TEST Engineering & Management

May - June 2020
ISSN: 0193-4120 Page No. 10991 - 10998

Expert mobile with 5G using Neural Network for Recognition of Brain Wave Signals

Iman Hafedh Yaseen[1], Ahmad T. Abdulsadda[2],
Computer and Systems Department, Technical Institute of Karbala, Al Furat Al Awast Technical University, 54001, Iraq
Communication Engineering Technical Department, Al Najaf Technical College, Al Furat Al Awast Technical University, 54001, Iraq. Email (A T A)

Article Info
Volume 83
Page Number: 10991 - 10998
Publication Issue:
May - June 2020

Article History
***Article Received**: 19 November 2019*
***Revised**: 27 January 2020*
***Accepted**: 24 February 2020*
***Publication**: 19 May 2020*

Abstract
Improving the quality of life for disabled patients and improving the overall concentration of human thought, particularly those suffering from Autism and Alzheimer's can be achieved with the help of the Brainwave Computer Interface (BCI). In this proposal,A Radial Base Functions (RBF) Artificial Neural Network (ANN) is developed and a BCI is introduced using the Neuro-SkyS EEG biosensor for brain signal recognition. The study is provided by considering a noisy system in which a BCI is implemented in real world applications. Each consideration acquires a set of 256 data points proposed. The data will be transmitted via Bluetooth for MATLAB documentation or any way the clinic's mobile phone or doctor receives how patient supervision and acknowledgement levels are reported at the maximum 70 per cent.

Keywords: brain signal, artificial neural networks, biosensors, 4G mobile networks.

I. INTRODUCTION

By and large, there are patients in somewhere and the clinical master need to screen patients' status remotely progressively and ceaselessly. Along these lines, need a wearable gadget can screen heartrate and blood oxygen level progressively over the worldwide web. In this paper, talked about the use of IoT innovation to screen persistent essential signs, for example, heartrate and blood oxygen level. Specialists, clinical specialists, or individuals who care about the patient's status can screen essential signs continuously from anyplace relying upon the proposed plan.

Artificial neural networks (ANNs) are a valuable method for helping doctors examine and understand complex and entangled clinical data in many medical and surgical fields. Neuroscientists like McCulloch, and Pitts, considered and developed the concept of an artificial neural network as early as 1943.

The theory was loosely speaking that an ANN should operate along lines analogous to the way a neuron operates in the human brain, namely that a neuron absorbs information, processes it, and generates output. The output is then transferred through multiple layers of the brain onto other neurons and still more neurons[6].

Process knowledge for ANN use among other things pattern recognition. For this purpose, they can also be used in areas where object identification is concerned. They can also be seen in fields such as bowel cancer diagnosis [7].

A neural network's core feature and biggest strength is its capacity and power to learn. An ANN has the potential to adjust as it stores the information in real time. This is partly done by a weight system. When the ANN handles information it assigns weights to different processing functions. Every relation (system unit) has a weight allocated,in other words a numerical value that governs the signal between

May - June 2020
ISSN: 0193-4120 Page No. 10991 - 10998

these two neurons. If the network generates a positive output, otherwise there is no need to change the weight factors. However, if the ANN produces a negative output, the system will have to respond by adjusting the weights before a positive output is achieved.

II. Medical application for ANN:

In any situation where variables and parameters are involved and where the parameters have a relationship with each other, ANN's might potentially be used. ANN comes into its own however, as the criteria have a complicated and dynamic relationship with none other.There are also many systems that use neural networks linked to Probabilistic statistics (which can estimate the probability density of function parameters based on available data) [12].

