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Ambient Sensors Fusion Smart Home

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Abstract
Abstract: Today, everyone is living in a fast-paced world where everything revolves around time is crucial. The global community, especially Generation Z is always looking for speed, efficiency in their daily life activities and hence has less concern for their health. Some of the common health problems that built up implicitly among most of them from their daily bad habits are sleep deprivation and imbalanced diet. The main objective of this paper is to monitor a human indoor activity by incorporate the use of a wrist wearable device which integrated Bluetooth and accelerometer sensors and predict their future activity. The wrist wearable device is used to collect the user movement data sets for building and training a user profile, then a prediction model will be constructed based on the earlier recognition movements in the training model. Then, alert or notification will be given to users when certain human movements reach a threshold level. In addition, recommendations on human activity will be given to the user as well to claim the user health and well-being. The system can recognize the human movements, the position of the user in the indoor space of a home, predict the patterns of a lifestyle of a user and give better recommendations on the next user activity based on the patterns learned in the prediction model.

Keywords: *Human Activity Recognition (HAR), Indoor Activity, Forecasting, Wrist Wearable Devices, Bluetooth, Accelerometer, PIR Sensor.*

I. INTRODUCTION

This research discusses about the Ambient Sensors Fusion Smart Home. There are many researches had been done on the human activity recognition in the past decades. Human activity recognition is a technology in the field of pervasive computing that focus on tracking and identifying the human movements. Today, there is not only simple basic movements like walking, running, sitting, standing and lying can be recognized, but complex daily activities like brushing teeth, cooking, eating, reading and watching TV can be recognized as well [9].

Most of the HAR systems are assisted by various sensing technologies, namely RGB cameras, depth sensors and wearable devices [1]. In general, human activity recognition system using wearable devices can be subdivided into two big classes that are supervised or unsupervised [9]. A supervised HAR system will need former training to label the data while an unsupervised HAR system can still use the unlabeled data to train a recognition model. This paper will focus on the using of the wearable device incorporated with NFC technology and accelerometer to collect the user movement datasets for building and training a user profile, then a prediction model will be constructed based on the earlier recognition movements in training model.

II. STATE-OF-THE-ART

Human activity recognition (HAR) through wearable is not something new. There are a lot of researches have been done on this topic. Lara and Labrador [15] have done a comprehensive survey for HAR using wearable sensors since late ‘90s until today. Attal et. al proposed three wearable sensors to recognize the activity done by the human where they place them at the chest, right thigh, and left ankle [16]. The state-of-the-art of HAR can be divided into several categories of data acquisition such as wearable device/sensor, accelerometer, near field communication, passive infrared sensor, and home

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interior physical layout. The details of each data acquisition technique are discussed in the following subsections.

A. Wearable Device

Currently, there are many existing HAR systems which had been applied using the wearable device to collect the datasets from users [6, 8]. These wearable devices have overcome the privacy problem along with the camera HAR system at which the users do not need to have a feeling of discomfort or intruded being watched all the time. Wearable device has also overcome the pervasive problem of the camera HAR system that it is convenient to bring to anywhere and give more flexibility. However, with a solely wearable device that using a single sensor, it might not provide enough information for the system to recognize the human actions accurately since there are some of the movements are similar in a single sensor data representation.

B. Accelerometer

The accelerometer is a type of sensor used to measure the acceleration that is the measurement of the rate of change in velocity or speed. Two types of accelerometer had been studied below that are triaxial accelerometer and Microelectromechanical Systems (MEMS) accelerometer. Triaxial Accelerometer (TA) is assembled from three orthogonally mounted accelerometers [2]. Hence, the orientation of the x-, y-, and z-axes in relation to the TA in its upright position can be detected [7]. Acceleration data that covering the amplitude and frequency ranges can be recorded by TA. Microelectromechanical Systems Accelerometer (MEMS) accelerometers are divided into two main types: piezo-resistive and capacitive based accelerometers [5]. The change in resistance in the piezo-resistive patch will produce an electric signal which is proportional to the acceleration of the vibrating object. The changes of the capacitance between a proof mass and a fixed conductive electrode are measured with a capacitive based MEMS accelerometer.

C. Near Field Communication (NFC)

Near field communication, or NFC, is a short-range wireless communication technology which is evolved from Radio Frequency Identification (RFID) [10]. It allows the communication between devices without physical contact. NFC is designed for low bandwidth (transfer data up to 424 Kbits per second) and short distance (up to 20 cm) communication. NFC works by using the magnetic induction generated when one of the communicating devices emits a small electric current. An important advantage of NFC technology is that it is compatible with existing RFID structures. NFC can be operated in three modes, which are peer-to-peer, reader and writer, or card emulation [4]. Table I shows three operating modes and bene its of them respectively.

