International Journal of Engineering and Science Invention (IJESI)
ISSN (Online): 2319-6734, ISSN (Print): 2319-6726
www.ijesi.org ||Volume 13 Issue 7 July 2024 || PP 01-13

Management of electrical assistance based on prediction by artificial intelligence for biomedical applications

Yassine Toughzaoui, Boubekeur Tala-Ighil, Philippe Makany, Hamid Gualous
Laboratoire LUSAC, université de Caen Normandie

Abstract- *Covid period has shown us the importance of telemedicine in the medical field in order to take care of the patients while avoiding the hospitals overload. These conditions have helped in the development of medical devices and improvement. In this paper, we will present an intelligent tricycle equipped with multi medical devices for the patients signal acquisition. Then using the internet of things, we connect the different devices to a Raspberry PI electronic board. After this, we implemented artificial intelligence algorithms in the Raspberry board to the processing of acquired signals and the prediction of ECG signal evolution using Long-Short Term Memory (LSTM) artificial neural network (ANN) in order to control the electrical assistance of the tricycle.*

Index Terms— *Internet of things, Artificial intelligence, Long-Short Term Memory (LSTM), Raspberry PI, electrical assistance.*

Date of Submission: 01-07-2024 Date of Acceptance: 12-07-2024

I. INTRODUCTION

Remote patient monitoring is a necessary element in the medical field and its importance appears especially in situations similar to that of Covid19, where hospitals were overcrowded and unable to accommodate more patients **[1]**. Lately many developers focused their studies on the telemedicine and developed many systems that helped in the improvement of tele-health field. A conversational Artificial Intelligence Chatbot was developed in India in order to provide telemedicine to promote social distancing and reduce the risk of Covid19 transmission **[2]**. The conversational AI is based on Natural Language Processing (NLP) to analyze the speech or the text written by the patient, so they can make healthcare accessible and affordable to all. The problem of this system is the lack of healthcare professionals and lack of access to facilities in rural and remote areas in India, in addition to the problem of language. In **[3]**, The author presented a web portal system to cardiovascular health monitoring and tested 7 machine learning algorithms for the classification of the signals, and showed that Random-forest algorithm achieved the highest accuracy of 95% of the test set. In **[4]**, A. L. Ruscelli et. al. presented a system for remote medical tutoring involved in emergency interventions allowing the doctors to follow and support the actions of the operators. The system provides a primordial pre-diagnosis especially in the case of critical pathologies such as heart attacks, heart failure, or stroke. In **[5]**, C. Fourati et. al. presented a state of art of analysis of different remote healthcare monitoring systems (RHMS) and tried to explain the general architecture of this kind of systems.

The most important tier in RMHS is the acquisition tier which involves the wearable sensors attached to the human body. This tier has known a fast improvement and many studies, describing new devices developed, were published lately. Among these publications, W. Jiang et al. presented different devices used to overview the impact of COVID19 on the patient's health, and then proposed a developed system to overcome the limitations of the devices used in the literature **[6]**. In **[7]**, P. Slade et. al. presented a wearable system for diagnosing human movements and compared its accuracy with optical motion capture systems which are considered as the standard for estimating kinematics. The developed device showed a competitive performance with the optical motion capture systems.

According to World Health Organization (WHO), cardiovascular diseases (CVDs) take approximately 17,9 million lives each year (32% of all deaths worldwide). Lately, many studies were conducted in the prediction of heart anomalies, which is a field gaining more and more attention in the medical environment, considering that it is an efficient way to save millions of lives each year.

In addition to the heart rate, the most used signal in these studies is the electrocardiogram (ECG) which is a graphical representation of the electrical activity of the heart. This electrical activity is linked to variations in the electrical potential of cells specialized in contraction (myocytes) and cells specialized in automatism and the conduction of impulses. It is collected by electrodes on the surface of the skin. This examination is quick, painless and non-invasive, devoid of any danger. It can be done in a doctor's office, hospital, or even at home. However, its interpretation remains complex and requires a methodical analysis and a certain experience of the clinician. It makes it possible to highlight various cardiac abnormalities and has an important place in diagnostic examinations in cardiology, such as for coronary heart disease. To overcome the problem of clinician's experience many studies suggested to use artificial intelligence algorithms which are known of their capacity of learning and solving complex problems. In **[8]**, B. Yuen et. al. proposed a CNN-LSTM model to predict or to detect the QRS complexes even in noisy ECG signals. CNN layers were used to extract features and LSTM ones were used to detect QRS complexes timing. The proposed algorithm was compared to different other algorithms (Pan and Tompkins **[9]**, GQRS, Wavedet **[10]**, Xiang et al.'s CNN **[11]** and Chandra et al.'s CNN **[12]**) and outperforms them and demonstrates a generalization ability. In **[13]**, M. A. Khan proposed an IOT framework to evaluate heart disease using a Modified Deep Convolutional Neural Network (MDCNN). The model uses as input signals the blood pressure and ECG and its role is to classify the received signals into normal and abnormal. If the outcome is abnormal, an alert message is delivered to the doctor to treat the patient.

