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Wireless Heart-Beat Monitoring System with Supervised Learning

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ABSTRACT

Most of the hospitals in Malaysia still utilise manual inspection by medical personnel to determine the health conditions of the patients. The data collected from the medical equipment would have to be analysed and verified by the hospital. Frequently, many patients need medical inspections. However, to provide a precise diagnosis, medical personnel requires more time. This limitation can be addressed by the development of automated and wireless health monitoring systems with health diagnostic feature supported by artificial intelligence (AI). In this project, the objective is to develop a prototype of a wireless (non-invasive) heartbeat monitoring system with supervised learning. This system monitors the heartbeat activity and predicts the condition of the user's heartbeat. Technically, a photoplethysmography-based (PPG-based) heartbeat sensor is used to build a heartbeat sensing device with a Bluetooth feature that communicates with an Android application. The Android application is developed to receive heartbeat data from the device and feed the data into an AI classification model to predict the heartbeat condition of the user. This AI classifier was built from heartbeat data collected from 10 healthy people. The additional heartbeat dataset was generated based on a sound source of heartbeat information to increase the volume of the training dataset. The completion of this project implementation results in a wireless heartbeat monitoring system that can be applied regardless of location and time. The accuracy of the AI prediction is 99 % when evaluated with a testing dataset. The empirical accuracy obtained by testing the system with actual implementation is 90 %.

Keywords: *artificial intelligence; Bluetooth; heartbeat monitoring system; machine learning; smartphone application*

1. INTRODUCTION

1.1 Background of the Project

The primary purpose of health monitoring is to allow people to inspect and understand the condition of their health so that preventative measures and corrective treatments can be taken. Hospitals are the institutions that widely utilise various monitoring systems. In hospitals, most of the health monitoring systems are still wired, including the sensors, processors, or display units. This also applies to the health monitoring systems that are designed for continuous monitoring. As a result, this can be inconvenient as it limits the movement of the user or patient.

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Health monitoring technology is high in demand since many years ago, which now it becomes even more sophisticated. Artificial intelligence (AI) is currently becoming the core of the technology in the present and the future. It is implemented broadly by a diversity of industries and sectors, including healthcare, to process a significant amount of data and produce heuristic deductions in solving problems [1] – [2].

1.2 Heartbeat Sensing Technology

There are two types of technology in sensing and reading heartbeat: electrocardiography (ECG) and photoplethysmography (PPG). Both are non-invasive techniques to sense the human heartbeat.

ECG is a conventional yet powerful technique for monitoring the human heartbeat. This method uses small metal pads (known as electrodes) on certain parts of the skin where the nerve impulses are strong. These electrodes sense the nerve or electrical impulses released by the sinoatrial (SA) node of the heart. Therefore, ECG provides highly accurate information and visualisation of a person's heartbeat. Technically, a standard ECG requires ten electrodes (12 leads) to be placed on a human body for a full interpretation of the heartbeat pattern. Only with this placement, the diagnosis of the heart can be appropriately executed to examine the heart condition [3]. If ECG is integrated with wearable technology, several problems will arise. In order for ECG to work correctly, the electrodes must be placed at the precise locations as mentioned by the experts and doctors since a long time ago. Commonly, the heart rate sensors developed by ECG technology are designed as thin chest straps and harnesses. These can be inconvenient for the users in some scenarios [4].

PPG is one of the main techniques used to measure heart rate. It is also known as Optical Heart Rate Monitoring (OHRM) [4] – [5]. This method employs an optical technique using a light-emitting diode (LED) to detect the changes in the blood volume flowing in the blood vessels under the skin. Its concept is to use an LED to send light waves into the blood capillaries. If the capillaries have a decent amount of blood (heart contracts), high intensity of light would be absorbed by the blood, and naturally high intensity of light will be reflected; if the capillaries have a low amount of blood (heart relaxes), low intensity of light would be reflected. This reflected light would be sensed by a photodiode (PD). The light intensity input into the PD will produce the corresponding levels of analogue output. By applying appropriate signal processing and algorithm, the heart rate of a person can be determined after a short time of reading the PD signal [4] – [7].

1.3 Machine Learning Technology

Machine learning is a branch of AI that allows a system to analyse its input and the significance of it without being explicitly programmed. As the name suggests, a machine that is equipped with this intelligence, can "learn" and "gain experience" to improve its performance for various applications including the prediction of a patient's disease, medical diagnosis, classification of texts or documents, image recognition, face detection, and signal filtering [8].

Machine learning can be split into unsupervised and supervised learnings. For supervised learning, the machine requires a dataset that contains the inputs and their respective outputs verified by professionals. The machine will then study this dataset to build (or train) a model that will be used to predict or determine the output of new inputs being fed in. Supervised

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learning involves teaching the machine to recognise the pattern of an existing dataset for the machine to generate an output based on the predictions. Technically, the dataset being provided consists of the input values with their corresponding output values (commonly known as labels). Each input value may have more than one variable, depending on the application.