Table I. Three Operating Modes of NFC

NFC Operating Mode	Data Flow	Benefits
Peer-to-peer	Between two NFC compatible devices	1. Easy data exchange between devices
		2. Pairing between devices
Reader and writer	From NFC tag to NFC device and vice versa	1. NFC device acts as an initiator and passive tag is the target which does not need any source of power
		2. Increase mobility
		3. Easy to implement
Card emulation	From NFC device to NFC reader	1. Physical object elimination
		2. Access control

D. Passive Infrared (PIR) Sensors

PIR sensors generally operate by detecting the changes in infrared radiation. All objects with a temperature will emit heat energy in the form of radiation including human. Hence, the movement of a person which has different temperature from the environment can be detected ideally using PIR. Every PIR sensor has a detection zone at where the human or object can be detected. Beyond the detection range, they may not be detected. The advantage of PIR

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includes it does not require any device or signal from detecting objects, unlike sound, ultrasound, or RSSI based localization schemes [12]. It can work in dark as well, whereas vision-based system cannot. It also does not cost much and not require huge computational power. Another advantage of PIR is that it is passive where it does not generate or radiate energy for detection purposes.

E. Home Interior Physical Layout

Furthermore, it might be a useful extra knowledge for us to learn about the interior physical layout of a home to effectively build an indoor system. Generally, the interior physical layout of a home will at least include the considered necessary four parts of area in a house floor plan. The main four areas in a home are living spaces (living room), cooking spaces (kitchen), sleeping spaces (bedroom) and wet areas (toilet or bathroom) [14]. Table II shows the analysis of the human activities that probably carried out in the four different home spaces.

Table II. Analysis of Human Activities Based on Human Movements in Different Home Spaces

Home Spaces	Human Movements	Human Activities
Living room	Sitting	Watching television, eating, reading
Kitchen	Sitting	Eating, drinking
	Standing	Cooking, washing dishes
Bedroom	Lying	Sleeping
	Sitting	Reading, makeup
	Standing	Change clothes
Toilet / Bathroom	Standing	Shower, brushing teeth, makeup
	Sitting	Defecating, urinating

III. METHOD

The scope of development includes all the developing of each components of the system. The system consists of Wrist Wearable Based HAR Module, which includes (Table III):

Table III. System Components List

Android Application	Primary platform for the user to interact with the system
	Send alert notification message to the user
	Remote activate the wrist wearable and PIR sensor to collect data
Wrist Wearable	Allow user to carry out training mode and prediction mode
	Collect user acceleration data from the built-in ADXL335 triaxial accelerometer
	Send data collected to server through the built-in HC-05 Bluetooth module
Smartphone GPS and PIR Sensor with Bluetooth	GPS detect user outdoor location data
	PIR sensor detect user indoor location data
	PIR sensor data is sent to server using Bluetooth
Python based Fuzzy Logic Prediction Algorithm	Interpret accelerometer data and recognize user movement

a. Sensor Setup

In this system, there are several sensors involved including accelerometer and PIR sensors. Firstly, we will need to look on how these sensors will be built up together with other complement components as a functional unit. The wrist wearable is developed by integrating an Arduino Mini Pro, an ADXL 335 triaxial accelerometer, a HC-05 Bluetooth module, a switch, a rechargeable battery, a charging knot, and a watch strap.

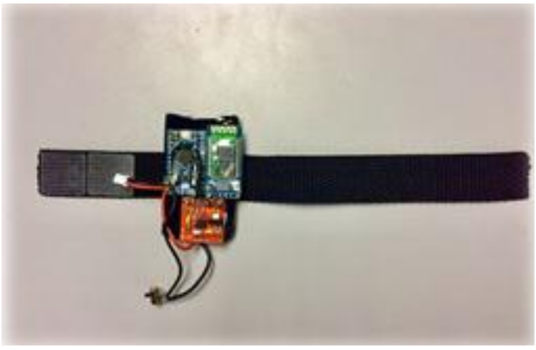

Fig. 1. Wrist Wearable.