Stroke Risk

Strokes can happen daytime or evening whenever. In a. There are 150,000 strokes alone in the UK (http:/www.stroke.org.uk). Numerous individuals close to the casualty are well on the way to encounter strokes that happen during the daytime. The snapshot of the beginning of the stroke is in this manner bound to be distinguished and enrolled. Be that as it may, a stroke can occur during rest around evening time. The second the stroke occurred at is substantially less liable to be recognized. This is indispensable to know the planning of the beginning of the stroke, in light of the fact that specific strokes (which happen from a blood coagulation in a vein in the mind's cerebral flow) are fitting for treatment with Alteplase (a coagulation busting specialist regulated intravenously to patients with strokes). All things considered, Alteplase must be conveyed inside 4.5 hours of the beginning of the stroke so as to be enough powerful [8]. Clearly if a stroke happens when the casualty is oblivious, the planning of the beginning of the stroke is difficult to state. This is currently gotten that if a stroke happens the furthest points (arms, legs) will be influenced by the stroke. Thus, the influenced arm or leg (of both) doesn't work exclusively just like the case with a run of the mill grown-up. Subsequently on the off chance that we had an approach to follow the normal movement of the appendages of a man (when snoozing) by announcing some noteworthy changes in ordinary action, for example Misfortune in willful appendage control (arm, leg or both) as those found in a stroke (influencing appendage engine capacities), we ought to have a gadget those recognizes the time that the stroke occurred. Actually, the gadget can make a family member or an emergency vehicle aware of a potential stroke happening inside that individual. This will require the stroke casualty to be immediately moved to emergency clinic and Alteplase organization in good time as needed. We propose such a system based on a neural network architecture, together with a real mattress grid (shown in Figure 1). The mattress is put in the patient's bed (maybe woven into the fabric of the furniture material). The ANN itself may be programmed to consider an individual patient's normal movement and therefore to accept impairment of limb control (as happens in a stroke). The data from sensors worn by the patients in e.g. wrist bands and ankle bands will then be wirelessly transferred to the ANN,that uses data to classify a single patient's possible stroke. This ANN is envisaged to be created and installed as an APP. Mobile phones may theoretically be used to store and access an APP like this. [9]. Such an ANN Device will be trained within the cell phone to identify natural activity for any given user.

Published by: The Mattingley Publishing Co., Inc.

May - June 2020
ISSN: 0193-4120 Page No. 10991 - 10998

Fig.1: Patient position on the electro mattress,[5].

IOT applications in medical:

The framework planned appeared in Fig. 2 comprises of a sensor to quantify the heartrate and blood oxygen, which associates with a chip by utilizing the synchronous sequential correspondence convention between coordinated circuit (I2C) is one of the correspondence conventions utilized in implanted frameworks. ESP32 get to the web through passage by utilizing Wi-Fi innovation utilizing MQTT convention. The framework has been intended to gauge the heartrate and blood oxygen, estimated information is sent to the server. The specialist or the individual who screens the patient's status can see the estimation brings about continuous from anyplace. Likewise, the deliberate information is put away in a server. Sparing outcomes in a server as a database offers chance to redisplay it again to know the advancement of the patient's wellbeing, [13-16].

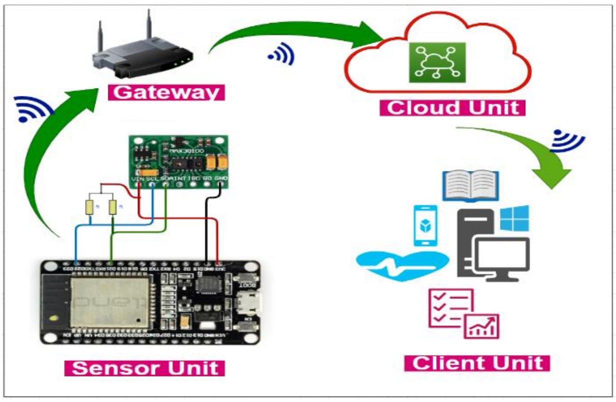

Fig.2 : General IOT MQTT system, [13].

the principle highlight of I2C is diminishing the quantity of wire. Has just two transport lines are required a sequential information line (SDA) and a sequential clock line (SCL). Continuously the ace sends the message to the captive to created the beginning of the association and the slave answers. The slave can't communicate something specific without being there demand from the ace. Likewise, the ace creates the check in this convention. Each slave has an interesting location so there is no requirement for an extra line to determine. The correspondence procedure among ace and slave is finished relying upon the exceptional location of the slave. In the event that the ace needs to converse with a slave just sent the location for the slave in the message. One of the benefits of this convention is the True multi-ace transport including crash location, discretion (utilizing wire-AND) and clock synchronization to forestall information debasement. Because of utilizing the wire - AND, have two draw up resistors for the clock line and the information line. The line is consistently in a high state with the goal that each ace or all slave does the yield cradle in the yield open channel state. Any individual who sends information on the line will cause the yield open channel to go to the ground and pull the line to a low state, [16-18].

