DEVELOPMENT OF A WEARABLE DEVICE FOR HEART RATE MONITORING AND FALL DETECTION USING MACHINE LEARNING TO ANALYZE AND DETECT EARLY ANOMALY OF CARDIOVASCULAR CONDITIONS

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Abstract - Cardiovascular disease is the leading cause of death globally. This research implements a system for monitoring heart rate, electrocardiogram, and providing alerts for potential risks to patients based on data collected using the LSTM machine learning model. The wearable device is compact in size with a long battery life. The information collected from the device can be remotely monitored by doctors through a visual interface on a web server model, and patients can self-monitor their electrocardiogram status through an application on a mobile device. By integrating the LSTM model into the design, this study has addressed two issues: predicting the trend of the electrocardiogram signal and detecting abnormalities in the predicted signal. This allows users to self-monitor their personal status and doctors to better adjust the treatment method for the patient's health.

Key words - Cardiovascular diseases; LoRa; LSTM; anomaly detection; wearable device

1. Introduction

Cardiovascular diseases (CVD) are the leading cause of death globally. In 2019, there were 17.9 million deaths due to CVD [1]. In Vietnam, cardiovascular diseases accounted for 31% of total deaths in 2016 [2]. Cardiovascular diseases caused approximately 19.91 million deaths globally in 2021 [3]. These statistics highlight the importance of health monitoring and prevention of cardiovascular diseases, especially for elderly patients who need medical support. Monitoring heart health not only helps detect early signs of cardiovascular diseases, but also allows doctors to adjust treatment methods and plan better health care. This can help improve the quality of life and reduce the risk of serious complications.

Today, science and technology have brought many achievements in various fields to improve the quality of human life. In the field of healthcare, the combination of the Internet of Things (IoT) and Artificial Intelligence (AI) has provided many health solutions for healthcare providers and patients. Some solutions such as remote monitoring and support, personal health care, pharmaceutical and medical equipment management, etc. Recent studies on remote cardiovascular health monitoring using IoT and Artificial Intelligence technologies such as the study by Peng Wang and colleagues [4] have developed an ECG data collection device and applied CNN combined with LSTM. The study proposes a semi-supervised method to process badly labeled data samples using confidence-level-based training. The test results show that the proposed method can achieve an average accuracy of 90.2%, which is 5.4% higher than the accuracy of conventional ECG classification methods. The study [5] proposes to develop a remote ECG monitoring system. The study developed a compact device using an ECG sensor and ESP8266 processing platform. The collected data is continuously and directly displayed on the cloud platform in the form of a graph. The collected data is then analyzed and classified by CNN. The device achieved a high accuracy of 96.6%. The study [6] designed and developed an embedded sensory system with a low power communication module to discreetly collect electrocardiogram (ECG) and body accelerations using a smartphone. The system uses GPS technology and an accelerometer to detect falls and the user's location information. The study [7] uses the Polar H10 heart sensor combined with machine-learning models such as convolutional neural network, and k-nearest neighbors to classify events from heart signals and uses wireless communication technology to transmit data to cloud computing. The survey results show that the k-nearest neighbor method provides the best classification efficiency for arrhythmias. The study [8] proposes to develop a remote ECG monitoring system. The study built a compact ECG signal monitoring device to capture and display the patient's heart signals, heart rate, blood oxygen levels, and body temperature. The measured data is displayed on the device through an OLED screen or transmitted to a web server to support users to access information remotely via an Android device.