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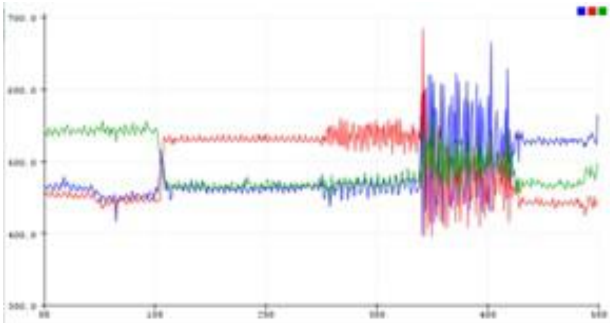

Fig. 2. Data Representation of ADXL 335 Accelerometer on Wrist Wearable.

The accelerometer data is recorded and converted into the 2 to the power 10 bits as shown in Fig.2. 3 different axis recorded different value while user is performing different movements. Hence, we can track the pattern of user movements and further predict on the user activity. For the PIR Sensor Module (Fig. 3), the components integrated together are a PIR Sensor, an Arduino Uno, a Raspberry Pi 3 Model B, an Arduino Uno USB Cable, a Network LAN cable, a Power Source, and a Male to Female Jumper Wire. In this system, there are four physical spaces divided in a home that are living room, bedroom, toilet and kitchen. Each space is placed with a PIR sensor to monitor user existence as shown in Fig. 4:

Fig. 3. PIR Sensor Module

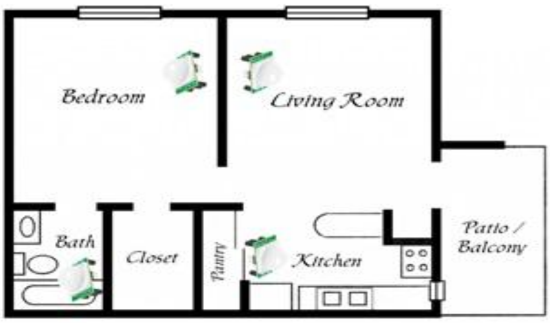

Fig. 4. Physical Spaces Division of the House

b. Web Application

Web application will be used by administrator and home users. Different users will have different functionality in the web application as the administrator has a higher privileges and authorization than the normal users. Fig. 5, Fig. 6, and Fig. 7 shown the review of activities percentage, activities timeline, and location timeline respectively.

Fig. 5. Web Application - Review Activities Percentage

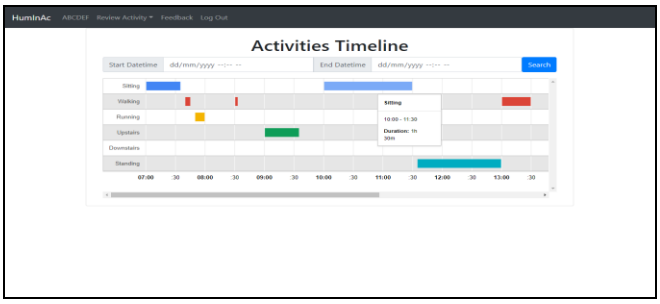

Fig. 6. Web Application - Review Activities Timeline

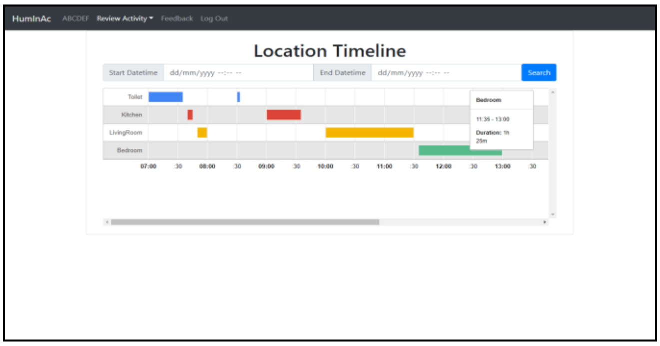

Fig. 7. Web Application - Review Location Timeline

When user clicks on the review activity button, a dropdown menu will be shown which include the activity percentage, activity timeline and location timeline button. In the activity percentage page, a pie chart with the user activities and duration of each activities in seconds will be shown. In the activity timeline page, a timeline chart with each activity and their occurrence time respectively will be shown. In

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the location timeline page, another timeline chart with location and the user existence time in each location respectively will be shown. User can select the specific datetime range and display the data in that range only in all the three pages.

c. Android Application

Android application is developed to collect data in real time. Sensors such as accelerometer and GPS are used in the data collection process. User location will be detected by using GPS and user activities will be detected by the triaxial accelerometer. In the android application, there are 2 major phases, which are training phase and prediction phase. In the training phase, user is required to perform each activity for a duration of time. Data collected in training phase will then be used to build the prediction model. In the prediction phase, the data collected in real time will be used to predict user current activity using the prediction model built earlier. Users are required to go through the training phase before their activity can be detected. In the training phase, users are required to perform each activity repeatedly in a duration of time. Each of the data represent a motion. Positive values of all these 3 reading indicate an increase in velocity while negative values indicate a decrease in velocity. Zero values indicate constant velocity. User should follow the instruction during performing each activity. The training data will be used to build the prediction model.

