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AN ENERGY-EFFICIENT WIRELESS SENSOR NETWORK FOR TELEMETRY OPERATION: "A CASE STUDY OF CARDIOVASCULAR PROBLEM

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Abstract

An Electrocardiogram (ECG) is the first diagnostic tool a medical practitioner uses to measure the electrical and mucular fitness of an individual heart. The use of ECG is so important because heart-related diseases are silent killers. In recent times, advancement and the further development of wearable devices and ECG sensors have made it possible to continuously measure and analyze the electrocardiogram and myocardium signals of the heart. However, it requires significant training and adeptness to interpret the recorded ECG correctly and effectively. An energy-efficient wireless sensor infrastructure for improved operation of cardiovascular problems in the development economy using the concept of fog technology was presented. The ECG data was collected from Federal Medical Center Umuahia Abia State, Nigeria. Discrete Wavelet Transform (DWT) at first to perform preprocessing of ECG data to eliminate noise from motion artifacts, power line interference, and high frequency sources, followed by the undecimated Wavelet Transform (UWT) at first to extract relevant features, which are of high interest to a cardiologist. The proposed system classifies a recorded heartbeat into four classes, namely Normal Beat, Premature Ventricular Contraction (PVC), Premature Atrial Contraction (PAC), and Myocardial Infarction. The study found that processing and analyzing health data at the fog resulted in total energy savings of 36% and 52% when compared to conventional processing.

Keywords: Wireless sensor Network (WSN), Energy-efficiency, Cardiovascular diseases (CVD), Electrocardiogram (ECG), Telemedicine

1.0 Introduction

A Wireless Sensor Network (WSN) is a collection of spatially disseminated sensor nodes, which are interconnected by using wireless communication (Ahmed *et al.*, 2020; Komali *et al.*, 2020). According to (Ye *et al.*, undated), wireless sensor networking is evolving equipment that has an extensive variety of prospective applications including environment monitoring, smart spaces, medical systems and robotic exploration. Verdu (2021) added that, over the last decade Wireless Sensor

Networks (WSNs) have been successfully applied in many engineering fields such as: structural health monitoring, industrial applications, environmental monitoring, traffic controls, health applications, etc.

Wireless monitoring devices are an ideal option for e-health solutions because of their usage convenience. Verdu (2021) maintained that**,** wireless network is any type of computer network which is not connected by cables. It is a method by which homes, telecommunications networks and business installations avoid the costly process of introducing cables into a building, or as a connection between various equipment locations.

Cardiovascular diseases (CVD) are the major cause of mortality globally. According to world health organization (WHO) analytics nearly 32% of adult deaths all over the world are due to cardiovascular diseases which are caused by disorders of the heart and blood vessels (Hou and Sha, 2021). These include various heart related diseases including coronary heart disease (heart attacks), rheumatic heart disease, raised blood pressure (hypertension), cerebrovascular disease (stroke), peripheral artery disease, congenital heart disease and heart failure. These types of cardiovascular diseases need continuous monitoring of certain body parameters which need long hospital stays. In the hospitals patients are monitored continuously by hospital staff using various instruments like bedside monitors. These instruments are bulky and immobile and thus keep patients stick to the bed. Their wired connections are very uncomfortable to patients and medical staff also. Due to mounting hospital costs and shortage of qualified healthcare professionals it is difficult to continuously monitor the essential body parameters of the patients suffering from CVD.

Wireless sensor network is an energy constraint network with the requirement of deploying battery to power remotely positioned nodes for a given network. Since the battery capacity of the nodes is always limited and usually, it is difficult to replace them when deployed, there is therefore, the need for energy management of the nodes in a network (Baek, Son and Choi, 2021). If the designed protocol is energy efficient it will enhance the life time of a wireless sensor network especially as it concerns the enhancement of Telemedicine operation in developing Nations. The burden of CVD is increasing rapidly in African, most importantly hypertension, stroke, Cardiomyopathies and coronary heart disease. Therefore the increasing in incidence cases of CVD across Southern Nigerian call for concerted efforts in dealing with energy requirement issues, so as to have an efficient Energy wireless sensor network with the objectives of balancing the increasing in routing load throughput of the network, bandwidth expansion, reduction in Bit Error Rate (BER) and to increase the lifetime of their network (Cui *et al.*, 2021). In related work, Islam *et al.* (2020) proposed a smart healthcare system in IoT environment that can monitor a patient's basic health signs as well as the room condition where the patients are now in real-time. In this system, five sensors are used to capture the data from hospital environment named heart beat sensor, body temperature sensor, room temperature sensor, CO sensor, and CO_2 sensor. The developed prototype is well suited for healthcare monitoring that is proved by the effectiveness of the system. However, the system was too bulky to handle and cannot proficiently handle cases of diabetes and respiratory problems.

Tolba *et al.* (2020) developed a health monitoring system that can monitor basic symptoms of a patient like heartmrate, percentage of oxygen saturation, body temperature, and eye movement in IoT network. In their work, they developed a system that used Heartbeat, SpO2, Temperature, and Eye blink sensors as capturing elements and Arduino-UNO as a processing device. The developed system was implemented but no specific performance measures are described for any patient.

