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A Comprehensive Study on Data Mining and WBSN for its applicability in Remote Health Monitoring System

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ABSTRACT: Of late, healthcare systems are very essential for the mankind. Owing to the inexpensive sensors and the advancements of smart phones, Wireless Body Sensor Networks (WBSN) hit the scene. This WBSN aims at attaching biosensors to the human body and the sensors track the health status of the patient. Thus, the patients can be tracked all the time irrespective of the location and time. On realising the importance of Remote Health Monitoring System (RHMS), this paper reviews the concept of WBSN and data mining for its applicability in RHMS**.**

KEYWORDS: Biosensors, data mining, healthcare systems, Wireless Body Sensor Networks, Remote Health Monitoring Systems**.**

I.INTRODUCTION

Remote Health Monitoring System (RHMS) is a boon to the society, which improves the quality of life. RHMS has gained substantial spotlight, as these systems track the health conditions of the patients continuously [1, 2]. The demand for these kinds of systems improves together with the development of wireless technologies. RHMS completely enjoys the benefits of wireless technology and hence it is named as Wireless Body Area Networks (WBAN), by Van Dam in 2001 [3]. The term Wireless Body Area Networks is used interchangeably with Wireless Body Sensor Networks (WBSN). RHMS is made possible by the implementation of biosensors. Biosensors are tiny and can be implanted over the human body or it can be worn. These sensors communicate among themselves and with the remote medical server. The remote medical server is responsible for taking decisions about the severity of the disease. The biosensors take several health parameters such as heart beat rate, blood glucose level, blood pressure rate, body temperature etc., into account, to decide the nature of disease. The overall view of biosensors is presented in [4-6] .

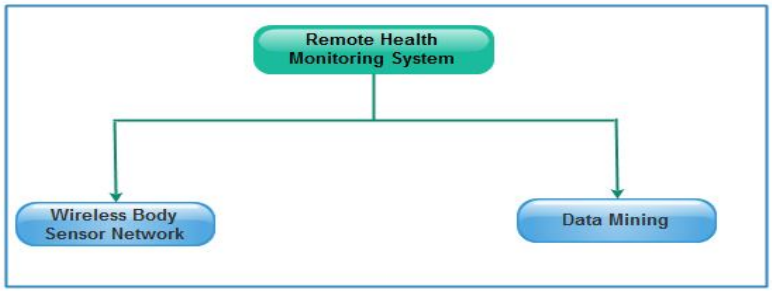

Fig 1: Remote Health Monitoring System

Owing to its simplicity and efficiency, RHMS is being paid much attention in the area of research. The smart healthcare system relies on a network of sensors and medical servers. The sensors track the health conditions of the patient and periodically forward the real-time. health data of the concerned patient to the medical server. Thus, the patient can be tracked continuously irrespective of location and time. In case of any abnormality observation, the system alerts the physician. Thus, RHMS saves lives of many patients however; making this application in real time is a big deal. Several issues are needed to be taken care, while developing a RHMS system. Some of the serious issues are

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energy restriction, lifetime of the network, congestion, security and so on. Though WBAN is based on WSN, the protocols being designed for WSN cannot be utilised for WBAN. Realizing the importance of RHMS, this paper presents an overview of RHMS. The forthcoming sections present the detailed review of literature.

II. TRACKING THE HEALTH STATUS OF THE PATIENT

The patient can recover from the disease at the earliest, provided the disease is treated with proper care. Hence, treatment of a disease is inversely proportional to the recovery from the disease. Many patients fall dead because of improper treatment of disease and unawareness. RHMS is a windfall to the mankind, which makes it possible to track the health status of the patient continuously. The health status tracking is made achievable by means of biosensors. These biosensors are wearable and can be positioned on the clothes or on the human body. Certain biosensors can be implanted beneath the skin. These biosensors are employed for tracking the medical parameters such as body temperature, heart beat rate, blood glucose level, blood pressure rate, ECG, respiration rate etc. It has been estimated that in 2015, about 20 million people may expire because of cardiovascular disease [7]. Another study claims that about 246 million people suffer from diabetes and the expectant count of diabetic patients by 2025 is around 380 million [8]. However, proper and frequent health examinations can save million lives. Some of the diseases that are being treated with the WBSN are hypertension, asthma, Alzheimer's disease, Parkinson's disease, diabetes, stress monitoring, heart diseases etc., [9-11]. People who suffer from these diseases are suggested to wear biosensors either on clothes or body. These sensors continuously track the health status of the patient and communicate with the medical server. In case of any abnormality, the system triggers an alarm to the physician.

