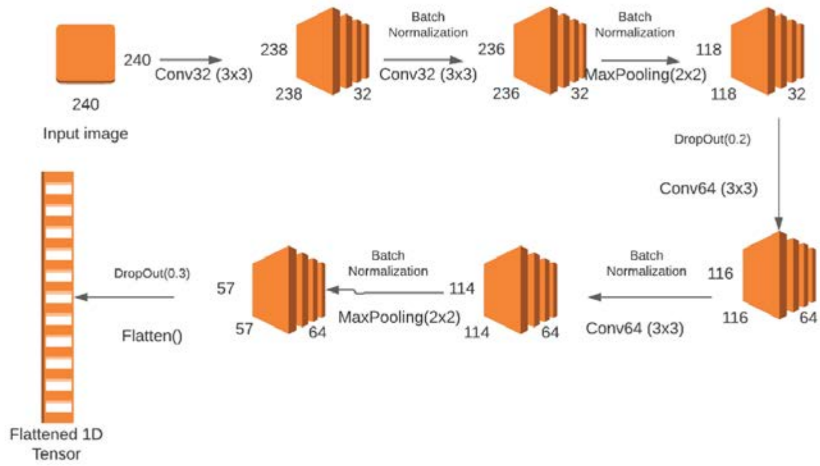


Figure 2. CNN Architecture Inspired from VGG Net

The figure above shows the flow architectures of the model we train using the previously mentioned methods. The architecture follows VGG Net's architecture as it is a proven model for high-resolution image data. A basic VGG block has three layers, two convolution layers, and one max pooling layer and we use such two blocks connected back to back. The input image was resized to 240x240 and fed to the first VGG block of two convolutional layers and one max pooling layer. As the image goes through the network, we can see that its width and height reduce and the depth increases as the number of filters/kernels is increasing. All convolutions are with kernels of size 3x3 and depth 32 and 64 respectively for the two blocks. Convolution is with the same padding so it reduces the image size by two in every convolution and the pooling reduces the image dimension in half. After each convolution, batch normalization is applied, and after each max pooling, dropouts of various values are applied for better performance. Finally, we get a 57x57 feature map of 64 kernels which is flattened to a one-dimensional tensor to be fed into the dense neural network for training. For the whole network to train, Adam optimizer and binary cross-entropy are used. For the above model, we need both classes of thermal images. But the availability and collection of class 1, the covid-19 thermal images might be difficult and time-consuming. So, we propose a One-Class Classification training for thermal images collected from open-source databases. The OCC models also known as unary classification models learn from a single class and consider the other class as an anomaly [10]. It takes the negative class as normal or inlier and the positive class as anomaly or outlier. Such algorithms are mainly used for anomaly detection. Here we can make the elevated temperature level an anomaly and train our model using the normal dataset. SVM (Support Vector Machine)- based and KNN (K Nearest Neighbour)- based OCC models are there. We can train CNN models also in an OCC mode. And after training and testing, the model will be encountering class 1 images. Since it is an online model which can continue even after deployment, the model can update the class 1 images as well.

2.3 Testing and deployment.

The preprocessed dataset is split into train and test in the ratio 70:30 for training and testing. Since it is a binary classification model, the performance can be evaluated simply by using a 4x4 confusion matrix. The main performance metrics we can derive from the confusion matrix are accuracy, sensitivity, and specificity.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

Sensitivity = (TP) / (TP + FN)

Specificity = (TN) / (TN + FP)

Sensitivity is related to the model's ability to identify/detect the condition correctly. It is obtained as the number of true positives (TP) divided by the total number of true positives and false negatives (FN) in a population/data sample. Specificity is related to the model's ability to exclude a condition correctly. It is obtained as the number of true negatives (TN) divided by the total number of true negatives and false positives (FP) in a population. Finally, accuracy is calculated by dividing the total number of successful results by the total population/samples. `After testing and evaluation, the best fit model is selected and the learned weight parameters are saved into the HDF file and loaded to the drone CPU. Since it is an online model, the weights can be updated during the service after deployment.