Abrol. (2020) introduced a healthcare monitoring kit in IoT environment. The developed system monitored some basic parameters of human health like Heartbeat, ECG, body temperature, and Respiration. The major hardware components which are used here are pulse sensor, temperature sensor, BP sensor, ECG sensor, and raspberry pi. The data were collected from sensors and sent it to raspberry pi for processing and again transmitted it to IoT network. The major drawback of the system is that no interfaces for data visualization are developed.

In order to diagnose cardiac arrhythmias using machine learning and the Internet of Things, Devi *et al*. (2020) suggested looking at the statistical and dynamic features of the ECG. The ECG signal is received, interpreted, and, in the event of an emergency, sent to a doctor by an Internet of Things platform for cardiovascular illness prediction that makes use of an IoT-enabled ECG telemetry system. The signal was assessed using the Pan Tompkins QRS detection algorithm in order to obtain the dynamic aspects of the ECG data. RR intervals from an ECG signal were extracted by the system in order to capture properties related to heart rate variability. There was poor accuracy in the classifier. Fuzzy Rules, an intelligent big data analytics model, was utilized by Safa *et al*. (2021) for effective cardiac disease prediction using IoT devices in the WSN. To assess the prognosis of coronary heart disease, the method looks through massive data sets. Provide a Fuzzy Rule-Based Intelligent Big Data Analytics Model (IBDAM) for Effective Cardiac Disease Prediction by IoT Devices in WSN. Using a multi-level fuzzy rule generation approach estimated with Cardiac Disease Infection Transmission Analysis (CDITA) weight, the objective was to identify the features that were carried over to heart disease prediction. Based on the medical professional's assessment of risk, the features were assigned to a class.

In order to predict cardiac stress, Safa *et al*. (2021) presented an integrated strategy that applies a machine learning algorithm to sensor-coupled IoT devices. The proposed work focuses on creating an Internet of Things (IoT) system that uses information from a sensor connected to a computer to determine a person's stress level. The Internet of Things can help people manage their stress. IoT Edge intelligent devices sensed signals from sensors and managed and monitored the output using the MQTT protocol. The stress analysis prediction model is made using a machine learning technique such as Decision Tree, K Neighbors Classifier, and Support Vector Classifier. A Cardiac Healthcare System based on the Internet of Things for Ubiquitous Healthcare was introduced by Umar *et al*. in 2021. With real-time observations, complete patient privacy, and few professional physical examinations in cardiac units, the proposed Smart Cardiac Care System looks to be a reliable and affordable solution for cardiac units. The hybrid combining of multiple factors and electrocardiographic (ECG) data improved the model's uniqueness. The System can also produce alerts and warnings for aberrant numbers. Access to a patient's record from any location is made possible by its presence on a cloud server. An ECG telemonitoring strategy based on connecting WSNs with the Internet of Things was proposed by El Attaoui *et al*. (2020) A wearable sensor node was used to measure the ECG signal, making it easier to suppress high-frequency noise. After that, the collected data was moved to the Gateway node, which carried out sophisticated processing. This included suppression of baseline and linear variations using polynomial interpolation, as well as R-peak extraction using the Multi-Layer Perceptron Neural Network. The heart rate variation was calculated using the extracted R peak. The Gateway node could collect the data for the heart rate's real-time visual telemonitoring using an IoT cloud and an IoT platform with the help of IoT technology.

A WSN-based ECG healthcare application for remotely detecting arrhythmias was presented by Karthiga and Santhi (2021). The various types of arrhythmias are represented by the information contained in the ECG signals. However, the non-linearity and complexity of the ECG make manual classification difficult. It was suggested to use deep learning techniques to optimize ECG classification. In order to maximize routing and network longevity, this work has made use of GWO and ABC. The CNN method for automatically identifying the various ECG segments is presented in this work. We have identified existing knowledge gaps among various literatures. Based on this, we have carried out research work on an energy efficient wireless sensor network for telemedicine.

2.0 Materials and Methods

The materials needed for this research work include base station module, power amplifiers, antenna interface, power supply unit, user equipment (UE) module, set of sensor nodes, medical server, an electrocardiogram (ECG), Hp laptop and Matlab/Simulink software.

2.1 Methods

2.1.1 Data acquisition from subjects

The ECG data was collected from Federal Medical Center Umuahia Abia State, sampled at 360Hz for performance evaluation of the proposed cardiac disorder detection platform. Four subjects with age of 24-35 years were taken to record signals for 10 minutes each. According to the report one subject with normal sinus rhythm (heart rate of 70 beats/ minute), one having atrial fibrillation, and other two with arrhythmia were considered. The bandpass filter (2-250Hz) was used to reduce the influence of noise such as power line interference, baseline wander and motion artifacts which are generally embedded with acquired signal. Then, the QRS complexes of ECG signals were detected. The block diagram of the proposed cardiac disorder detection technique is shown in Figure 1.

