Social Distancing Detector with Deep Learning and Parallel Computing on Android Application

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Abstract

Due to pandemic on this year, social distancing has been recommended by the government, since this can reduce the spread of disease. With the help of technology, social distancing violation can be determined by using computational devices, such as mobile phones. To determine social distancing violation, firstly, humans are detected by using deep neural network. Then, the distance is calculated among detected humans. This dissertation proposes a social distancing detection on Android application with the purpose of performance maximisation by using all tools and techniques. Parallel computing and NEON instruction are used for performance enhancement. To detect humans by using deep neural network, OpenCV, a third-party library, is used in this project. OpenCV is used for network initialisation, and forwarding preprocessed input through the network. To understand performance maximisation, we provide comparisons among detection models, technologies, and programming languages. Comparisons and evaluation of the performance are presented. The results show that parallel computing and NEON instructions improve the application's performance. Processing 31 frames of video by using OpenCV without NEON instructions and using 8 threads took 10.624 seconds, while OpenCV with NEON took 2.890 seconds. In addition, the performance is better when OpenCV is manually built. Processing 31 frames with 8 threads by using official built OpenCV took 4.954 seconds, while manually built OpenCV took 2.890 seconds. Moreover, the performance is improved with speedup up to 52%.

Education Use Consent

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Name: Jinkawin Phongpawarit Signature:

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Contents

Chapter 1

Introduction

1.1 Motivation

Humanity has been faced several pandemics over hundreds of years, and many lives are threatened. For example, there was the black death in 1346, and the flu pandemic in 1918, and millions of people died during each pandemic [7] [25]. This year, humanity is confronting the other pandemic, which is named as coronavirus or COVID-19.

However, a threat from illness or the impact of the outbreak can be reduced by using technology and scientific discovery. For instance, social distancing has been recommended since there were Influenza A (H1N1) outbreaks in 2009 [14]. Social distancing is able to reduce the spread, and slow down and reduce the size of the epidemic peak [12] [13]. Consequently, the infection curve is flattened, and the number of deaths is reduced. Currently, scientific researchers are still working on this pandemic with the aim of reducing the infection rate. In addition, technology can be integrated with scientific theory to gain more advantages.

Due to competitive advantage and business competition, the ability of computable devices have been improved, which is capable of executing very complex tasks. Mobile phones, which are part of a highly competitive market, become powerful devices. People use mobile phones for many purposes, such as entertainment, education or business. Likewise, in application development, there are advantages to mobile devices. The first advantage is performance. As the aforementioned competition, the hardware of mobile phones has been improved over the years, including CPU, GPU, and memory. Thus, the capability of mobile phones is sufficient for performing heavy calculation tasks. The second advantage is portability. Most of the mobile phones provide necessary features, such as a camera, sensor, and GPS. In addition, mobile phones has a battery, which does not require a charger during being used.

For the advantages above, a mobile application can be used as a tool to help human determine social distancing.

1.2 Aim and Objectives

The aim of this project is determining distances between people, and maximising the performance of the application to achieve the highest frame rate (frame per second or FPS). To accomplish the aim, the objectives of this project are specified as follows:

- Determine objects from the given image and video by using Deep Neural Networks (DNNs).
- Determine distances between people in real-time from a camera.
- Process inputs simultaneously by using parallel processing techniques.
- Use advanced single-instruction multiple-data (SIMD) NEON instructions to improve the calculation performance.

1.3 Structure

The content of this dissertation is structured as follows:

- Chapter 2 provides background knowledge of Mulithrading in Android application, social distancing determination, hardware specification, and existing applications.
- Chapter 3 shows an overview of the system and describes implementation details in various aspects.
- Chapter 4 evaluates and compares the result of the performances of each implemented technology.
- Chapter 5 concludes the results of the project, limitation of this project, and future works.

1.4 Demonstration

The demonstration video can be accessed from https://youtu.be/T-ZQpJyAhw4

Chapter 2

Background and Related Works

This chapter aims to introduce background knowledge that relates to this project including deep neural network, android development, and distance calculation. Then, this chapter gives examples of related works.

2.1 Deep Neural Network

A Deep Neural Network (DNNs) is a deep learning's architecture, which is a part of machine learning, and it is based on artificial intelligence. DNN is stimulated from the human nervous system, which contains cells. These cells are called neurons, and they are fully linked [5]. Likewise, DNNs are composed of multiple layers between input and output, and each layer has neurons, which are entirely connected [27]. These layers turn input to output by passing data through each layer and doing some computation, and this is called forward propagation [5], [18]. DNN can be applied in many fields such as computer vision (CV), speech recognition, or object detection [18].

2.2 Threading in Android

Threads in Android development are split into two main categories: the main thread and a worker thread. A main thread or UI thread is a thread that dispatch events of user interface widgets. The events are dispatched regarding Android's activity lifecycle, and all events are managed by only one thread. In other words, threads will not be spawned for handling a single event or component. Thus, if there is a long-running task, which is run by UI thread, events cannot be delivered because long-running task block UI thread. If UI thread is blocked more than 5 seconds, an application will show "Application not Responding" [2].

A working thread is separated from the UI thread to avoid freezing application, and it is called worker thread or background thread. This thread is able to process a long-running task in the background without interrupting the UI thread. In addition, the priority of the thread can be set from -20 to 19—the lowest priority is 19 and the highest priority is -20. The default value of background threads priority is 10, and the default value of foreground threads is -2 [1].

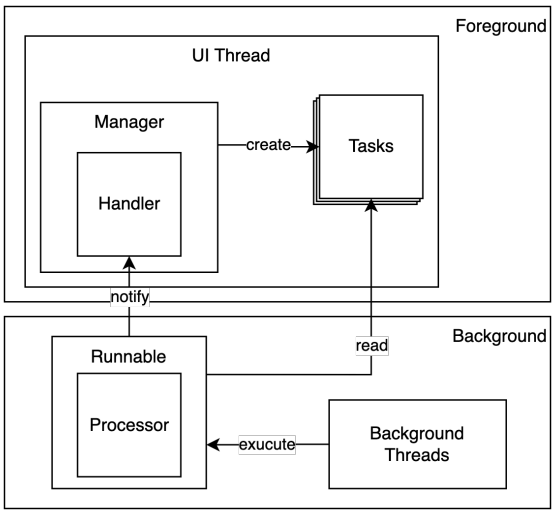


Figure 2.1: Threading Overview

UI thread and background thread run on different threads, thus a Handler is needed when there is communication between these threads. For example, as shown in Figure 2.1, processes are divided into two parts: foreground and background. Tasks are created by a manager which is running on the UI thread. Then, Runnable, a component that can be run by background threads, will read tasks. After that, Runnable will be executed by background threads. Finally, Runnable will notify the manager through Handler.

