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The integrated smart system to assist elderly at home

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ABSTRACT

Some elders prefer to live independently rather than in a nursing home. However, they need to be assisted because of health and safety reasons. We developed an integrated system consisting of a smart home, a mobile robot, and a wearable device, using message queuing telemetry transport (MQTT) protocol to communicate with each other. The smart home can be monitored and controlled via a mobile application. We use the telepresence robot equipped with a light detection and ranging (LIDAR) sensor to perform simultaneous localization and mapping (SLAM) and autonomous navigation. The wearable device application is used to detect older adults' heart rate, the steps taken, and the burnt calories. We also add pose detection and location estimation using a depth camera powered by an efficient deep-learning algorithm. We also developed an Android application as a dashboard that monitors and controls all system components. Our system can facilitate communication between its various components.

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1. INTRODUCTION

The population of older people is increasing from time to time. For example, in Indonesia, the proportion of older adults was 5% in 2010, which is expected to increase to 11% in 2035 [1]. Data from the Central Bureau of Statistics in Indonesia also shows that life expectancy in Indonesia is estimated to increase from 72.51 in 2015 to 75.47 in 2045 [2]. In Indonesia, it is common for elderly people to live together with their families. However, this is not always the case, as the family may not have enough resources, or older adults prefer to live alone. We may use technology to support older adults in living independently. Wicaksono *et al.* [3] proposed a voice-controlled smart home to help older adults who do not want to access a complex application interface. Lakshmi *et al.* [4] proposed a smart door equipped with face recognition technology to increase the security level of a house, where they utilized a local binary pattern histogram mechanism for image matching purposes. Human pose detection might also be done inside the smart home using principal component analysis, long short term memory, and support vector machine [5]. Maswadi *et al.* [6] conducted a literature survey about the smart home for elderly monitoring, while Zhang *et al.* [7] analyzed smart home usage for elderly care in China.

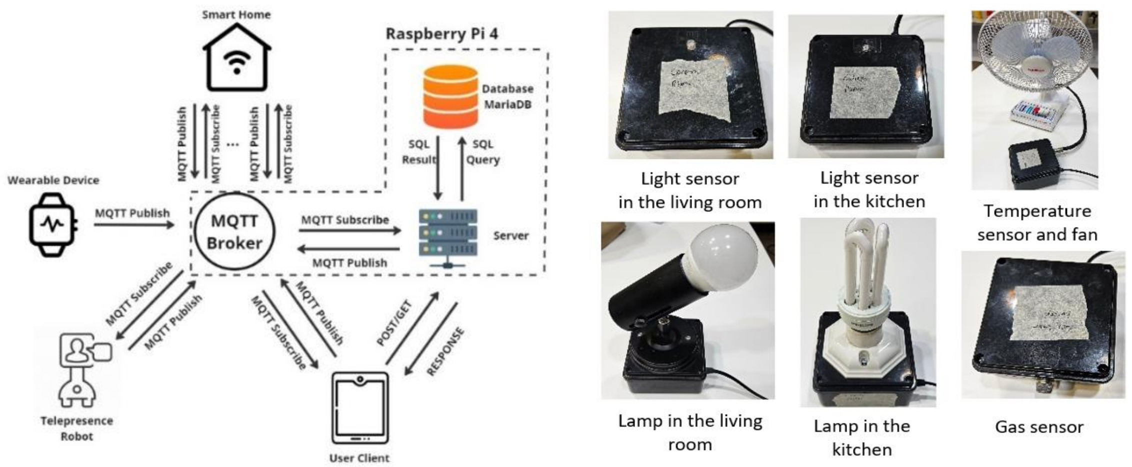
Another useful technology to assist elders is robotics. Koceska *et al.* [8] developed an affordable telemedicine robot equipped with autonomous navigation ability. It is able to move its arm to perform pick and place. On the other hand, Isabet *et al.* [9] used a social telepresence robot to reduce loneliness and isolation among older adults who live at home care. Wearable devices are another valuable technology. Vega *et al.* [10] developed an elder monitoring system where the sensor in the bracelet detects the heart rate, body temperature, and blood oxygenation. It is paired with a mobile application that displays sensor readings, stores the elder's medical records, and provides a communication medium. Yacchirema *et al*. [11] proposed a fall detection system utilizing a 3D axis accelerometer embedded in an IPv6 over low power personal area network (PAN) wearable device to capture the movement of the elders. Random forest is implemented to detect the elder's fall.