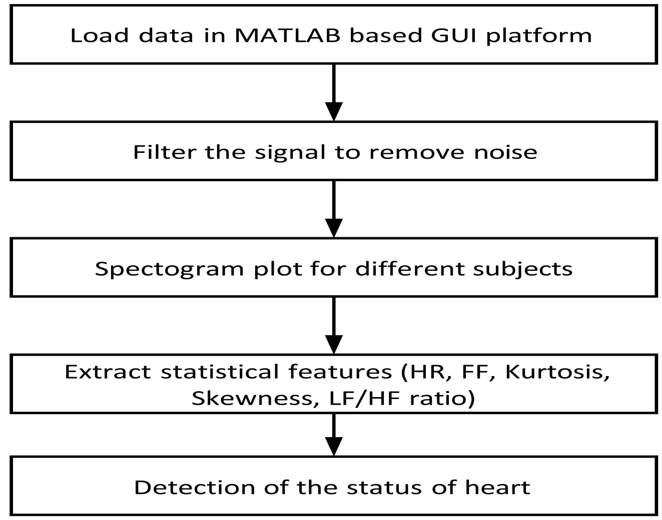

Figure 1: Block diagram of proposed cardiac disorder detection technique

2.1.2 Signal processing in MATLAB GUI to determine PSD

The obtained signal has noise due to high frequency, motion artifact, or power line interference. The significant QRS peaks of the signal were extracted through a bandpass filter at 1-300 Hz and sampled at 200 Hz to obtain the signal x(t). The signal, x(t) was segmented into three part $x_i(t)$ according to the three frequency spectrum, i = 1, 2, 3. After the $x_i(t)$ was obtained, WT was used to compute its wavelet power coefficients, WT(t, a) as follows (Daubechies, 1990):

$$WT(b,a) = \frac{1}{\sqrt{a}} \int x_i(t)\varphi^*\left(\frac{t-b}{a}\right) dt \qquad (1)$$

$$WT(t,a) = \sqrt{a} \int e^{jwt} x_i(w)\,dt\, \varphi^*(aw)\,dw \qquad (2)$$

where w, $x(t)$, $\varphi(t)$ represents angular frequency, the signal in the ith state, and Morlet wavelet respectively. The scaling factor, a and shifting factor or space, b are real and a > 0. Actually, the WT is not a function of time and frequency but time b and the scaling factor a. As scale is related to frequency, $P_{WT}(t, a)$ defines spectral density of time and scale (Daubechies, 1990).

$$P_{WT}(t,a) = \frac{1}{2\Pi C a^2} |WT(t,a)|^2 \qquad (3)$$

Where the constant C is chosen to obtain the energy by using WT,

$$C = \int \frac{|\varphi(w)|^2}{|w|} dw \quad (4)$$

A reference frequency w_r is chosen from $w = \frac{w_r}{a}$ to obtain a time-frequency density. Finally, wavelet time frequency analysis can be expressed by equation (5) (Daubechies, 1990).

$$P_{WT}(t, w) = \frac{w_r}{w^2} P_{WT}(t, \frac{w_r}{w}) \quad (5)$$

$$P_{WT}(t, a) = \frac{1}{2\Pi C w_r} |WT(t, \frac{w_r}{w})|^2 \quad (6)$$

Then, the instantaneous power, $P(t, a)\ WT$ is obtained from Equation (7), which contains the messages of time and frequency. For assessing the instantaneous power of independent frequency components of signal, the power spectrum at different frequency is divided into three parts:

(i) The power spectrum for very low frequency (VLF, 0.003–0.6 Hz) is: (Abrol, 2020).

$$P_{VLF}(t, a) = \int_{0.003}^{0.6} P_{WT}(t, f) df \quad (7)$$

$where\ f = {}^{w}/_{2\Pi}$ frequency interval is related to the scaling factor a.

2.1.3 Statistical features extraction for disorder detection

Two statistical features such as heart rate (HR) and form factor (FF) were extracted to differentiate among infected and non-infected heart beats.

1) Average heart rate: Instantaneous heart rate values are obtained by the inverse of the RR interval of each beat.

$$IHR = [\frac{60}{t_{RR1}}, \frac{60}{t_{RR2}}, \frac{60}{t_{RR3}}, \dots \dots \dots \dots \dots \frac{60}{t_{RRn}}] \quad (8)$$

$where\ t_{RR_1}$, t_{RR_2}, $t_{RR_3}, \dots \dots \dots \dots \dots \dots \dots .\ t_{RR_2}$ are time instants at which the QRS complexes occur in the ECG signal. (Abrol, 2020).

$$AHR = \frac{60}{t_{RR_{Average}}} \quad (9)$$

2) Form Factor: It is the ratio of the mobility of the first derivative of the signal to the mobility of the signal itself. It discriminates between normal and infected heart beats.

