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Sadia Din, Anand Paul

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Smart Health Monitoring and Management System: Toward autonomous wearable sensing for Internet of Things using Big Data Analytics

Sadia Din, Anand Paul

School of Computer Science and Engineering, Kyungpook National University, Daegu, Korea
research.2486@gmail.com , paul.editor@gmail.com

Abstract— The current development and growth in the arena of Internet of Things (IoT) are providing a great potential in the route of the novel epoch of healthcare. The vision of the healthcare is expansively favored, as it advances the excellence of life and health of humans, involving several health regulations. The incessant increase of the multifaceted IoT devices in health is broadly tested by challenges such as powering the IoT terminal nodes used for health monitoring, real-time data processing and smart decision and event management. In this paper, we propose a healthcare architecture which is based analysis of energy harvesting for health monitoring sensors and the realization of Big Data analytics in healthcare. The rationale of proposed architecture is twofold: (1) comprehensive conceptual framework for energy harvesting for health monitoring sensors, and (2) data processing and decision management for healthcare. The proposed architecture is three-layered architecture, that comprised (1) energy harvesting and data generation, data pre-processing, and data processing and application. We also verified the consistent data sets on Hadoop server to validate the proposed architecture based on threshold limit value (TLV). The study reveals that the proposed architecture offer valuable imminent into the field of smart health.

Key Words: IoT, Energy Harvesting, Big Data Analytics

1. INTRODUCTION

In recent years, researchers have placed a great deal of attention on the machine to machine (M2M) and Internet of Things (IoT) technologies and markets [1]. M2M and IoT refer not only to mobile phones and personal computers connected to the Internet but to increase the efficient utilization; it also refers to the wireless interconnection of all the billions of devices and “things” through local area networks (LANs) or the Internet [2]. Consequently, with the billions of things appear billions of batteries that must be powered, maintained, purchased, and disposed-off. Energy harvesting presents a straightforward and clear-cut solution for powering the “things” or IoT devices efficiently using unpolluted energy (clean) [3] [14]. The things or devices embedded with wireless terminals include sensors which are connected to a network and collect the data and information about the surrounding environment. There are several types of sensors which are used by wireless sensor terminals for humidity, temperature, illumination, pressure, motion, stress, position, distortion, flow rate, gas, and so forth. Some of these sensors include blood pressure measurement sensors [4] and the sustainable power sources in electronics used by consumers [5].

The key obligation for IoT is the capability to put the sensor in all types of spots to collect data. But there is a big issue that is the power supply or, the life of the battery or the time phase for battery substitution. There are worries not only for the cost of battery but also the massive scale of maintenance. One of the great solutions is provided using energy harvesting [3]. Energy harvesting technologies use power generating elements that are piezoelectric elements, solar cells, and thermoelectric elements to convert vibration (piezoelectric effect), light, and heat energy into electricity. Piezoelectricity is having a broad set of material choices and designs and provides the basis for several applications [6-8] of growing interest. Also, this technology is particularly extensively favored in wearable systems. A variety of alternative can be taken into consideration for the utilization of piezoelectricity in such situation. Therefore, this harvesting method can be applied to power the sensors used in IoT environment.

On the other hand, the various the sensor placed, the greater the variety and precision of the data will be. This data often called big data that assist in analyzing, process, monitor, and predict the unseen patterns that were previously unachievable, and new services and businesses as well as [9]. The experts suggested that the Big Data is one of the most significant research challenges for the horizon of 2020. The model depends on the acquirement and aggregation of the huge volume of data to carry innovation in the future [10-12]. Big data analytics in healthcare plays a vital role in the context of health monitoring and surveillance. Big Data analytics can take out useful information from the big data produced by different sensors implanted in the human body. Several proposals have been made by researchers for the health monitoring to have real-time data processing and decision-making. Thereupon, processing an enormous amount of becomes the necessity for healthcare in recent time. Hadoop is selected as the processing unit for the heterogeneous data collected from different human body sensors. Hadoop uses MapReduce method for analyzing data. MapReduce performs two distinct tasks that are mapping and reducing. Mapping is used to transform the data into another and Reduce merges the data produced in mapping, and the result is reduced in quantity [13].