III. COMPONENTS OF WBSN

A common WBSN is composed of sensors, actuators and a smart device. Sensors employed in WBSN are called as biosensors. These biosensors collect the health data from the human body with respect to time or movement. The collected health data can be shared among sensors or can be forwarded to the medical server. A biosensor consists of a sensing hardware, processor, memory, power supply and a transmitter [12]. Actuators are optional components of a WBSN. Actuators are medicine dispensers that are put into action by alarms generated by sensors. For instance, when a sensor senses the lower blood glucose level, a message is passed to the actuator. On receiving the message, actuator injects the insulin to the human body. Thus, the actuators can work when it receives instruction either from sensors or from human. Actuators contain actuator hardware, processor, memory, power supply, receiver and space to contain medicine. A smart device collects all the health data from the sensors and actuators and the smart device is responsible for letting the physician or the user about the health condition. In WBSN, both the sensors and actuators are called as nodes. Usually, a WBSN consists of 20 to 50 nodes [13, 14].

IV. ISSUES IN WBSN

Some of the major issues associated with WBSN are energy restriction, reliability, usability and security. The sensors present in the WBSN possess limited energy and thus the energy utilization must be given utmost care. Energy of a node is consumed during sensing, data forwarding and local processing of health data [12]. The lifetime of biosensors must preferably be longer and this can be achieved by effective energy utilization. For instance, a glucose monitor should at least work for five years. Thus, the energy of biosensors must be exploited in a proper way to ensure a longer lifetime of implanted sensors. Reliability is another major issue, which makes sense that the health data being sent must reach the intended destination. Apart from this, the health data has to be transferred in a minimal period of time. Reliability has serious impact over the quality of RHMS. As RHMS deals with real time health monitoring of patients, time delay is not tolerable. Time delay in data transmission may put an end to the life of the patient [15]. Hence, reliability must be rendered as much attention as possible.

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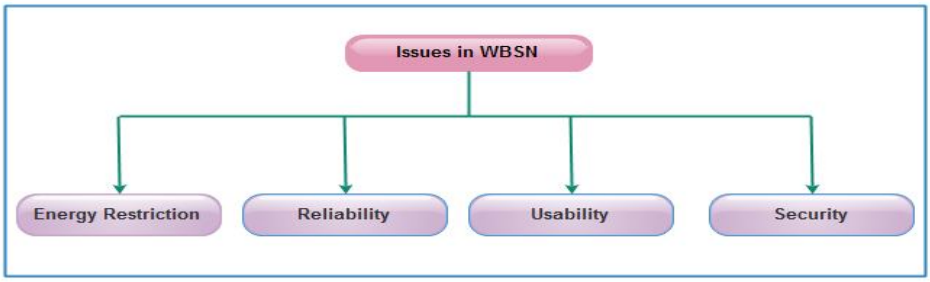

Fig 2: Issues in WBSN

The RHMS must have a greater degree of usability. The term usability means that the system must be operable by any kind of user. Furthermore, a new sensor must be able to attach itself to the network, as soon as it gets attached to the human body. The third party intervention must be eliminated as much as possible. The health data being sensed by the sensors are transmitted over internet. This introduces several security breaches. The health data of patients is highly confidential and should be kept private [16]. A strict security policy must be enforced such that the health data can be protected from adversaries. RHMS prefers a lightweight security mechanism. Thus, the design of an RHMS must focus on energy consumption, reliability, usability and security. Obviously, the system may suffer from the trade-offs between the aforementioned parameters. A perfect RHMS must consume energy as minimum as possible. On the other hand, the reliability, usability and security of RHMS must be as great as possible.