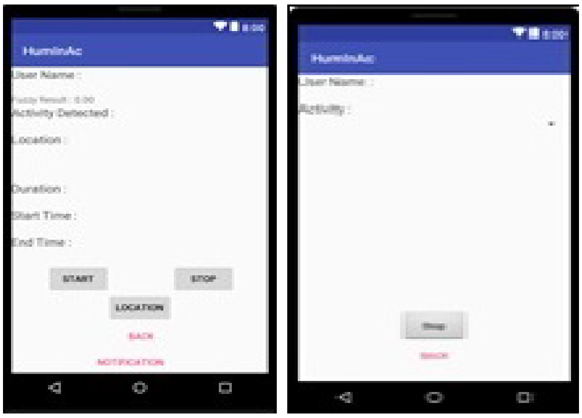

Fig. 8. Training Model and Prediction Interface

In the prediction phase, real time data collected using accelerometer is being analyses using the prediction model to predict and detect user activities. In the data collection process, instead of predicting on every single data entry, we will use a specific length of window frame to collect an enough amount of data before carrying out the prediction. To reduce the traffic input into database, the input frequency is given after two different activities performed where only inserted database function will be carried out. The prediction is only valid on the user who has provided the training data since the prediction model is built based on the training data. If other user tries to use the prediction model to detect their activity, the prediction result will not be accurate. Based on the logging of the activity in the prediction phase, we can get valuable insights from the analytic of the activity data. We can know the user activity percentage in the specific time range in the past. Then we may calculate the sitting percentage of the user. The interface for the training model and prediction models are shown in Fig. 8. According to the research done in [13], we can measure the body fatness using age- and sex-specific prediction formulas. Body Mass Index (BMI) and Body Fat Percentage (BFP) will be calculated by using the profile information of the user inserted earlier which include the age and gender generated from the user IC number, height and weight. The BFP of an adult can be then calculated using the following formula:

$$\text{AdultBFP} = (1.20\text{BMI}) + (0.23\text{Age})(10.8\text{Sex})5.4 \quad (1)$$

BMI and BFP in children were found to differ from that in adults due to the height-related increase in BMI in children. A different formula will be applied to children aged 15 years and younger as below:

$$\text{ChildBFP} = (1.51\text{BMI})(0.70\text{Age})(3.6\text{Sex}) + 1.4 \quad (2)$$

In both formulas above, sex is 1 for males and 0 for females. Sitting percentage and the BFP will be used to build the fuzzy logic healthiness model to check health status of the user. The Table 4 below from the American Council on Exercise shows which category that the user belongs to according to BFP result value:

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Table IV. Health Status Category according to BFP Result Value.

Description	Women	Men
Essential Fat	10-13%	6-13%
Very Lean	14-20%	6-13%
Lean	21-25%	14-17%
Normal	26-31%	18-22%
Overweight	32-39%	23-29%
Obese	40% or more	30% or more

d. Prediction Algorithm Analysis

After doing some study and research on related work, we found fuzzy logic is suitable in recognizing the user activity from the accelerometer data that is fluctuated in the small range along with the user's movements. Standard logic applies only to concepts that are 'completely true'(having degree of truth 1.0) or 'completely false' (having degree of truth 0.0). On the other hand, fuzzy logic is a generalization of standard logic, in which a concept of 'partially true' or 'partially false' where a degree of truth anywhere between 0.0 and 1.0 can be posed. Fuzzy logic is supposed to be used for reasoning about inherently vague concepts, such as accelerometer data that result from the user body movements which is not easily translated into the absolute category of activity. Firstly, with the prediction model built in the training phase, we can extract few features from each axis of the accelerometer data such as mean, standard deviation and root mean square. Besides that, the real-time accelerometer data will also go through the feature extraction process to get the required features for recognizing the user activity. These features will be input into the fuzzy system to draw the membership function of activities they belong to respectively and a set of membership function for each output of activities.