In another study, S. Mohan et. al. proposed a hybrid HRLFM approach combining the characteristics of Random Forest (RF) and Linear Method (LM). HRFLM proved to be quite accurate in the prediction and classification of heart disease **[14]**. In **[15]**, P. Panindre et. al. used heart rates measurements for remote classification of cardiac arrhythmia. For this purpose, the author tested different artificial intelligence methods, and he shows that Bi-LSTM outperformed machine learning methods in processing the large amount of data used. In **[16]**, H. M. Rai et. al. presented a CNN-LSTM model for automatic prediction of cardiac arrhythmias using ECG signal. The model showed an accuracy of 99%. In **[17]**, N. Strodthoff et. al. presented a method for ECG signal analysis using deep learning algorithms and showed that CNN networks give the strongest performance among deep learning classification algorithms. In **[18]**, J. Malik et. al. presented 1D self-organized Operational Neural Networks and used them for ECG classification. For the training of his model, the author used the MIT/BIH arrhythmia dataset. In **[19]**, M. U. Zahid et al. used a 1D CNN to detect R-peaks in ECG signal. The model was tested on 2 Datasets (MIT-BIH Arrhythmia Database and China Physiological Signal Challenge) and it showed very good performances. In **[20]**, A. Ul Haq et. al. proposed a machine-learning based support system which can assist the doctors to diagnosis heart patients efficiently using different machine learning algorithms.

These algorithms were also used for other health applications such as the classification of Covid19 cases by using Convolution neural networks (CNN) to process Chest X-Ray images **[21]**. In **[22]**, D. Ravì et al. showed the contribution of deep learning and artificial neural networks in different fields of health informatics.

Our project consists on implementing medical sensors on an intelligent tricycle allowing the acquisition of patient's signals in real time. Then, a CNN-LSTM model was implemented in a Raspberry PI 3B electronic board on the tricycle allowing the prediction and the classification of ECG signal. The tricycle is equipped with an electric motor which was automated depending on the measured signals and the results of the prediction model. The automation process of the electric motor is insured by an Arduino UNO board.

The rest of the manuscript is organized as follows: section II details the algorithms and methods used in our study. Section III presents the results of the developed models and shows the validation of our methods.

II. METHODOLOGIES AND ALGORITHMS

A. Data acquisition:

For the data acquisition, we used many sensors to measure different signals such as: electrocardiogram, heart rate, oxygen saturation level and cycling power.

The sensors used in our study are represented in the figures below:

- ECG electrodes

Fig. 1. ECG electrodes

The principle of the ECG is to record the electrical impulses at the origin of heart contractions. The electrical impulses are recorded away from the heart, through the skin, using the electrodes above.

- The MAX-ECG-MONITOR sensor for heart rate

Fig. 2. MAX-ECG-MONITOR

The operating principle of the MAX-ECG-MONITOR sensor is the same as the classic sensor, but this time the electrodes are glued to the belt, which allows ease of use during physical activities.

- The oxygen saturation rate sensor (oximeter)

Fig. 3. Oximeter

The oximeter measures the amount of oxygen with which the blood is saturated. This measure is used to monitor the condition of patients prone to respiratory disorders or suffering from diseases of the respiratory system. The oximeter is equipped with a transmitter and a light receiver which will make it possible to determine the blood oxygen saturation using a calculation on the quantity of light absorbed

- Cycling power sensors

Fig. 4. Cycling power sensors

The pedals are based, for the calculation of the mechanical power, on the deformation of the strain gauges. Thanks to the constant deformation of these calibrated parts, the system measures the force torque (in N.m). The measurement of angular velocity corresponds to the cadence of pedaling. The power is then calculated by the following expression:

$$Power\ (W) = Torque\ (N.m) *\ Angular\ velocity$$

The sensors mentioned above send data to a Raspberry PI 3B board (through Bluetooth) where we have implemented our prediction and classification models.
The measured data is displayed on a screen implemented on the tricycle and equipped with a Raspberry card allowing it to manage the display of the results, in order to allow the patient to visualize his measurements and have an idea about his state of health.

B. LSTM

A recurrent neural network (RNN) is an artificial neural network with recurrent connections. Recurrent neural networks are suitable for variable size input data. They are particularly suitable for the analysis of time series, and the most used type of RNN for this purpose is Long-Short Term Memory (LSTM). As mentioned in the introduction LSTM networks were used in the prediction of ECG signal and showed good performances. A standard LSTM unit can be decomposed to three gates: the

B.1- Forget Gate

This gate decides which information should be kept or discarded: the information from the previous hidden state is concatenated to the input data then we apply the activation function to it in order to normalize the values between 0 and 1. There are many activation functions used such as sigmoid, tanh, etc. For the sigmoid function If the output is close to 0, it means that we must forget the information and if we are close to 1 then we must memorize it for the future. The calculation function is explained below:

$$f_t = \sigma\left(W_f . [h_{t-1}, x_t] + b_f\right) \qquad (1)$$

x_t : current input of the network
h_{t-1}: previous output state
W_f : neurone weight matrices
b_f : neuron bias
σ : sigmoid activation function, which returns a value between 0 and 1. The result is stored in the variable f_t.
$[h_{t-1}, x_t]$: designates the concatenation of the arrays x_t and h_{t-1}
$f_{\ t}$: the forget gate's output

