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IoT system for monitoring sick and disabled

Streszczenie. *Celem było zbudowanie systemu monitorowania chorych i niepełnosprawnych. Budowę systemu oparto o mikrokontroler i zestaw czujników zbierających dane o pacjencie. Opracowano moduł diagnozy choroby serca w oparciu o dane z czujników. Wyznaczono standardy dokładności w jakich musiał działać system. Zbadano dokładność systemu i porównano z wyznaczonymi standardami. (**IOT system do monitorowania osób niepełnosprawnych**)*

Abstract. *The aim of the study was to build a system for monitoring the ill and disabled people. The construction of the system was based on a microcontroller and a set of sensors that collect data about the patient. A heart disease diagnosis module was developed based on sensor data. Accuracy standards were set in which the system had to operate. The accuracy of the system was tested and compared with designated standards*

Słowa kluczowe: Internet Rzeczy, monitoring, system, sztuczna inteligencja
Keywords: Internet of Things, monitoring, system, artificial intelligence

Healthcare is an essential and significant part of public services worldwide. In order to maintain the health of patients, constant monitoring is necessary. This process becomes more important when individuals reach a certain age and are unable to properly track their health without special medical personnel or advanced equipment to implement monitoring. The COVID-19 infectious disease pandemic caused by the SARS-CoV-2 coronavirus illustrated today's problem of hospital bed availability in emergency situations. In many cases, even a slight delay in providing medical observation can lead to serious consequences, including the death of the patient. The process of transferring a patient to hospital for medical observation can result in a delayed response by doctors during the period of disease determination.

Therefore, a number of studies have been carried out and a system for monitoring sick and disabled people has been developed using IoT solutions. The research system-built works on the principle of a microcontroller to which small medical sensors are connected. A website was created as the graphical interface of the system, where the readings can be observed. An application to classify heart diseases based on the data taken from the sensors was also part of the system. Hypothesis presented: the developed system meets the standards set and can be used to monitor and diagnose sick and disabled people.

Application of the Internet of Things in medicine.

The Internet of Things (IoT) is a new paradigm of the Industrial Internet Consortium focused on the proliferation of internet technologies, which includes different types of devices: computers, tablets, watches, everyday objects. Devices these have embedded sensors that exchange data with each other. The Internet of Things is making a major contribution to the healthcare sector and improving the quality of life for people around the world. Cloud computing, artificial intelligence, big data and soft computing are advanced IoT technologies that are being used to monitor the health of patients. Electrocardiograms, glucose monitoring and detection, emergency healthcare or wheelchair management are all connected via these devices to a computer network.

The Internet of Medical Things (IoMT) not only ensures the reliability of technology, it also serves the safety and health of people without forgetting to reduce healthcare costs [1]. The classic healthcare system consists of many participants; including hospitals, patients, doctors and research organizations. Systems equipped with medical sensors track the health status of patients, provide medical care through virtual assistants, and use the internet to deliver remote services; many clinical decisions are made by doctors through diagnostic support systems.

IoMT has been proposed to improve the quality of healthcare services worldwide. It was created mainly to monitor and notify patients of updates regarding their health. Telemedicine is a new term that has recently been successively used and refined for specific health units [2]. It can be of many types; starting with remote advice from a doctor via a customized platform and ending with the detection of abnormalities in the body via sensors. Using sensor nodes with communication technologies such as mobile phones i.e., PDAs, General Packet Radio Service (GPRS), 3G and the internet, the sensor network can inform the patient, carers and doctor, as well as trending and detecting changes in in health status [3].

Features comparison of current solutions.

Today, one of the most important points of Telemedicine is to ensure stable and optimised device communication. Bluetooth is a widely used communication protocol found in most commercial mobile devices. It is also referred to as the IEEE 802.15.1 standard and operates in the industrial, scientific and medical band - 2.4 GHz.

Wi-Fi is the trade name for the IEEE 802.11 standard describing wireless local area network (WLAN) protocols. It is the most common way devices connect wirelessly to local area networks and the Internet. Wi-Fi operates in the 2.4 GHz and 5 GHz. To avoid interference with neighbouring networks, the radio link is dynamically allocated to separate communication channels (13 channels in Europe, 11 in the US and 14 in Japan). It can operate in both ad hoc and infrastructure mode. In ad hoc mode, there is no access point and all connections are peer-to-peer. In infrastructure mode, all devices connect to an access point [4].