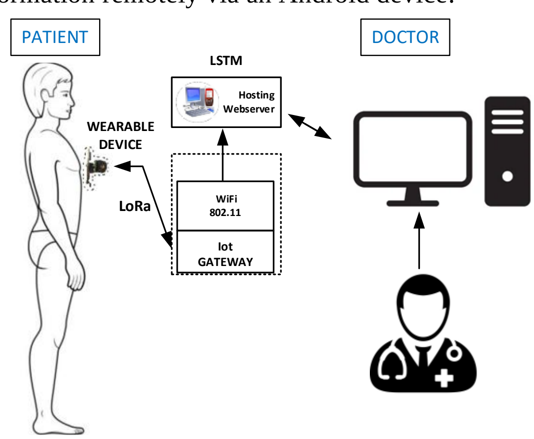

Figure 1. *Overview of the System Block Diagram*

2. Heart Health Monitoring and Fall Detection Device

Currently, there are many methods of electrocardiogram (ECG) measurement to diagnose cardiovascular diseases. To fully examine the heart's activity, patients are fitted with electrodes on the skin and measured immobile in a sitting or lying position. Although the accuracy of this method is the highest, the drawback is that the measuring device is bulky, not highly portable, and difficult to monitor the patient's condition over a long period. To overcome this drawback and be more suitable for daily monitoring, the portable Holter monitor [9] was introduced to allow long-term monitoring for patients who need to regularly monitor ECG and heart rate without disrupting their daily activities. Thanks to its ability to record data in real-time, the Holter [9] monitor helps doctors accurately diagnose cardiovascular problems, such as arrhythmias, high or low blood pressure. Although the portable Holter monitor is more compact than the wired version, wearing the device for a long time can cause discomfort to the patient. However, the device still needs to be equipped with bulky electrodes and measurement buttons, and the high cost. Thus, the requirement is that the heart signal monitoring device needs to be designed compactly, low cost, and convenient for the user. The data measured from the wearable device needs to be transmitted to a high-performance computer for processing and making necessary decisions. To increase mobility, the wearable device needs to support wireless communication technologies.

***Table 1.** Characteristics of some wireless communication standards*

	Bluetooth	Wi-Fi	Zigbee	LoRa
Standard	**IEEE 802.15.1**	**IEEE 802.11**	**IEEE 802.15.4**	**LoRaWAN R1.0**
Freq.	2.4 Ghz	5 ÷ 60 Ghz	868/915 Mhz, 2.4 Ghz	900 Mhz
Bandwidth	1 ÷ 24 Mbps	1 ÷ 6.75 Gbps	40 ÷ 250 Kbps	0.3 ÷ 50 Kbps
Distance (m)	8 ÷ 10	20 ÷ 100	10 ÷ 20	< 30.000
Power cons.	Very high	High	Low	Very low
Price	Low	High	Low	High

It can be seen that the method of connecting and transmitting data between measurement points is the most important when deploying a system with multiple measurement and monitoring points. Table 1 presents survey data on the characteristics of some popular wireless communication standards such as Bluetooth, Wi-Fi, Zigbee, and LoRa. Based on the characteristics of the data transmission methods mentioned, Wi-Fi combined with LoRa is considered an effective solution when deploying a large-scale measurement system. However, Wi-Fi requires high power consumption when transmitting a large amount of data, which is not suitable for wearable devices that continuously transmit data over time. To reduce power consumption on the device, LoRa communication for sensor networks when collecting information from many sensors with small data volume is considered a solution to overcome the above drawback as it can transmit data far in a noisy environment with low power consumption and does not depend on Wi-Fi infrastructure.

Based on the above analysis and previous research results, this study focuses on experimenting with a low-cost, small-sized device that applies IoT and AI technology in remote monitoring and alerting of heart health for patients, as illustrated in Figure 1. The device has the ability to connect heart signal measurement sensors, detect falls, and transmit data to cloud computing for remote monitoring of patients' medical signs. A machine learning model will collect this data, process it, and issue early warnings. In this solution, doctors can remotely monitor the patient's parameters without having to directly visit the patient. This solution can support more convenient doctor visits and help patients adjust their daily activities more appropriately.

3. System implementation

3.1. Hardware of the system

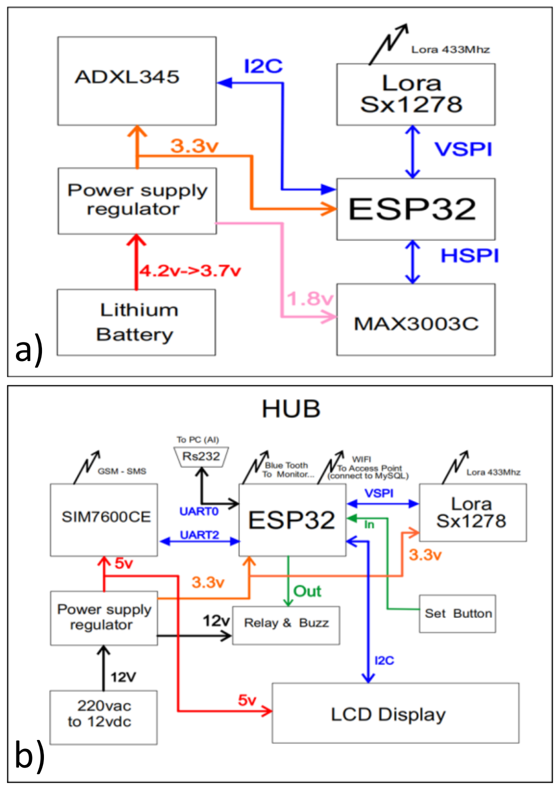

***Figure 2.** Hardware Block Diagram a) Wearable device comprising measurement sensors b) Gateway device collecting information via LoRa and transmitting data to the server (IoT Gateway Circuit)*