B.2- Input Gate

The role of the input gate is to extract information from the current data. We will apply in parallel a sigmoid and a tanh to the two concatenated data as expressed by the equations below:

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (2)$$
$$\tilde{C}_t = \ tanh(W_c.[h_{t-1}, x_t] + b_c)$$

i_t : input gate's output
$\tilde{C}_t$: the result of the hyperbolic tangent function
The following calculation make it possible to keep only the important information, the others being almost replaced by 0:

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \quad (3)$$

B.3- Output Gate
Finally, the output gate decides what will be the next hidden state, which contains information about previous entries in the network and is used for predictions.

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (4)$$
$$h_t = o_t \times \tanh(C_t)$$

C. CNN
Convolutional neural network is a type of feed-forward artificial neural network in which the connection pattern between neurons is inspired by the visual cortex of animals. This type of algorithm is particularly used to classify images, but lately it has been widely used for time series processing. A CNN is essentially based on two major operations: the convolution and the pooling.
- Convolution: The role of convolution part is to find similarities and common characteristics between input data
- Pooling: The pooling layer helps to reduce the number of parameters and calculations in the network. It improves the efficiency of the network and avoids over-learning.

One of the most used activation layers for CNN, thanks to its efficiency, is the rectified nonlinear unit (ReLU).

D. The CNN-LSTM hybrid network
To benefit from both the advantages of CNN and LSTM networks, we can combine them together. The CNN can serve a feature engineering algorithm to extract the features from input data, find common characteristics between them and reduce their size without affecting their significance. The output of the CNN network will then be sent to the input of LSTM network to make predictions. In the training phase, the CNN and the LSTM will adapt to the data so that the first understands what to extract and the second what it must analyze from one sequence to another.

III. RESULTS AND INTERPRETATIONS

A. Data set
The MIT-BIH Arrhythmia Database is a dataset extracted from recordings done by the BIH Arrhythmia Laboratory between 1975 and 1979. The recordings were collected from a population of patients at Boston's Beth Israel Hospital. Two or more cardiologists annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database.

B. Acquisition results

The acquisition results are displayed on a screen implemented on the intelligent tricycle. We can show an example in the figures below:

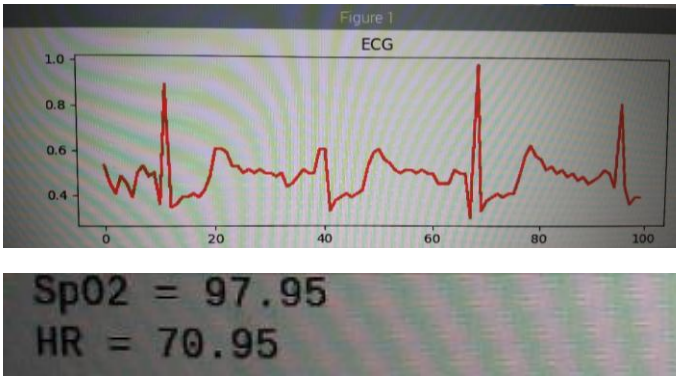


Fig. 5. Acquisition results

C. Prediction results

The model used in our study can be truncated into a prediction model and a classification one.

The first model receives as input the historical data of ECG signal and using this data, it tries to predict the following values. The predicted values are fed to the second model which classifies this signal to a normal or abnormal ECG. The concatenation of the two models gives us the opportunity to anticipates each heart risk and notify the doctors in advance so they can save the patient's life.

The architecture of the model is given as follows:

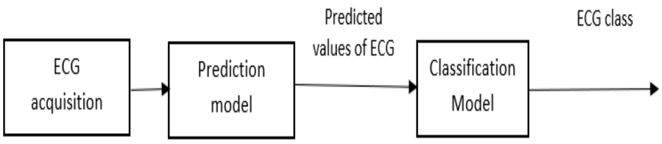


Fig. 6. The model's architecture

The prediction model is a CNN-LSTM hybrid model and the classification one is a CNN model. In the prediction model, the CNN is used for features engineering, it filters the input data so the LSTM network can process the filtered data easily and rapidly. The detailed architectures of the two models are given as follows:

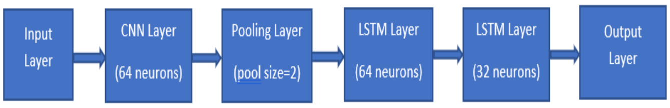


Fig. 7. The architecture of the prediction model

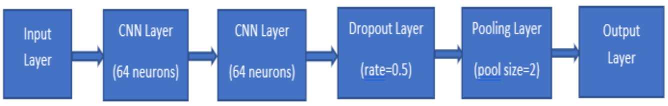


Fig. 8. The architecture of the classification model

The figures below show the results of the prediction model. The blue figures show the prediction values, and the orange ones show the real values.