In this research article, we highlight the advances in the energy harvesting and emphasis on underlying perceptions. A particular conceptual module summarizes the functionalities and the comprehensive analysis of the piezoelectricity in the context of human health monitoring sensors. Also, it further highlights the key design strategy in the context of human body actions for piezoelectric effect and its devices. Furthermore, the human actions and gestures are discussed to demonstrate the design of mechanical energy harvesting. The analysis suggests a capable prospect for the use of piezoelectric for health monitoring sensors. On the other hand, in this research article, Big Data analytics are incorporated with smart health the real-time data processing and decision-making in healthcare systems. The proposed architecture is able of real-time data processing, intelligent decision-making and self-contained data collection. In this study, Hadoop is selected as the processing unit for the heterogeneous data collected from different human body sensors. The Hadoop processing is followed by the generation of intelligent decisions.

The remaining paper is arranged as follow: Section 2 describes a bird's eye view in the background of Energy Harvesting in IoT and Big Data Analytics for Healthcare. Section 3 highlights the research issues and challenges. Section 4 gives the detailed description of the proposed architecture. Section 5 provides the analysis and results. Finally, the conclusion is given in Section 6.

2. ENERGY HARVESTING IN IOT AND BIG DATA ANALYTICS FOR HEALTHCARE: A BIRD'S EYE VIEW

The rapid progress of IoT takes away the focus of attention of researchers in the direction of an intelligent architectural design for healthcare. The standard healthcare architecture can offer different advantages to the researchers. Also, a variety of research methods related to IoT and Big Data analytics from conceptual to an absolute set of operations are being covered by the IoT and Big data in healthcare. In recent times, research groups are working on developing a different solution to describe the general structural design for healthcare based on IoT and Big Data analytics.

2.1. Why the Internet of Things Needs Energy Harvesting

The Internet connections expected to be attached to sensors, embedded systems, instruments, controllers, cameras, vehicles, wearable electronics, and other objects. These objects are mostly wireless sensor-based terminals that a lot of them are relatively small. These stand-alone IoT nodes are powered using batteries mostly, but batteries are not an effective solution to fit a battery into a tiny package. Hence, providing the power needed to keep all these sensors carrying out functions for their expected lifetime was a key player that could potentially short-circuit the IoT. Therefore, engineers have been working to hunt energy from the IoT node's environment. The primary term for this cluster of hunter technologies is called Energy Harvesting. This is not to declare that there is no exercise for a battery in these systems. Once the ambient energy is collected, it must be then stored to provide the required current at a time when: 1) it is needed (IoT nodes have low duty cycles, that is, a sensor taking periodic air temperature samples might only be active a few milliseconds per hour and can be in sleep mode the rest of the time) or 2) when the source of energy is not available (the sun's rays, for example, are not present at night). Conventional rechargeable coin cell batteries can be used in this manner and so can thin film rechargeable solid-state batteries as well as supercapacitors.

2.2. Energy Harvesting

Energy harvesting is the process that is used to derive energy from external sources that are solar, thermal, wind energy, ambient electromagnetic energy, kinetic energy, motion and so forth. Energy harvesting techniques use power generating elements to convert light (solar), heat (thermoelectric), vibration (piezoelectric), or RF energy (such as that emitted from cell phone towers) into electricity in a stable manner and without lots of loss. The working principles and application fields of energy harvesting is shown in Fig 1. Special circuits are designed for wireless nodes with energy harvesting [15]. The energy harvester is used to capture and store the energy to power the small wireless autonomous devices, for instance, in wearable electronics and wireless sensor networks. These technologies play a vital role in IoT, M2M communication system, and wearable biomonitoring systems [16].