2.1.4 Network Layout

In this study, 35 clinics wards located at Federal medical centre Umuahia, according to 2022/2023 data were selected to monitor patients of the applications. The patients of a clinic are considered to be located at the clinic due to the uncertainty in their precise locations. Potential BSs to serve patients are selected by looking into the distance between the clinics and the BSs.

Note that the locations of clinics and BSs (i.e. latitude and longitude) refer to the actual locations found in Umuahia, which had been obtained from Google Maps

In this work, LTE-M was considered to serve the health application with a coverage radius of less than 11km. Hence, patients could be served by a BS within 11km from their registered clinics. The 26 nearest BSs to the clinics were selected to serve patients to reduce the model complexity.

Table 1 presents the deduced total number of patients registered at each ward who have been expected to experience postoperative AF.

2.1.5 Time for processing and analysis

For the ECG monitoring application, a 30-second ECG signal is required to be sent to monitor postoperative AF of cardiac surgical patients. This signal is retrieved from the Arrhythmia database. Note that, the 30-second ECG signal offers accurate results for the analysis, as recommended. Such 30-second of un-processed ECG signals has a volume of 252.8 kbits.

The ECG signals are processed using Pan Tompkins algorithm to extract heart rate and QRS duration for further analysis. The calculation of the heart rate from the 30-second ECG signal is based on the number of R waves within the 30 seconds and this number is multiplied by 2 to obtain the heart rate in beats per minute. The QRS duration is obtained based on the time between Q and S waves found in the ECG signal.

WARD	NO OF PATIENTS MONITORED USING ECG	WARD	NO OF PATIENTS MONITORED USING ECG
1	20	18	28
2	18	19	6
3	13	20	68
4	23	21	20
5	6	22	15
6	29	23	16
7	13	24	30
8	13	25	32
9	8	26	8
10	10	27	24
11	14	28	4
12	11	29	16
13	27	30	16
14	25	31	10
15	21	32	9
16	12	33	6
17	44	34	19

The PS selected in central cloud to process ECG signal is Intel Core i5-4460 with 3.2 GHz CPU and 500 Gbyte hard drives. An experiment was conducted using MATLAB with a parallel processing function to determine the correlation between time and number of patients for processing and analysis of raw ECG data. This was carried out by performing the processing task on the 30-second ECG signals generated by 10k to 50k patients in 10k steps. At each 10k step, the processing operation was repeated 5 times to calculate the average time for the processing duration. Note that, the 30-second ECG signals are made up of 1 ECG record repeated for all patients. Also, note that the time to perform the processing using MATLAB consists of both the time to submit the data for parallel processing and the time to run the algorithm.

2.1.6 Equipment ipower iconsumption

The power consumption of all networking equipment and PS consist of an idle part and a linear proportional part. The idle power of BS, PS, and content server are obtained from datasheets and references while the idle power for the other networking devices was considered to be 90% of the power consumption at maximum utilization. The maximum power consumption of the networking equipment and the PS and their maximum capacity is given by the manufacturers. As for FMC, the maximum capacity is considered as the summation of the maximum uplink capacity, i.e. 1.25 Gbps and maximum downlink capacity, i.e. 2.5 Gbps, to obtain *Eb*. Note that, the networking devices are shared by multiple applications while the considered PSs and Ethernet switch are dedicated for the healthcare application. As discussed for the link capacity, in this work we consider 0.3% of the idle power of the shared devices is contributed by our healthcare applications while 0.42% for LTE-M BS. Note that, the LTE-M shares capacity, antenna, radio, and hardware with the legacy LTE networks (20MHz). Due to this, the calculated idle power of the BS (0.42%) contributed for healthcare applications is based on 7% allocation of LTE-M network from the legacy LTE network (i.e. 1.4MHz/20MHz) and 6% [70] allocation of healthcare application from the total M2M application supported by LTE-M network. Note that, the 6% allocation refers to the estimated total number of RBs that is dedicated for healthcare applications which gives 360 PRBs per second as there are numerous types of M2M applications served by LTE-M. However, the maximum idle power is considered for the unshared devices.

Due to cooling, lighting and other overheads in the network, the total power consumed in a site is higher than the power consumed by the communications and computing equipment. The ratio of the total power consumed to the power consumed by the communications and computing equipment is defined as the power usage effectiveness (PUE). PUE is used to describe the energy efficiency of each site (core node site or building, cloud site or building or fog site). A PUE of 1.5 is considered for IP over WDM, metro, and access networks. A PUE of 2.5 is considered for small distributed clouds in this work.

Table 2 depicts the input parameters of the models for the network architecture.

Parameter	**Values**
Maximum power consumption of core router	12300W
Core router capacity	4480Gbps
Maximum power consumption of content server pcs	380.8 W
Idle power consumption of content server, ICS	324.82W
Content server capacity, CCS	1.8Gbps
Maximum power of aggregation router, PAR	4550W
Aggregation router capacity, CAR	560Gbps
Maximum power consumption of LTE based station, PBS	528W
Ethernet Switch capacity, CES	0.57W

This section present simulation UE uplink transmits power under open loop power control. The simulations were performed using MATLAB/SIMULINK. To analyze the UE energy consumption's dependency on the path loss compensation factor (a) and eNodeB sensitivity (P_o) are applied.