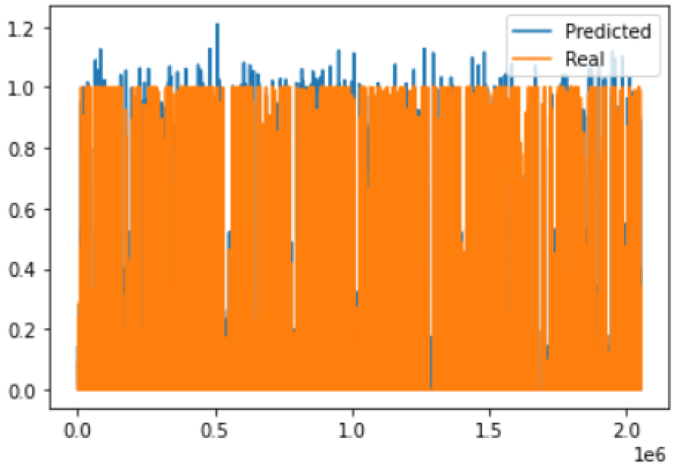
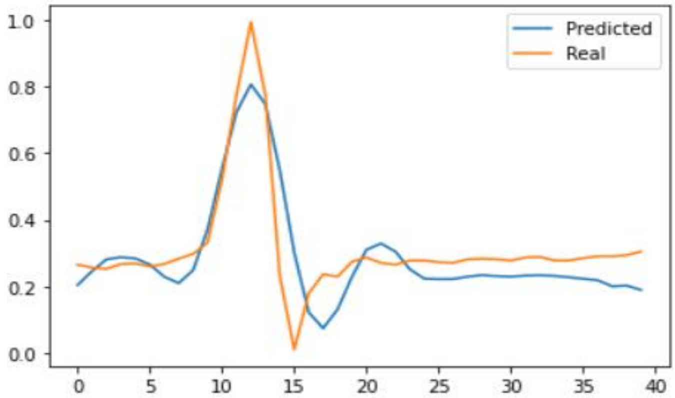
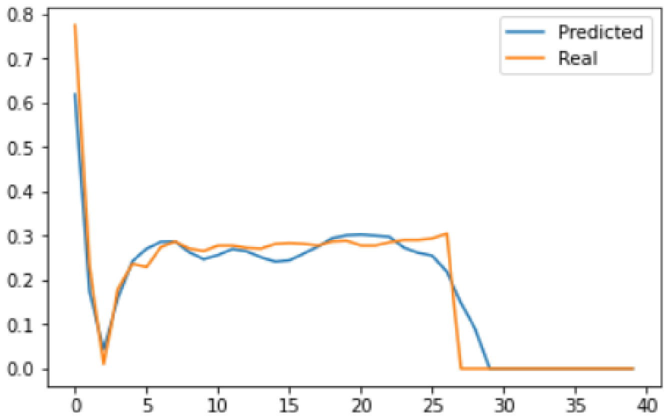


Fig. 9. Prediction results

We can zoom in in some parts of the figures above and we obtain the following figures:





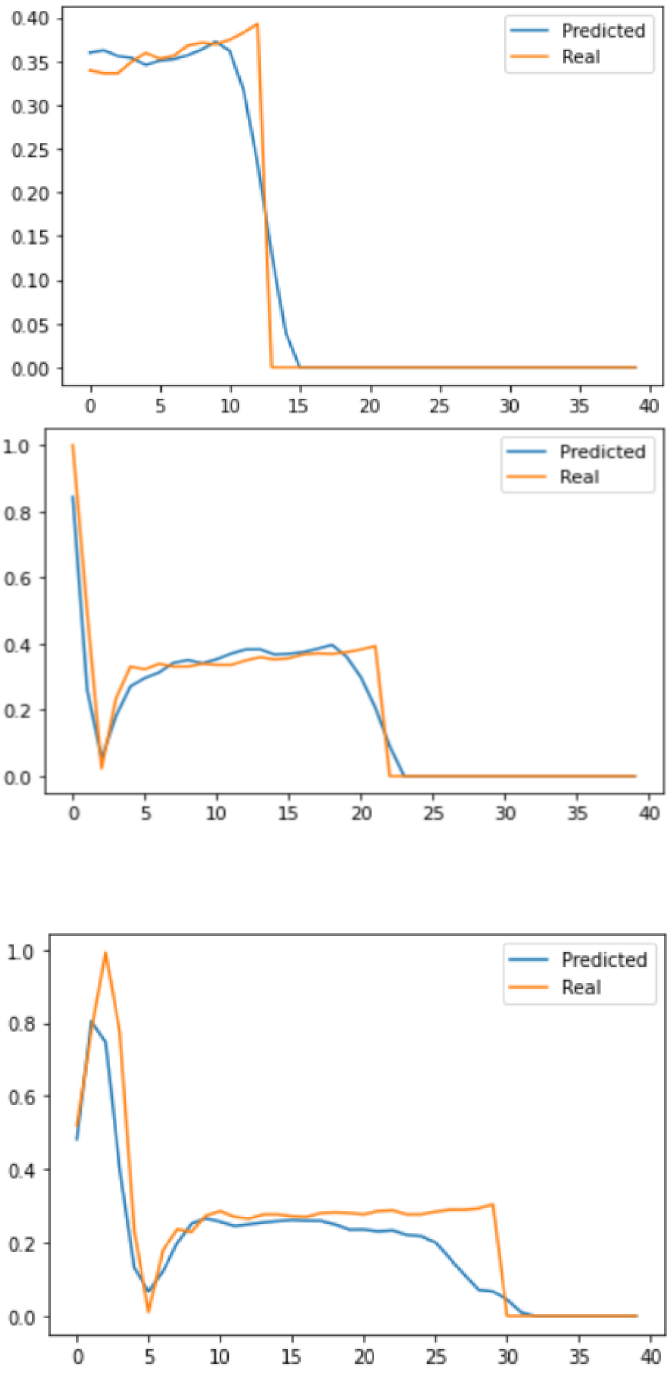


Fig. 10. The prediction model results zoomed

The table below summarize the performances of the prediction model

TABLE III: PREDICTION RESULTS

Model	**Evaluation Criterion**		
	MSE	**RMSE**	**MAE**
Prediction model	0.00274	0.0523	0.012

As mentioned in the paper **[23]**, the CNN layers were used to take benefit of the short prediction time which is mandatory in our study.
For the classification model, the accuracy reached was greater than 98%, which is close to the results found in **[7]**

The results of both models can be improved by using medical sensors and a larger data set extracted from measurements using the same sensors so that we can improve their performances and their accuracy

D. Electrical assistance:

The electric assistance can be linked to different signals. At this stage, we have chosen to link it to the heart rate sensor (max-ECG-Monitor) because it is more accurate and more compatible for sports activities, we linked it also to ECG sensor and SpO2 sensor to have a general idea about the state of health of the patient.

Our electric assistance is made up initially of 5 different levels of assistance (which can be modified) and each level corresponds to a voltage that will be sent to the BAFANG M400 type electric motor.

To understand how the behavior of electric assistance system, we used the reverse engineering method. In this method, we used an oscilloscope to study the behavior of the signals when sending a command by the buttons of the electric assistance. After studying this behavior, we tried to reproduce these signals using an Arduino UNO board and relays electrically controlled by this board, in order to automate the triggering of this assistance. The assistance automation system is described in the image below:

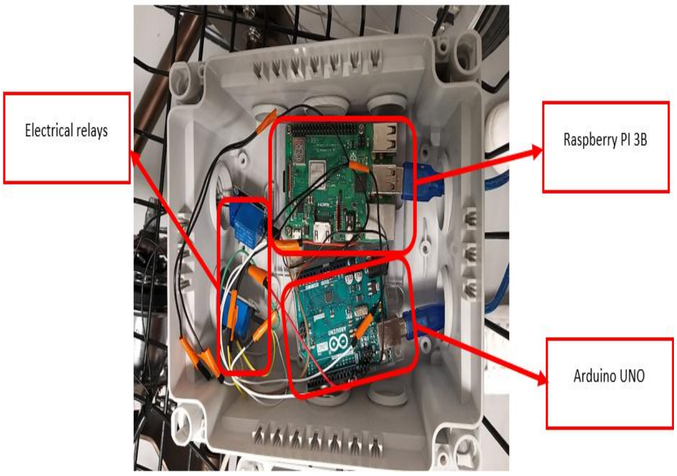


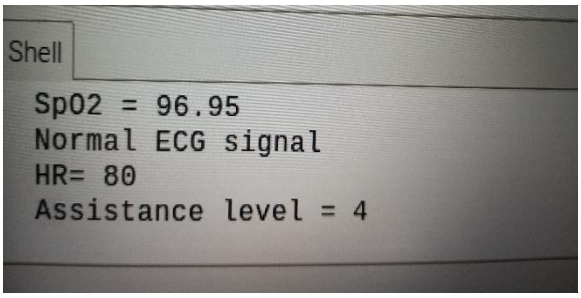
Fig. 11. Electrical assistance automation system

Below, the triggering of electric assistance conditions are given:

- If predicted ECG signal is abnormal → automatic triggering of the motor
- If SpO2 < 90% → automatic triggering of the motor
- If Heart rate > 90 rpm → automatic triggering of the motor
- If 80 rpm < Heart rate < 90 rpm → 4^{th} level of assistance
- If 70 rpm < Heart rate < 80 rpm → 3^{rd} level of assistance
- If 60 rpm < Heart rate < 70 rpm → 2^{nd} level of assistance
- If 50 rpm < Heart rate < 60 rpm → 1^{st} level of assistance
- If Heart rate < 50 rpm → no assistance

These conditions can be changed depending on the severity of the patient’s health and the doctor’s instructions.