Zigbee is a wireless communication protocol developed primarily for the creation of low-power multi-node ad hoc networks, such as personal area networks (PANs) (PANs) and wireless sensor networks (WSNs). It is defined in the IEEE 802.15.4 standard. There must be only one main device (node) in each network, called a Zigbee Coordinator, which can provide a bridge to neighboring networks. The Zigbee Router manages the traffic within the network. Terminal device is the last device in the Zigbee hierarchy [5].

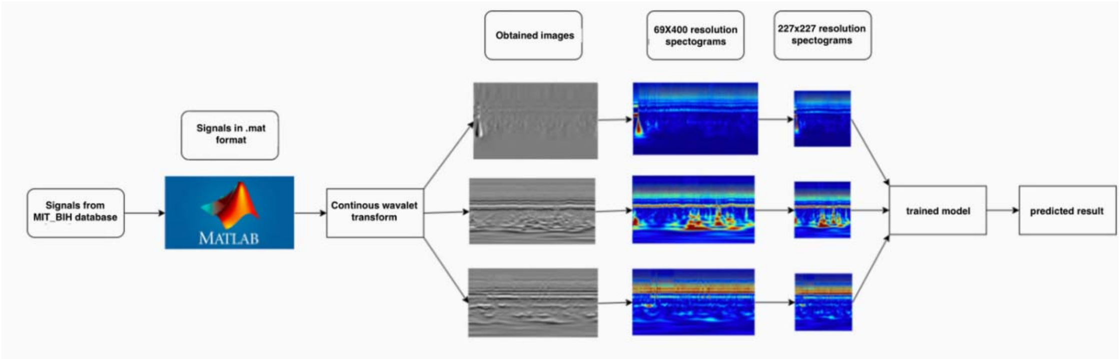

Fig. 1. Data flow during network learning process

Table 1. Comparison of wireless communication protocols

	Bluetooth	WiFi	Zigbee	6LoWPAN	IrDA
IEEE standard	802.15.1	802.11 a/b/g/n/ac	802.15.4	802.15.4	
Frequency band / Wavelength	2.4 GHz	2.4/5 GHz	2,4 GHz 868/915 MHz	2,4 GHz 868/915 MHz	850nm to 900nm
Max data rate	24 MBps (ver. 3.0) 2Mbps (BLE)	54 Mbps (802.11n) 1300 Mbps (802.1ac)	125 Kbps	125 Kbps	4 Mbps (FIR)
Channel modulation	GFSK	BPSK, QPSK COFDM, CCK, M-QAM	Q-PSK (2.4 GHz), BSK (915/868 MHz)	Q-PSK (2.4 GHz), BSK (915/868 MHz)	RZI PPM
Data protection	24-bit CRC and FEC (BLE)	32-bit CRC and FEC	16-bit CRC and FEC	16-bit CRC and FEC	16-bit CRC

Table 2. Comparison of coverage and energy consumption of wireless communication protocols

	Bluetooth	WiFi	Zigbee	6LoWPAN	IrDA
Nominal range	10m	100m	100m	100m	1m
Nominal Tx power	-20 to 10 dBm	15 to 20 dBm	-25 to 0 dBm	-25 to 0 dBm	Approx. 40 mW
Typical power consumption	Less than 10 mW (BLE)	250 mW	250 mW	250 mW	10 m

Table 3. Summary of sensitivity, specificity and precision values for each class

Class	TP	TN	FP	FN	Sensitivity [%]	Specificity [%]	Precision [%]
ARR	47	103	4	3	94,0	96,2	92,2
CHF	49	101	1	1	98,0	99,0	98,0
NSR	47	103	2	3	94,0	98,0	95,9

Table 4. Comparison of calculated values for diode and pulse oximeter intensities