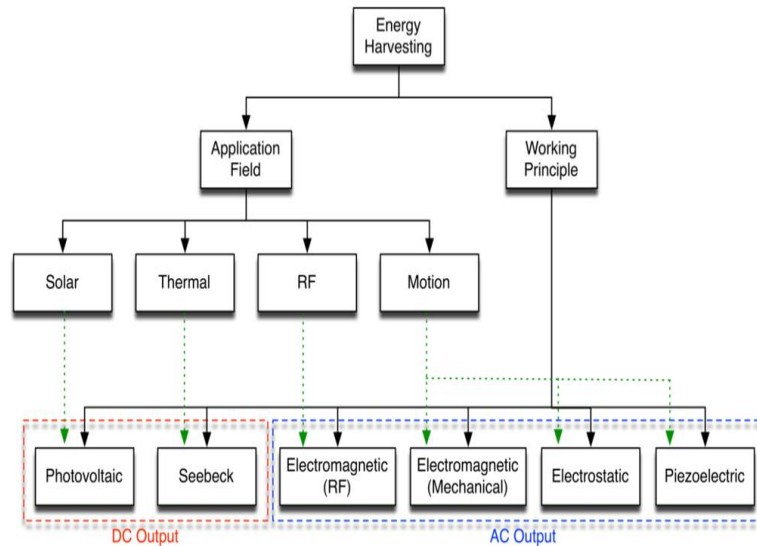


Fig. 1. Energy harvesting

2.3. Piezoelectricity

The capability of certain resources to produce an alternating current (AC voltage) based on some mechanical stress pressure or vibration is called Piezoelectricity. A piezoelectric word derived from Greek word “piezo” means to press, pinch or squeeze, and “Piezo” means push. When the piezoelectric device (material) is placed under mechanical pressure or stress, a shifting of the negative and positive charge centers in the instrument occurs, resulting in an exterior electrical field. Piezoelectricity is one of the non-conventional energy harvesting methods based on vibration, motion or pressure. This energy is renewable, low cost, and pollution free. The Piezoelectric transducers generate electric power if they have been stressed [17]. The fundamental principle of piezoelectric effect is shown in Fig 2. When a mechanical stress or force is applied to a quartz crystal, then it produces electrical charges on the surface of quartz crystal and vice versa [19-20]. The quantity of charge is directly proportional to the amount of stress. Some of the materials which produce piezoelectricity are a quartz crystal, Rochelle salt, barium titanate which can be embedded in the IoT devices.

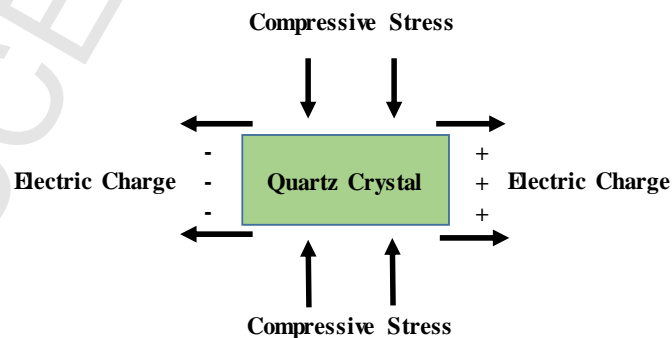


Fig. 2. Principle of piezoelectric effect

The energy generated can be calculated from the following equations.

$$E = \frac{1}{2} CV^2$$

This equation represents the energy stored in capacitors. Where E is the energy stored in the capacitor, C is the capacitance and V are voltage measured across the capacitor. If the units of voltage V are volts, then the units of energy E is joules. Energy generated for each tap on the piezo element has been calculated equation given below.

$$E = \frac{1}{2} CV_1^2 - V_0$$

Where V_0 is the voltage before tap and V_1 is voltage after a tap on the piezoelectric element. By growing the crystal surfaces and the force, more power can be derivation applications comprises of the things including sensor nodes which would be controlled by some microcontroller embedded devices. These IoT devices consume very less power and the power generated by piezoelectric transducers is enough.

2.4. Big Data Analytics in Healthcare

The health-related data is formed and collected uninterruptedly resulting in an implausible volume of data. Data is collected in real-time and at a quick stride, or velocity. The continuous stream of new-fangled data collecting at unparalleled rates that present novel challenges. As the variety and volume of data that is gathered and stockpiled have changed, so the velocity at which it is generated has also changed [21]. This change in velocity is very essential for retrieving, comparing, analyzing, and decision-making. The velocity of rising data increases with data that signifies consistent monitoring that is diabetic glucose measurements on a daily basis and multiple times (or even more incessant control using the insulin pumps), blood pressure (BP) of human body readings, and electrocardiogram (EKG or ECG). In the meantime, in various medical circumstances for patients, continuous real-time data can mean life of the human such as trauma monitoring for BP, working area screens for anesthesia, heart monitors placed at bedside, etc. Also, real-time data application such spotting infections as early as possible, recognizing them quickly and providing the precise actions could decrease patient indisposition and humanity and even thwart hospital outbreaks.