We can see some examples of the results of the developed algorithm in the figures below:



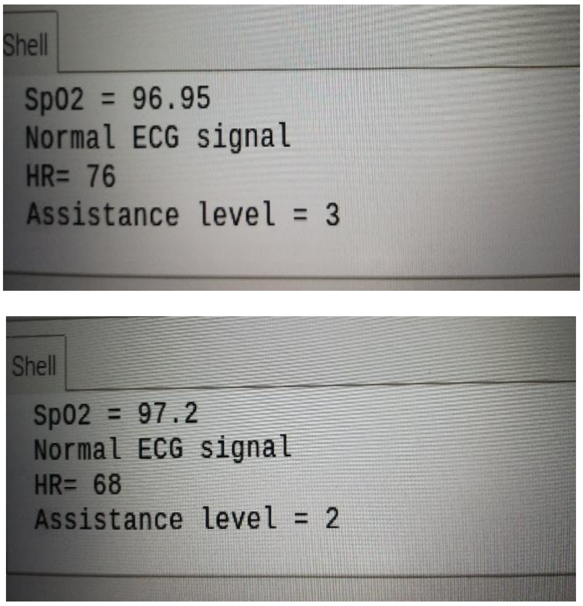


Fig. 12. Automation system results

To test the effect of SpO2 signal, we removed our finger from the oxymeter and the results received is shown in the figure below :

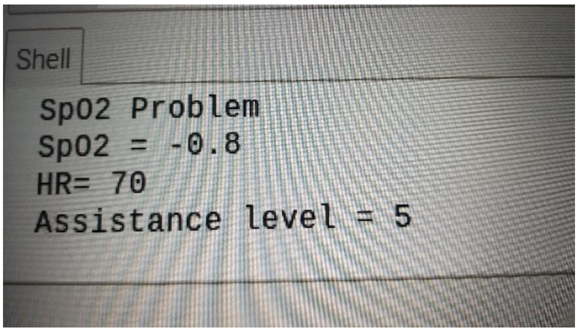


Fig. 13. SpO2 problem

So, as we can see, even if the heart rate is 70 Rpm, the assistance level is 5 because of the SpO2 problem

E. Electrical assistance system validation:

To validate the results obtained from the control of electrical assistance of the tricycle, we prepared a validation circuit. The tools used in our test bench are:

- An oscilloscope to measure the voltage in the electric wires of the assistance
- Electrical connectors
- The electrical assistance

The following figure shows the validation circuit

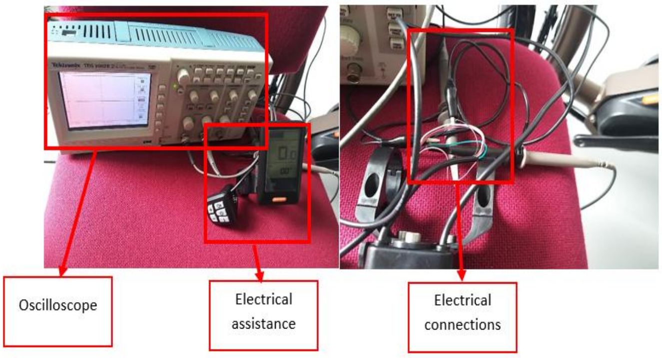


Fig. 14. Validation circuit

When clicking on a button the voltage in the corresponding wire drops from 3.3V to 0V. So, to validate our system, we will measure the voltage in the wires using an oscilloscope, to see the variation when one of the conditions defined in the previous chapter is verified.

The figure below shows the variation of the voltage in the (+) wire

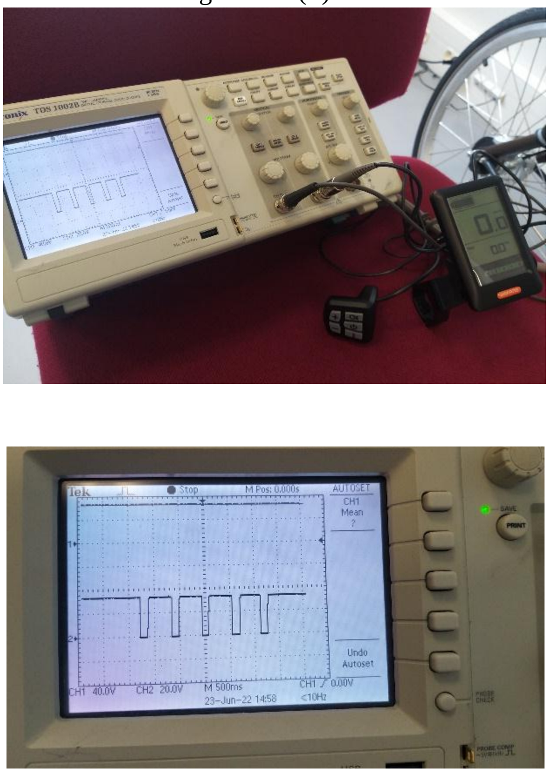


Fig. 15. The variation of the voltage in the (+) wire

We can see from the figure that the voltage drops to 0V and returns back to its initial value 5 times, which means that the level of assistance was incremented 5 times and reached the 5th level as we can see in the figure below

