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A Review of Health Monitoring Systems for Cardiovascular Related Diseases: Processes and Techniques

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Abstract- The increased number of elderly people and the growing population of cardiovascular-related diseases have put more strain on the already ill-fated health facilities in developing countries. One approach to alleviate this problem is to employ a sustainable healthcare system that monitors and manages the patient remotely and in a real-time manner. Many researchers across the globe have invested in the design and development of monitoring systems for cardiovascular-related diseases. However, designing such a system requires taking a holistic view of the design lifecycle. The paper aims to conduct a holistic review of the existing literature to identify techniques and discuss approaches used at each stage of development. Also, this paper examines existing research on a monitoring system for cardiovascular-related diseases to identify the stages used in the development cycle with the view to identifying gaps in the existing literature.

Indexed Terms- Monitoring System, Cardiovascular, Technology, Processes

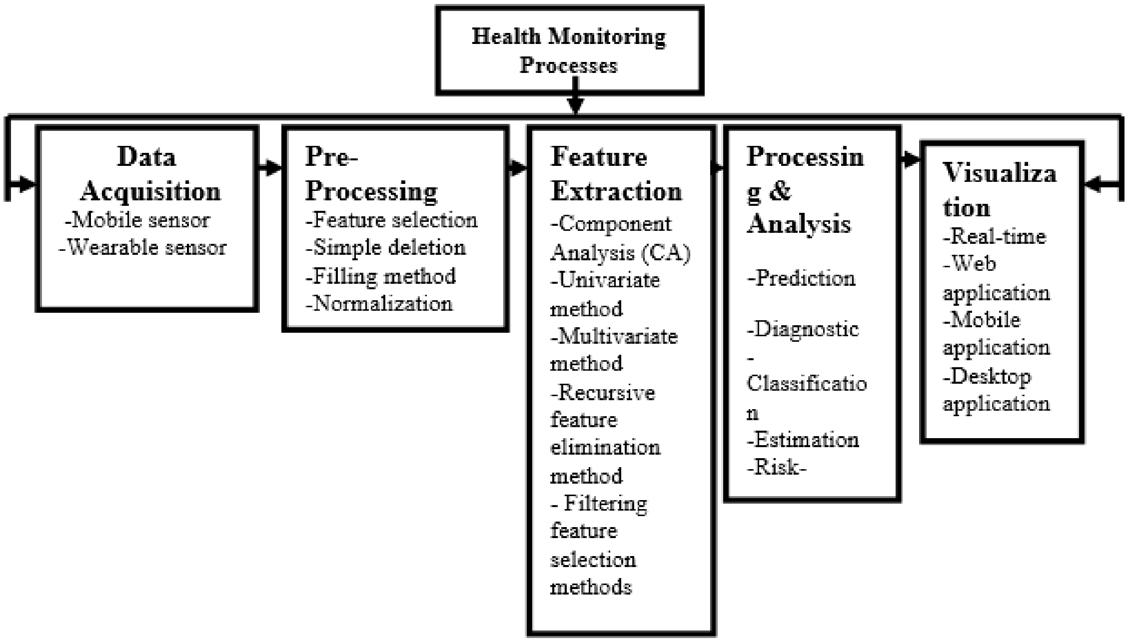
I. INTRODUCTION

The number of aged people and the increasing number of cardiovascular disease (CVDs) patients in Nigeria is worrisome. In 2016, the total number of deaths from noncommunicable diseases in Nigeria was estimated to be about 29%, and 11% of the deaths were attributed to CVDs. Some of the cardiovascular-related diseases that are on the increase in Nigeria include stroke, hypertension, and heart failure [1]. Research shows that hypertension is the commonest risk factor for CVD and the leading cause of mortality worldwide [2]. The poverty index of Nigeria has changed the pattern of treatment and management of CVDs. The diagnosis and treatment of cardiovascular disease come at a price. The World Bank estimated that about 53.5 % of Nigeria's population earns less than $1.90 a day [1]. This figure shows that Nigerians who earn less than the amount would not be able to treat and manage cardiovascular-related diseases. This statistic indicates that there is an absolute burden of CVDs in Nigeria. Thus there is a need for a system that helps to monitor patients' health and to reduce the burden of CVDs. This need is not limited to Nigeria but extends to other developing countries.