The wearable device is capable of collecting electrocardiogram signals and uses an accelerometer sensor to detect falls and alert the user to abnormal fall conditions via SMS. The wearable device must be compact, have low power consumption, and transmit data to a computer for collection for prediction and early warning purposes. The wearable device is detailed in Figure 2a, where the ESP32 block is the central processing component powered by 3.3V. The ESP32 will handle data processing from the sensors and transmit the processed information via the LoRa communication standard. The ADXL345 accelerometer sensor block, which is responsible for fall detection, communicates with the ESP32 via the I2C protocol with a supply voltage of 3.3V. The MAX30003 heart sensor block collects the patient's heart signal information. This block communicates with the ESP32 module via the HSPI protocol with a supply voltage of 1.8V. The LoRa SX1278 block communicates with the ESP32 module via the VSPI protocol with a supply voltage of 3.3V. The operating frequency of the LoRa block is 433MHz, which is in line with the permitted frequency standard in Vietnam. The wearable device will be primarily powered by a Li-ion battery for an output voltage of 3.7V, and the voltage regulator circuit will be responsible for creating different voltages to power the blocks.

The IoT Gateway device will function as a component for information transmission. This block will be able to communicate with the database, and users can use the application on mobile devices to know about their health status or doctors can monitor the health of patients remotely. In addition, the system integrates an artificial intelligence-based processor to issue early warnings about abnormal health conditions based on ECG data. As shown in Figure 2b, the ESP32 block is the central processing component powered by 3.3V. This block handles data processing and controls other functional blocks. The SIM7600CE block uses a 5V supply voltage, takes on the function of sending SMS alerts to users, and communicates with the ESP32 block via the UART protocol. The 5V source will be supplied to the SIM7600CE module and the module communicates with the ESP32 via the UART protocol. Similarly, in the wearable device section, the Lora SX1278 block communicates data transmission with the ESP32 module via the SPI protocol to process the data string received from the Lora module on the wearable device through the Lora 433 Mhz wave. The display block through the LCD screen serves to display the general status of the system.

The MAX30003 [10] sensor used integrates functions to measure blood oxygen concentration (SpO2) and detect heart rate and ECG waveform with only 1 measurement channel, the sensor is a high-precision solution, suitable for mobile applications with ultra-energy-saving design, applied in health monitoring. Compared with the MAX30100 [11] sensor, BMD101 [12], and AD8232 [13], the MAX30003 has higher accuracy, supplemented with some advanced features such as detecting and classifying heart rate events. Therefore, the cost of the MAX30003 sensor is higher than others. This study has conducted actual ECG signal testing at a private medical facility that supports ECG measurement and compared with the actual results taken from the device manufactured by this study. From the measurement results and comparison of 2 devices, it shows that the measurement results from the device set have about 80% similarity compared to the commercial device.

The LoRa SX1278 [13] data transmission block used in this study is popular and uses the SPI communication protocol. In terms of energy consumption, the SX1278 is designed to save energy, suitable for IoT wearable applications that allow extended battery usage time. In addition, the LoRa SX1278 has the ability to respond quickly and stably, allowing efficient two-way data transmission. Compared to the LoRa E32 design, the LoRa SX1278 [14] has a lower transmission distance, often used for applications in urban areas or environments with medium and low construction density, with data transmission within a narrower range such as inside buildings. The LoRa SX1278 is suiTable 1n the context of information transmission as illustrated in Figure 1, when heart patients at the hospital will wear measuring devices on the body. Then the data will be collected remotely, concentrated to the IoT Gateway device through the LoRa transmission standard.

Heart rhythm disorders, coronary artery occlusion, and problems due to heart failure leading to falls are very common. To timely detect the patient's falling condition, the product in this study integrates an additional accelerometer. The ADXL345 [15] accelerometer used is a type of 3-axis tilt sensor, small size, low energy consumption with only 23uA, high resolution up to 13-bit allows measuring small tilt changes. Combined with the ability to detect the falling state, the ADXL345 sensor is suitable for the need to detect the state of a person falling. In addition, the location information of the person in need of help will be transmitted via SMS with the support of the SIM7600CE [16]. This is a design that supports 4G/3G/2G and global satellite positioning, especially it consumes very low power and is compatible with many current microcontroller lines.