2.3 Distance Calculation

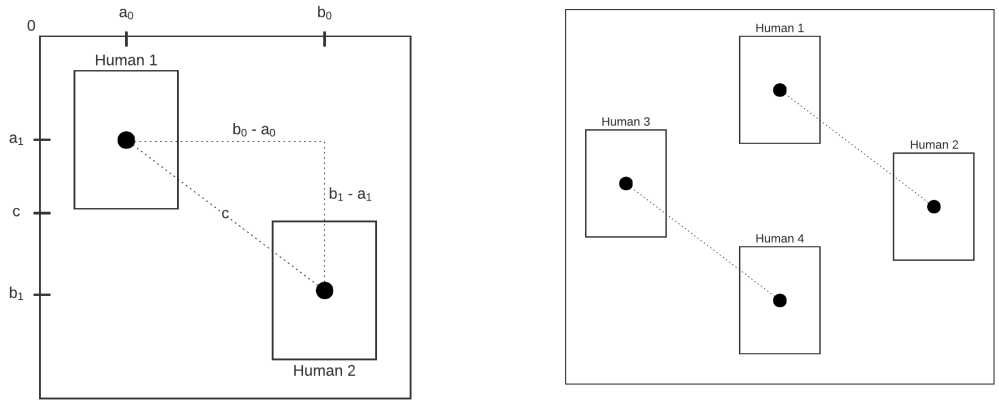
According to Gurucharan [17], to measure a distance between 2 people, the reference points of them are used for calculation. The reference point is the coordination of the 2 people, which is the centre of the detection frame. The calculation formula is based on Euclidean distance:

$$d = \sqrt{(a_0 - b_0)^2 + (D/c) \times (a_1 - b_1)^2}$$

$$c = \frac{a_1 + b_1}{2}$$

However, a three-dimensional space is captured into a two-dimensional image, so depth and perspective can be seen in Figure 2.2a. Thus, a couple of variables are added into the formula. The first variable is D, which is the diagonal of the image. The second variable is c, which is a calibration. These two variables will determine the depth of people in the image.

For example, according to Figure 2.2b, if the distance is calculated without calibration, the distance between 2 groups of people will be the same. Naturally, the distance between Human1 and Human2 must be further than the distance between Human3 and Human4.



(a) Distance calculation

(b) A difference of 2 distances

Figure 2.2: Determining Social Distancing

2.4 Related Work

2.4.1 Object Detector

Object Detector is an Android application[1], which is able to detect objects through a camera. This application is implemented by a deep learning library from TensorFlow [4] with MobileNet model[2] [15] [21] and COCO dataset [19]. There are two modes in this application, which are detection mode and classification mode. The processing time of each frame is 250 to 300 milliseconds. The screenshot of the application can be seen in Figure A.1.

2.4.2 TensorFlow Object Detection

TensorFlow Object Detection is an object detection application[3], which is run on the Android operating system. TensorFlow's library is used in this application, along with the MobileNet model. This application is able to detect objects in real-time from the camera. The screenshot of the application can be seen in Figure A.2.

2.4.3 Computer Vision Detection

Computer Vision Detection application operates on the Android operating system[4]. This application is able to process real-time video from a live camera, and OpenCV is used as a library [9]. There are 12 options of algorithms, such as colour detector, canny detector, motion detector, and shape detector. Besides, this application is able to detect human faces and smiling faces. This application

[1] https://play.google.com/store/apps/details?id=com.tecomen.android.objectdetector

[2] https://tfhub.dev/tensorflow/lite-model/ssd_mobilenet_v1/1/metadata/1?lite-format=tflite

[3] https://play.google.com/store/apps/details?id=org.tensorflow.detect

[4] https://play.google.com/store/apps/details?id=com.pobeda.ivan.opencvdetect

is able to process around 13 frames per second. The screenshot of the application can be seen in Figure A.3.

2.4.4 Real Time Object Detection and Tracking Using Deep Learning and OpenCV

Demonstrates and explains how objects are detected and tracked in real-time [10]. Objects are detected by using Single Shot Detector algorithm (SSD), which is trained with MobileNet. In this paper, many techniques are used to enhance the performance of the detection. At the first step, frames are extracted from the camera. Then, a local mean algorithm is applied to filter noise, and reduce the complexity and computing time of preprocessing. In addition, background subtraction is used to localise the detected object in the frame. The detected object is considered as a foreground object, and it is separated from background for further processing. Furthermore, the object will be tracked after the object is detected, which reduce the processing time because detection can be processing a few frames, while tracking the object can be processed faster. The result of this research shows that SSD can process the given image faster than YOLO model, and SSD can detect the object with confidence over 98%. In addition, this work shows that humans can be detected with an accuracy of 99%

Chapter 3

Design and Implementation

This chapter shows the overview of application design. The MoSCoW statement will describe the functional requirements and the implementation details will be explained in many aspects, including Native library, social distancing detection process, parallelisation and processed video rendering.

3.1 MoSCoW Statement

The aim of this method is prioritising the requirements, which are determined from usability, cost, or performance. The prioriy is divided into 4 categories: must have, should have, could have, and won't have [6]. Next, we describe the requirements of each of them.

3.1.1 Must have

- The application **must** be able to detect people in the given image or video.
- The application **must** be able to determine distancing between people in the given image or video.
- The application **must** save the processed image of video.
- The application **must** allow the user to choose image or video from device's storage.

3.1.2 Should have

- The application **should** be able to stream video from camera.
- The application **should** be able to show detected people on camera.
- The application **should** support parallel computing.

3.1.3 Could have

- The application **could** choose computation options between sequencial or parallelism.

- The application **could** support NEON techonology.
- The application **could** be able to process the given tasks in background.

3.1.4 Won't have

- The application **won't** detect other objects which are not human.
- The application **won't** support GPU computation.

3.2 Interface Design

This application consists of three main processing functions: using video, using a picture and live from a camera. When a user opens the application, the user will navigate to the main menu, which can be seen in Figure B.1a. The user will be able to choose the processing function by clicking buttons. As can be seen in Figure B.1b, video and picture button, the first two buttons, will navigate the user to the device's directory for choosing a file. The file will be processed in the background when a file is chosen, and the status bar will be updated regarding the progress. When processing is done, as it shows in Figure B.2, video or image will be shown at the top of the application The detected human will be drawn a red rectangle if the detected human is breaching social distancing detection, while the detected human will be drawn a green rectangle if the detected human is retaining social distancing. In addition, the user is able to use the camera to determine social distancing in real-time. The user will navigate to the camera activity when clicks the rightmost button in the application, as can be seen in Figure B.4.

3.3 Preparation

Application is implemented on the Android Operating System, and the target Software Development Kit (SDK) version is set at level 29, namely Android Q. This application is compiled and built by Android Studio version 3.5.3, and CMake is used for compiling C++ library with C++ version 11. Furthermore, OpenCV version 4.4.0, which is built as a shared library, is used for image processing and object detection. For object detection model, two models are used: You Only Look Once [24] and MobileNet SSD [15] [21].