Most approaches and technology we mentioned above are not integrated. They work well separately in isolation; however, the isolated solution is insufficient to tackle complex problems such as elder monitoring. In this paper, we proposed a novel integrated system to assist elders at home, which includes these features: i) integration of the smart home, the mobile robot, and the smartwatch application; ii) the pose detection and the estimated location by the depth camera; iii) an integrated dashboard that is able to monitor and control all system components; and iv) utilization of a standard protocol used by each system component to ensure smooth communication. We continue our previous work, where we envisioned the integration of heterogeneous controllers in an internet of things (IoT) network. We also combined the mobile robot and smart home technology to assist the elders [12], where the robot is treated as one "thing" in the IoT network.

2. METHOD

2.1. The system architecture and components

Overall system architecture and devices are shown in Figure 1(a). Three system components (a smart home, a telepresence robot, and a wearable device) can communicate using the message queuing telemetry transport (MQTT) protocol [13]. A RaspberryPi 4 is utilized as a server, where the MQTT broker and MariaDB database are installed. A mobile application is developed using Android Studio. The application also implemented representational state transfer (REST) ful application programming interface (API) to communicate with the server for user authentication purposes. Our smart home system is equipped with several sensors (two light sensors, a temperature sensor, and a gas sensor) and actuators (two lights, a fan, and a buzzer). They are shown in Figure 1(b) every sensor and actuator are connected to a Wemos D1 Mini.



(a) (b)

Figure 1. Overall system and devices in the smart home: (a) architecture and (b) sensors and actuators

Our second component is a telepresence robot as shown in Figure 2(a), which provides a connection between a user and a participant (in a distant location) [14]. Initially, our robot (made by Ohmni Labs) was controlled remotely using its own interface. We then added a light detection and ranging (LIDAR) sensor so it could perform simultaneous localization and mapping (SLAM) [15] and autonomous navigation. Since we are using robot operating system (ROS) [16], we can reuse the existing SLAM package and navigation stack. Our last component is a Samsung Galaxy Watch 4 (OS: WearOS 3.5) to develop a simple application to monitor the heart rate (by reading the heart rate sensor and on-body sensor of the smartwatch), the steps taken, and the burnt calories (by implementing the passive monitoring client library). We also created an "save our souls" or "save our ship" (SOS) page in case an elder has an emergency situation. The wearable device and application pages are shown in Figures 2(b) and 2(c).

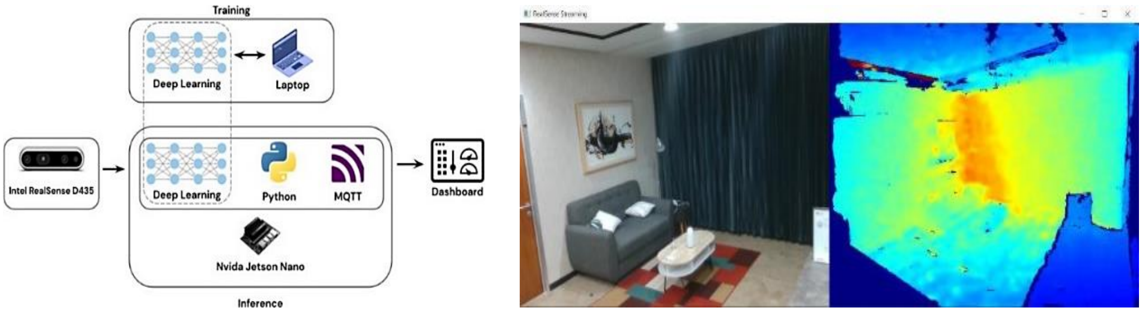
Main Page SOS Page

(a) (b) (c)

Figure 2. The robot and the mobile application for the elder: (a) the telepresence robot, (b) the smartwatch, and (c) mobile application

2.2. The pose and location detection

Our system can detect the pose and estimate a person's location in the room using a camera. We use you only look once (YOLO), an efficient deep-learning algorithm that is fast and suitable for real-time detection. Specifically, we use YOLOv4-Tiny [17], [18]. The model training is done in a laptop (Intel® i7-5700HQ @ 2,70 GHz, Nvidia GeForce GTX 965M 2 GB GDDR5, Memory 16 GB DDR3L), and the model inferencing is implemented in a NVidia Jetson Nano (built in a reComputer J1010). The learning stages are shown in Figure 3(a) while images captured by depth camera are shown in Figure 3(b).