Classification and regression are basic examples of supervised learning. Specific examples of supervised learning include Boosting Algorithm, Naïve Bayes, Maximum Entropy Method (Maxent), and Support Vector Machines (SVM) [9]. For supervised learning, Turki has experimented with algorithms to identify the types of cancer contracted by the patient [10]. The performances among the algorithms used are compared. The author has claimed SVM exhibits a better performance on the accuracy of the output than the others.

In contrast, for unsupervised learning, the machine is expected to deduce a conclusion without any guidance or existing information on the input. The most common technique in unsupervised learning is clustering. This technique involves grouping and exploration of data to identify the patterns and insights of the data. The resultant output would be the categorisation of data in clusters.

The main objective of this research is to incorporate the elements of AI into wireless health monitoring and medical diagnosis systems. Specifically, this project aims to design a heartbeat monitoring system that is supported by AI technology to produce a prediction algorithm. This algorithm will be leveraged to predict the condition of the user based on the heartbeat data read from the user [11]. This monitoring system will be wireless and portable in terms of communication and power.

1.4 Wireless Communication Protocols

For wireless communication networks, there are different types of area network: personal area networks (PANs), local area networks (LANs), neighbourhood area networks (NANs), and extensive area networks (WANs) [12]. The features and specifications of these network ranges are tabulated in Table 1 [12] – [15]. In terms of the protocols, Bluetooth, Zigbee, and Wi-Fi are the current technologies available for the development of different projects based on their requirement.

Bluetooth is suitable for the exchange of medium-sized files, data of measurements, or control between devices. In this context, Lethaby [12] states that applications such as fitness, gadgets, and automotive have employed this technology because of its decent data rates. The critical factor for designers or developers to decide on using Bluetooth in their project is the communication range. Typically, the coverage of Bluetooth ranges from 1 to 10 metres. For Bluetooth version 5, a choice of data rate is offered as 2 Mbps, 1 Mbps, 500 kbps, and 125 kbps. The lower the data rate, the longer the communication range [12]. Bluetooth will be the ideal wireless communication protocol for wearable technologies, headsets, smartphones, personal computers, and car dashboard systems.

Zigbee (IEEE 802.15.4) is one of the popular wireless communication protocols, which is mostly applied to facilitate IoT solutions [16]. This protocol is tailored to provide a whole connectivity solution for device interoperability and cloud connectivity [12]. Its primary benefit is the capability in transmitting and receiving data in small packets or short frames (low data rate), effectively minimising transmission time, and power consumption. Zigbee is suitable for

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systems to work in a wireless personal area network (WPAN) or wireless local area network (WLAN). With its decent coverage of 1 to 100 metres (in ideal places with an obstacle, about 20 metres), this protocol can be implemented in areas such as homes, classrooms, cafeteria, greenhouses, hospital wards, and offices. The low data rate up to 250 kbps is useful for sending data from system monitoring, temperature, or humidity values from various sensors and health information from medical devices. Resulting from its standards of area coverage and data rate, Zigbee's feature of low power consumption allows battery-powered applications and producing fully wireless devices.

Table 1. Comparison between various area network types

Area Network Types / Network Ranges	Personal Area Network (PAN)	Local Area Network (LAN)	Neighbourhood Area Network (NAN)	Wide Area Network (WAN)
Characteristics				
Area coverage	About 10 m	100 m	About 25 km	Relatively large (global, satellite communication)
Applications	Wireless headset, smartwatch, fitness device (Bluetooth)	PCs, smartphones, TV, IoT devices (Home Wi-Fi network)	Smart grid network (RF system)	Internet
Devices power consumption	Low	High	High	Relatively high
Wired or wireless	Usually wireless	Both	Wireless	Wireless

Wi-Fi (IEEE 802.11), developed and maintained by Wi-Fi Alliance, is a replacement for the conventional wired IEEE 802.3 Ethernet standard. From a technical perspective, the dominant factors for design consideration to implement Wi-Fi technology in a product or service include the memory, processing power, and power sources of the devices to be connected. Wi-Fi is integrated with Transmission Control Protocol/Internet Protocol (TCP/IP). This induces a large and complicated software to be installed in a device to adopt the Wi-Fi feature properly. Consequently, this device will require a powerful processor and memory module, which naturally leads to high power consumption by the Wi-Fi connected device [12]. Based on the above statements, standard devices that leverage Wi-Fi technology to perform numerous tasks such as PCs, laptops, smartphones, and tablets usually use constant power connectivity or high-capacity batteries to support their usage. Wi-Fi has features that are suitable for applications such as streaming visual content, initiating long-distance communication, and storing information to cloud service.

2. METHODOLOGY AND IMPLEMENTATION

In this research, the methodology applied to produce a prototype of a wireless heartbeat monitoring system with a self-learning feature has been proposed. Figure 1 shows the system

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architecture of the proposed prototype in the form of a unified-modelling language (UML) diagram.