3.4 Java Native Interface

The implementation is divided into 3 layers which can be seen in Figure 3.1. The first layer is a Java layer, which mainly interacts with the user, checks permissions, handles activity lifecycle, communicates with Java Native Interface (JNI), and loads native libraries. Native libraries are compiled and built into shared libraries by a Native Development Kit (NDK) [20]. The second layer is JNI, which is written in C or C++. The task of the JNI layer is an intermediate connection between the Java layer and a C++ layer. The last layer is the C++ layer, which alternatively performs calculation tasks, including Deep Neural Network and distance calculation.

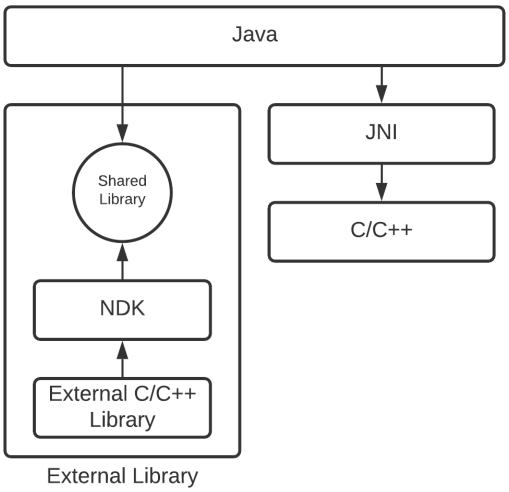


Figure 3.1: Application Layers

However, Deep Neural Network and distance calculation can be implemented in all layers. According to the Android Developer Guide [2], Native Development Kit (NDK) is recommended for compiling C and C++ code into the native library, which is able to achieve higher performance. Thus, executing both tasks in the JNI and C++ layer gains a better performance. Furthermore, there are two advantages to implementing JNI. The first advantage is reducing JNI calling. Performing both tasks in an application layer requires to call JNI methods many times, and this adds a cost overhead. Thus, manually implementing JNI reduces the number of JNI calls. The second advantage is memory management. C++ is able to access values in memory by using a pointer. Thus, values can be directly accessed without copying.

Java and JNI communicate through native function, which is written in the Java layer, and the example of the code can be seen in Listing 3.1. Memory addresses of the pre-processed frame in Mat format will be pass as a parameter through native function, and it will be converted from Java type to Native type as can be seen in Listing 3.2. Then, the given addresses will be converted back into Mat format.

```
1  public class NativeLib {
2      static {
3          System.loadLibrary("native-lib");
4      }
5
6      public native static void process(long imageAddr);
7  }
```

Listing 3.1: Java Native Function

```
1  Java_com_jinkawin_dissertation_NativeLib_process(jlong matAddr){
2      Mat &frame = *(Mat *) matAddr;
3      ImageProcessor::process(frame);
4  }
```

Listing 3.2: C++ JNI Method

3.5 Social Distancing Detection

There are three main processes that are implemented to determine social distancing violation from image and video, as shown in Figure 3.2.

The first process is pre-processing the given image, video, or video stream. The given video will be extracted into an array of images. Then, images will be converted into Bitmap and Mat format with RGBA colour model respectively. After that, the colour will be converted, which depends on the detection model. As mentioned in Section 4.1, two models are used for detecting humans in the given picture and video: YOLO model and MobileNet SSD model [4], [24]. Colour will be converted to RGB if the detection model is YOLO, while MobileNet SSD requires BGR colour model.

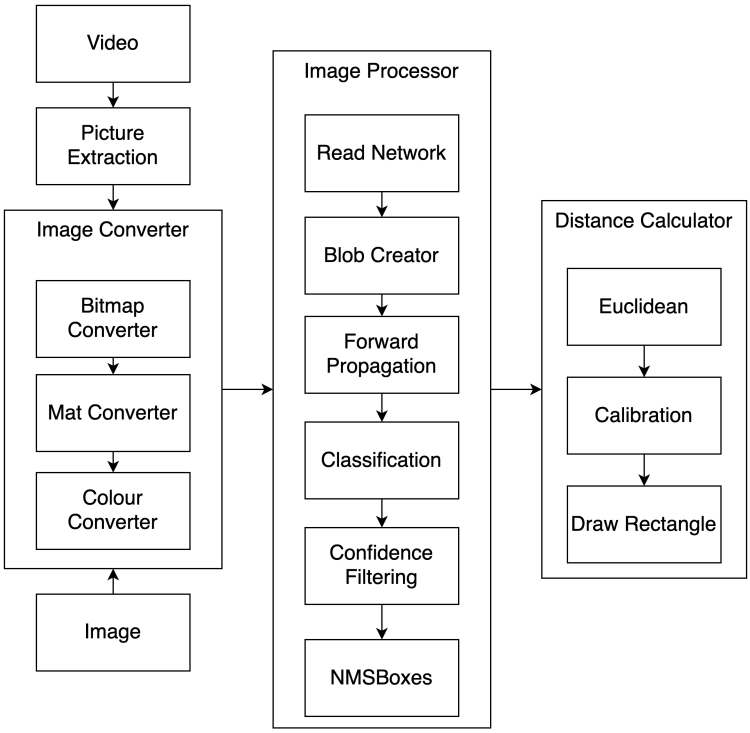


Figure 3.2: Detection System Overview

The second process is object detection. Detection models are set up and configured differently before processing images. First of all, YOLO is used with Darknet [23], which is an open-source neural network framework, while MobileNet SSD is used with Caffe framework [16]. Then, the threshold will be set for determining the confidence score of the detected object. The confidence score threshold of YOLO model will be set to 0.5 or 50 per cent. In other words, the detected object will be rejected if YOLO model cannot guarantee that a detected object is human, and its confidence score is lower than 50 per cent. In contrast, the confidence score threshold of MobileNet SSD model will be set to 0.3 or 30 per cent. Because of MobileNet SSD model has a lower ability to detect an object, the confidence threshold is set lower. After models are set up and configured, the image will be processed in 5 steps. For the first step, the pre-processed image will be converted to input Blob by passing Mat image to $blobFromImage()$ function, and scale factor will be passed as a parameter. Blob will be used for the forward propagation in the neural network. Secondly,

the blob will be passed to the network through $forward()$ function, and the network's output is a list of detected boxes with a label and a confidence score. Then, detected objects will be classified. Non-human objects will be removed by considering the label of the detected object. After that, a confidence score will be filtered by considering the threshold that is set in the configuration step. Finally, $NMSBoxes()$ performs non-maximum suppression, which will reduce overlapping detected boxes.

The last process is determining social distancing. After a list of detected object boxes is filtered, the distance between each box will be calculated by using the formula which is based on Euclidean distance[1]. If the value of the calculated distance is lower than the threshold, this means that the two people are too close, and they are breaking the social distancing rule. The application will change the box's colour to red. In contrast, if the value of the calculation is greater than the threshold, there is no breaching of social distancing rule, and the box's colour will be changed to green.