The vast variety of data is an exciting dimension that makes healthcare data challenging. Healthcare requires more effective traditions to combine and renovate varieties of data including automating transformation from structured to unstructured data. In healthcare data assurance or veracity plays a vital role as well which means that the big data, analytics, and results are error-free and reliable. Data quality issues are of serious worry in healthcare for two motives: life or death verdicts depend on accurate information, and the quality of healthcare data is extremely mutable and frequently incorrect. The capability to achieve real-time analytics against such high-volume data in gesture and crossways all specialists would revolutionize healthcare. As the nature of health data has advanced, so too have analytics techniques mounted up to the multifaceted and sophisticated analytics necessary to accommodate volume, velocity, and variety.

3. OPEN RESEARCH ISSUES AND CHALLENGES

IoT provides the foundation for smart health with the assistance of heterogeneous sensors such as heart beat sensor, temperature sensor, glucometer, and so forth. The key obligation for IoT is the capability to put the sensor in all types of spots to collect data. But there is a big issue that is the power supply or, the life of the battery or the time phase for battery substitution. Similarly, The IoT devices supply massive amounts of data that can be analyzed by the techniques of Big Data analytics and provide an open and user driven echo system. Big data analysis is applied to large datasets to reveal hidden patterns and correlations for efficient decision-making. The major issues and challenges faced by IoT devices and data analysis are highlighted below.

3.1. Challenges in Powering IoT Things

In IoT application many of things or wireless terminals have been interconnected; therefore, providing and managing power to these nodes using batteries is a complex task. The following are the challenges for powering the IoT terminal nodes.

- **Limited Energy Resources:** The significant energy resource for IoT devices are batteries which can be classified into two classes such as primary and secondary. The primary batteries are not rechargeable, and their energy is limited, and it is not recommended to use for billions of IoT things. The batteries of the second type are rechargeable, and most of the IoT devices have been powered by rechargeable batteries since these are cost effective and flexible. The rechargeable batteries are Nickel-metal Hydride, Nickel Cadmium, and Lithium cobalt oxide. The IoT application nodes require continuous power supply so that batteries must be charged continuously. This is an enormous challenge with rechargeable batteries.
- **Replacement:** The primary batteries have been used in portable nodes, where there is no chance of recharge. These batteries need to be replaced when their power is a drain. It interrupts the continuous data supply for some IoT applications [16].
- **Ecological Limitations:** The applications like satellite monitoring system use the batteries which are neither replaced nor recharged by humans. The energy harvesting devices play a significant role such requests, for instance, solar energy is being used in a satellite system.
- **Environmental Risk:** Deploying the large scaled applications with WSN (Wireless Sensor Networks) requires scores of the battery to operate wireless sensors, which cause a serious environmental risk with the disposable hundreds of batteries every day [18].

3.2. Challenges in Big Data for Healthcare

A smart health is a new proposal to switch the conventional mode of health services to the smart and well-groomed approach. This exchange is going to be a very exigent and hard because there is no straightforward prescription to fabricate a flourishing smart health. Big Data analytics entails several diverse stages including data recording and acquisition, data cleaning, data integration, data aggregation, data querying, data representation, and data analysis. Every one of the mentioned phases brings in issues challenges which are highlighted below.

- **Data Aggregation:** The data need to be aggregated properly as it comes from some diverse and heterogeneous sources and brings the complexity.
- **Data Format:** Data is in the shape of diverse types, format, representation, and semantic.
- **Incompleteness:** Incomplete data refers to the missing of data field values, and undersupplied data engenders reservations through analysis.
- **Timeliness:** Since the quantity to be processed augments, it will grasp the additional time to examine the data, and in different situations, instant results are required.
- **Scaling:** Organization the massive and speedily rising amount of data is a complicated issue.
- **Normalization:** Data gathering is typically slackly controlled, resulting in the values out-of-range (e-g., patient heart rate -10 Celsius), and unreasonable data incorporation (e-g., patient-sex: male, pregnant: yes). Consequently, the results could be misleading
- **Noise Removal:** Partition of the precious data and noise is a challenging issue. The data value is defined based on the context of the service domain.
- **Queuing:** An immediate response to carry on the processing direct to stop and hindrance in the processing. It is significant to evade the close and wait during processing.

4. PROPOSED SYSTEM ARCHITECTURE

The proposed energy harvesting based smart health architecture is a layered architecture which is composed of three different layers: (1) energy harvesting and data generation layer, (2) data pre-processing layer, and (3) data processing and application layer. An overview of the proposed architecture is given below.