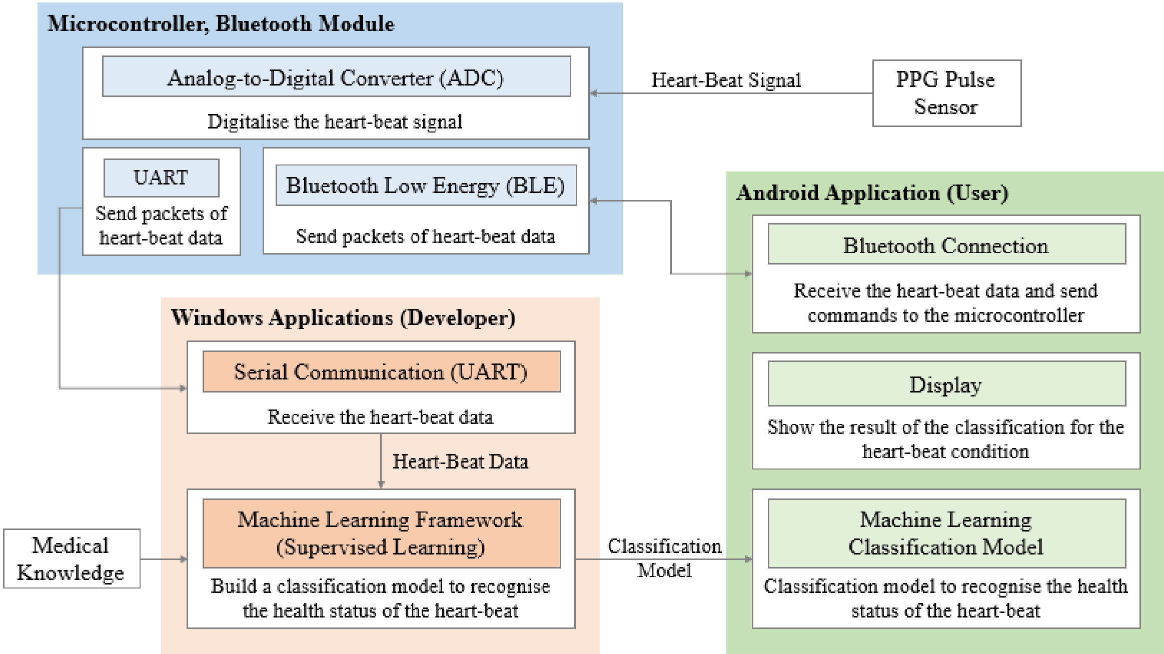

Figure 1: System architecture in the form of a Unified Modelling Language (UML) diagram

The prototype consists of three main blocks: heartbeat sensing device, smartphone application, and machine learning model training platform. The heartbeat sensing device is built by utilising a pulse sensor with PPG technology—a microcontroller that has ADC and BLE technology, battery, and peripheral components to support the full electronic circuit. A PC is used to develop the AI—machine learning classification model using proper heartbeat data collected from several healthy people. The acquisition of the heartbeat data will be executed using the heartbeat sensing device constructed. The smartphone application is Android-based, developed using Android Studio. This application is installed with the machine learning classification model developed from the computer to analyse and interpret the heartbeat condition of the user. Figure 2 shows the main blocks of the project. This project is a combination of software, hardware, and embedded system, which is integrated into a complete wireless heartbeat monitoring system with supervised learning. Each sub-section shows the techniques and technical approaches taken as the solution to create the final prototype.

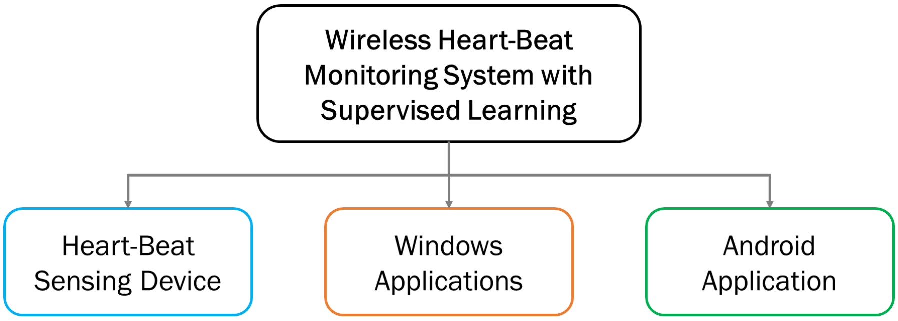

Figure 2: The main blocks of the full system

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2.1 Heartbeat Sensing Device

The function of this device is to read the user's heartbeat signal and the signal processing to output as a set of heartbeat data in digital form. The heartbeat data is sent to a Windows application (see section 2.2) via serial communication and an Android application (see section 2.3) via BLE. Figure 3 shows a plug-and-play sensor that reads a human's heartbeat using PPG technology. The sensor can be attached with a Velcro strap or an ear-clip to read from the user's fingertip or ear lobe respectively.

The Pulse Sensor works by emitting a specific luminosity (green light) through the human skin and detect the amount of blood in the capillaries. The light reflection from the capillaries is then detected by the photodiode (reflectance system), where the photodiode output is processed by the embedded circuitry to produce a heartbeat signal that ranges from 0.3 V to supply voltage, V_{DD}, as stated in the datasheet. Based on the schematic in [17], this sensor is equipped on-board low-pass filter and amplification; thus, it fits for any plug-and-play application.