Both hardware blocks use the ESP32 platform as the main central processing unit to collect data from sensors and transmit information to cloud computing. The ESP32 is a system on a chip (SoC) integrating Wi-Fi/Bluetooth with fast processing speed with two CPU cores. The ESP32 is designed to consume low power, helping to extend battery life suitable for IoT and wearable devices.

3.2. The machine learning model for data analysis and alerting

The collected data is a time-series of ECG signal events, the main goal of this study is to predict early abnormalities in the ECG signal of the wearer. Therefore, the design needs to use models that can predict and detect abnormalities in the data. Among neural networks, LSTM [17-18] is specially designed to handle data series, i.e., data organized over time. LSTM has the ability to remember information during learning, which makes it effective in modeling data series with repeating patterns or patterns that change over time, such as heart rate waveforms. Based on these characteristics, this study uses Long Short-Term Memory (LSTM) for predicting ECG signals, then uses LSTM-Autoencoder to detect abnormalities in the ECG signal output from the previous LSTM model.

The machine learning model deployed in this study is illustrated by Figure 3. The ECG signals collected from the sensors will be passed through a preprocessing block to classify and filter out noise. The signals, after going through the preprocessing block, will be continuously fed into the Prediction Model. This model is trained to make predictions about the next values of the heart rate and the patient's condition. The predicted value is important for the Anomaly Model to determine whether there are signs of abnormality in the patient.

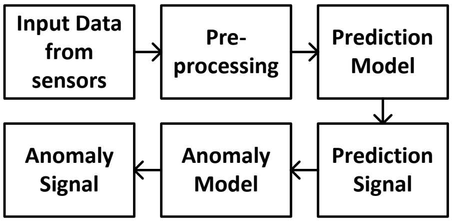

Figure 3. *Data processing flow diagram from sensors and providing warning signals to the terminal user*

Experimental Results

Figure 4a shows the hardware of the IoT Gateway device aimed at collecting data from wearable devices monitoring the ECG. Figure 4a shows an enlarged image of the hardware of the wearable device used by the patient. The wearable device with sensors collecting ECG and heart rate will be processed by the microcontroller on ESP32 and transmit information through the LoRa block at 433Mhz frequency.

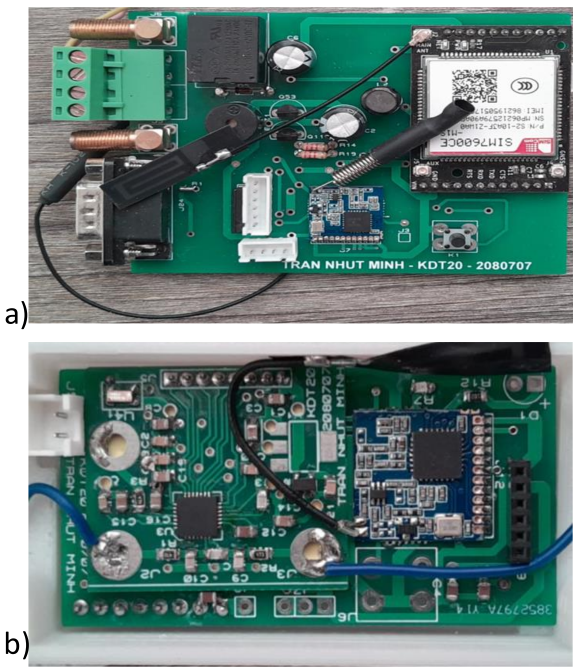

Figure 4. *Hardware product a) Electrical circuit on the iot gateway device b) Electrical circuit on the wearable device (enlarged image)*

Regarding the data processing model as presented in Figure 3, the models were trained on hardware using a GTX 1650 graphics processor. The LSTM model was trained for 100 epochs with 128 mini-batches. The data was divided into the following sets: 85% allocated to the training set, 10% to the validation set, and the remaining 15% to the test set. The model learns very well, the deviation value from the Loss function between the train set and the validation set is quite small. The model makes very accurate predictions of the signal trend, almost similar to the actual value as shown in Figure 5a. In the anomaly detection model, the LSTM-AE (Autoencoder – AE) model was trained for 200 epochs with 128 mini-batches, using 85% of the data for the training set, 10% for the validation set, and the remaining 15% for the test set. The results from Figure 5b show that the model learns very well, the deviation value from the Loss function between the train set and the validation set is quite small, almost equal to 0. The model reconstructs the abnormal signal very well with a very small difference. For the input is an abnormal signal, the model has reconstructed and brought out the contrast between the abnormal and normal signal very clearly.