Firstly, with the prediction model built in the training phase, we can extract few features from each axis of the accelerometer data such as mean, standard deviation and root mean square. Besides that, the real-time accelerometer data will also go through the feature extraction process to get the required features for recognizing the user activity. These features will be input into the fuzzy system to draw the membership function of activities they belong to respectively and a set of membership function for each output of activities (refer Fig. 9).

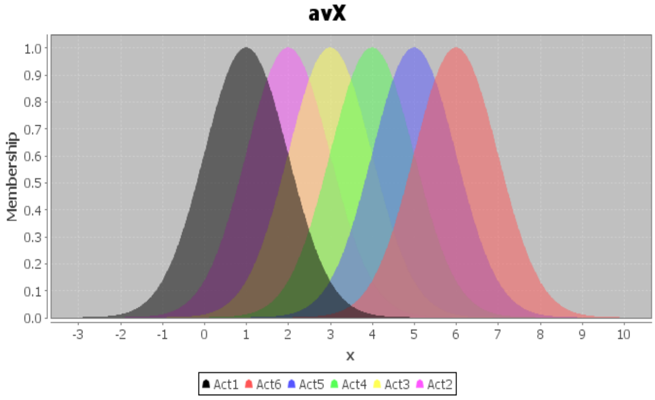

Fig. 9. Membership Function of Input Activity Feature

Then, a set of rules is then applied to the membership functions to yield a "crisp" output value as shown in Fig. 10.

```
RULEBLOCK No1
    AND : MIN;        // Use 'min' for 'and' (also implicit use 'max' for 'or' to fulfill DeMorgan's Law)
    ACT : MIN;        // Use 'min' activation method
    ACCU : MAX;       // Use 'max' accumulation method

    RULE 1 : IF avX IS Act1 AND avY IS Act1 AND avZ IS Act1 AND sdX IS Act1 AND sdY IS Act1 AND sdZ IS Act1 AND RMS IS Act1 THEN Activity IS Sitting;
    RULE 2 : IF avX IS Act2 AND avY IS Act2 AND avZ IS Act2 AND sdX IS Act2 AND sdY IS Act2 AND sdZ IS Act2 AND RMS IS Act2 THEN Activity IS Standing;
    RULE 3 : IF avX IS Act3 AND avY IS Act3 AND avZ IS Act3 AND sdX IS Act3 AND sdY IS Act3 AND sdZ IS Act3 AND RMS IS Act3 THEN Activity IS Walking;
    RULE 4 : IF avX IS Act4 AND avY IS Act4 AND avZ IS Act4 AND sdX IS Act4 AND sdY IS Act4 AND sdZ IS Act4 AND RMS IS Act4 THEN Activity IS Jogging;
    RULE 5 : IF avX IS Act5 AND avY IS Act5 AND avZ IS Act5 AND sdX IS Act5 AND sdY IS Act5 AND sdZ IS Act5 AND RMS IS Act5 THEN Activity IS Upstairs;
    RULE 6 : IF avX IS Act6 AND avY IS Act6 AND avZ IS Act6 AND sdX IS Act6 AND sdY IS Act6 AND sdZ IS Act6 AND RMS IS Act6 THEN Activity IS Downstairs;

END_RULEBLOCK
```

Fig. 10. Fuzzy rule set for Activity Detection

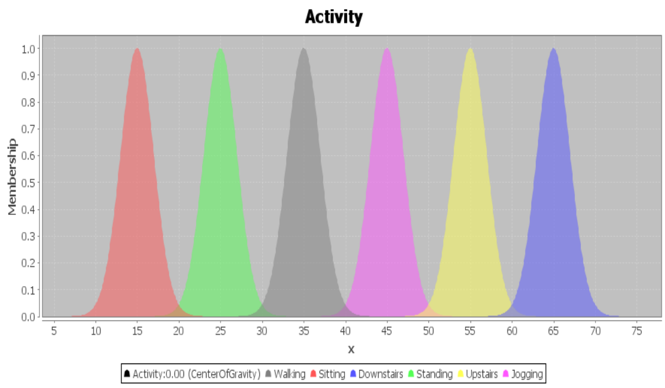

Fig. 11. Membership Function of Output Activity Result

In this system, fuzzy logic avoids the using of a fixed threshold to recognize an accelerometer data input as a valid user activity, but it analyzes the degree of membership of the accelerometer data input belongs to a certain degree of activity category in between the value of 0.0 to 1.0. By using a proper feature input into the fuzzy system or increase amount of proper training data (as shown in Fig. 11), the activity recognition accuracy will be improved.