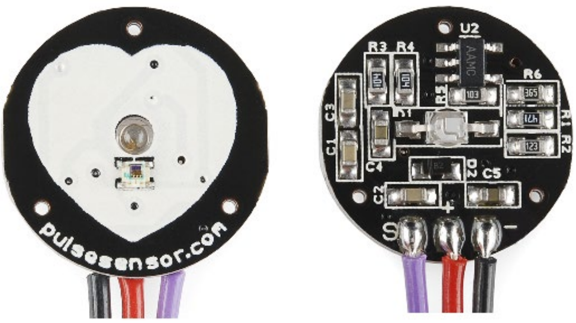

Figure 3: Pulse Sensor developed by World Famous Electronics LLC. [18]

Before applying this sensor into the project, the functionality is tested to inspect the heartbeat waveform from a PPG sensor. The output of the Pulse Sensor is measured using an oscilloscope. Each segment as labelled in the figure is the critical part of the heartbeat activity. Different amplitude for each segment reflects different diagnosis result of a human heart.

By comparing Figure 4 with Figure 5, only the R, S, and T waves are visible in the PPG signal. This is expected because PPG technology reads the heartbeat by detecting the volume of blood in the capillaries, while ECG obtains the heartbeat by detecting the electrical impulses released by the heart, which is relatively more accurate. This shows that a PPG sensor is only capable of showing the general shape and pattern of a human heartbeat. Nevertheless, this information is sufficient to diagnose certain heart conditions.

A microcontroller unit known as ESP32 is used to read the output from the Pulse Sensor. ESP32 is a microcontroller unit (MCU) that can perform as a complete standalone system or as a slave device to a host MCU [19].

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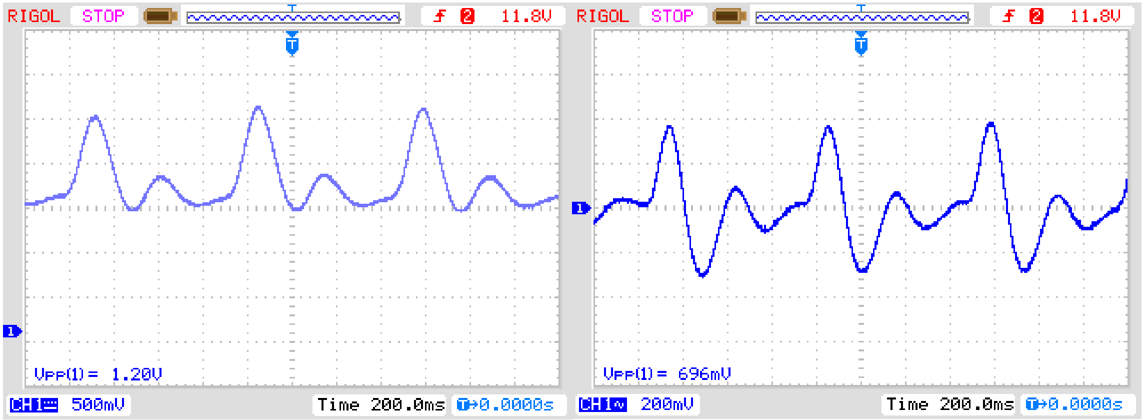

Figure 4: Output of the pulse sensor (left) DC coupling mode (right) AC coupling mode

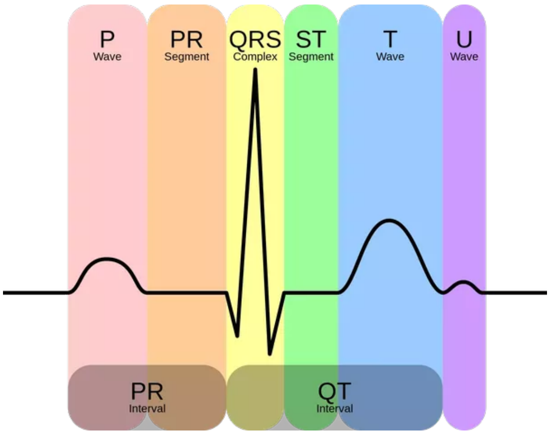

Figure 5: Typical ECG waveform [20]

2.2 Windows Application

The function of the Windows applications in this system is to produce a method for collecting heartbeat data and train the AI classification model (commonly referred as classifier or model) that predicts the user's heartbeat condition based on the heartbeat data input. These programs are designed to allow medical experts to supervise and collect data for building an accurate AI model. In this case, the applications are used by the developer for the system prototype.

Based on Figure 6, two applications are developed to achieve the purpose of this block. The program, "CSV Generator for Heart-Beat Dataset" is used to store the relevant heartbeat data read from the user or patient in comma-separated values (CSV) format. This dataset is used as the input to train the deep neural network (DNN) classification model in another program known as "DNN Classifier Training System". The output classifier file generated from the

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training system (which is mobile-friendly) is then integrated into the Android application for the user.