Figure 2 highlights the overall CDV detection system with the ECG signal selector acting as input to the system and figure 3 shows the Simulink model of Fog monitoring system.

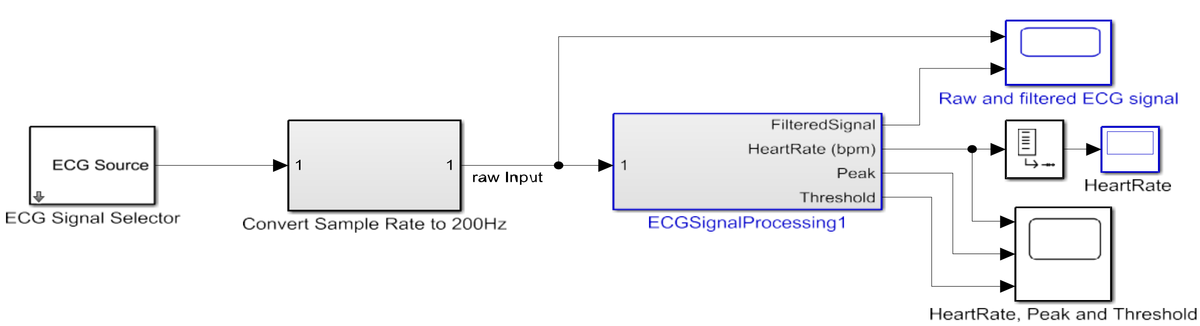

Figure 2: Overall CDV detection system using ECG signal processing

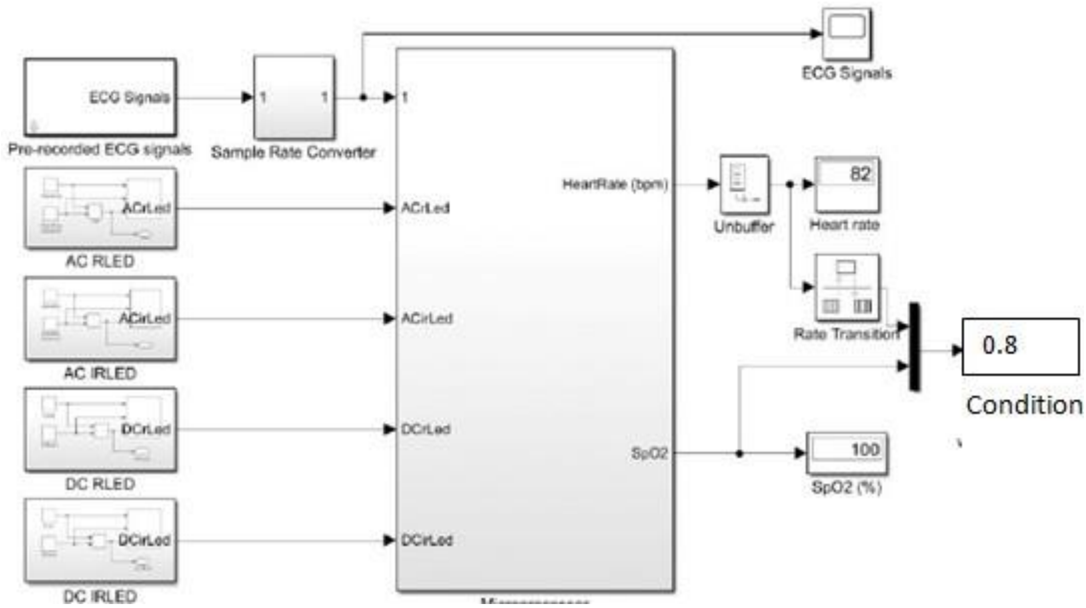

Figure 3: Simulink Model of Fog Monitoring System

3.1 Energy consumed by networking equipment

Based on the outcomes of the model, the energy consumed by the networking equipment has been determined via two approaches. Table 3 shows the calculated input parameters for the ECG monitoring applications. Note that, we consider single Processing server (PS) to serve all patients (*Pat* = 669 patients). Also, we consider a scenario where we only allow one PS at each candidate node (*N*=1) as the limited space at the node can be shared by multiple applications.

Figure 4 shows the energy consumption of networking equipment and processing for the ECG monitoring applications model. The energy saving of networking equipment achieved by the ECG model using fog server method as compared to what is obtainable at FMC Umuahia is 83.1%, as illustrated in Figure 4. This is because in the proposed model, the location of PS (i.e. fog server) is optimized at the access layer which is at the FMC as it is the nearest shared point to the patients (the FMC is connected to all BSs in the network).

Processing the raw health data at the fog server limited the network journey of this data i.e. only the feedback data and permanent storage data (i.e. processed data) is sent to the cloud, resulting in reducing the metro and core network energy consumption by reducing the data traversing the network and reducing the utilization time of the network equipment, i.e. reducing the idle power consumption.