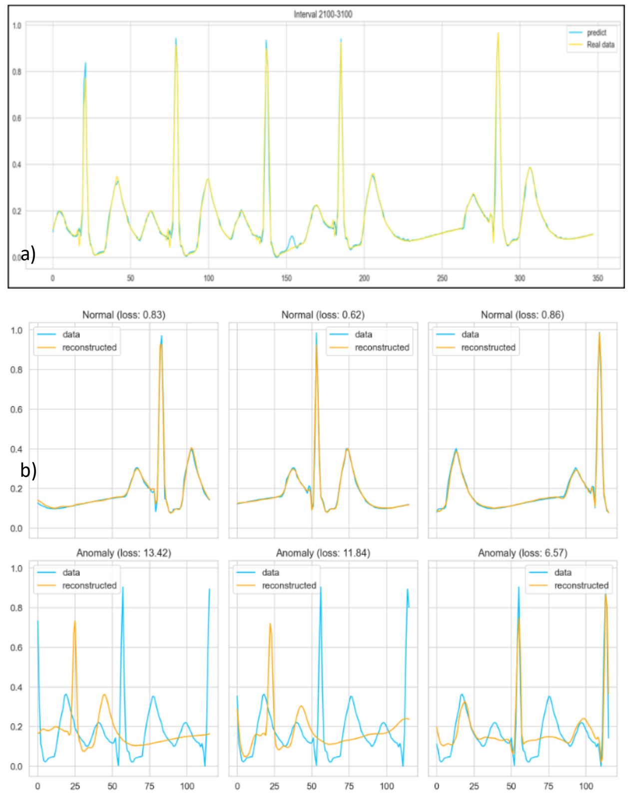

Figure 5. *Electrocardiogram signal a) Predicted value for the next 3 seconds based on 10 seconds of the collected value b) Normal signal, abnormal signal with the signal reconstructed from the collected data*

Technical parameters such as Precision, Recall, F1-score, MAE, MAPE, MSE are used to evaluate the performance of the Long Short-Term Memory model implemented in this study. In which, precision measures the ability of the model to correctly classify positive predictions. Precision is useful in cases where it is important to avoid false positive predictions, such as in problems of high importance in terms of determination and avoiding mistakes that can cause serious consequences. The higher the precision, the better the model is at predicting the positive class. Recall does not provide information about false positive predictions. Therefore, when evaluating the performance of the model, recall should be combined with precision or F1-score to have a comprehensive view of the performance of the classification model. The higher the recall, the better the model. F1 score is a composite metric used to evaluate the performance of classification models. MAE is a measure to evaluate the average deviation between the predictions of the model and the actual value in the test data. MAPE measures the average error in percentage of the predictions compared to the actual value. MSE is another measure to evaluate the average square deviation between the model's predictions and the actual value. The lower the values of MAE, MAPE, MSE, the better the model. Table 2 presents the values of basic parameters measuring the performance of the network. Based on the values in the table below, it can be seen that in the prediction model, the values of MAE, MAPE, MSE are very low, approaching 0. Meanwhile, in the anomaly detection model, the F1-score has a value over 95% showing that the model is trained and achieves high efficiency. Table 2 compares the performance parameters of the model implemented in this study with those of related research [19].

Table 2. *Performance evaluation parameters*

	This study	[19]
MAE	$7{,}30.10^{-3}$	
MAPE	1.31%	
MSE	$4{,}80.\ 10^{-5}$	
Precision	0.94	0.9559
Recall	0.98	0.2555
F1-score	0.96	0.9306