III. Proposed model

a. Mattress model

The mattress, which will underlie the patient seen in Figure 1, has an interactive grid (X,Y coordinates) showing where the patients' limbs (arms, legs) are. The mattress transmits the X Y dimensions of the person's arms and legs to a handheld cell phone device. The X, Y coordinates will shift as the person shifts his or her legs and arms during sleep,therefore it means that the patient naturally moved his muscles and did not have a stroke. However, if the patient has a stroke, then their limbs (arm, leg or both) will not function naturally and all other changes / deviations from normal would be registered by the neural network.The details would then be sent on a cell phone to the device, and the smartphone might warn the relative of the victim or an ambulance to render assistance to the stroke patient if necessary.

We assume that such a qualified ANN, used in combination with smart sensors in, for example, wrist bands and ankle bands, combined with a mobile APP, may theoretically detect stroke, and

Published by: The Mattingley Publishing Co., Inc.

ISSN: 0193-4120 Page No. 10991 - 10998

thereby save life. Whilst such a system could be useful everywhere, at any time, we believe it would be especially useful and appropriate for the diagnosis of stroke at night and for people living in alone. Bassetti and Aldrich[10] reported that 23 of the 100 patients in their study reported a nocturnal onset of transientischaemic attack or stroke in contrast to the number of strokes that occur at night.
Multi Layer Perceptron neural network (MLP) is typically a multilayered network consisting of one layer of hidden units. Within the next layer of the network, each unit within the network is related in a forward direction to another unit. The input layer is aligned with the system's hidden layer, and the output layer is connected with a weighting and biasing device.

The biasing applies both to the hidden layers and to the output. The FFNN has one law only, which is that the triggering flow is in one direction, i.e. from the input layer to the output layer that moves through the hidden layer. In several ways the algorithm that includes back propagation is identical to a multilayer feed forward network (shown in figure 2).

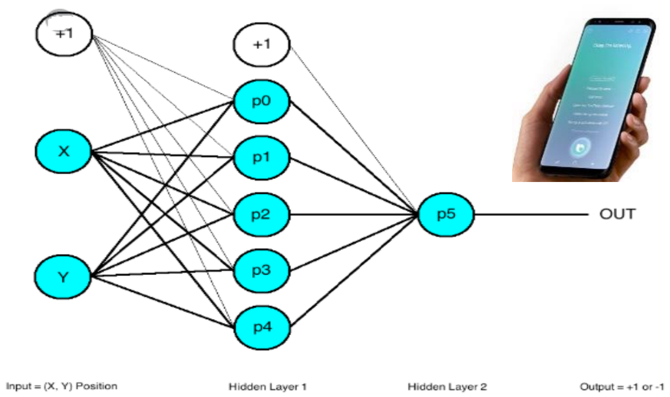

Fig.3 : MLP structure which is using in patient monitoring system.

The errors propagate backwards from the output nodes to input nodes. For back propagation the FFNN can be trained using the Levenberg Learning Algorithm, [11](shown in Figure4). This was chosen because this particular algorithm looks for a solution even though it begins way off the final target.

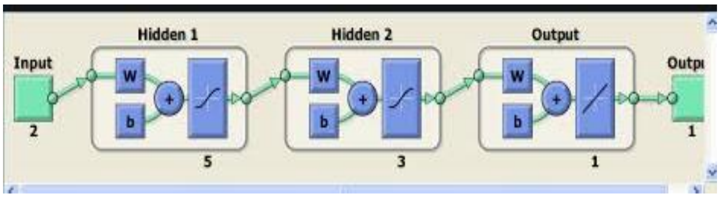

Fig.4: Simulink MLP Neural

Training phase and evaluating samples phase are normalized between 0 and 1 by using a binary standardization scheme to match the data The tests produced a gross 0.15 error (Figure 5).