4.1. Overview

An overview of the proposed architecture is provided in this section before giving the detailed description. The objective of this architecture is twofold: (1) conceptual framework for energy harvesting for health monitoring

sensors, and (2) data processing and decision management for healthcare. The energy harvesting is based on the piezoelectric effect produced by human body vibration or pressure while the big data processing is carried out using Hadoop processing based on MapReduce mechanism. The overview of the proposed architecture is given in Fig 3.

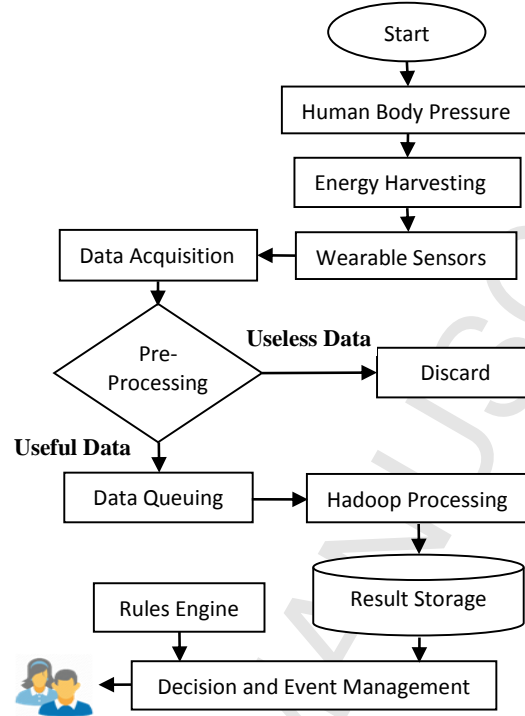


Fig. 3. Overview of proposed architecture

The piezoelectric devices can be attached to human body parts. The pressure area causes the piezoelectric devices to produce the piezoelectric effect which resulting in the generation of electric energy. This energy is supplied to the wearable health monitoring sensors implanted on the human body. Data acquisition systems are used to acquire the data from different sensors. To devise efficient smart health architecture, the data should be carefully inspected and analyzed, therefore, preprocessing is performed to aggregate, transform, clean, and filter the data. The useful data is sent to the queue for further processing while other data which is not useful is discarded. After pre-processing, the data is processed using Hadoop two nodes' cluster, and the processed data is stored and maintained using distributed storing mechanisms such as HDFS. Also, the rules engine is maintained by setting various threshold limit values (TLVs) and defining different rules, based on which the dataset is evaluated. Lastly, the processed data and rules are used for the decision making and event management to notify the corresponding user. In this paper, architecture is proposed that incorporates and realize the Big Data analytics into smart health planning. The principal aim of this study is to utilize realistic, smart health structure to improve the data processing efficacy to facilitate real-time decision-making. Moreover, the analysis of the energy harvesting for health monitoring sensors is also given to overcome the powering challenges. Furthermore, the proposed scheme is not a conventional Big Data embedded smart health as it acts upon different other filters and algorithms.

4.2. Proposed Architecture

The proposed architecture is a layered architecture which is comprised of three different layers: (1) energy harvesting and data generation layer, (2) data pre-processing layer, and (3) data processing and application layer as shown in Fig 4. The exhaustive explanation of each layer of is given below.

4.2.1. Energy Harvesting and Data Generation Layer

Energy Harvesting and Data Generation is the bottom most layer of proposed architecture. The comprehensive analysis and utilization of energy harvesting integrated with the health monitoring wearable devices is discussed in this layer. It is worth mentioning here that this is a virtual layer. It shows the importance and need of the energy

harvesting in IoT particularly in health monitoring sensors which are required to be functional 24/7 with zero tolerance of maintenance. The piezoelectric devices can be attached to different human body parts which are certain pressure areas. The pressure areas cause the piezoelectric devices to produce the piezoelectric effect which resulting in the generation of electric energy. This energy is supplied to the wearable health monitoring sensors implanted in the human body shown in Fig 5.

There are many of human gestures to derive the energy using piezoelectric effect. Each human action and human gesture can produce a different type of pressure areas to generate the energy. The human actions and its corresponding pressure areas are discussed below and shown in Table 1 with proper gestures.