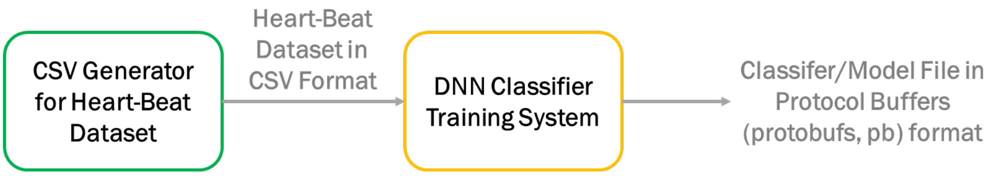

Figure 6: Windows applications developed for this health monitoring system

The CSV Generator program is developed to communicate with the heartbeat sensing device via UART for heartbeat data collection. A graphical user interface (GUI) is developed for this program to ease the process of data collection in terms of convenience and clarity. It is developed in Visual Studio, programmed with C# as a Windows Form Application.

The DNN Classifier Training System is developed to read the training and testing datasets generated by the CSV Generator program for building the DNN classifier for heartbeat condition prediction. The process and output of this program are displayed in Windows terminal. This system enables the developer to run the Python script multiple times to train the classifier.

There are several parameters in machine learning, known as hyperparameters. A hyperparameter is a parameter or setting that is used to configure the base structure of a neural network. Analogous to a human, a hyperparameter can be considered as the character or personality of a person. These parameters affect the prediction capability of a neural network directly with its training process. Therefore, as the training or learning of the classifier progresses, the hyperparameters must be adjusted to achieve optimum performance.

In this context, the hyperparameters configured for the DNN classifier used in this system are learning rate, batch size, and the number of hidden layers. The tuning of the hyperparameters is required to build a fully optimised AI classification model. The final configuration used for this project is shown in Table 2.

The heartbeat data for each condition is generated (especially the heart rate) based on a valid, standard, and reliable source of the heartbeat information [21] to prepare the training dataset. To preserve the precision of the classifier, the data obtained from the volunteers is used as the benchmark to maintain the viability of the heartbeat data generated. The standard heart rate information for different heartbeat conditions is researched and modified professionally to be implemented into this system [22].

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Table 2. Hyperparameters defined for the implementation of the DNN classifier

Size of Training Dataset	1000
Size of Testing Dataset	1000
Learning Rate/Step Size	Stage 1: 500 for 15000 steps Stage 2: 250 for 5000 steps
Batch Size	500
Input Layer	Five neurons
Hidden Layer	2 hidden layers with 50 neurons each: [50,50]
Output Layer	Six neurons

2.3 Android Application

This Android application is designed for the end-user in which the user can interact with the Android application and connect wirelessly (via BLE) to the heartbeat sensing device to initiate the heartbeat reading (Figure 7). The Android application is installed with the heartbeat condition classifier, then predicts the user's heartbeat condition and displays the heartbeat condition inference to the user.

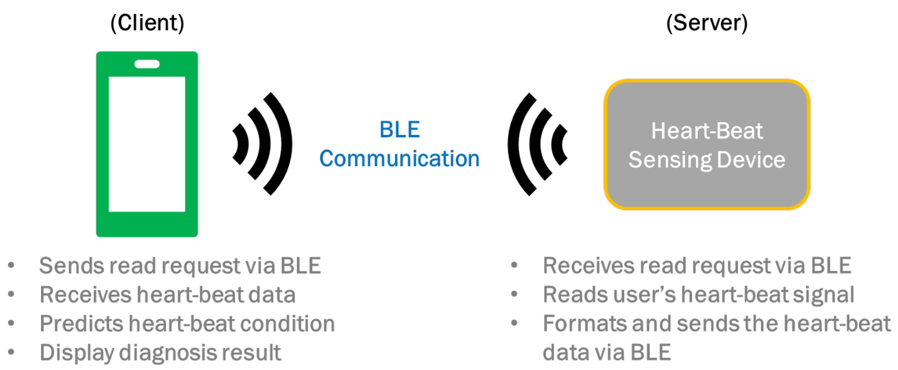

Figure 7. Implementation of the Android application in this wireless heartbeat monitoring system

This Android application is developed to provide convenience for the end-user to interact with the heartbeat sensing device. The application (prototype) is named as "Heart Diagnosis Prototype" in this project. Android Studio as the IDE is used to develop this application. Java and Extensible Markup Language (XML) are the programming languages used to code the algorithm and GUI respectively. The minimum target for the Android version to run this application is Android 4.4 – KitKat (API Level 19). Android 7.0 – Nougat (API Level 24) is used during the development and testing of "Heart Diagnosis Prototype".