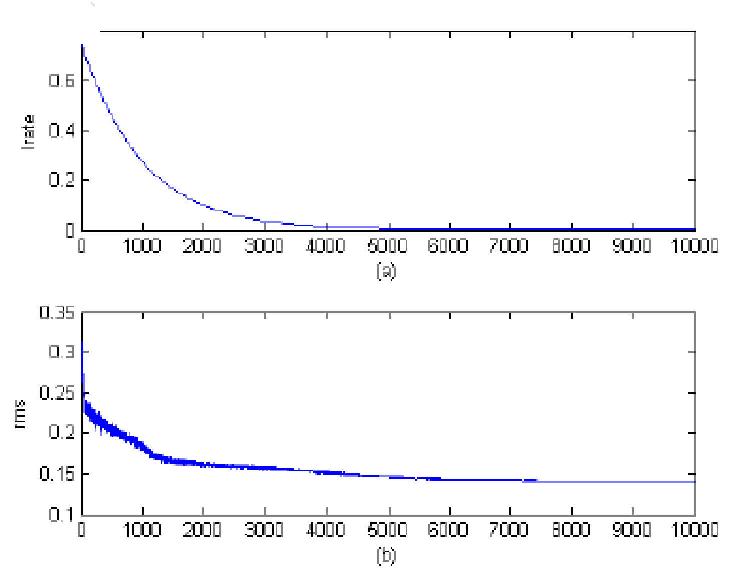

Fig.5: MSE and number of iteration in training phase.

This representation of the neural network consisted of 3 layers in the first layer of 10 neurons, 2 neurons in the second layer and 1 neuron in the third layer. Every neuron is connected through a weighted link to the next layer. As regards trends, we used clustering to train the neural network. It is useful for providing insight into and simplifying data before further analysis. We used a value set of four clusters as input data. The work presented in this paper is a pilot study on applying ANN's to the recognition and diagnosis of strokes. We assume that the use of other adjuncts, such as fuzzy logic, may further develop our pilot study model. This may be the focus of further research.

b. Brain model

Essentially, EEG designs have different qualities which depend on the estimation's spatial field. Although some EEG changes are summarized and transparent across the entire surface of the cerebrum, there are only a few ideal models present in littler regions which make definite estimates necessary in specific areas. We analyzed the spatial distribution of the changes so as to have the opportunity to discern HREC with a solitary or a few cathodes. The improvements in hypoglycaemia usually occur on a wide portion of the scalp region. When characterizing the ideal cathode condition, the spatial dispersion of the relics particularly obtained from muscle activity during facial copying, feeding, eye development and rest related developments should be considered. Those ancient rarities are gradually restricted rather than the HREC, which makes the region important. Antique associated with advances in the anode and cathode contact dynamics are not based on the spatial area [19-21]. Figure 6 indicates the capacity to recognize the HREC when ancient rare signals are available; Where the HREC signal in five patients with diabetes is detected from a single cathode tube.

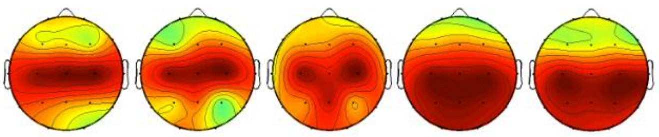

Fig. 6: Representation of the spatial impact on the capacity to distinguish the HREC worldview.

Thinking about a spatial impact and a cathode type we have picked the last estimation area appeared in Figure 7.

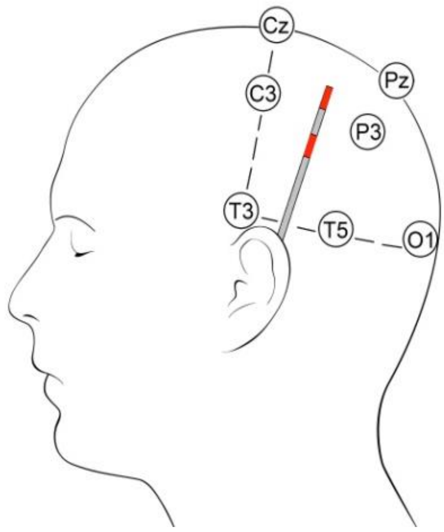

Fig.7: Area of the subcutaneous EEG anode,[18].

A neurophysiologist, who is studying the EEG waveforms, may recognise the HREC through visual examination. Be it as it can, this must be achieved automatically using a measure if the diabetic patients' EEG is to be broken down constantly for the rest of the day. The estimation mechanism for the position of hypoglycaemia appears in Figure 8.