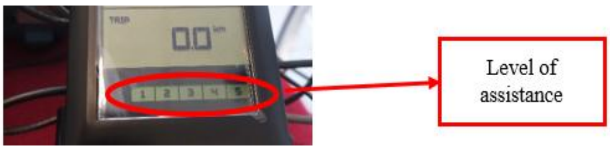


Fig. 16. The increase of assistance level

The following figure shows the variation of the voltage in the (-) wire

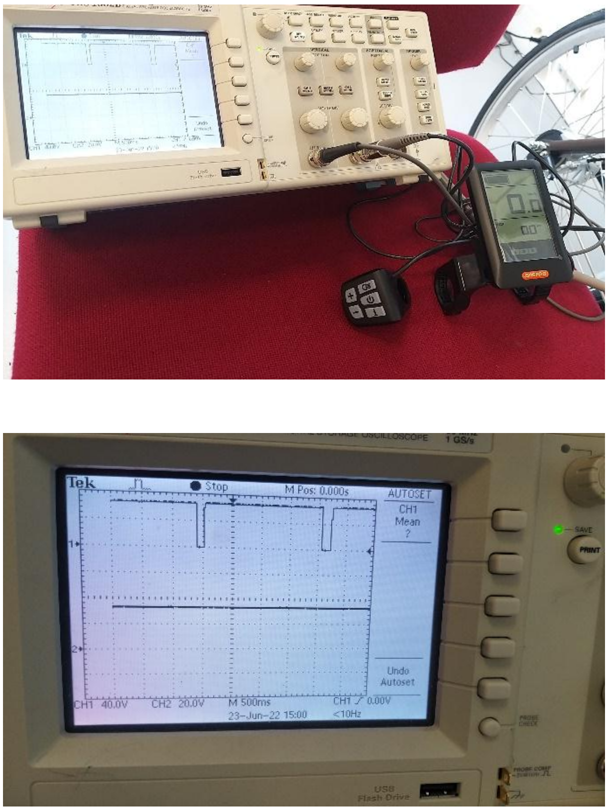


Fig. 17. The variation of the voltage in the (-) wire

There are two steps of the voltage which means that the assistance level was decremented 2 steps, so they reached the 3rd level as we can see in the figure below:

Fig. 18. The decrease of assistance level

IV. CONCLUSION

This paper presents an intelligent tricycle using the basis of internet of things and artificial neural networks to process medical signals and ensure the real time patients monitoring in the medical field. Using Rapberry PI and Arduino electronic boards, we processed the acquired signals and we automated the electrical assistance of the tricycle. The proposed method can be used also in the normal life to predict heart failures and to the patients real-time state of health monitoring.

REFERENCES

[1]. Ellen Sano, Emily Benton, James Kenny, Erica Olsen, Anisa Heravian, Jimmy Truong « Telemedicine Use by Older Adults in a COVID-19 Epicenter » The Journal of Emergency Medicine. 7 February 2022.

[2]. U. Bharti, D. Bajaj, H. Batra, S. Lalit, S. Lalit and A. Gangwani, "Medbot: Conversational Artificial Intelligence Powered Chatbot for Delivering Tele-Health after COVID-19," 2020 5th International Conference on Communication and Electronics Systems (ICCES), 2020, pp. 870-875, doi: 10.1109/ICCES48766.2020.9137944.

[3]. M. Talha, R. Mumtaz and A. Rafay, "Paving the way to cardiovascular health monitoring using Internet of Medical Things and Edge-AI," 2022 2nd International Conference on Digital Futures and Transformative Technologies (ICoDT2), 2022, pp. 1-6, doi: 10.1109/ICoDT255437.2022.9787432.

[4]. A. L. Ruscelli, G. Cecchetti, I. Barsanti, M. Manciulli, P. Paolini and P. Castoldi, "A medical tele-tutoring system for the Emergency Service," 2021 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops), 2021, pp. 410-412, doi: 10.1109/PerComWorkshops51409.2021.9431030.

[5]. Chaari Fourati, L., Said, S. (2020). Remote Health Monitoring Systems Based on Bluetooth Low Energy (BLE) Communication Systems. In: Jmaiel, M., Mokhtari, M., Abdulrazak, B., Aloulou, H., Kallel, S. (eds) The Impact of Digital Technologies on Public

Health in Developed and Developing Countries. ICOST 2020. Lecture Notes in Computer Science(), vol 12157. Springer, Cham. https://doi.org/10.1007/978-3-030-51517-1_4

[6]. W. Jiang et al., "A Wearable Tele-Health System towards Monitoring COVID-19 and Chronic Diseases," in IEEE Reviews in Biomedical Engineering, vol. 15, pp. 61-84, 2022, doi: 10.1109/RBME.2021.3069815.