	7.6 mA Pulse	7.6 mA SpO2	20.8 mA Pulse	20.8 mA SpO2	33.8 mA Pulse	33.8 mA SpO2	50 mA Pulse	50 mA SpO2	Contec CMS50DL Puls	Contec CMS50DL SpO2 [%].
Average	66,10	93,83	69,50	94,23	72,93	94,86	74,80	94,23	73,90	94,74
Median	66,00	94,00	69,00	94,00	73,00	95,00	75,00	94,00	74,00	95,00
Standard deviation	2,85	0,37	2,55	0,49	2,60	0,33	2,58	0,42	1,56	0,42
Variation	8,15	0,13	6,51	0,24	6,79	0,11	6,69	0,17	2,46	0,18
Average deviation error	10,36	0,95	5,87	0,63	2,34	0,31	2,78	0,77		
Accuracy	89,63	99,04	94,12	99,36	97,65	99,68	97,21	99,22		

6LoWPAN stands for IPv6 low-power wireless personal area network. The idea behind its creation is to allow even the smallest devices to adopt the IP protocol. It is designed to create IoT applications by enabling the transmission of IPv6 packets in the IEEE 802.15.4 standard. 6LoWPAN implementations include remote monitoring and control scenarios in a home or industrial environment and connectivity with a smart grid.

The IrDA (Infrared Data Association) protocol describes wireless communication that relies on the infrared part of the electromagnetic spectrum. The characteristics of infrared communication are determined by its relatively short wavelength (850 Nm to 900 Nm), which makes propagation through physical obstacles difficult. As a result, the effective range is much shorter than competing implementations such as Bluetooth or Wi-Fi, while requiring line-of-sight communication with devices in the line of sight [7].

Architecture of the convolutional network used

It was decided to use deep learning algorithms and a convolutional neural network, popularly used for image classification. 162 ECG recordings from three PhysioNet databases were used: the MIT-BIH Arrhythmia Database, the MIT-BIH Normal Sinus Rhythm Database and The BIDMC Congestive Heart Failure Database. All recordings were analyzed and labelled by several cardiologists. All ECG signals were resampled to a fixed sampling rate of 128Hz and normalized.

A convolutional neural network typically consists of a convolution layer, a linking layer, a fully connected layer and an output layer. The first two, the convolution layer and the linking layer, perform feature extraction, while the third, the fully connected layer, maps the extracted features into the final output, such as classification [11].

The convolutional layer is the main part of a conventional neural network and consists of multiple convolutional nuclei. In conventional neural networks, each neuron must be connected to all neurons in the previous layer, resulting in a large amount of computation. In contrast, in a convolutional network, each neuron only extracts feature from the local perception of the previous layer, reducing the number of parameters.

Learning the network did not require building a convolutional network from scratch, using millions of input images and powerful hardware. In the training process, images were fed into the last three layers of the AlexNet Network [13]. The data flow during the classification process is shown in Figure 1.

The data were transformed from one-dimensional signals to two-dimensional color scalogram images using the wavelet transform (CWT). The CWT method allows signals to be mapped in the time domain.

Each activation can take any value, so the output was normalized using the *mat2gray* function. All activations are scaled so that the minimum activation value is 0 and the maximum activation value is 1. In order to effectively use the convolutional network for transfer learning, most of the compiled model was retained along with the relevant weights and biases. However, the last three layers were reconfigured to create a new trained model. The learning weights and bias learning coefficients, were set to 20. Training options were then defined; a stochastic gradient descent algorithm with momentum was used to update the training parameters, and the maximum number of epochs was set to 5, as the model did not significantly change in accuracy after 5 epochs. After passing each epoch, all data were reshuffled [12].

In order to obtain the best possible accuracy of the model, the number of signal samples was changed during training. The effect of the number of slices taken from the signal and the signal length for each image was tested; increasing the signal length for an image reduces the edge effect of the cone of influence on the signal. First, images of 500 samples were used, resulting in 130 images per patient.

Figure 2 shows the signal scalograms as a function of the number of samples. By adjusting the batch size from the initial 49 to 4, no significant increase in performance was seen. Most of the training processes used an epoch size of 5. However, in order to maximize the accuracy of the final model, the range of epochs was increased to 20, resulting in a 3% increase in accuracy, resulting in a final accuracy of 95.33%.

Construction and testing of the developed system.