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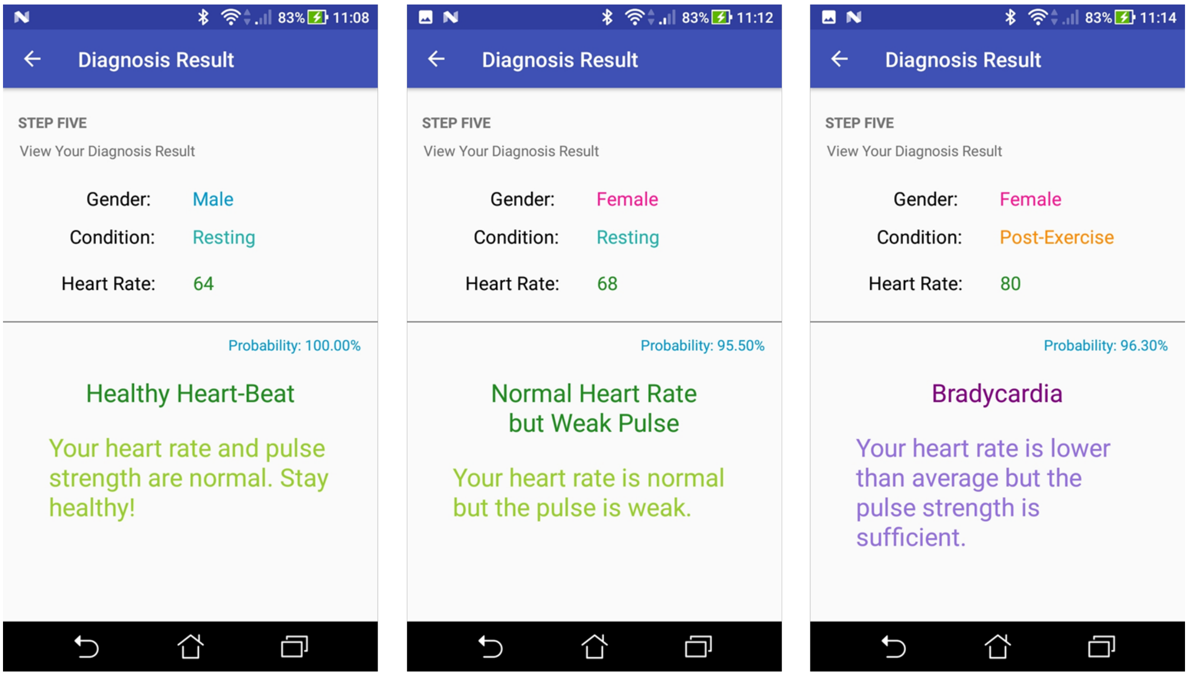
3. RESULTS AND DISCUSSION

3.1 Design of the System

In terms of the hardware, the appearance of the heartbeat sensing device is shown in Figure 8.

Figure 8. The heartbeat sensing device

In terms of the Android application, the possible outputs of the user's diagnosis result are shown in Figure 9.



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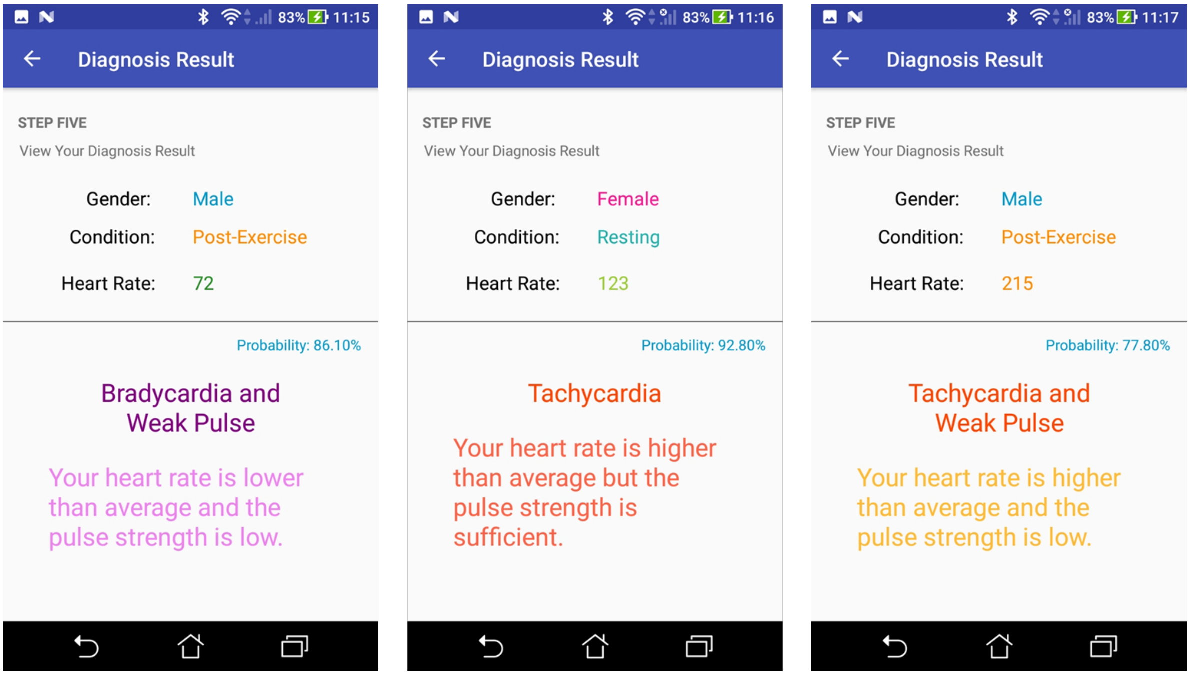

Figure 9. Possible outputs of the Android application

3.2 Performance of the System

The system was tested to ensure the entire system is functional and reliable for the user. For the developer side, the heartbeat sensing device is used to collect heartbeat data to train and optimise the DNN Classifier. The performance of the DNN classifier is visualised by plotting the test accuracy against the number of training iterations.