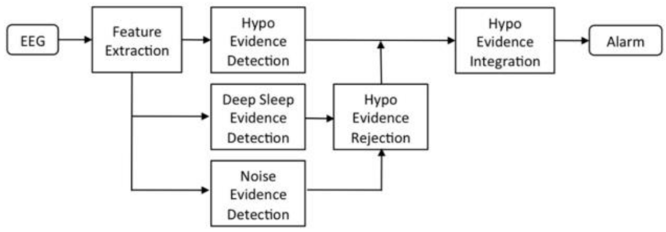

Fig. 8: Brain electro model schematic diagram.

We agreed to use a two-layer feed-forward ANN (shown in Figure 9) classifier system to execute all hypoglycaemia precautionary order errors. The ANN has various cladding units and uses the tanh sigmoid power for non-direct mappings. When investigating EEG, the sign is customarily part into 5 recurrence groups (delta, theta, alpha, beta, and gamma). Nonetheless, this recurrence goals aren't

May - June 2020
ISSN: 0193-4120 Page No. 10991 - 10998

adequate for an ideal presentation of the hypoglycaemia location system.

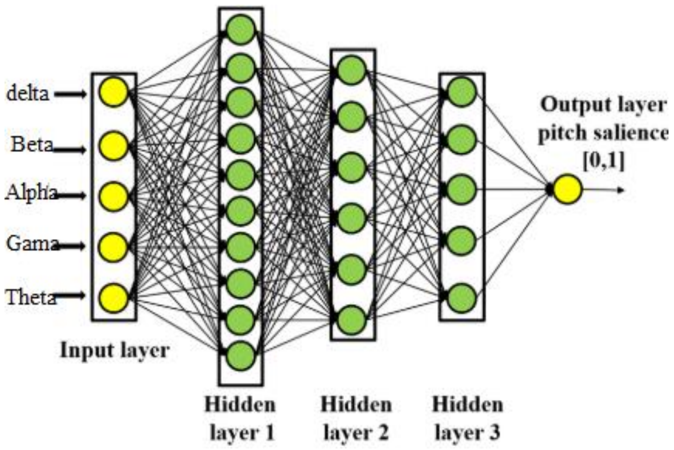

Fig. 9: ANN brain electron classifier.

A significant piece of the calculation is the classifier, which decides whether there is proof of hypoglycaemia in a little piece of the EEG signal. The classifier puts together its judgment with respect to the extricated highlights, which speak to the measurable properties of the EEG during 1-second ages (shown in figure 10). The classifier consolidates the information measurements in a numerical articulation that outcomes in either a "1" if the EEG has a hypoglycaemia design or a "0" in any case.

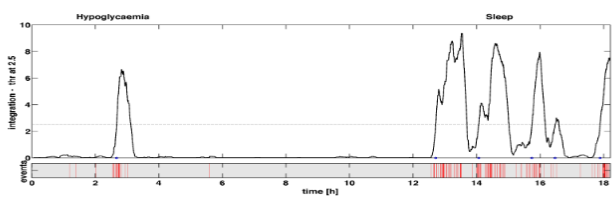

Fig. 10: Original Signal, adapted [7].

On this knowledge the first calculation was set, and the calculation was advanced to distinguish hypoglycaemia from deep rest. Ten patients with type 1 diabetes (mean age 52 years, diabetes extending 25 years, HbA1c 7.5 percent) all suffering from ignorance of hypoglycaemia were subjected to instigated hypoglycaemia through insulin implantation tested during daytime as well as at rest evening time. EEG was reported from a single terminal, where three estimation focuses were subcutaneously placed in the flickering locale and continuously broken down. When EEG-changes reached a predefined cap, the patient received a sound-related warning. Before now, patients were advised to devour a sandwich and a juice at the warning hour. Figure 11 delineates the night-try scheme.

