Machine Learning Based Low-Resolution Infrared Head Localization for Disease Situation Awareness via Mobile Skin Temperature Analysis

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Keywords: COVID-19, Fever, Infrared Imaging, Machine Learning, Computer Vision, Android.

The highly disruptive and potentially lethal virus which causes COVID-19, SARS-CoV-2, inherits more than just its name from the 2003 SARS-CoV virus to which it is distantly related. Patients infected by both pathogens exhibit fever as a common symptom (Centers for Disease Control and Prevention, 2020; Institute of Medicine, 2004), and in response to both outbreaks, researchers have attempted to leverage infrared imaging for fever detection to limit the spread of the viruses. Although several studies responding to the 2003 outbreak of SARS-CoV achieved partially successful results (Ng et al., 2004), the applications of such technologies were ultimately limited by their inaccessibility; the sensors and computing hardware necessary to make use of these systems often required significant investment and a strictly controlled environment (Chan et al., 2006). Now, the outbreak of COVID-19 has rekindled interest in infrared fever detection. Unlike in the early 2000's, however, there is now widespread access to a tool that did not yet exist in 2003: the smartphone.

The intention of this research is to develop and deploy the Infrared Fever Indication System (IRFIS). IRFIS extends prior research into fever detection via infrared imaging in two key ways. Firstly, the system utilizes a modern, machine learning based object detection model for detecting heads, supplanting the traditional methods that relied upon shape matching (Alkhayat et al., 2015; Surabhi et al., 2012). Secondly, IRFIS is capable of running from the Android mobile platform using a small, commercial-grade infrared camera. From this platform, IRFIS is capable of performing live head detection and temperature analysis to inform mobile users of nearby individuals who may be exhibiting unusually elevated temperatures.

IRFIS was developed by training an object detection model in two stages. The first stage involved selecting and training a model to locate people within infrared images. The second stage leveraged the previously trained human detector model to instead detect heads from low-resolution infrared images.

For the first stage of learning, FLIR's ADAS dataset, which consists of 640x512 resolution infrared images, was used to retrain several object detection models in order to select one to serve as a base for the second stage of retraining. The initial model candidates were selected based on their size, as a small model would be needed in order to run efficiently from a mobile platform. Of the retrained models, EfficientDet-D0 (512x512) was selected to proceed with stage two.

For the second stage, a new dataset composed of low-resolution (120x160) thermal images of various human subjects was collected using FLIR One Pro cameras mounted on Android devices. Annotation files were generated for each image to establish ground-truth values regarding where the head regions lay within each image. The initial model was retrained on this second dataset and then evaluated to determine if it would serve as an effective head detector.

To analyze the model's detection capabilities, two primary metrics were used: Average Precision (AP) and Average Recall (AR). Both metrics depend upon the chosen Jaccard Index, or Intersection over Union (IoU), a ratio of areas used as a threshold to determine if a detected bounding box is considered overlapping with a ground-truth bounding box. When evaluated on a dataset of unseen images, IRFIS achieved an AP of 96.7% with an IoU of 0.50 and an AR of 75.7% averaged over IoU values between 0.50 and 0.95, with a maximum threshold of 100 head detections per image. For comparison, a research team at Google achieved an AP of 52.2% on IoU 0.50 when employing EfficientDet-D0 as a general object detector trained on Microsoft's COCO dataset (Tan et al., 2020). Thus, IRFIS marks an increase in AP of 44.5% on the same IoU when utilizing EfficientDet-D0's architecture to detect heads, despite the poor-quality image data provided by the commercial-grade sensor. Coupled with an AR of 75.7%, these figures indicate that the detector was highly discerning and accurate.

The IRFIS head detector is currently deployed on the Covid-ID Android application, where infrared images from a scanning interface are passed through the detection model and the corresponding head instances are stored in the Cloud. The next phase in developing IRFIS will be to pass the localized head regions to a routine capable of performing temperature analysis to identify humans with potentially elevated temperatures, with our preliminary system simply extracting the maximum temperature detected within the head region, then provide live visualization of possible fever instances to the user. Other methodologies for temperature analysis will be explored in the future but are not the focus of this abstract.

IRFIS presents a new tool for smartphone users to increase their situation awareness with respect to COVID-19, and the Covid-ID mobile application under continuing development could bring IRFIS to a global userbase. The system also serves as a proof-of-concept for the development of future mobile systems that could leverage machine learning based object detection techniques in the infrared spectrum for a variety of applications, both medical and non-medical in nature.

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