(a) (b)

Figure 3. Learning stages and the images acquisition: (a) learning stages and (b) images captured

We determine five classes of human pose: stand up (SU), sit on the chair (SC), sit on the floor (SF), lay down on the chair (LC), and lay down on the floor (LF). We consider lying down on the chair and lying down on the floor to be an abnormal pose. We then collect images for the dataset for each pose. The dataset consists of 890 images (680×480 pixels). The number of pictures for each pose can be seen in Table 1. The examples of captured images are shown in Figure 4(a). The photos are taken from a camera in the corner, on the top of a shelf shown in Figure 4(b). We divide the room into four divisions (A, B, C, D), each 1.5×1.5 m shown in Figure 4(b). This location will be sent to the robot, so it knows the estimated location of the elder.

YOLOv4-tiny model is designed based on YOLOv4 [19] (the review of YOLO development has been discussed [19]), however, it has faster object detection [17]. YOLOv4-tiny method uses CSPDarknet53-tiny as the backbone to replace CSPDarknet53 in YOLOv4. YOLOv4-tiny is trained using 29 convolutional pre-trained layers, while YOLOv4 is trained using 137 convolutional pre-trained layers. These trade-offs enable YOLOv4-tiny to detect objects faster than YOLOv4 while sacrificing a small amount of detection accuracy.

Table 1. Pose classes and amount of dataset

No	Pose	Abbreviation	Dataset
1	Stand up	SU	106
2	Sit on the chair	SC	251
3	Sit on the floor	SF	213
4	Lay down on the sofa	LS	187
5	Lay down on the floor	LF	133

(a) (b)

Figure 4. The pose and location detection: (a) the example of captured images and their labels and (b) camera location and the room division

2.3. The integrated dashboard and system mechanism

Our dashboard is designed in an 8" Android tablet to show the status of all of our system components. Initially, a caregiver must log in to the system. Then he can choose the elder's name and proceed to see the overview page, the smart home page, the robot page, and the wearable device page. The overview page design is shown in Figure 5. We use MariaDB as our database server, installed in a RaspberryPi 4. In the database, we make some tables that relate to each other in many-to-many relationships. For example, we make the elder_caregiver table, which relates a particular caregiver to a specific elder he cares for.

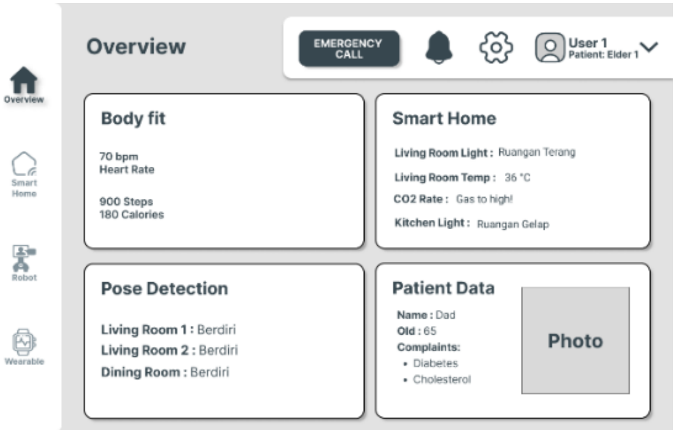


Figure 5. Design of the overview page

Besides the monitoring via the dashboard, we implement a mechanism that involves all system components. When our system detects an abnormal situation (the abnormal pose, the abnormal heart rate reading), it will notify the caregiver and send the estimated location of the elder to the robot, which then will navigate autonomously to that location. Once the robot is there, as it has teleconference capability, the caregiver may try to communicate with the robot. The mechanism is also written in following pseudocode.