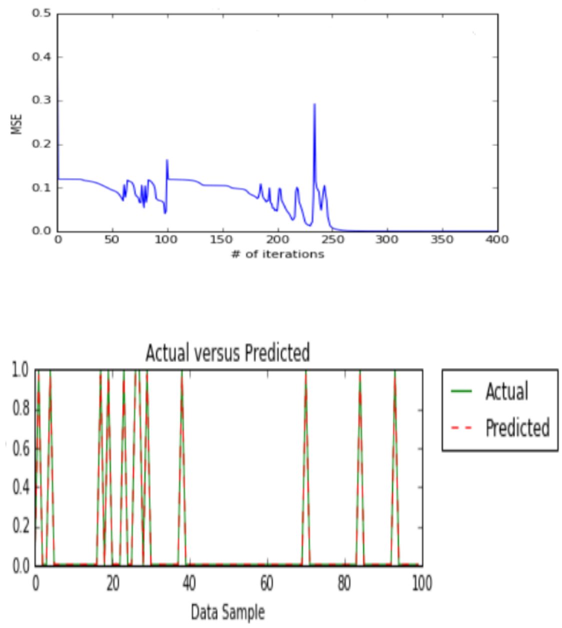

Fig. 11: The simulation results of the brain model.

IV. CONCLUSION

In this paper we presented a pilot study on the potential application of an ANN model to the recognition and diagnosis of strokes. We assume that the ANN (coupled with the feedback from smart sensors worn by the patient and placed in wrist and ankle bands or example) could be further evolved and incorporated into a mobile Device, which could then be used to alert the emergency services or a career.

(Patient's) if stroke happens. We conclude that such a device may theoretically be particularly useful for

Published by: The Mattingley Publishing Co., Inc.

May - June 2020
ISSN: 0193-4120 Page No. 10991 - 10998

strokes that occur at night, and/or for people living alone or in remote areas (especially the elderly).

The hidden clinical examinations of steady EEG recording and continuous data getting ready during insulin-incited hypoglycaemia in type 1 diabetes patients show that it will be possible to predict scenes of extraordinary hypoglycaemia before the patients are truly emotional blocked both during daytime and rest. The assessments coordinated up until this point, be that as it may, have happened in clinical research units. We are right now attempting the hypoglycaemia alert in an out-determined setting.

While we understand that our work is a pilot test, we believe that further research and development is potentially worthwhile.

REFERENCES

[1] Filippo Amato, Alberto L6pez1, Eladia Maria, Pefia-Mendez, Petr Vanhara, Ales Hampl, Josef Havel1. Artificial neural networks in medical diagnosis. J Appl Biomed. 11: 47-58, 2013. DOI 10.2478/v10136-012-0031-x.ISSN1214-0287.

[2] Catalogna M, Cohen E, Fishman S, Halpern Z, Nevo U, Ben-Jacob E. Artificial neural networks based controller for glucose monitoring during clamp test. PloS One. 7: e44587, 2012.

[3] Er O, Temurtas F, Tanrnkulu A. Tuberculosis Disease Diagnosis Using Artificial Neural Networks. J Med Syst. 34: 299-302, 2008.

[4] Elveren E, Yumuşak N. Tuberculosis disease diagnosis using artificial neural network trained with genetic algorithm. J Med Syst. 35: 329-332, 2011.

[5] Dey P, Lamba A, Kumari S, Marwaha N. Application of an artificial neural network in the prognosis of chronic myeloid leukemia. Anal Quant CytolHistol. 33: 335-339, 2012.

[6] Barwad A, Dey P, Susheilia S. Artificial neural network in diagnosis of metastatic carcinoma in effusion cytology. Cytometry B ClynCytom. 82: 107-111, 2012.

[7] Barbosa D, Roupar D, Ramos J, Tavares A and Lima C. Automatic small bowel tumor diagnosis by using multi-scale wavelet-basedanalysis in wireless capsule endoscopy images. Biomed Eng Online. 11: 3, 2012.

[8] K. Hung, and Y.T. Zhang, "Implementation of a WAP-Based Telemedicine System for Patient Monitoring", IEEE Transactions on Information Technology in Biomedicine, vol. 7, n° 2, June, 2003.

[9] Bassetti, C., and Aldrich, M. "Night time versus daytime transient ischaemic attack and ischaemic stroke: a prospective study of 110 patients" J. Neurol Neurosurg Psychiatry 1999;67:463-467 doi:10.1136/jnnp.67.4.4 http://jnnp.bmj.com/content/67/4/463.full63.