- **SITTING**-Pressure area: lower portion of the whole body
- **WALKING**-Pressure area: shoe soles, legs movement, hands, shoulders
- **SLEEPING**-Pressure area: back side of the whole body
- **RUNNING**-Pressure area: shoe soles, legs movement, hands, shoulders
- **CYCLING**-Pressure area: foot, legs movement, hands, shoulders
- **DRIVING**-Pressure area: palms, hands, foot
- **CARRYING**-Pressure area: palms, hands, foot
- **TYPING**-Pressure area: hands, palms, finger tips
- **SPORTS**-Pressure area: whole body area
- **EXERCISE**-Pressure area: whole body area
- **RELAXING**-Pressure area: lower portion of whole body
- **LABOUR**-Pressure area: palms, shoes soles, hands, legs, shoulders
- **CARRYING BACKPACK**-Pressure area: back, shoulders

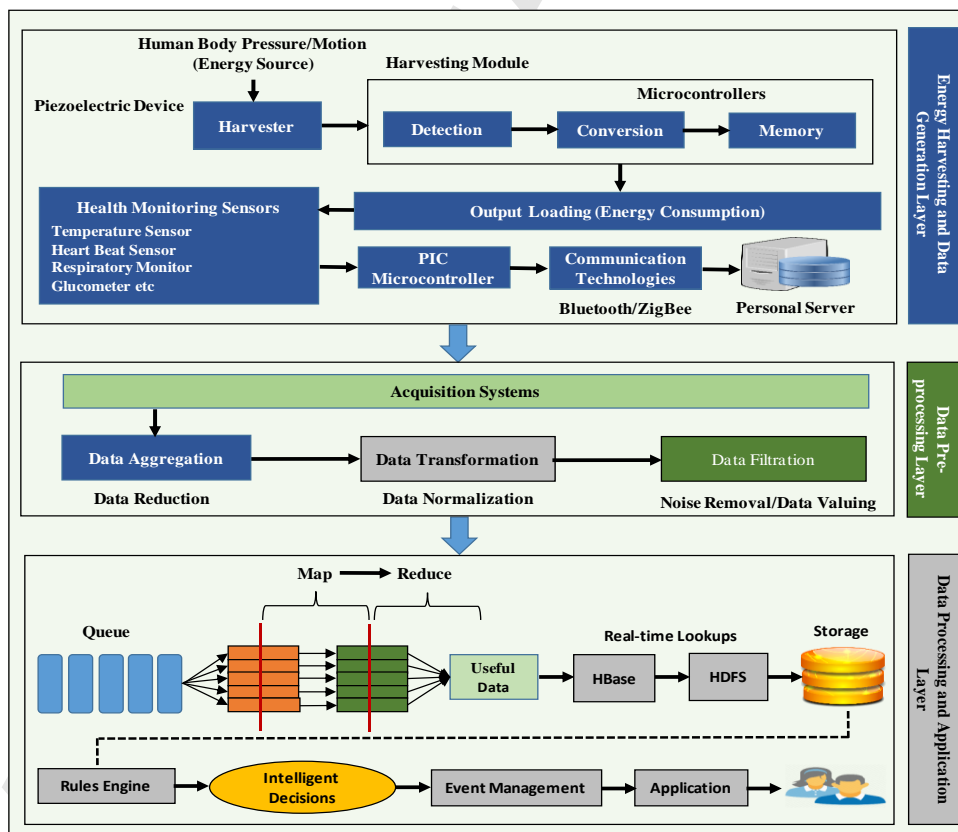


Fig. 4. Proposed System Architecture

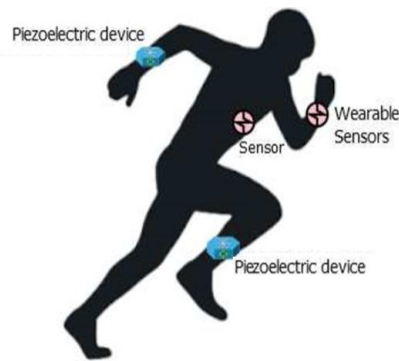













Fig. 5. Piezoelectric devices embedded with human body

The human body pressure is supplied to the harvester (piezoelectric device) to produce energy. The harvesting module, which is responsible for harvesting, detects the pressure (piezoelectric effect) and converts the mechanical energy to electric energy using various microcontrollers. Later, the energy is stored and maintained in the memory used for harvesting. Once the energy is stored, it is loaded (consumed) to the various health monitoring sensors. With the help of microcontroller and communication technologies, the data generated from sensors is stored in the personal storage embedded with the sensors.