The system developed is responsible for monitoring the health status of a sick or disabled person. Its main purpose is to provide read-out data collected from the Internet of Things modules for analysis on the graphical interface. The sensors used are the MPU6050 accelerometer and gyroscope, the MAX30100 heart rate sensor and pulse oximeter, and the AD8323 ECG sensor. These sensors operate independently of each other. The data reading process is carried out by the ESP8266 microcontroller using I2C communication lines. The microcontroller saves the read ECG data to a text file from where it is retrieved by the cardiac classification module. A convolutional neural network model automatically classifies heart diseases from ECG signals in real time. The relationships between the components of the system are shown in the diagram in Figure 3. Sensor indications are taken in real time from the microcontroller. The system is based on commonly available programming languages; Javascript, PHP and C, and partly Matlab. It uses the XAMPP package, an Apache HTTP server and a MySQL database. Sensor data is transmitted over a wireless network using HTTP, and received and processed by the server using a PHP script.

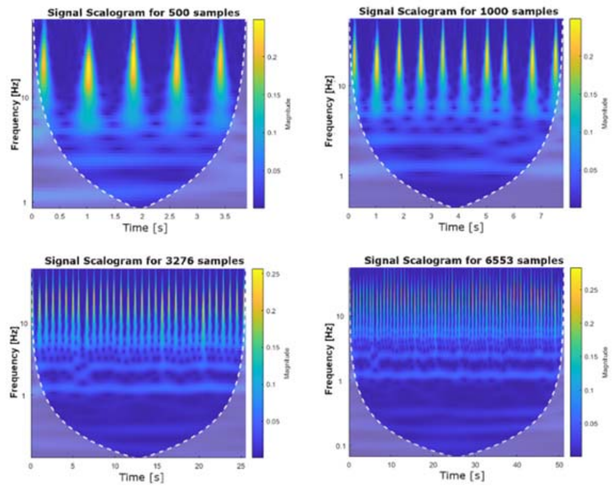

Fig. 2. Signal scalograms depending on the number of samples

Sensor indications are taken in real time from the microcontroller. The system is based on commonly available programming languages; Javascript, PHP and C, and partly Matlab. It uses the XAMPP package, an Apache HTTP server and a MySQL database. Sensor data is transmitted over a wireless network using HTTP, and received and processed by the server using a PHP script.

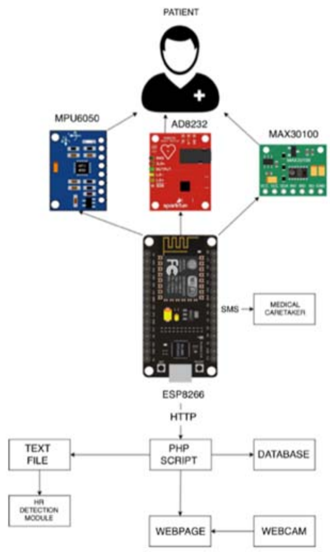

Fig. 3. Wiring diagram of the developed system

The main reason for the lack of sensitivity or positive predictive value of the discrete wavelet transform framework is that a specific phase does not match the patient's heart signal exactly. Deep transfer learning was used to classify ECGs into arrhythmia (ARR), congestive heart failure (CHF) and normal sinus rhythm (NSR). Learning the network did not require building a convolutional network from scratch, using millions of input images and powerful hardware. In the training process, data was fed into the last three layers of the AlexNet network. In order to determine the quality of the system for the classification problem, statistical measures such as sensitivity, specificity and Cohen's kappa coefficient were used [14]. A test result is assumed to be good when the sum of sensitivity and specificity is greater than 1.5, while the kappa coefficient must be greater than 0.75 to consider the result acceptable. For body-worn devices, a threshold of

5% is considered an acceptable margin of error of accuracy with respect to the reference device. To test accuracy, a series of experiments were conducted on the system under study [8][9][10]. The system must consist of lightweight components that do not impede the monitored person from performing basic activities. The weight of the system has been calculated and it has been checked that it does not restrict the movements of the monitored person, on an observational basis. The following hypothesis was set: the developed system meets the standards set and can be used to monitor and diagnose sick and disabled people.

Analysis of the ECG classification module

Evaluation of the performance of the designed ECE classification model is based on the measures detailed in formulae (1.1) to (1.3)

$$Sensitifity = \frac{TP}{TP + FN} \quad (1.1)$$

$$Specificity = \frac{TN}{TN + FP} \quad (1.2)$$

$$Precision = \frac{TP}{TP + FP} \quad (1.3)$$

where: TP - true positives, TN - true negatives, FP - false positives, FN - false negatives.