3.6 Parallelisation

Multithreading is used to reduce the processing time, which can achieve nearly real-time processing. The strategy of multithreading is dividing an input video into frames, and assign frames to threads by considering a number of available cores.

There are two things that will be considered while the application is performing multithreading to avoid overheads. Firstly, Input/Output (I/O) operation must be avoided by threading. Secondly, all variables should be considered due to limited memory. Variables that consume a large space of heap will be initiated as static by using static block. In addition, the usage of the short-lived variables will be reduced to avoid garbage collection. Furthermore, a task will be recycled after a thread finished processing the given frame.

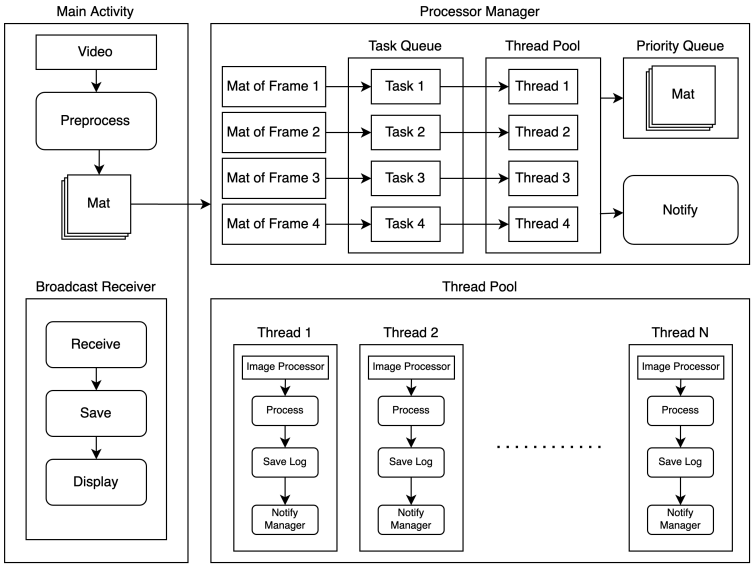


Figure 3.3: Parallel Computing Diagram

[1] an explanation was given in chapter 2.3

In Java multithreading, a processor manager is implemented for managing threads efficiently. To ensure that the processor manager will be created at once, the processor manager is designed with singleton pattern and static block. Thread pool and queues are fundamental operators in the processor manager. As can be seen in Figure 3.3, frames in Mat format will be assigned as a task and queued in TaskQueue. Then, tasks will be mapped with thread orderly by the thread pool. A working thread will process the given task. After a thread finishs the given task, the thread will write a log regarding social distancing detection, and notify the processor manager. Then, a task will be recycled to free up memory. When the processor manager receives a notification from workers, a processed frame will be retrieved and ordered in the priority queue. After the process manager retrieves all processed frames, the process manager will notify the main activity. All of these processes are run in the background to avoid a frozen application.

On the other hand, multithreading in C++ is slightly different, which can be seen in Listing 3.3. The central concept of multithreading is the same as Java, except thread management. A thread pool is implemented in Java to manage and handle threads, while parallelism framework in OpenCV is used in C++ [9]. This framework is compiled with Threading Building Blocks (TBB), which is developed by Intel.

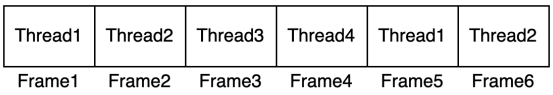


Figure 3.4: Multithreading in C++

```
1     virtual void operator()(const cv::Range& range) const{
2         for (size_t i = range.start; i < size; i += threadNo){
3             cv::Mat &frame = *(cv::Mat *) frames[i];
4             ImageProcessor::process(frame);
5         }
6     }
```

Listing 3.3: The example of multithreading in C++

To reduce the processing time, the threads will process the frame which has the same index as itself, and the index will be increased by the number of total available cores. For example, as can be seen in Figure 3.4, the first thread will process the first frame and the fifth frame. Theoretically, if the frame rate of the video is 30 FPS, each frame should be processed within 33 miliseconds. Thus, if there are four threads, the first thread will have about 100 milliseconds to finish processing the first frame before moving to the fifth frame.

3.7 Frame Rendering

The maximum processing frame rate of this application is 10 FPS, which will be discussed in Chapter 4. At this frame rate, video cannot be displayed smoothly in live camera; thus, there are steps that help video to be displayed in a higher frame rate. First of all, when a frame is streamed from the camera, the frame will be considered to be processed or not be processed. Processing will be determined from the capability of the device. In other words, the maximum processing frame rate will be used as a threshold. If a number of processed frames in 1 second exceeds the threshold, the frame will not be sent to the processor manager. After that, the main activity will check a

processed frame in a priority queue from processor manager. If there is a processed frame in the priority queue, the processed frame will be displayed to the screen. Otherwise, the main activity will read the last log of the processed frame and retrieve all detection rectangles. Then, the main activity will draw those rectangles on the incoming frame and display it on the screen.

Chapter 4

Evaluation and Testing

This chapter presents an evaluation of the application, which is divided into three parts. The first part will show variables that must be controlled for the reliability and stability of the result. The second part evaluates the application's performance, which are comparisons among models, programming languages, and technologies. The last section shows a usability testing of this application.

4.1 Controlled Variables

To ensure the result of the performance will not be varied by other factors, some variables must be controlled as following:

1. All testing cases will be run on Samsung Galaxy S10+.
2. All running background applications will be closed, and memory will be freed before testing.
3. To prevent CPU's speed is limited, a power management mode will be set to "Optimised".
4. The total number of frames in the testing video will be set to 31.
5. The testing video resolution will be set to 540x480 pixels.

4.2 Experimental setup

The proposed application is developed and tested on using the device specification shown in Table 4.1:

Device	Device	Samsung S10+
Operating System	Operating System	Android 10 (Q)
Processor	CPU	Samsung Exynos 9820
	Cores	8
	Architecture	2x ARM Cortex-A75 2.73GHz 4x ARM Cortex-A55 1.95GHz 2x Samsung Exynos M4 1.95 GHz
	GPU	Mali-G76
Memory	RAM	8 GB

Table 4.1: Device specification

However, the GPU is not used in this experiment due to the limitation of the OpenCV library. In addition, 2 models are used in this experiment: You Only Look Once [24] and MobileNet SSD [15] [21]. The sample of pre-recorded video is obtained from Ben Benfold and Ian Reid [8].

4.3 Performace Evaluation

In this section, the performance of detection models will be compared, and the result will be discussed. There are three sections of discussion. The first section will show the result of processing a single frame. The second section will compare the performance among a number of threads. The last section will discuss the result of NEON instruction and improvement. Computation time and frame rate are used as a metrics to o evaluate the performance of the application. The Frame rate is the number of frames that application can process in 1 second.