Based on Figure 10, the DNN classifier has shown the behaviour as seen throughout the training process. In the early stage, the classifier is considered to have high test accuracy for the prediction executed. However, there is a slight decline in the performance as the classifier has reached a region of false convergence in the early training stage. When the training resumes, the prediction of the classifier is stabilised and maintained at a high level of test accuracy.

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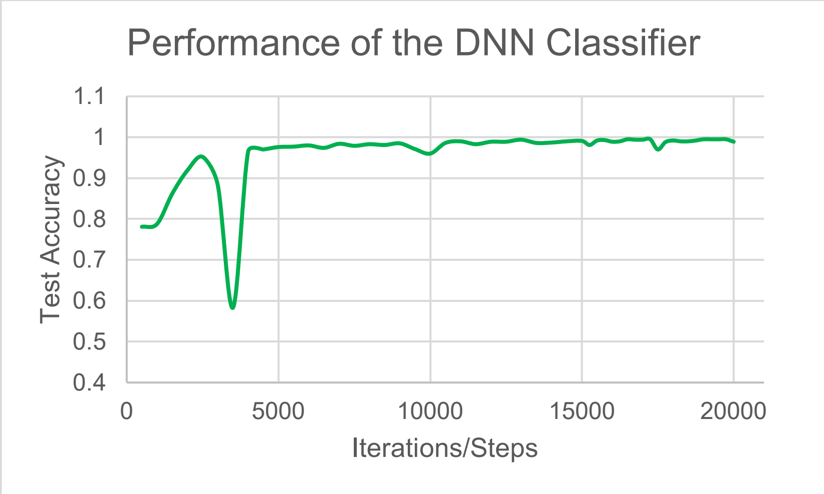

Figure 10. Performance of the DNN Classifier of this project

Specifically, by using the hyperparameters for this training process, the performance of the classifier has achieved a test accuracy of approximately 99% for 20 000 training iterations. This level of performance is possible as the optimisation of the training process is applied based on the analysis of DNN classifier training from various aspects. The achieved test accuracy is useful to predict the heartbeat condition of the user.

The consistency and accuracy of the classifier were tested by the ten volunteers previously assisted in building the training heartbeat dataset. The empirical accuracy of the classifier was determined. Table 3 shows the testing results of the optimised classifier.

Table 3. Testing result of the heartbeat monitoring system with optimised classifier

User	Monitoring Condition	Predicted Heartbeat Status	Actual Heartbeat Status	Heart Rate Computed (BPM)	Prediction Result (True/False)
User 1 (Male)	Resting	Healthy	Healthy	75	True (99.94%)
User 2 (Female)	Resting	Healthy	Healthy	64	True (98.56%)
User 3 (Male)	Resting	Healthy	Healthy	81	True (99.99%)
User 4 (Male)	Resting	Normal Heart Rate but Weak Pulse	Normal Heart Rate but Weak Pulse	102	True (90.52%)
User 5 (Male)	Resting	Healthy	Healthy	81	True (99.86%)
User 6 (Female)	Post-Exercise	Normal Heart Rate but Weak Pulse	Normal Heart Rate but Weak Pulse	96	True (96.05%)

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User 7 (Male)	Post-Exercise	Healthy	Healthy	129	True (100%)
User 8 (Male)	Post-Exercise	Normal Heart Rate but Weak Pulse	Bradycardia	75	False (55.87%)
User 9 (Male)	Post-Exercise	Healthy	Healthy	110	True (96.75%)
User 10 (Male)	Post-Exercise	Healthy	Healthy	122	True (99.99%)

In Table 3, the column "Prediction Result (True/False)" shows the prediction results with the probability of the inference by the classifier. The value of "True/False" is determined by comparing the predicted and actual heartbeat status. The probability of the inference is obtained by reading the display from the Android application. Based on the number of accurate predictions, the empirical accuracy of the classifier is 9/10 = 90% for the test conducted.

4. CONCLUSION

A heartbeat monitoring system that is supported by AI, specifically a DNN classifier was successfully designed and developed. The DNN classifier was built using heartbeat data collected from 10 healthy people (as the benchmark for the healthy heartbeat condition) and generated based on the standard heartbeat data referenced from valid sources. The classifier designed can successfully predict and determine the heartbeat condition based on the heartbeat data read from the user. The heartbeat monitoring system developed is wireless and portable. In this case, the developed heartbeat sensing device is battery-powered, assembled in a 3D-printed casing. The wireless communication is achieved by developing the system to enable BLE communication between the heartbeat sensing device and the Android application. From the result of this project, it is proven that AI can be integrated into mobile devices to solve a specific problem when combined with other devices.