One approach to alleviate this problem is to employ a sustainable healthcare system that monitors and manages the patient remotely and in a real-time manner. Many researchers across the globe have invested in the design and development of monitoring systems for cardiovascular-related diseases. Considering the complexity of the system, designing such a monitoring system requires incorporating all the stages that will bring the system from conception to the final stage. Generally, a health monitoring system consists of a subsystem that involves inputs, transformation processes, and outputs. Each unit in the subsystem contributes to the better performance of the developed system. When any unit of the subsystem is not properly incorporated into the design, the performance of the developed system may be rendered inefficient. This paper aims to conduct a holistic review of the existing literature to identify techniques and discuss approaches used at each stage of development. Also, this paper examines existing research on a monitoring system for cardiovascular-related diseases with the view to identifying gaps in the existing literature.

II. STAGES OF DESIGNING MONITORING SYSTEM FOR CARDIOVASCULAR-RELATED DISEASES

Generally, the health monitoring design process includes a data acquisition phase, data pre-processing phase, feature extraction/selection phase, processing and analysis phase, and visualization phase. Figure 1 presents details of five stages of health monitoring design processes.



III. DATA ACQUISITION

In designing a health monitoring system, the method of collecting data is the first stage to be identified. This is called data acquisition. It is the use of medical sensory devices to collect vital signs signals from a patient. Example of such sensors includes a mobile sensor and a wearable sensor. In the data acquisition layer, real-time and continuous acquisitions of vital/environmental signs are handled. Several researchers employ the use of different sensors for specific data acquisition. Generally, the sensor used in data acquisition depends on the signals required. In cardiovascular disease, most signals required for diagnosis and monitoring include pulse wave, photoplethysmography (PPG), electrocardiogram (ECG), seismocardiogram (SCG), Ballistocardiogram (BCG), phonocardiogram (PCG), and blood pressure,[3]. In blood pressure, sensor like BMP180[4], HEM-1000, OMRON[5] etc are used. In post-stroke, patient different data are obtained from the patient for decision-making. Such data include pulse rate, sleeping-wake pattern, and walking steps[6]. Data such as activities and movement hospital assessment are used for post-stroke rehabilitation[7]. A sensor named Holter (AthenaDiax, Medtronic) is used in measuring ECG[8], and ANNE^{TM} One (Sibel Health; Niles, IL, USA) was used in [9] to collect overnight sleep data from a post-stroke patient. Research conducted by [6] used Fitbit to collect pulse rate, sleeping-wake pattern, and walking steps from a post-stroke patient. A review work done by [7] reveals that IMUs sensor was substantially used by researchers to collect data from a post-stroke patient. In the case of heart failure, sensors like cardioMEMS were developed to monitor pulmonary artery pressures, PPG sensor was used [10] to detect the variation of the blood flow in the finger. An optical-based heart rate monitoring sensor was developed to monitor the heart rate of patients [11]. Table 1 presents a list of some sensors used for obtaining vital signs from cardiovascular patients.