4.3.1 Single Frame Comparison

In this section, the performance of 2 detection models will be compare, regardless of other tools and techniques. To evaluate the performance, each model will process on a single frame. The resolutions with 960×540 and 540x480 are used as inputs for comparing the performance and understanding the variation of calculation time.

Model	YOLO		SSD	
Size	960×540	540x480	960×540	540x480
Total Process Time (second)	4.235	3.827	0.337	0.323
Forward Propagation per frame (second)	3.456	3.019	0.284	0.278
Forward Propagation per frame (perenctage)	81.61%	78.89%	84.27%	86.07%

Table 4.2: Picture Processing Performace

As can be seen in Table 4.2, the processing time of the YOLO model significantly increases when the size of the picture is increased. In contrast, MobileNet SSD is able to process the given picture faster than YOLO model [4], [24]. The processing time of MobileNet SSD slightly increases when the size of the picture is increased.

4.3.2 Multithreading

In this section, the performance of both models will be evaluated with multithreading technique, and the evaluation will be divided into three parts: sequential computing, YOLO with multithreading, and MobileNet SSD with multithreading. As mentions in the previous section, in this evaluation, controlled variables are set. The number of frames in the testing video will be set to 31.

For the first part, the application will process the testing video sequentially and measure the performance. This measurement will be compared to multithreading and evaluate the improvement of the performance. As shown in Table 4.3 and 4.4, the YOLO model took 102.972 seconds to process 31 frames of video, while MobileNet SSD model took 7.132 seconds. In addition, cells in the table that have no data will be represented as dash.

Model	YOLO				
	Sequential Computing	Parallel Computing			
		1 Thread	2 Threads	4 Threads	8 Threads
Total Process Time (second)	102.972	117.805	96.415	92.242	99.441
Garbage Collector (second)	-	0.102	0.280	2.024	11.333
Process Time without GC	-	117.703	96.136	90.218	88.108
Forward Propagation (Total)	79.097	-	-	-	-
Forward Propagation (Average)	2.553	2.872	4.840	9.231	19.713
Forward Propagation (Min)	2.213	2.564	4.003	5.478	14.733
Forward Propagation (Max)	2.693	3.092	6.436	12.566	21.815
Number of frame	31	31	31	31	31
Process per frame (second)	3.322	3.800	3.110	2.976	3.208
Improvement			18.16%	21.70%	15.59%

Table 4.3: Video Processing with YOLO Model with official build

Then, a multithreading technique is implemented to increase performance and achieve real-time processing. To evaluate the improvement of multithreading, number of cores will be doubled as follows: 1, 2, 4, and 8. In the testing device, there are 8 physical cores, so it can effectively process up to 8 threads.

Model	MobileNet SSD				
	Sequential Computing	Multithreading			
		1 Thread	2 Threads	4 Threads	8 Threads
Total Process Time (second)	7.132	8.237	6.873	6.270	5.064
Garbage Collector (second)	-	-	-	-	-
Process Time without GC	-	-	-	-	-
Forward Propagation (Total)	7.019	-	-	-	-
Forward Propagation (Average)	0.226	0.235	0.401	0.738	1.133
Forward Propagation (Min)	0.218	0.212	0.353	0.406	0.466
Forward Propagation (Max)	0.243	0.320	0.456	1.477	2.582
Number of frame	31	31	31	31	31
Process per frame (second)	0.230	0.266	0.222	0.202	0.163
Improvement			16.56%	23.88%	38.52%

Table 4.4: MobileNet SSD Model with OpenCV official build in Java

As shown in Table 4.3, the performance of 2 threads is improved only by 18.16%, and it reaches the best performance at 21.7% by using 4 threads. However, the performance of 8 threads is worse than 2 threads. One of the factors is the Garbage Collection (GC). The application was frozen while GC is collecting garbage. GC is not collecting only short-lived objects but long-lived objects as well, and GC collects garbage more often when the number of threads is increased.

As shown in Figure 4.2, memory was allocated by double and array of double, and GC was freeing these allocation 10 times within 5 seconds. Consequently, CPU usage is dropped when GC is working. This problem can be seen in Figure 4.1. The progress status will be green when a thread is working. It will be yellow when a thread is interrupted by GC, and it will be grey when a thread has no activity.

For the MobileNet SSD model, the calculation time of 2 threads is improved only 16.56%, and 8 threads give the best performance with 38.53% as can be seen in Table 4.4. Objects are not collected by GC in this model, but memory will be freed after processing is finished. The improvement of computation time of 8 threads by using MobileNet SSD model is better than YOLO model, but the speedup of both models is still much lower than the ideal.