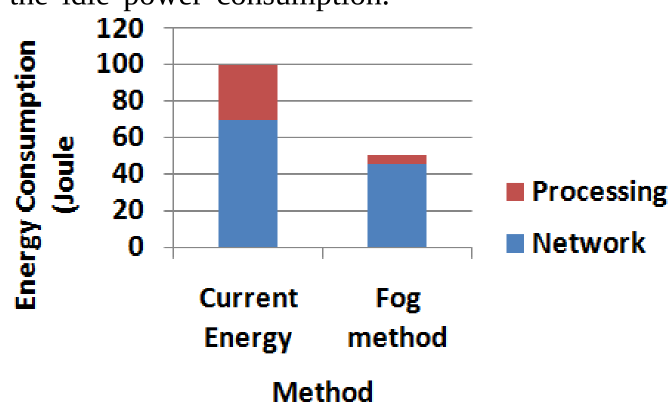

Figure 4: Graph of the energy consumption of networking equipment and processing for the ECG monitoring applications model

It should be noted that the larger the size of the data and the longer the transmission duration, the higher the energy consumption.

Comparing that to Current energy method used in FMC, higher energy is consumed by the networking equipment in the metro and core layers in the Current energy method as the un-processed data is sent to the central cloud to be processed.

From Figure 4, it could be seen that the energy consumption for processing in the Fog model is slightly higher than the current energy method used in FMC by 0.5%. This is due to the high utilization time of the processing server in the Fog model compared to the current energy method. Note that the same number and the same type of processing server are utilized in both models. In the Fog model, the processing server is on idle mode for 0.76s and 0.73s while sending the analyzed data for feedback and permanent storage, respectively, while it is idle for 0.38 s and 32 ms in the current energy method model. This is due to the link capacity limitation in the access layer where the processing server is located in the Fog model which limits the data rate to send the analyzed data to the clinic and cloud storage compared to the current energy method. However, the total energy saving that includes the networking equipment and processing achieved by the Fog model compared to the current energy method is 35.7%.

Also the performance of the Fog compared to the current method shows that the Fog has a better performance as compared to the current method in terms of the networking and processing energy consumption. The total energy saving of the Fog model compared to that obtainable in FMC is 38% when a single PS serves 20% of the total number of patients in the network, as shown in Figure 5. This saving is attributed to the fact that the location of the PSs in the fog model is the cloud, thereby reducing the amount of networking equipment utilized to transmit the raw health data traffic to the PS. Therefore, considerable energy is consumed in the metro and core layers to transmit the raw health data traffic to the PSs in FMC.

Figure 5 also shows that when a single PS serves 80% of the patients, the fog model saves 0.7% of the processing energy as compared to that obtainable in FMC. This saving is attributed to the low utilization time of the PS with the fog model to transmit the raw health data traffic to the PSs. Note that reducing the utilization time of the PSs reduces the energy consumption of the processing.

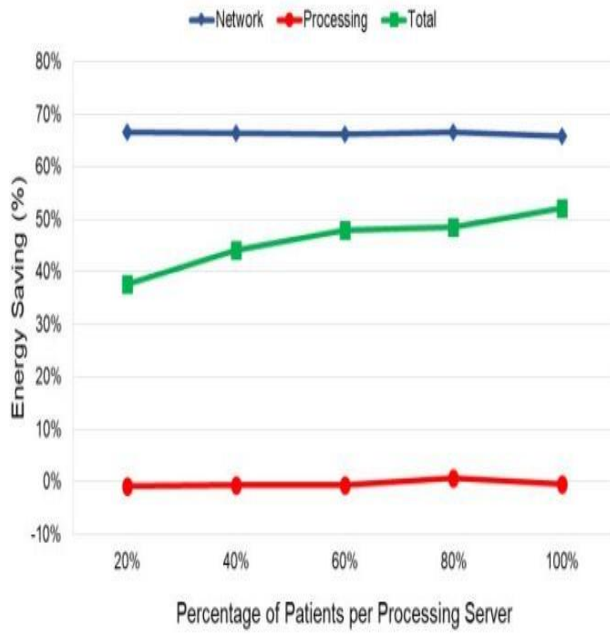

Figure 5: Graph of energy savings and percentage per processing server

Energy saving increases as the percentage of patients served by a single server increases. This is because allowing more patients to be served by a single PS reduces the available time to send the raw video recording to the PSs, which in turn reduces the energy consumed to keep the networking equipment and the PS in idle state.

The Simulation provides results of the ECG, heart rate, and the SpO_2 . In comparison with a typical ECG theoretical cycle wave, the ECG generated demonstrates the patient's normal sinus with a resting heart rate range of 78 and 83 BPM. The heart rate at the input was set between 78 and 83 beats per minute, and as shown in Figure 5, the heart rate is 82 beats per minute. Confirming that the fog algorithm used to estimate the HR in this simulation is acceptable.