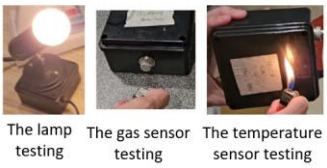
```
IF (the abnormal pose detected in the camera OR the heart rate reading of the smartwatch is
abnormal) THEN
        Send a notification to the caregiver;
        Send the estimated location to the robot;
        IF (the robot is arrived at the location) THEN
                The robot must stop; //The caregiver may communicate with the elder
        ELSE
                The robot navigates autonomously to the location;
```

3. RESULTS AND DISCUSSION

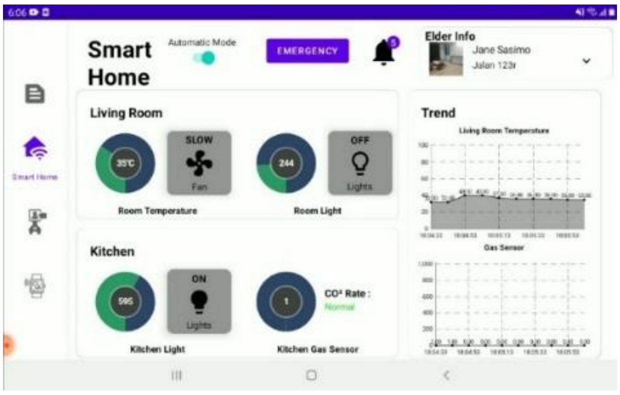
In this section, we explain the experiment results of each component: the smart home, the robot, and the wearable device. We also describe the pose detection and the location estimation results. Finally, we will explain the integrated system mechanism involving several components.

3.1. The smart home experiments

The simple testing on the sensors and actuators are shown in Figure 6(a). The values of the sensors are displayed on the smart home tab of the dashboard as shown in Figure 6(b). There are numerical value displays and gauge-style displays. The values of the temperature sensor and the gas sensor are also shown in the trend form so the user can monitor the historical value of the parameters. Additionally, all the parameters are also stored in the database. In manual mode, the user can also manually control the actuators by pushing the page buttons.



(a)

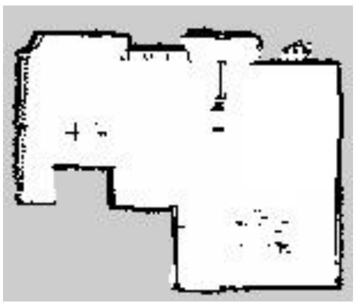


(b)

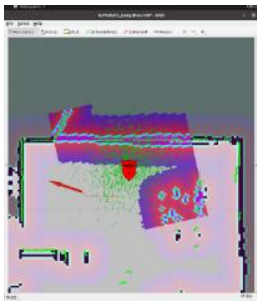
Figure 6. The smart home experiments: (a) sensors and actuators testing, and (b) their appearance on the dashboard

3.2. The mobile robot experiments

We start experimenting with a mobile robot by performing the SLAM operation to produce the map of our laboratory. The resulting map is shown in Figure 7(a). Once we have the map, we can conduct an autonomous navigation experiment by commanding the robot to navigate to a particular location by clicking the point in Rviz as shown in Figure 7(b).



(a)



(b)

Figure 7. The mobile robot experiments: (a) the map produced by SLAM, and (b) the robot navigates to a specified location

Once it arrives at the location, we measure how far the robot is shifted from its original goal coordinate. After several navigation experiments to a different section of our laboratory as shown in Table 2, we get the measurement results that the movement error in the X axis is 0.05 m, the error in the Y axis is 0.05 m, and the error in direction (angle) is 0.31 radian. These errors are caused by the inaccuracy of the Ohmni robot itself (it is a little bit shaky when moving), the variety of our laboratory surfaces (there are sections that have carpet on it), and the LIDAR's inaccuracy. However, in our case, these errors are still acceptable.