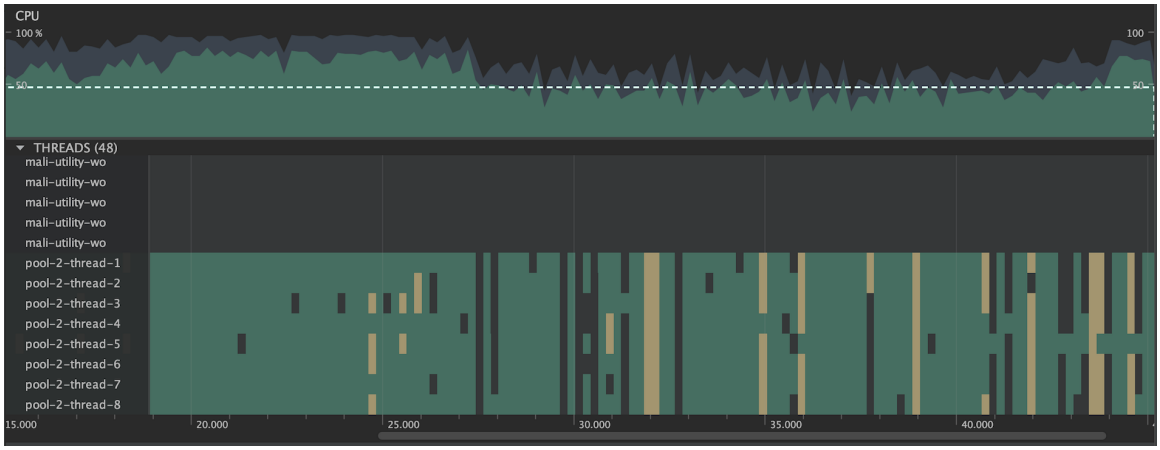


Figure 4.1: CPU Usage of YOLO Model with 8 threads

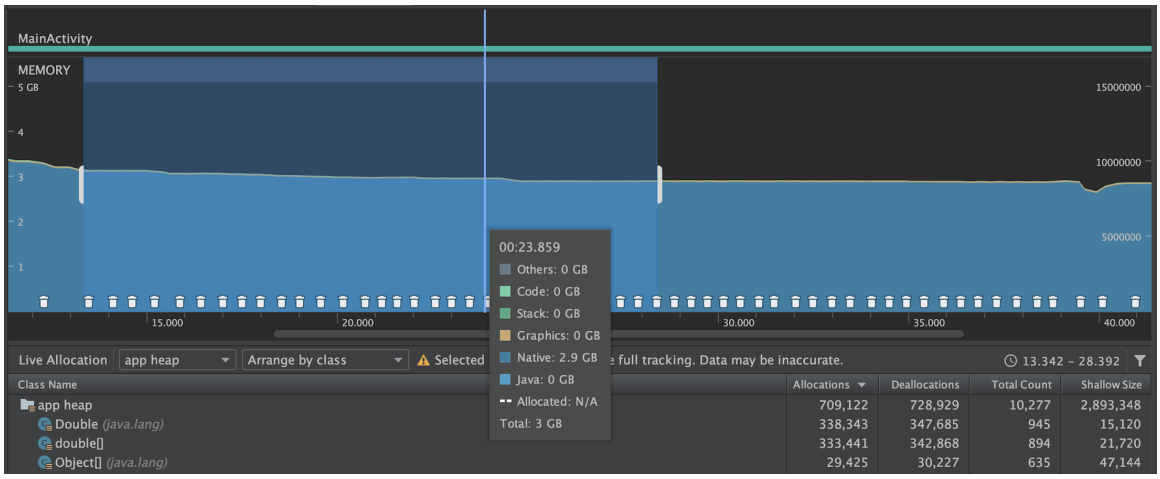


Figure 4.2: Memory Usage of YOLO Model with 8 threads

In summary, the overall performance of the YOLO model with multithreading is slightly improved, and it becomes worse when using 8 threads. One of the obvious factors of these problems is GC. In contrast, the speed-up scale of MobileNet SSD is better than YOLO model because there is no GC during processing. The YOLO model uses more memory than MobileNet SSD in terms of variables in double type.

4.3.3 Android Native Development Kit

As mentioned in Chapter 3, detection process and distance measurement can be written in C++ to achieve higher performance. As it can be seen in Table 4.5, the performance of using 2 threads is improved 44.79% when compared to using 1 thread, and the performance is fastened up to 58.54% when using 8 threads. However, there are 2 issues in this implementation. The first issues is the forward propagation time. Theoretically, the processing time of sequential computing and using a single thread should be the same. In contrast, the forward propagation time of single thread was doubled, which causes the total process time to increase. this is due to the thread management system in C++ that is different when compared to Java. In C++, the thread is managed by OpenCV's parallelism framework, while the thread pool is used in Java which is recommended by Android's

Model	MobileNet SSD				
	Sequential Computing	Multithreading			
		1 Thread	2 Threads	4 Threads	8 Threads
Total Process Time (second)	6.773	11.949	6.597	6.150	4.954
Garbage Collector (second)	-	-	-	-	-
Process Time without GC	-	-	-	-	-
Forward Propagation (Total)	6.659	-	-	-	-
Forward Propagation (Average)	0.215	0.382	0.408	0.613	0.970
Forward Propagation (Min)	0.198	0.363	0.394	0.405	0.407
Forward Propagation (Max)	0.236	0.401	0.421	1.043	2.691
Number of frame	31	31	31	31	31
Process per frame (second)	0.218	0.385	0.213	0.198	0.160
Improvement			44.79%	48.53%	58.54%

Table 4.5: MobileNet SSD Model with OpenCV official build in C++

document [2], [9]. The second issue is the total process time. Although writing in C++ is able to achieve theoretical speedup, the overall performance improves by 92 milliseconds when compared to Java.

4.3.4 NEON Instructions

The OpenCV library provides a shared library, which is called OpenCV4Android. This library is officially built by OpenCV, and it is used. However, the library is built to support all CPU chipsets, and many features and conditions were flagged during building. The library requires to be manually built from scratch to evaluate the performance of NEON [3]. The OpenCV shared library was manually built into two versions: version with NEON and version without NEON. To maximise the performance of the NEON version, OpenCV is forced to be built with NEON instruction regardless of any condition, and it will support only ARMv8-A 64-bit architecture.

Model	MobileNet SSD without NEON				
	Sequential Computing	Parallel Computing			
		1 Thread	2 Threads	4 Threads	8 Threads
Total Process Time (second)	17.308	19.030	15.172	11.797	10.624
Garbage Collector (second)	-	-	-	-	-
Process Time without GC	-	-	-	-	-
Forward Propagation (Total)	17.193	17.848	-	-	-
Forward Propagation (Average)	0.555	0.576	0.926	1.416	2.462
Forward Propagation (Min)	0.519	0.545	0.582	0.756	1.310
Forward Propagation (Max)	0.586	0.654	1.412	2.593	5.308
Number of frame	31	31	31	31	31
Process per frame (second)	0.558	0.614	0.489	0.381	0.343
Improvement			20.27%	38.01%	44.17%

Table 4.6: MobileNet SSD Model with OpenCV manully build (**without** NEON)

After The OpenCV library is manually built and forced to be compiled with NEON instruction, the performance of human detection is significantly improved. As can be seen in Table 4.6 and 4.7, the sequential computing took 4 second for processing human detection, which is 76.85% faster than OpenCV without NEON. In addition, multithreading can process 31 frames of the video up to 2.890 seconds, which is 72.79% faster than OpenCV without NEON and 42.93% faster than the OpenCV official build. For this performance, video can be processed at 10.75 frames per second.

Model	MobileNet SSD with NEON				
	Sequential Computing	Multithreading			
		1 Thread	2 Threads	4 Threads	8 Threads
Total Process Time (second)	4.006	6.079	4.208	3.127	2.890
Garbage Collector (second)	-	-	-	-	-
Process Time without GC	-	-	-	-	-
Forward Propagation (Total)	3.927	4.950	-	-	-
Forward Propagation (Average)	0.126	0.159	0.225	0.339	0.645
Forward Propagation (Min)	0.117	0.128	0.131	0.190	0.266
Forward Propagation (Max)	0.135	0.250	0.295	0.596	1.798
Number of frame	31	31	31	31	31
Process per frame (second)	0.129	0.196	0.136	0.101	0.093
Improvement			30.78%	48.56%	52.46%

Table 4.7: Video Processing with MobileNet SSD Model (**with** NEON)

In addition, according to the rendering technique in Chapter 3, a real-time video from the camera can display up to 25 frames per second.