V. DATA MINING IN RHMS

RHMS exploits the concept of data mining for diagnosing the nature of disease along with disease prediction. Data mining can effectively predict the disease and also can diagnose the disease with the help of health patterns [17]. A standard RHMS involve in data collection, data transmission and data storage [18, 19]. Apart from this, disease diagnosis is achievable by mining the sensed data.

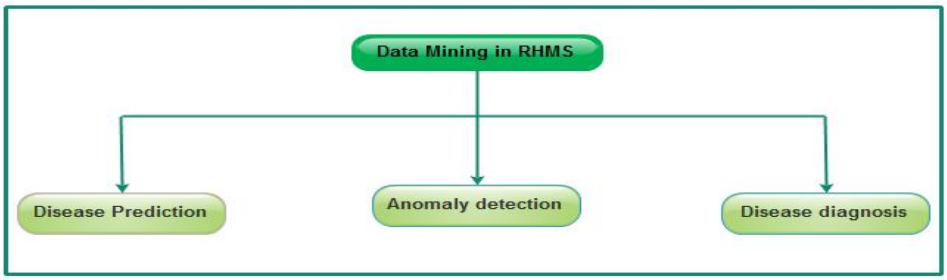

Fig 3: Applicability of data mining in RHMS

Data mining helps in predicting the disease by creating patterns and disease diagnosis is achieved by grouping related data together with a label. Usually, data mining tasks are beneficial to RHMS in prediction and diagnosis of the disease. Disease prediction and anomaly detection take place in the user side, whereas diagnosis happens in the server side. In substance, the most important processes of data mining are disease prediction, anomaly detection and disease diagnosis. All these processes are explained in the forthcoming sections.

1. Disease prediction: Prediction is the most interesting concept of data mining. Prediction is forecasting the chance of occurrence of disease by taking the historical health information into account. However, it varies from person to person. The biosensors collect the health information from the human body and prediction is made possible by comparing the current data with the historical health data. This method is also called as supervised learning method [20]. A supervised learning method involves feature extraction, training and testing processes. Feature extraction is the process that aims at extracting necessary features from an entity, which can be claimed as the deciding factors. The extracted features pave way for effective classification of diseases. Training the system is the process of providing

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knowledge to the system about the normal and abnormal data. Testing is the process in which the trained system classifies between the normal and the abnormal health condition by the knowledge it gained during the training process. For instance, in the works presented in [21,22] predicts the stress range of the entity. Similarly, the blood glucose level can be predicted as in [23].

2. Anomaly detection: Anomaly is the abnormality or irregularity detected from a set of normal values. In other words, anomaly detection is the process of detecting values which do not comply with the expected values [24]. These abnormal values help the physician to take accurate decision with respect to the current health status of the patient [25]. Anomaly detection can be carried out by classifier models such as Support Vector Machine (SVM) [26]. These classifiers can differentiate between normal and abnormal values. In certain works, the irregular patterns of ECG signals and blood glucose levels are analysed [27-29]. An alarm can be generated to the physician, whenever an abnormal pattern is generated [30].

3. Disease diagnosis: Disease diagnosis is the process of decision making, which completely depends on the collected health data. The disease diagnosis is accomplished by taking the environmental condition, situation of the patient into consideration. On the other hand, anomaly detection aims at detecting the abnormal patterns of health data with respect to the historical health information alone. The papers [31-38] diagnoses the disease such as chronic diseases, sleep irregularities, health condition assessment and emotion identification.

VI.CONCLUSION

This paper has presented a comprehensive overview of Remote Health Monitoring System (RHMS). The general concepts that are applicable for biosensors are studied. RHMS is described in terms of Wireless Body Sensor Networks and data mining respectively. Some of the main works being proposed in this category are discussed. Thus, this paper presents the basic knowledge about designing a Remote Health Monitoring System. By considering all these points into account, we propose to design a better RHMS in future.

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