[7]. P. Slade, A. Habib, J. L. Hicks and S. L. Delp, "An Open-Source and Wearable System for Measuring 3D Human Motion in Real-Time," in IEEE Transactions on Biomedical Engineering, vol. 69, no. 2, pp. 678-688, Feb. 2022, doi: 10.1109/TBME.2021.3103201.

[8]. B. Yuen, X. Dong and T. Lu, "Inter-Patient CNN-LSTM for QRS Complex Detection in Noisy ECG Signals," in IEEE Access, vol. 7, pp. 169359-169370, 2019, doi: 10.1109/ACCESS.2019.2955738.

[9]. J. Pan and W. J. Tompkins, "A Real-Time QRS Detection Algorithm," in IEEE Transactions on Biomedical Engineering, vol. BME-32, no. 3, pp. 230-236, March 1985, doi: 10.1109/TBME.1985.325532.

[10]. Martínez JP, Almeida R, Olmos S, Rocha AP, Laguna P. A wavelet-based ECG delineator: evaluation on standard databases. IEEE Trans Biomed Eng. 2004 Apr;51(4):570-81. doi: 10.1109/TBME.2003.821031. PMID: 15072211.

[11]. Xiang, Y., Lin, Z. & Meng, J. Automatic QRS complex detection using two-level convolutional neural network. BioMed Eng OnLine 17, 13 (2018). https://doi.org/10.1186/s12938-018-0441-4

[12]. Chandra BS, Sastry CS, Jana S. Robust Heartbeat Detection From Multimodal Data via CNN-Based Generalizable Information Fusion. IEEE Trans Biomed Eng. 2019 Mar;66(3):710-717. doi: 10.1109/TBME.2018.2854899. Epub 2018 Jul 11. PMID: 30004868.

[13]. M. A. Khan, "An IoT Framework for Heart Disease Prediction Based on MDCNN Classifier," in IEEE Access, vol. 8, pp. 34717-34727, 2020, doi: 10.1109/ACCESS.2020.2974687.

[14]. S. Mohan, C. Thirumalai and G. Srivastava, "Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques," in IEEE Access, vol. 7, pp. 81542-81554, 2019, doi: 10.1109/ACCESS.2019.2923707.

[15]. P. Panindre, M. Dama, V. Gandhi and S. Kumar, "Assessment of Artificial Intelligence Techniques for Automated Remote Classification of Cardiac Arrhythmia using Instantaneous Heart Rates," 2021 International Conference on Artificial Intelligence and Computer Science Technology (ICAICST), 2021, pp. 25-30, doi: 10.1109/ICAICST53116.2021.9497825.

[16]. H. M. Rai, K. Chatterjee, C. Mukherjee, « Hybrid CNN-LSTM model for automatic prediction of cardiac arrhythmias from ECG big data » 2020 IEEE 7th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), 2020, doi : 10.1109/UPCON50219.2020.9376450

[17]. N. Strodthoff, P. Wagner, T. Schaeffter and W. Samek, "Deep Learning for ECG Analysis: Benchmarks and Insights from PTB-XL," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 5, pp. 1519-1528, May 2021, doi: 10.1109/JBHI.2020.3022989.

[18]. J. Malik, O. C. Devecioglu, S. Kiranyaz, T. Ince and M. Gabbouj, "Real-Time Patient-Specific ECG Classification by 1D Self-Operational Neural Networks," in IEEE Transactions on Biomedical Engineering, vol. 69, no. 5, pp. 1788-1801, May 2022, doi: 10.1109/TBME.2021.3135622.

[19]. M. U. Zahid et al., "Robust R-Peak Detection in Low-Quality Holter ECGs Using 1D Convolutional Neural Network," in IEEE Transactions on Biomedical Engineering, vol. 69, no. 1, pp. 119-128, Jan. 2022, doi: 10.1109/TBME.2021.3088218.

[20]. Amin Ul Haq, Jian Ping Li, Muhammad Hammad Memon, Shah Nazir, and Ruinan Sun « A Hybrid Intelligent System Framework for the Prediction of Heart Disease Using Machine Learning Algorithms » School of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China Department of Computer Science, University of Swabi, Khyber Pakhtunkhwa, Pakistan. Published 2 December 2018.

[21]. S. Tabik et al., "COVIDGR Dataset and COVID-SDNet Methodology for Predicting COVID-19 Based on Chest X-Ray Images," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 12, pp. 3595-3605, Dec. 2020, doi: 10.1109/JBHI.2020.3037127.

[22]. D. Ravì et al., "Deep Learning for Health Informatics," in IEEE Journal of Biomedical and Health Informatics, vol. 21, no. 1, pp. 4-21, Jan. 2017, doi: 10.1109/JBHI.2016.2636665.

[23]. Yassine Toughzaoui, Safieh Bamati Toosi, Hicham Chaoui, Hasna Louahlia, Raffaele Petrone, Stéphane Le Masson, Hamid Gualous « State of health estimation and remaining useful life assessment of lithium-ion batteries: A comparative study », Journal of Energy Storage, Volume 51, 2022, 104520, ISSN 2352-152X, https://doi.org/10.1016/j.est.2022.104520.