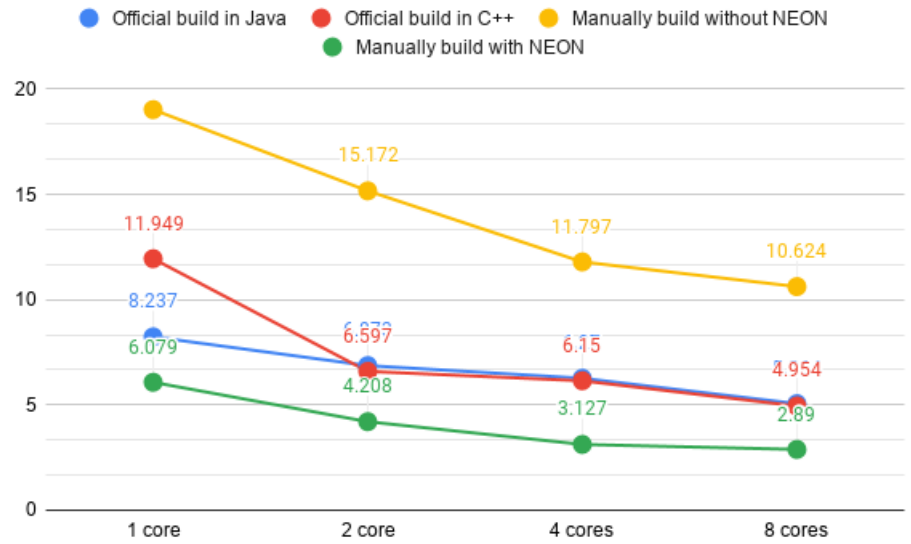


Figure 4.3: Video Processing with OpenCV and MobileNet SSD Model

In summary, using the MobileNet SSD model with OpenCV has a better performance than YOLO model. In addition, OpenCV can be enhanced by manually build. According to Figure 4.3, the fastest processing time is manually built OpenCV with NEON, which is 2.89 seconds to process 31 frames of video. However, these results were not achieved the theoretical performance, and this application did not achieve processing and displaying 30 FPS even if multithreading and NEON are implemented. This underachieved performance could be caused by mulithreading itself. A forward propagation time, which took most of the computation time, is doubled when the number of threads is increased. One of the issues that emerge from this finding is parallelisation in the OpenCV library. Some function underneath the forward propagation function is parallelised by using multithreading. Then, when a frame processing thread is created, a number of threads may exceed the number of physical cores. Thus, threads are interrupted, and it causes a context switching overhead. Besides, the calculation time of using a single thread is always greater than the calculation time of sequential computing and it could be caused by this problem.

Chapter 5

Conclusion

This project was undertaken to build a social distancing detection application on the Android operating system, and to maximise detection performance by using various technologies and techniques.

The results of this implementation show that the combination of the MobileNet SSD model, manually built OpenCV with NEON, and using 8 threads provides the best performance [4], [9], [3]. The computation time of a pre-recorded single frame took 93 milliseconds or 10.752 frames per second, and this application can display 25 frames of video in 1 second on a live camera with the help of rendering technique. The accuracy of the YOLO model was higher than MobileNet SSD model. However, computational time and memory usage of the YOLO model was worse than MobileNet SSD. The YOLO model computation time of 31 frames by using 8 threads was 99.441 seconds, while the MobileNet SSD model took 5.064 seconds. In addition, if NEON is implemented the MobileNet SSD mobile is able to process 31 frames in 2.890 seconds.

5.1 Limitation

Limitations of this application have been found during development. There are 3 main limitations of this application. The first limitation is processing with a graphics processing unit (GPU). Due to OpenCV, currently, supports 3 GPUs which are Intel, Nvidia, and AMD. However, the testing environment, Samsung Galaxy S10+, has an ARM Mali GPU. Secondly, processing video in real-time with the YOLO model cannot be achieved. YOLO model requires a great amount of resources including computing power and memory. Because of limited memory and high demand of memory, garbage collector causes interruptions and frozes the application. In addition, using only CPU cannot achieve an ideal processing time even though multithreading is applied. However, the YOLO model is able to detect human more efficiently than the MobileNet SSD. Thus, there is a tread-off between processing time and accuracy. Finally, the resolution of the video is limited. Regarding performance, the proposed application processes video in low resolution, which is 540x480 pixels. Processing high-resolution video needs more computing power and resources to process in real-time, which are limited in mobile phones.

5.2 Future Work

Considering the studies and limitation of this project, there are many possible aspects that can be done for further development.

The first aspect that may improve the performance is using GPUs. According to the findings, these show that the performance cannot be enhanced further by using CPU with OpenCV library. The more accuracy and performance, the more computing power is needed. Using GPUs to compute forward propagation may significantly reduce the processing time. To support using GPUs, the library must be changed from OpenCV to others that support GPU implementation, such as TensorFlow [4]. Also, OpenCL can be used with TensorFlow to do parallelisation. These can be implemented in Native code to maximise the performance and may achieve higher accuracy, FPS, and resolution.

The second aspect is implementing single instruction, multiple data (SIMD) in other modules, which may gain processing performance. There are parts of the implementation and function that are written in Java, and these do not support SIMD. To maximise the performance, rewriting the programme in C or C++ with SIMD is needed. For instance, calculating the distance between detected humans is written in Java, so this function can be rewritten in C++ to support SIMD. In addition, implementing SIMD can be done in other environments for comparing performance and gaining insight. For example, Streaming SIMD Extensions (SSE) can be implemented on Intel's processor and AMD's processor to improve the performance [26]. Besides, processing on Intel's processor can be optimised by using the Math Kernel Library (MKL) [11]. Implementing SIMD and evaluating other environments may gain an understanding of limitation and overhead of computation by using CPU.

Finally, another aspect is improving the usability of the application. Features can be added to the application to improve practical usability. For instance, face mask detection can be implemented into the application [22], and the performance can be enhanced by using multithreading and SIMD. In addition, this application can be integrated with other systems for practical usage such as a security system.