Table 1: Summary of selected sensors used for data acquisition in cardiovascular-related disease

Ref.	Sensor	Disease	Application
[12]	Piezoelectric sensor	Coronary Heart Disease	To detect abnormal waveforms
[13]	CardioMEMS	Heart Failure	Measuring blood and pulmonary artery pressure
[10]	PPG sensor	Heart Failure	To detects the variation of the blood flow in the finger
[8]	Holter monitor	Stroke	Record electrical activities
[9]	ANNE one	Post-stroke	Measure electrical activities and skin temperature
[6]	Fit bit	Post-stroke	Heartbeat rate
[4]	BMP180	Blood pressure	Measure temperature and pressure
[5]	HEM-1000, OMRON	blood pressure	Heartbeat detection

IV. DATA PREPROCESSING

Sensor error, duplication records in the data, and missing values are some of the challenges that can come up during data collection and gathering. Preprocessing data can reduce this error by filtering the unusual data. [14]. Data preprocessing is crucial to health monitoring systems, especially in the area of data transformation. In data mining, data preprocessing perform the task of replacing missing values, data normalization, eliminating duplicate records, and removal of noise. [15]. Table 2 presents different techniques for data preprocessing.

Table 2: Summary of selected techniques in Data preprocessing

Ref.	Techniques	Task	Disease
[16]	Median studentized residual approach	Replacing Missing Values, Normalization	Heart disease
[17]	Z-score	Normalization	Stroke
[18]	Kalman filtering	Remove noise and duplicate records from the data	Heart disease
[19]	Feature Selection	Eliminate duplicate data	Blood pressure
[20]	Noise filtering and Signal segmentation	to remove noise from original ECG signals, To reduce the signal variation and	Blood pressure
[21]	Kalman filtering	To remove such noise from the data	diabetes, BP, mental health, and drug reviews
[22]	Kalman filtering	Remove noise, and Inconsistencies	Heart disease

V. FEATURE EXTRACTION

Many futures in the dataset can result in the model suffering from overfitting. It is very important to reduce some futures which may not be too necessary for data mining processes. The feature extraction technique is used to form new features from the original feature. Researchers used a different approach to extract features from the original feature. This includes component analysis [23], univariate/multivariate method[24], recursive feature elimination method [25] combination of filtering feature selection methods [26] proposed a combination of filtering feature selection methods. A crow search algorithm is used to extract features from preprocessed heart disease data [16]. A 2-dimension feature based on PM was used for feature extraction in [27]. Fast Fourier Transformation (FFT) was used in [28] to extract the power values of waveforms signals from EEG. Framingham risk factor (FRF) extraction was used in [22] to extract features related to the heart disease dataset.

VI. PROCESSING AND ANALYSIS METHODS

Different algorithms have been proposed for processing data in a cardiovascular monitoring system. In a health monitoring system, data obtained from the acquisition unit is stored in the database. Then real-time processing takes place using an algorithm such as LR, NB, SVM, ANN, and ensemble methods. The purpose of real-time processing is to make remote and real-time diagnoses, predictions, and classifications. Table 3 presents selected algorithms and their application in cardiovascular-related diseases

Table 3: Selected algorithms and their applications in cardiovascular-related diseases

Ref	Algorithm	Disease	Application
[31]	CNN	Chronic stroke survivors	Activity recognition
[32]	ANFISA	Hypertension	Classification
[16]	ANFISA	Heart disease	Classification
[33]	ANN	Stroke	Diagnosis
[34]	Fuzzy Decision Tree	Hypertension	Estimatimation
[35]	Naïve Bayes	Heart disease	Document classification
[18]	Deep learning	Heart disease	Prediction
[28]	Ensemble methods	Stroke	Prediction
[22]	Deep learning	Heart disease	Prediction
[36]	Ensemble method	Diabetes and hypertension	Prediction
[37]	Ensemble method	Heart disease	Prediction
[38]	deep learning model	Heart failure	Detecting patient survival
[9]	Ensemble method	Stroke	Classification of sleep stages
[39]	Deep learning	Blood pressure	BP estimation

ANN: artificial neural network, CNN: Convolution Neural Network, ANFIS: adaptive neuro-fuzzy system

VII. VISUALIZATION

As mentioned earlier, the last unit of the health monitoring subsystem is the output unit also called Visualization. This is the last phase of the development life cycle that is used to display the result of data processing in real time. In the health monitoring system, visualization performs the task of converting vital signs signal analysis into a visual format for the patient and medical professional to understand and deduct useful decisions from the reading. Different software and off-the-shelf devices are used in visualization. However, the software packages are depended on the nature of the information to be displayed. For example, the authors in [40] employ ThingSpeak to display results generated from the reading of heart rate and body temperature. A web application was used in [41] to provide data generated from a wearable sensor. The author in [42] adopts LabVIEW to evaluate data by medical professionals. Adafruit GFX graphics core was identified in [43] as a communication medium between the user and the system through an application.