Table 1. Human Body Energy Sources

| Human Action | Gesture | Pressure Area |
|-------------------|---|--|
| Sitting |  | Lower portion of the whole body |
| Walking |  | Shoe Soles, Legs movement, Hands, Shoulders |
| Sleeping |  | Back side of whole body |
| Carrying Backpack |  | Back, Shoulders |
| Running |  | Shoes soles, Legs movement, Hands, Shoulders |
| Cycling |  | Foot, Legs movement, Hands, Shoulders |
| Driving |  | Palms, Hands, Foot |
| Carrying |  | Palms, Hands, Foot |
| Typing |  | Hands, Palms, Finger tips |
| Sports |  | Whole body area |
| Exercise |  | Whole body area |

| | | |
|----------|---|--|
| Relaxing |  | Lower portion of the whole body |
| Labor |  | Palms, Shoes soles, Hands, Legs, Shoulders |

4.2.2. Data Pre-processing Layer

Today's real-world Big Data are extremely susceptible to inconsistencies, missing values, different formats, and noise due to their characteristically massive size and their prospective origin from multiple, heterogeneous sources. The low-quality data will lead to low-quality processing results. Data processing methods, when applied before the actual processing, can noticeably improve the overall quality of the data processing and the time required for the actual processing. The proposed architecture includes the data aggregation, data transformation, and data filtration pre-processing techniques.

Data Aggregation: The data aggregation is used for data reduction. Sophisticated data analysis and processing on massive amounts of data can take a long time, making such analysis impractical or infeasible. Therefore, data reduction techniques can be applied to obtain a reduced representation of the data set that is much smaller in volume, yet carefully maintains the integrity of the original data. That is, processing on the reduced data set should be more efficient yet produce the same (or almost the same) analytical results.

Data Transformation: In data transformation, the data are transformed or consolidated into forms appropriate for mining. Min-Max Normalization technique is used to process the data by scaling the data to a particular certain and small range. Min-Max Normalization is used to change a particular value M to another value N in the particular range $[x-y]$

$$N = \frac{M - X_{min}}{M_{max} - X_{min}} * (y - x) + x$$

Where M is the value to be normalized, M_{min} is a minimum value, M_{max} is a maximum value, y is the upper limit, and x is the lower limit. The algorithm 1 is used for the said purpose

Algorithm 1: Normalization using Min-Max

Min-Max Normalization

```

BEGIN:
Input: = dataset
    Max value of dataset
    Min value of dataset
Output: = transformed value
1. Set the x, y
2. Identify  $M_{max}, M_{min}$ 
3. For each datum do

```

$$N = \frac{M - M_{min}}{M_{max} - M_{min}} * (y - x) + x$$

```

END

```

Data Filtration: Data in the real world's dirty which means lots of potentially incorrect data is observed in the real data. The purpose of filtration is to remove noise, inconsistencies, and incompletes. The noise may include data which is not valuable does not affect the real-time processing. Inconsistencies are discrepancies in data, where, incomplete data means lacking attribute values or certain characteristics of interest. The KF is the most advantageous filter that eliminates such noise from the data.

4.2.3. Data Processing and Application Layer

Data Processing and Application Layer is responsible for the overall processing and decision making. This layer includes the following units; the queue, Hadoop server, storage, rules engine, and decision and event management unit.

Queuing process offers a way that places data unit on top of queue that does not require a prompt response to performing the processing. The purpose of the queue is to evade halt and interruption in the processing. The queue works in a way that the queue receives the D data item at a time and then forwarded to the following element accordingly. The queuing processing is handled by a handler H shown in Fig 6. The M/M/1 queuing model is applied in the proposed queuing architecture due to its effective functioning.