Figure 6 displays the pre-recorded ECG signals that were used to synthesize the ECG signals. In comparison with a regular ECG theoretical cycle wave, the ECG signal clearly demonstrates the patient's normal sinus with a resting heart rate of 78–83 BPM. The amplitude of the signals is indicated on the y-axis in mV, and the time is indicated on the y-axis in seconds. The P, R, and T waves have peak amplitudes of 0.79 – 0.88mV, 1.01 – 1.28mV, and 0.95 – 1.05mV, sequentially. The T wave has larger peak amplitude than the P wave, as predicted.

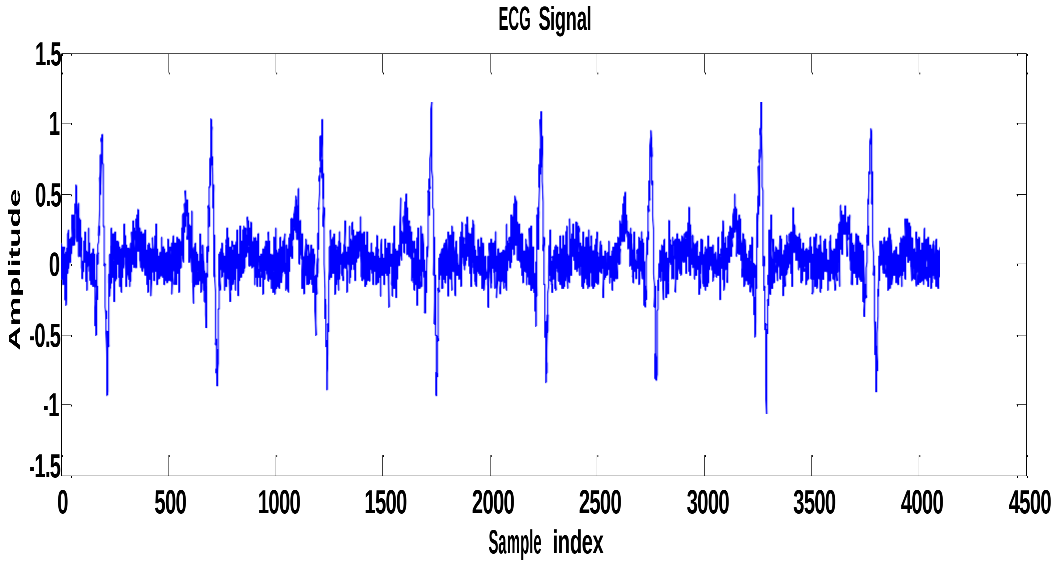

Figure 6: Graph of amplitude and sample index generated by ECG signal

The moving average window generates a signal that contains information about the QRS complex's slope and breadth. The last stage in signal processing for R peak detection is shown in Figure 7

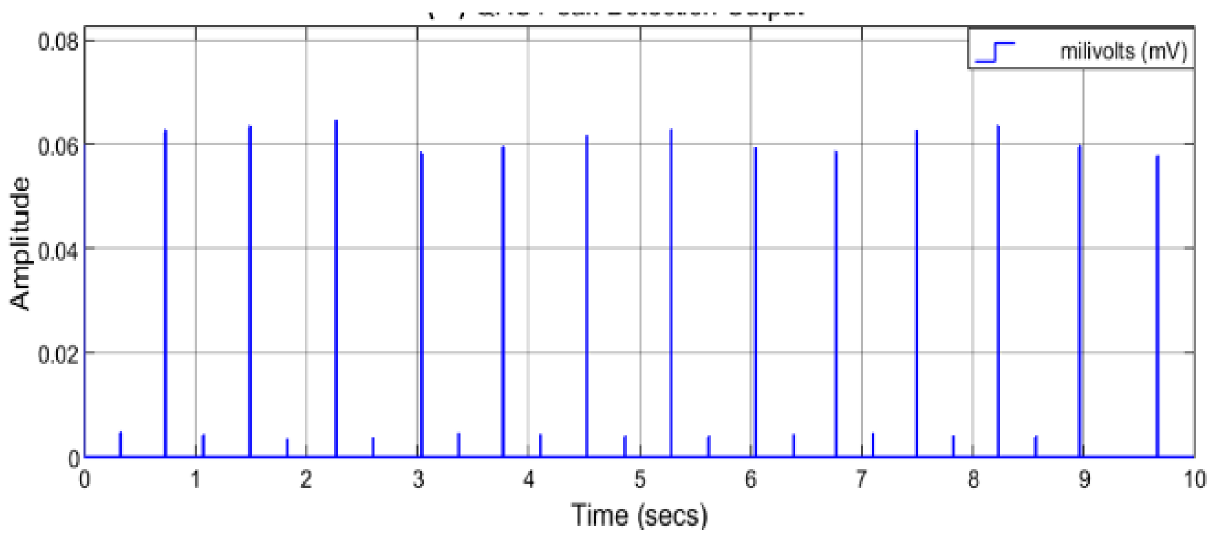

Figure 7: QRS Peak Detection Output

After applying the adaptive thresholds, the processed data display a stream of pulses indicating the positions of the QRS complexes. At the same time, the P, T, and U are totally filtered out by the moving average window. The amplitude of these pulses is between 0.05 and 0.07 millivolts.
Table 3 shows the ground truth parameters used for decision.
The proposed system classifies a recorded heartbeat into four classes, namely Normal Beat, Premature Ventricular Contraction (PVC), Premature Atrial Contraction (PAC) and Myocardial Infarction.