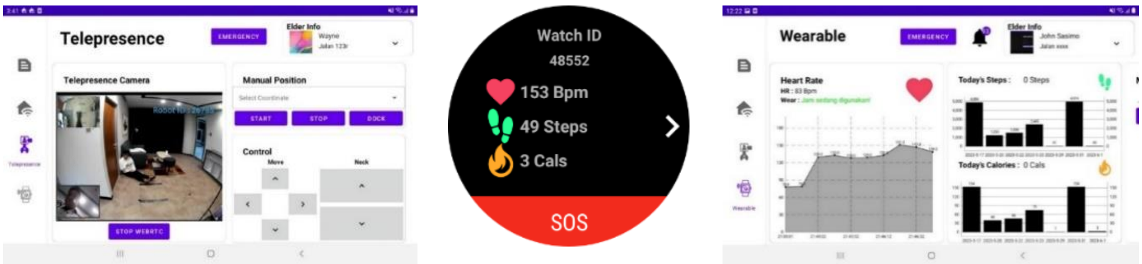
Table 2. Robot movement error

Navigation goal	Movement error		
	X(m)	Y(m)	Radian
Kitchen	0.05	0.07	0.23
Dining room	0.05	0.05	0.38
Living room	0.04	0.02	0.25
TV	0.03	0.05	0.35
Bedroom	0.05	0.06	0.27
Bathroom	0.04	0.04	0.37
Average	0.05	0.05	0.31

The user can control the robot manually by pressing the buttons in the telepresence robot tab in the dashboard as shown in Figure 8(a). The user can also select a point in the coordinates, and the robot will move to that position. The robot's camera is also shown on the dashboard. It uses web real-time communication (WebRTC) technology to stream the robot camera into the telepresence robot tab.

3.3. The wearable device experiments

The smartwatch measures the heart rate, the steps taken, and the burnt calories as shown in Figure 8(b). Those values can also be monitored by the wearable tab in the dashboard as shown in Figure 8(c). The heart rate is displayed in trend, so the user can monitor it from time to time. The steps and calories are shown in the histogram chart. All of these parameters are stored in the database. We also test the heart rate sensor by comparing its reading to the oximeter. From 10 experiments, we found that the average error is small: 1.13 %.



(a) (b) (c)

Figure 8. The wearable device experiments: (a) the telepresence robot page, (b) smartwatch application, and (c) the wearable device page

3.4. The pose and location detection experiments

We conducted the experiments to test the accuracy of our pose detection and location estimation algorithm. Eight persons became the subject of experiments. They must perform all five pose categories, and the system must detect their poses. From those experiments, we find this system has 92% accuracy in detecting the human pose (the complete data is shown in Table 3). These experiments are done in bright conditions. When the lighting is decreased, the accuracy will get worse. In our experiments, the persons in our training dataset mostly use black cloth, so the accuracy tends to be higher when the person uses black cloth. In the future, we should vary the fabric used by the persons for the training dataset.

For location detection, we perform testing in each location 20 times. The average accuracy is also pretty good: 93% (see Table 4 for complete results). Although the result is good, we must remember that the estimated location area is quite big: 1.5×1.5 m (as it is enough for our current application). Our system might show worse accuracy performance when the area is decreased.

Table 3. Pose detection testing results

Person	Pose detection accuracy					Total (%)
	SU (%)	SC (%)	SF (%)	LC (%)	LF (%)	
1	100	71	77	100	95	89
2	95	100	82	100	88	93
3	96	100	100	100	97	99
4	100	100	97	100	82	96
5	91	91	90	100	87	92
6	100	78	96	92	89	91
7	100	68	97	100	50	83
8	73	97	96	100	85	90
Average	94	88	92	99	84	92

Table 4. Location detection testing

Location	Correct prediction (out of 20)	Accuracy (%)
A	18	90
B	17	85
C	19	95
D	20	100
	Average	93

3.5. Integrated system experiments

We aim to develop our dashboard to show all three components (the smart home, the robot, and the wearable device) on one page. This has been achieved in the overview page as shown in Figure 9(a). Communication between components can also be seen when abnormal conditions occur. If the elder's heart rate or pose is odd, the system will notify the tablet as shown in Figure 9(b). The alarms are also displayed in the telepresence tab (highlighted in yellow as shown in Figure 9(c), so the user might be aware of the unusual condition and take action. As we have explained in section 2.3, the robot will navigate autonomously to the elder's estimated location when the abnormal condition happens. Figure 10 shows the point of view of the home camera (Intel RealSense D435 camera) and the robot camera when the robot successfully reaches the location.