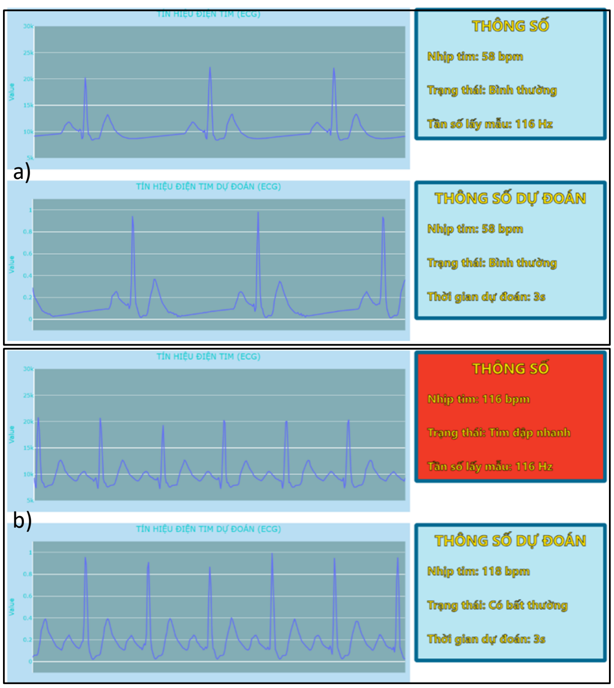

Figure 6. *Waveform of the ECG signal and processed information in the case of a) Normal condition b) Abnormal condition*

An interface displaying the waveform of the ECG, and information about the heart rate, the state of the ECG signal will be displayed on the screen to help doctors easily monitor the status of the person wearing the heart rate monitoring device. The determination of upper and lower threshold values to detect abnormalities is often based on statistical methods and absolute error (MAE). When the collected value exceeds the calculated threshold, it means that an abnormal sign has occurred. The normal state in the case monitored by the device is described in Figure 6a. At this time, the interface including information parameters will change color to alert the condition of the heart beating fast or slow as illustrated in Figure 6b.

In addition, users of the wearable device monitoring heart rate and ECG can self-monitor the measurement indicators through a mobile application on the Android operating system developed by this study as illustrated by Figure 7a. The IoT Gateway system will process data and issue warning messages about abnormal changes when detecting a risk of falling as shown in Figure 7b.

In summary, the wearable device monitoring heart rate and detecting falls applying machine learning to analyze and early warn cardiovascular conditions is a product that not only continuously monitors your heart rate, but also analyzes data to detect abnormal signs, helping to early warn cardiovascular problems. In addition, the device also has the ability to detect falls - a very useful feature, especially for the elderly. When detecting a fall event, the device will automatically send a warning, helping users receive timely support from relatives. With advanced machine learning technology, this device can learn and adapt to specific heart rate models and user movement behaviors, thereby providing accurate and personalized analysis. With a compact design, energy-saving, easy to wear, this product is a powerful tool to monitor health. The research results of the topic are used to apply in basic medical monitoring, warning abnormalities of health such as heart rate, cases of falls. The device set is very easy to equip for most people who need to monitor health at home, healthcare workers can easily monitor remotely based on the IoT Gateway system and display screen.

a)

b)

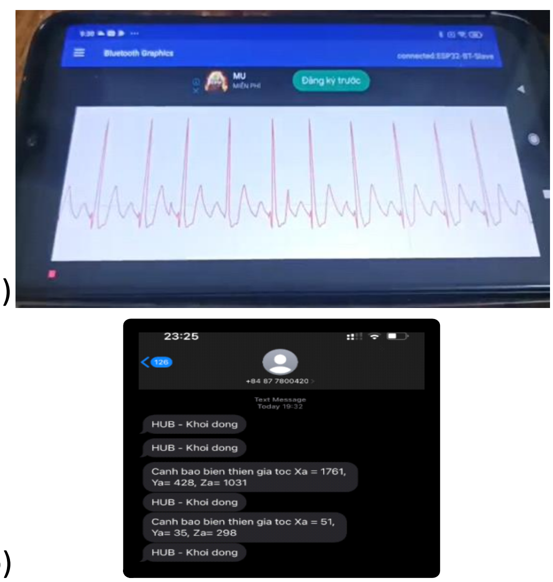

Figure 7. *Information displayed on a) Android application for ECG heart sensor data retrieved from wearable device b) SMS message via Sim7600 module sending alert for accelerometer sensor values to the user*

4. Conclusion

This study has fully implemented a system to monitor heart rate, electrocardiogram, and issue warnings of potential risks to patients from collected data based on the LSTM machine learning model. The wearable device is compact in size with a long battery life. The information collected from the device can be remotely monitored by doctors through an intuitive interface on the Webserver model, and patients can self-monitor their electrocardiogram status through an application on a mobile device. By integrating the LSTM model into the design, this study has solved two problems: predicting the trend of the electrocardiogram signal and detecting abnormalities in the predicted signal. For the trend prediction model, the model has been able to predict 3 seconds ahead from 10 seconds in the past. However, 3 seconds is still too short for the time in serious health cases. Therefore, future research will continue to develop the design to be able to predict abnormalities in a longer time.

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