Table 3: Ground truth parameters used for decision.

Parameters	Range	Interpretation
160 – 230	0 – 50	Critically Low
	50 – 70	Bradycardia
	70 – 100	Normal
	100 – 160	Tachycardia
	160 – 230	Critically High
SpO_2	30-70	Critically Low
	70 – 95	Low
	96 – 100	Normal

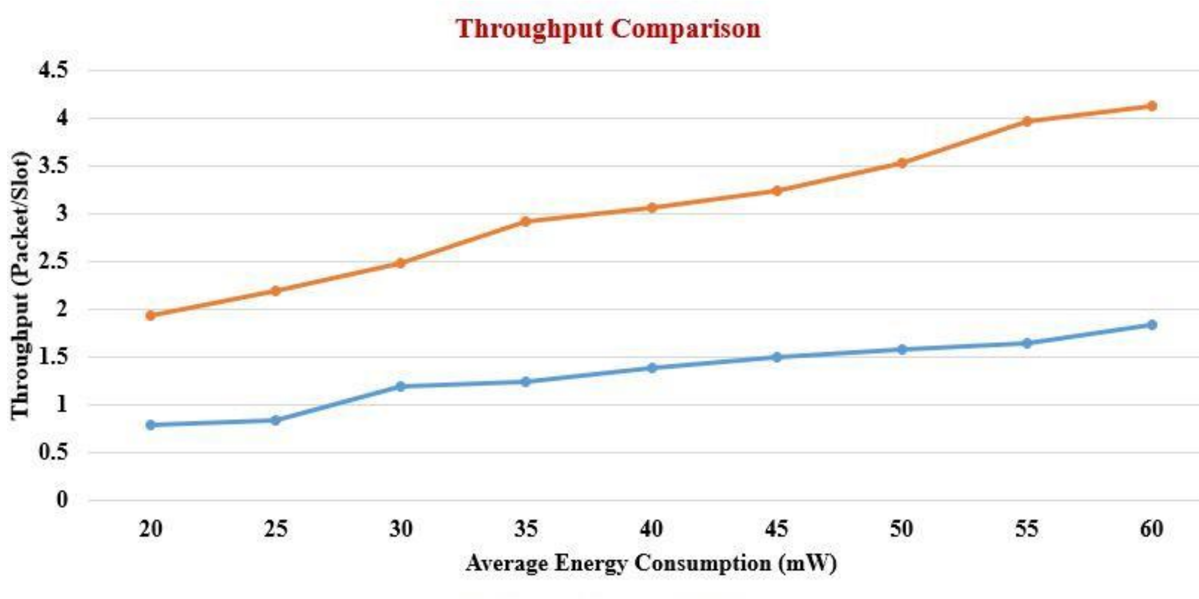

Figure 8: Graph of throughput and average energy consumption

The throughput of the proposed Fog system is compared with work done by Zang *et al.* (2021) in Figure 8, and it was observed the throughput of the Fog system is improved. This improvisation is done using the routing protocol based on the Fog algorithm. The number of sensed data packets received by the sink node is known as the throughput and it should be maximum. The throughput of the model depends on the number of sensor nodes that are successfully participating or active. The number of data packets sent by TX node to the sink node is directly proportional to the number of successfully participating active or alive sensor nodes in the network. Especially in the case of the Fog model, the sensed patient data packets are important and crucial and need a secure route for transmission.

4 CONCLUSION

The popularity of Internet of Things is increasing on daily basis in the area of remote monitoring system of patient. Monitoring system is based on monitoring the patients' heart beat automatically through connected networks. The system can able to detect the critical condition of a patient by processing sensors data and instantly provides notification to doctors. The doctor can monitor the patient at the place where ever he is. The patient is monitored and the sensed data is send to the server through the Wi-Fi. So it is easy for the doctor to monitor the patient through the web server. In the server the patient body temperature, heartbeat can be sensed time to time and get updated through Wi-Fi. So the doctor can monitor the patient every time he wants. If the heart beat is high the notification is sent to the doctor using GSM.

In this research work, an energy-efficient wireless sensor network for improved operation on cardiovascular problems in development economy using the iconcept of Fog technology was presented. The Fog technology in ithe system is highly significant as continuous monitoring of patients' health is done in real-time. Fog system also facilitates medical practitioners to observe critical health conditions of patients remotely from anywhere or any location. However, the usage of Fog systems in real-time is very limited as maintaining the limited residual energy of the sensor nodes is very difficult. The outcome of the istudy revealed ithat a total energy saving of 36% and 52% are attained via processing and analysis the health data at the fog in comparison to conventional processing.

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