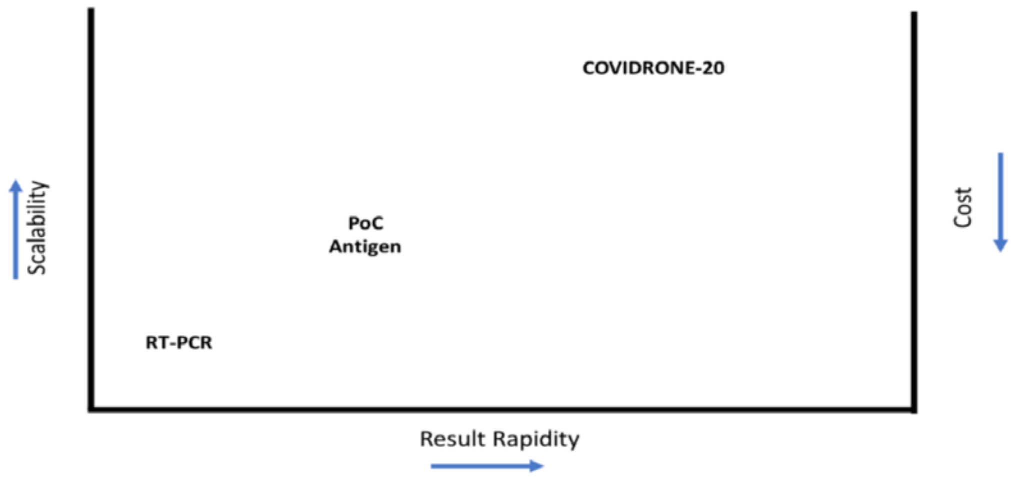
3. Public Health Implications

The drone technology makes it easier to monitor the crowd from a distance, especially during a viral outbreak. This type of surveillance tool prevents the direct transmission of pathogens from an infected person to the person who does the test. Moreover, these kinds of monitoring devices can be used to track the body temperature of patients in public spaces or social gatherings. However, individuals may have worries about their privacy and health data since available technologies make it easier to invade them[21]. Furthermore, the introduction of more and more affordable drones makes the airspace more crowded, and hence visual pollution. Besides that, the noise while operating them can make the public uncomfortable [22]. Sound sources have different characteristics, psychological effects and the implications can be different for different humans.

The Federal Aviation Administration (FAA) rules for small unmanned aircraft systems (UAS)operations cover a broad spectrum of commercial and government uses for drones weighing less than 55 pounds. COVIDRONE users will take advantage of both the FAA certificate of authorization (COA) to function as a "public aircraft operator" and FAA-certified pilots. Furthermore, rather than certifying pilots and registering aircraft under Part 107, agencies may choose instead to request a COA from the FAA to become a public aircraft operator. This would allow agencies to self-certify drone pilots and drones for flights to perform governmental functions. Drones will be flown within Visual line-of-sight (VLOS) and will not be flown higher than 400 ft.

4. Economic Benefits of COVIDRONE-20

Rapid testing and isolation of infected individuals would remain as the primary mitigating strategy for controlling the pandemic[19]. Reverse Transcription- Polymerase Chain Reaction (RT-PCR) testing and Point-of-care antigen testing are two widely used testing mechanisms currently. Availability and cost of these testing mechanisms rendered them symptomatic and contacts of infected people. Moreover, because the test positivity rate is below 10% in the US[20], the economic value of testing can be improved by using a low-cost scalable mechanism to prioritize RT PCT testing. The mass screening capability of COVIDRONE-20 using thermal images and drones with negligible cost per person screened would certainly provide the most economically valuable and viable screening strategies. The non-invasiveness of this screening method is an added advantage to the people being screened. Figure 1 provides the comparative representation of various testing methods.



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Using drone technology, machine learning models, and IR technology a new more efficient, and more versatile COVID-19 monitoring and diagnosis system has now been created. This proposed design will be able to diagnose individuals in both small and close spaces like traditional IR cameras, but also in large open spaces where the use of traditional IR cameras is not plausible. This design will also allow for mass diagnosis of the disease in larger vicinities especially in areas prone to high concentration populations which can serve as hotspots for the disease. This drone is also capable of sending data about possible COVID - 19 patients to designated health officials through local computers or even other smart devices. Unlike traditional techniques for monitoring COVID-19 patients such as thermal scanner COVIDRONE-20 diagnoses or monitors individuals through noninvasive manners to avoid the risk of transmission of the disease from the tester and the individual being tested. COVIDRONE-20 not only uses elevated body temperature like traditional systems used for monitoring or diagnosis like IR cameras and thermal cameras but also takes advantage of machine learning models to identify specific thermal signatures of thermal physiological patterns unique to COVID -19 patients which it can then look for in input data. This is especially important as high body temperature is not something unique to COVID-19. In conclusion, early identification of disease is vital for the prevention of possible future outbreaks, however current techniques and methods being used to monitor and diagnose potential patients in real-time lack versatility, efficiency, and accuracy [23, 24]. Therefore a new system was needed, hence the development of COVIDRONE - 20, a more efficient, more accurate, and more versatile diagnosis or monitoring system [25-30].

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