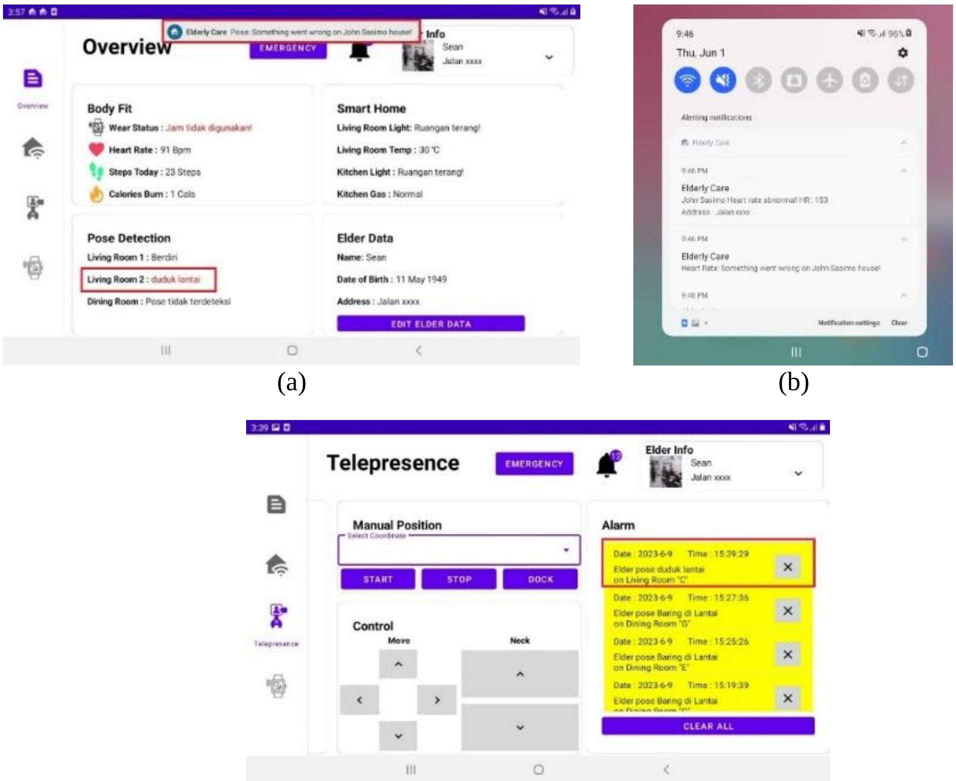


Figure 9. Integrated system experiments: (a) the overview page, (b) the alarm notification, and (c) the alarm on the telepresence tab

Figure 10. Point of view of the home camera and the robot camera

3.6. Discussions on the security feature

Smart home automation offers improved security and comfort, particularly beneficial for the elderly by providing accessible and efficient control over home appliances. In IoT applications, a smart home system endeavors to link and regulate all devices via cloud computing or internet network gateways. Hence, it is imperative to develop a robust access control system to guarantee that only authorized individuals can enter the home and utilize the smart home system. Despite a growing body of research on the security of smart home systems [20], [21], it remains in an early stage, and the protective features of these IoT devices are notably deficient. Future research initiatives could focus on establishing secure communication protocols within the smart home system to safeguard sensitive information. Additionally, integrating artificial intelligence (AI)-based systems [22]–[25] for behavioral analysis could be explored to detect anomalies that might signal potential security risks within the smart home environment. Implementing cybersecurity measures necessitates ensuring that all devices within the smart home are equipped with the latest security technologies. This includes the implementation of robust authentication and encryption protocols for transmitted data. Currently, our system only implements a very simple security mechanism.

4. CONCLUSION

We concluded that we have achieved our goal of developing an integrated system to assist elders at home. We have developed each component: the smart home, the mobile robot, and the smartwatch application. Users can monitor those components and perform manual and automatic control (of the smart home and the robot) via the dashboard. We also perform pose detection and location detection with 92% and 93% accuracy. We also have demonstrated the communication between components via the MQTT protocol. When the smartwatch detects an abnormal heart rate or the camera detects an abnormal pose, the robot then navigates autonomously to the elder's estimated location. In the future, we must improve our system in some areas, starting with improving pose detection and location estimation accuracy. A better pose detection algorithm might be used, the indoor positioning system might be utilized, and the security features must be improved.

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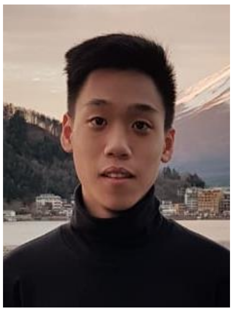

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