Appendix A

Existing Applications

Figure A.1: Object Detector

Figure A.2: TensorFlow Object Detection

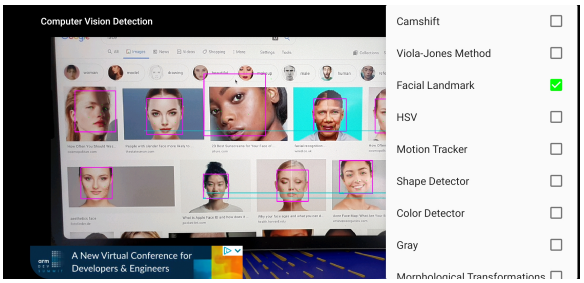
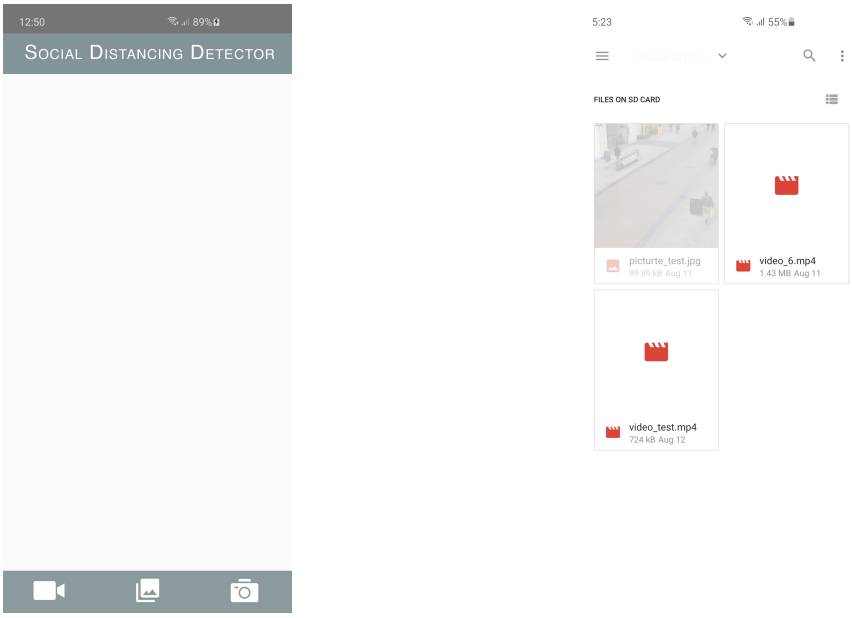


Figure A.3: Computer Vision Detection

Appendix B

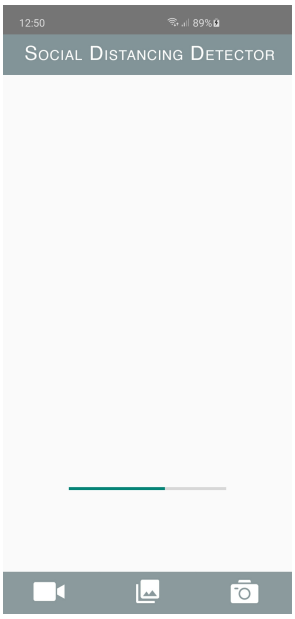
Proposed Application

This chapter is an appendix of application screenshot, which shows application's interface, functions and the result of the application. The application features and usage are decribed in chapter 3.

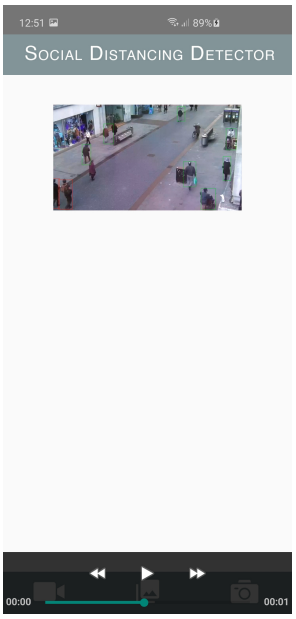


(a) Main Menu (b) Choosing Existing File from Gallery

Figure B.1: Application Interface



(a) Status Bar While Processing



(b) Display a proessed image or video

Figure B.2: Processing pre-recorded file

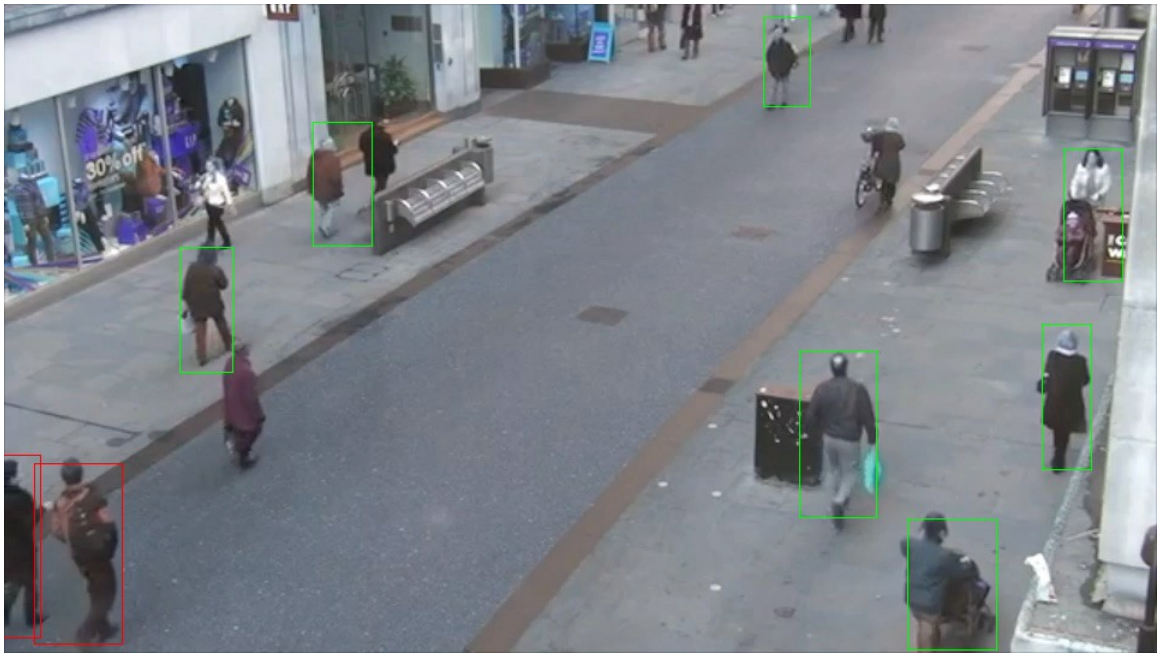


Figure B.3: Social Distancing Detection from Picture

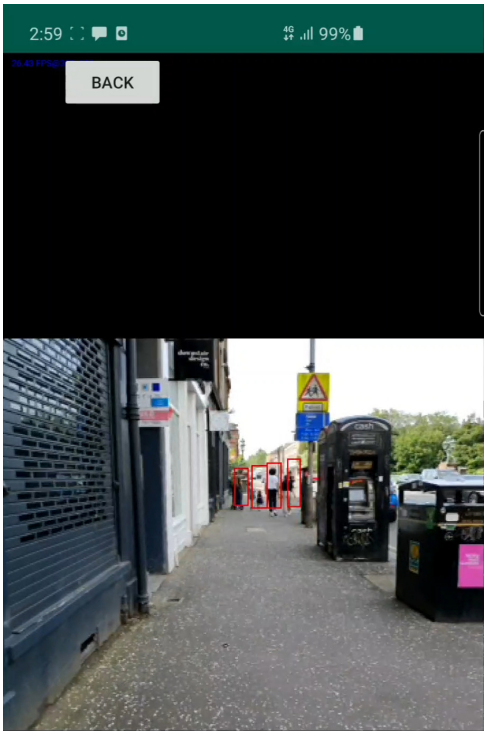


Figure B.4: Social Distancing Detection by Using Camera

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