[10] http://uk.mathworks.com/help/nnet/ref/trainlm.html.

[11] T. Zrimec and I. Kononenko, "Feasibility analysis of machine learning in medical diagnosis from aura images", University of Ljubljana, 2004.

[12] A.Mishra, A.Kumari, P. Sajit, and P.Pandey, REMOTE WEB BASED ECG MONITORING USING MQTT PROTOCOL FOR IOT IN HEALTHCARE, International Journal of Advance Engineering and Research Development, vol. 5, pp. 1-6, 2018.

[13] M. Al-khafajiy, T. Baker, C. Chalmers, M.Asim, H.Kolivand, M. Fahim, and A.Waraich, Remote health monitoring of elderly through wearable sensors, Multimedia Tools and Applications, pp. 1-26, 2019.

[14] L. J. Ramírez López, , A. Rodriguez Garcia, and G. Puerta Aponte, Internet of things in healthcare monitoring to enhance acquisition performance of respiratory disorder sensors, InternationalJournal of Distributed Sensor Networks, vol. 5, pp. 1-10, 2019.

May - June 2020
ISSN: 0193-4120 Page No. 10991 - 10998

[15] F. Adochiei, C. Rotariu ,R.Ciobotariu, and H. Costin, A wireless low-power pulse oximetry system for patient telemonitoring, In 2011 7th International Symposium on Advanced Topics in Electrical Engineering (ATEE), pp. 1-4,2011.

[16] Y.Jingjing , H.Shangfu , Z.Xiao , G. Benzhen , L.Yu , D.Beibei , and L.Yun, Family Health Monitoring System Based on the Four Sessions Internet of Things, Telkomnika,vol. 13, pp. 1-7, 2015.

[17] R.Adiputra, S.Hadiyoso, and Y.SunHariyani, Internet of Things: Low Cost and Wearable SpO2 Device for Health Monitoring. International Journal of Electrical and Computer Engineering, vol. 8, pp. 1-7, 2018.

[18] D.P.PuspitaIndriani, Y.Yudianingsih, E. LusianaUtari, PERANCANGAN PULSE OXIMETRY DENGAN SISTEM ALARM PRIORITAS SEBAGAI VITAL MONITORING TERHADAP PASIEN, Respati, vol. 9, pp. 1-15, 2014.

[19] A. SakharamEkhare, and U.M. Chaskar, Design and Development of Low Unit Cost and Longer Battery Life Wireless Pulse Oximetry System, In 2014 Fourth International Conference on Advances in Computing and Communications ,IEEE, 2014.

[20] K.AlSharqi, A.Abdelbari, A.Abou-Elnour, and M.Tarique, Zigbee based wearable remote healthcare monitoring system for elderly patients. International Journal of Wireless & Mobile Networks, vol. 6, pp. 1-15, 2014.

[21] Y.Dai, and Jian Luo, Design of noninvasive pulse oximeter based on bluetooth 4.0 BLE,In 2014 Seventh International Symposium on Computational Intelligence and Design, vol.1,pp. 1- 4,2014.

[22] Auniq, Reedwan Bin Jafar, Md. Nazim Uddin Chy, Md. Adnan, Ajoy Roy, Mohammad Ashraful Islam, Tourna Nahrin Khan, Md. Zahid Hasan, Suhel Ahmed, Mohammad Forhad Khan, Nazmul Islam, Muhammad Ismail Khan, Md. Alamgir Hossain, Md. Alamgir Kabir, Md Tareque Hassan Mukut, Sabrina Islam, and . "Assessment of anti-nociceptive and anthelmintic activities of Vitex Peduncularis Wall. leaves and in silico molecular docking, ADME/T, and PASS prediction studies of its isolated compounds." Journal of Complementary Medicine Research 10 (2019), 170-185. doi:10.5455/jcmr.20190805024523

[23] Patil, V., Patil, H., Shah, K., Vasani, J., Shetty, P.Diastolic dysfunction in asymptomatic type 2 diabetes mellitus with normal systolic function(2011) Journal of Cardiovascular Disease Research, 2 (4), pp. 213-222. DOI: 10.4103/0975-3583.89805