Figure 4 shows a confusion matrix showing the number of ECG signals of each type correctly classified. The green cells show the number and percentage of correct classifications by the trained network. Both 47 arrhythmia (ARR) and normal sinus rhythm (NSR) images were classified correctly, representing 31.3% of all correctly classified images. For congestive heart failure the network correctly recognised 49 images, corresponding to 32.7 % of the total. The left side shows the precision value and false discovery rate, while the column at the bottom indicates the sensitivity and false negative rate. Of all arrythmia images, 3 was incorrectly classified as normal sinus rhythm and 1 as congestive heart failure. One image of congestive heart failure and 2 of normal sinus rhythm were misdiagnosed as arrythmias. The model had an average sensitivity of 95.3%, specificity of 97.7% and precision of 95.4%. The calculated kappa coefficient was 0.94. These values are in line with the assumptions made.

Analysis of the pulse oximeter and pulse oximeter module

Research of the pulse oximeter module was carried out on a male patient, aged 23 years, without heart disease. The actual value and observed value of pulse and blood oxygenation were determined from the built system with the MAX30100 sensor. The sensor readings were taken simultaneously using the developed system and a Contec CMS50DL commercial pulse oximeter. Readings for individual sensor diode intensities (7.6 mA, 20.8 mA, 30.8 mA and 50 mA) compared with the pulse oximeter are shown in table 4. The sensor achieved the smallest mean deviation error and also the highest accuracy of 97.65% for 33.8 mA diode intensity. A difference of 2.35% is considered acceptable, given that the main purpose of the module was to perform a monitoring function rather than patient diagnosis. As with heart rate, the most similar average value was recorded for the diode intensity of 33.8 mA. A median of 95 was also recorded at this intensity level, as with the pulse oximeter. The standard deviation and variance values were similar for both devices indicating a more stable reading than for the pulse. The highest accuracy 99.68%, was achieved by the sensor for an intensity of 30.8 mA. A sensor with a fixed diode intensity of 30.8 mA was found to meet the standards set. It provides a stable, accurate reading compared to a professional device. It enables the system to act as a monitor of both the patient's pulse and blood oxygenation.

Analysis of the fall detection module

Fall detection systems based on acceleration calculations are used to distinguish falls from everyday activities. However, some activities such as sitting down quickly are characterised by high vertical acceleration. The MPU6050 sensor was used for this research. Figure 5 shows the accelerations and angular velocities for running and stair climbing. No fall was detected in any of these cases.

Figure 6 shows the acceleration and angular velocity for fast sit and fall. This study was based on 30 tests for each condition. In the first case there is a simultaneous increase in acceleration and angular velocity. The orientation remains unchanged. In the second case the acceleration values reach both defined thresholds and there is a change in angular velocity within a designated time. Table 5 collects and presents the test results as a matrix. During the tests, it was also detected that sudden rotational movement of the hand and abrupt immobilisation of the hand can activate the alarm. Therefore, in order to achieve the greatest accuracy, it is necessary that the sensor is attached to the patient's torso and not to one of the limbs. The system achieved a fall detection accuracy of 93.3%, while taking into account the differentiation of the fall condition from daily activities, the overall accuracy of the module was 97.5%. Fall detection precision was 96.5%, sensitivity 93.3% and specificity 97.7%.

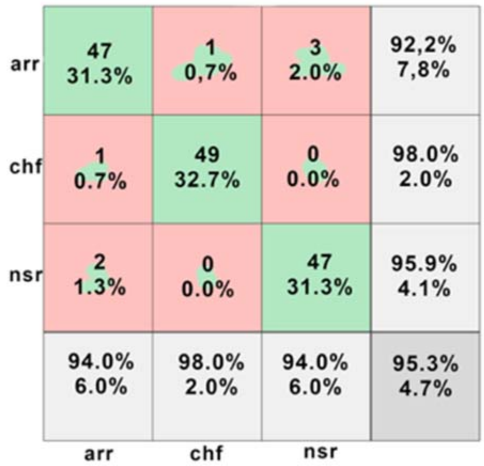

Fig. 4. Confusion matrix of the trained network.