REFERENCES

[1] M. Chen, Y. Hao, K. Hwang, L. Wang and L. Wang, "Disease Prediction by Machine Learning Over Big Data from Healthcare Communities," *IEEE Access*, vol. 5, pp. 8869-8879, 2017

[2] H. Yin and N. K. Jha, "A Health Decision Support System for Disease Diagnosis Based on Wearable Medical Sensors and Machine Learning Ensembles," *IEEE Transactions on Multi-Scale Computing Systems*, vol. 3, no. 4, pp. 228-241, 1 Oct.-Dec. 2017

[3] R. G. Wilkerson, "Introduction to ECGs," [Online] Available: http://www.aast.org/Assets/c6030506-f3e5-4ffd-b1c8-fc5d9dd8ba11/636076322142970000/ powerpoint-presentation-of-the-basics-of-ekgs-from-r-gentry-wilkerson-uploaded-2015-pdf [Accessed May 19, 2018]

[4] D. T. Weiler, S. O. Villajuan, L. Edkins, S. Cleary, and J. J. Saleem, "Wearable Heart Rate Monitor Technology Accuracy in Research: A Comparative Study Between PPG and ECG Technology," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 2017, pp. 1292-1296

p-ISSN 1675-7939; e-ISSN 2289-4934

[5] Z. Zhang, "Photoplethysmography-Based Heart Rate Monitoring in Physical Activities via Joint Sparse Spectrum Reconstruction," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 8, pp. 1902-1910, Aug. 2015

[6] A. T. Ayance, H. S. Ramírez, J. M. R. Pérez, and C. G. T. Palacios, "Low-Cost Microcontrolled Based Wireless Heart Rate and Oxygen Saturation Monitor," *2018 International Conference on Electronics, Communications and Computers*, 2018, pp. 176-180

[7] J. B. Bathilde, Y. L. Then, R. Chameera, F. S. Tay, and D. N. A. Zaidel, "Continuous Heart Rate Monitoring System as an IoT Edge Device," *Sensors Applications Symposium (SAS), 2018 IEEE*, 2018 pp. 1-6

[8] H. K. Gianey, and R. Choudhary, "Comprehensive Review on Supervised Machine Learning Algorithms," *International Conference on Machine Learning and Data Science*, 2017, pp. 37-43

[9] A. Rathor, and M. Gyanchandani, "A Review at Machine Learning Algorithms Targeting Big Data Challenges," *International Conference on Electrical, Electronics, Communication, Computer and Optimisation Techniques (ICEECCOT)*, 2017, pp. 753-759

[10] T. Turki, "An Empirical Study of Machine Learning Algorithms for Cancer Identification," *IEEE 15th International Conference on Networking, Sensing and Control (ICNSC)*, 2018, pp. 1-5

[11] J. Saluja, J. Casanova and J. Lin, "A Supervised Machine Learning Algorithm for Heart-Rate Detection Using Doppler Motion-Sensing Radar," *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, vol. 4, no. 1, pp. 45-51, March 2020

[12] N. Lethaby, "Wireless Connectivity for the Internet of Things: One Size Does Not Fit All," *Texas Instruments Incorporated*, 2017, pp. 1-16.

[13] F. Gu, J. Niu, S. K. Das and Z. He, "RunnerPal: A Runner Monitoring and Advisory System Based on Smart Devices," *IEEE Transactions on Services Computing*, vol. 11, no. 2, pp. 262-276, 1 March-April 2018

[14] Y. B. Shu, L. Kang, and P. Lanctot "Internet of Things: Wireless Sensor Networks," *International Electrotechnical Commision*, 2014, pp. 1-78

[15] M. G. R. Maldonado, "Wireless Sensor Network for Smart Home Services Using Optimal Communications," *2017 International Conference on Information Systems and Computer Science,* 2017, pp. 27-32

[16] Zigbee Alliance, "About Us" [Online] Available: http://www.zigbee.org/zigbee-for-developers/about-us/ [Accessed May 15, 2018].

[17] J. Murphy, "Pulse Sensor Amplified," 2012. [Online] Available: https://cdn.shopify.com/s/files/1/0100/6632/files/PulseSensorAmpd_-_Schematic.pdf?1862089645030619491 [Accessed Sept. 10, 2018].

[18] J. Murphy and Y. Gitman, "About Us," 2018. [Online] Available: https://pulsesensor.com/pages/about-us [Accessed Oct. 02, 2018].

[19] Espressif Systems, "ESP32: A Different IoT Power and Performance," 2018 [Online] Available: https://www.espressif.com/en/products/hardware/esp32/overview [Accessed Oct. 03, 2018].

[20] Wikimedia Commons, "Schematic Representation of Normal ECG," 2014 [Online] Available: https://commons.wikimedia.org/wiki/File:EKG_Complex_en.svg [Accessed Sept. 03, 2018].

[21] American Heart Association, "About Arrhythmias" 2016 [Online] Available: http://www.heart.org/en/health-topics/arrhythmia/about-arrhythmia [Accessed Sept. 23, 2018]

[22] American Heart Association, "Know Your Target Heart Rates for Exercise, Losing Weight and Health" 2015 [Online] Available: https://www.heart.org/en/healthy-living/fitness/fitness-basics/target-heart-rates [Accessed Sept. 23, 2018]

p-ISSN 1675-7939; e-ISSN 2289-4934