IV. RESULTS

A few case scenarios have been designed to test the system functionalities in a complete manner. Each scenario is tested to ensure system produced expected result. It is assumed that the mobile application user had been authenticate and login during the test scenario.

Table V. Test Case for Web Application

Case 1: User that does not own an account wants to sign in to the system.	User is only able to access the system after the sign up and login process
Case 2: User that update their profile information.	User can check the updated profile information in the web application.
Case 3: User that does not go through prediction phase review activity and location history.	No data will be shown until the user go through the prediction phase.
Case 4: User give feedback to the system.	The system administrator can view the user feedback in admin page.
Case 5: Admin access to the admin web pages.	The system administrator will be able to view the system user list, insert user, update user profile, delete user, review user activity and location history.

To test the performance of the classification model, confusion metric is used for the purpose. Classification performance will be evaluated via sensitivity, fallout, precision, and accuracy. For Sensitivity, classification considers is True Positive or True Positive with False Negative. For Fallout, classification considered is False Positive and combination of False Positive and True Negative. For Precision, classification considered is True Positive over combination of True.

Table VI. Test Case for Android Application

Case 1: User that does not own an account want to sign in the system.	User is only able to access the system after the sign up and login process.
Case 2: User that does not go through training phase and straight to prediction phase.	The system is only able to predict user activity after training had been done.
Case 3: User that does not go through prediction phase does not receive alert notification message in smartphone.	Alert notification will be interpreted based on the user activity done previously, user must go through the prediction phase to get notification message.

Positive and False Positive with for Accuracy, classification considered is combination of True Positive and True Negative over Total URL. This system is using ECHONET Lite as to link it to the Smart Home system which has been developed [11]. This wearable can as be used as Human Activity Recognition (HAR) [3]. This system is fully integrated to the Smart Home system which other sensors or actuators including robots can be easily connected in with this system to complete the whole eco-system for the Smart Home initiative.

V. CONCLUSION

This Human Indoor Activity Prediction System is created to be able to track and detect human indoor activity by making use of the wrist wearable device technology. This system will be able to identify and train human movement activities like walking, running, sitting, standing and lying and user position within an indoor space by using positioning technology. This system will also capable to detect activities and provides analytic in recognizing activities and predicting user lifestyle. Notification or alerting mechanism will be activated based on pre-defined user behavior. Some recommend action or tips towards a healthy living when any deviation events are detected. In short, this system may be able to improve the health condition of user toward a healthier lifestyle.

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AUTHORS PROFILE

Chow Yee Suen received the Bachelor of Computer Science (Honours) Majoring in Network Computing from the Universiti Sains Malaysia, Penang, Malaysia, in 2018. He has held Software Engineer intern positions at Intel Microelectronics, Malaysia for half a year. He is currently a Software Engineer at TT Vision Holdings Bhd, Malaysia.

Ting Wen Shin is the bachelor's degree holder in Computer Science, University Sains Malaysia. He did his academic research in IoT projects, which involved in a smart home-based eldercare system. This system named as SAHOMASI, which using the

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ECHONET-Lite as the communication protocol to construct the home network. He had been researched for a year and he acquired the knowledge in applying the ECHONET-Lite communication protocol into the home appliances. He connected the microelectromechanical (MEMS) sensor onto the appliances to collect the data and performed the user's activity analytics based on the data pools. Mr. Ting also developed the front-end web application to monitor user activity.

Manmeet Mahinderjit Singh is a senior lecturer attached with the School of Computer Sciences, Universiti Sains Malaysia. She graduated from University of Queensland in 2012 with a PhD Degree in Data Security. Dr Manmeet passion in the field of Information Security, cybercrime and Internet of Things is demonstrated with her research, lecturing and training pathways which are focus within these fields. She has ventured into training and consultancy in various courses such as educational pedagogy such as Computational Thinking courses, Information Security (Big Data and IoT Security) and Internet of Things (MWICOM microcontroller boards). She has published several papers in the domain of expertise. Dr Manmeet has been working in the field of providing mitigations and safeguards measurement for mission critical infrastructure since 2014.

Mohd Nadhir Ab Wahab is a lecturer at School of Computer Sciences, Universiti Sains Malaysia. He received his B.Eng. (Hons.) Mechatronics Engineering in 2010 and M.Sc. Mechatronics Engineering in 2012. After that, he received his Ph.D in Robotics and Automation System in 2017. His main researches are mobile robotics, optimization, navigation, and path planning.