VIII. COMPARATIVE STUDY OF HEALTH MONITORING DESIGN PROCESSES

This section examines the existing research on a monitoring system for cardiovascular-related diseases to identify the stages used in the development cycle with the view to identify gaps in the existing literature. Table 4 presents a summary of selected literature indicating the design processes.

Table 4 Summary of selected literature and the design processes.

Ref.	Application	Signal Acquisition	Signal Preprocessing	Feature Extraction	Processing	Visualization
[16]	Heart disease	MVCU	Missing value and normalization	LCSA algorithm	MSSO-ANFIS	Not mentioned
[33]	Stroke	Not mentioned	Not mentioned	Not mentioned	ANN	Mobile base system
[34]	Hypertension	ESP8266	Not mentioned	Not mentioned	Fuzzy decision tree	Not mentioned
[18]	Heart disease	MVCU	Kalman filtering	Not mentioned	fuzzy inference system/ Bi-LSTM	No specific device mentioned
[28]	Stroke	MVCU	Z-score	FFT	Real-life processing algorithm not mentioned	No specific device mentioned
[22]	Heart disease	Medical and activities sensors	Kalman filtering	Framingham risk factor extraction	Ensemble deep learning	Not mentioned
[36]	Diabetes and hypertension	BP and Glucose monitoring device	Not mentioned	Technique not mentioned	SVM	No specific device mentioned
[37]	Cardiovascular	MVCU	Not mentioned	Not mentioned	Ensemble learning	Not mentioned
[38]	Heart failure	Heart monitoring sensors	Not mentioned	Not mentioned	CNN deep learning	Not mentioned

[9]	Stroke rehabilitation	ANNE™ One	Not mentioned	FFT	Ensemble	Not mentioned
[39]	Blood pressure	ECG monitoring sensor	Noise filtering, Signal segmentation, and Normalization	Not mentioned	Deep learning	Not mentioned
[32]	Hypertension	Web-based	Not mentioned	Not mentioned	ANFIS	No specific device mentioned
[31]	stroke rehabilitation	watch style W270, LG	Not mentioned	Not mentioned	CNN	Not mentioned

LSTM: long short-term memory,MVCU: Multi-vital signal collector unit, LCSA: Levy-based crow search algorithm, MSSO: Modified salp swarm optimization, FFT: Fast Fourier Technique, , SVM: Support Vector Machine

Evidence from Table 4: shows that none of the selected research incorporated the five stages of the development lifecycle except research conducted in [28]. However, the research did not specify the visualization tool. About 69% of the study did not put visualization into consideration. Even the remaining 31% did not give details of the visualization tool. The processing stage is core to designing a health monitoring system. All the selected research described the processing technique for the design of a health monitoring system. However, some processing modes were not in a real-time manner. From the table, most researchers do not take signal pre-processing and feature extraction into consideration. All the selected studies put acquisition into consideration except research in [33].

CONCLUSION

This paper aimed at investigating the design approach and techniques of a cardiovascular monitoring system. Different techniques used for each subsystem were identified. Also, this paper examined the existing research on a monitoring system for cardiovascular-related diseases to identify the stages used in the development cycle. The finding from the study reveals that most of the existing research especially on cardiovascular-related health monitoring systems did not address a complete process of a health monitoring system. This will affect the performance of a designed system. In the future, a holistic design process for hypertension health monitoring systems will be developed.

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