Table 5. Matrix for recorded activities

	Run	Climbing	Sitting	Collapse	Precision
Run	30	-	-	0	100%
Stairs Climbing	-	30	-	0	100%
Sitting	-	-	29	2	93,5%
Collapse	0	0	1	28	96,5%
Sensitivity (%)	100	100	96,6	93,3	Accuracy 97,5%

Analysis of the energy consumption of the system

The ESP8266 microcontroller allows the data rate to be changed to one of three wireless network standards: 802.11b, 802.11g and 802.11n. It was also possible to change the transmit power of the antenna between 0 and 82, where one unit corresponds to 0.25 dBm. Table 6 shows the effect of transmit power level and Wi-Fi standard on system power consumption.

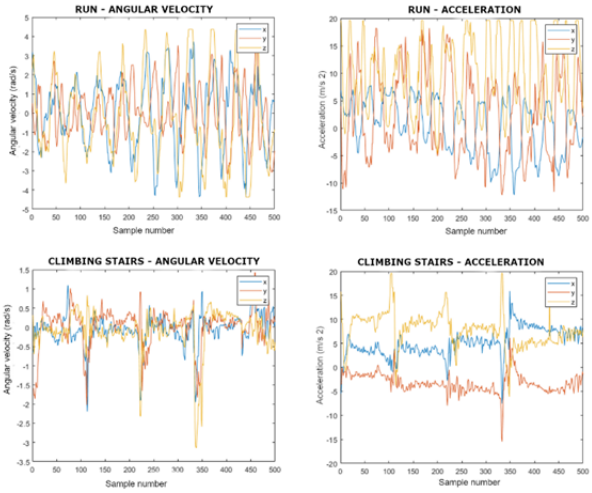

Fig. 5. MPU6050 sensor indications while running and climbing stairs

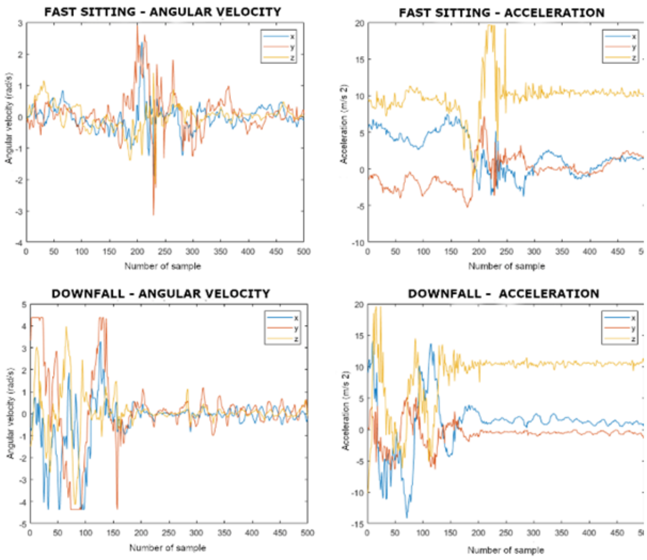

Fig. 6. MPU6050 sensor indications while fast sitting and downfall

Table 6. Effect of transmit power level and Wi-Fi standard on system power consumption

	802.11b	802.11g	802.11n
5 dBm	115.5 mA	115.9 mA	116.5 mA
10 dBm	117.6 mA	117.6 mA	118.2 mA
15 dBm	120.9 mA	120.7 mA	121.8 mA
20.5 dBm	125.1 mA	125.2 mA	126.4 mA

Results and conclusions

The designed ECG classification model achieved high accuracy on the test data set. However, the ECG classification module did not achieve the requirements due to the low accuracy of the sensor used.
Therefore, it had to be limited to a basic monitoring function only and not a replacement for patient health analysis.

By investigating the effect of the current level of the pulse oximeter sensor diode, it was possible to find an optimum accuracy that did not differ significantly from one of
a professional device. The module can be used for pulse and blood oxygenation testing in a medical environment. The fall detection module achieved satisfactory accuracy. Problems with the correct detection of all falls, were related to the time-conditioning of the designed algorithm. When optimising the system for energy consumption, it was found that the Wi-Fi protocol standard used had no impact on energy costs. In order to reduce energy consumption, the transmitting power of the antenna had to be reduced, but this was at the expense of range. Ultimately, it was decided to leave this value at the maximum default level.

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