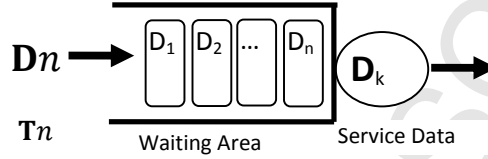


Fig. 6. Queue working

Hadoop server is responsible for the core processing. This unit is the major unit of processing in the proposed architecture that carries data in one server form. The Hadoop server is used to process and store massive data sets in distributed form. Hadoop can make it possible to execute requests with thousands of nodes, and to hold thousands of terabytes of data, where rapid data transfer rates among nodes are being facilitated. The Hadoop server uses MapReduce technique for analyzing the data which performs processing in two stages, first is he processes of mapping where the data is transformed to another set of data. Then, the Reduce process which combines the mapped data and results. Each distinct data item of datasets is taken and produced the results like:

$$\sum_{i=1}^n MN_i \Rightarrow \sum_{i=1}^n DN_i$$

The storage device is planned to stockpile the processed results which are used for decision-making in the later stage. The data storage plays a vigorous role in the healthcare data analytics. Therefore, the proposed architecture makes use of the following storage techniques, that is, HDFS and HBASE to make possible the data storing easily. The HDFS is the core storage of Hadoop, and it supplements the MapReduce implementation on smaller subsets of a larger data cluster since the storage of HDFS is distributed. Moreover, the HDFS simplifies the scalability requirement of the Big Data processing. Similarly, HBASE is utilized to improve the processing speed on Hadoop as it offers real-time lookups enhances the usability and the fault tolerance.

The rules engine is used to maintain the various rules and thresholds defined for evaluation of processed data. The threshold is a precise value denoted by TLV (Threshold Limit Value). TLVs are defined based on data such as body temperature TLV for the alarming high temperature of human body. Likewise, several rules are defined. The rules are TLV based if/then statements which are used for decision making and event management. The rules definition approach is given as Algorithm 2.

Algorithm 2: Rules Definition using IF/THEN

```

Rules Definition
BEGIN:
  IF Temp > TLV
    High Temperature ()
    // and so forth
END

```

Decision and event management unit are responsible for making intelligent decision generating and communicating events based on intelligent decisions to the corresponding citizens. It classifies the events and generates the decisions. It is the mediator between the proposed system and the end user. The intelligent decisions describe the decision per ontology that is used to unicast the events and the corresponding departments or user distinguish high-level and low-level events. The high-level events are stored at the departmental level and are forwarded in unicast to the recipients, whereas the low-level events are not moved further. The subservience events layer generates the respective event and transmits to the embedded notification component. Fig 6 represents the

layered structure of the event generation which includes departmental, services and subservience level. The self-directed decisions are unicasted to the separation unit, where the proper separation is performed, and the decisions are sent to the corresponding user.

5. IMPLEMENTATION ANALYSIS AND RESULTS

The section describes the comprehensive analyses on results found using proposed scheme. Analyses are carried out on diverse datasets, which are collected from varied reliable sources to assess the proposed architecture. The proposed architecture of pre-processing and processing exclusively depends on the processing of the former data that is collected from diverse sources. Initially, the data is fuzzy including raw data. Therefore, we perform pre-processing on top of Hadoop processing. Hence, notable optimization of the processing in the context of time and efficacy of Hadoop is realized. Furthermore, the pre-processing assists in processing the real-world data with less time.

5.1. Implementation Detail and Data Sources

The proposed system is implemented at Apache Hadoop with MapReduce Java programming on a single-node Hadoop setup. In mapping, the series file offset is taken as a key, and the values (heart) are taken as the parameter value. Also, the datasets are acquired from different reliable and valid sources which are explicitly accessible and authenticated. The datasets include the medical datasets, such as rate of heartbeat corresponding to various activities, and ECG corresponding to various activities [23-25]. On the whole, greater than 2 GB data is examined. Where, heartbeat dataset has 54 attributes, and ECG dataset has 24 attributes for every record.

5.2 Analysis Findings and Discussion

The heartbeat rate dataset includes the reading of heartbeat rate of three different patients while doing different activities like computer work, driving, cleaning, and playing soccer. Furthermore, the heartbeat rate of ICU patient is also examined containing a few serious readings to take emergency action. Cleaning and computer work are not a hard task to do. Therefore, the lower heartbeat rate is found. In contrast, playing soccer and driving are a bit tough tasks, so it requires more hard work and the user's heartbeat rate was more other work. Also, heartbeat rate progressively increased while playing the game as the user has more pressure. The system measures these heartbeat rates and produces an event when the rate exceeds normal TLV. When the rate goes beyond the serious TLV, then some emergency action is required. The TLVs are measured based users' age and the corresponding tasks they performed. The overall heartbeat rate is shown in Fig 7.

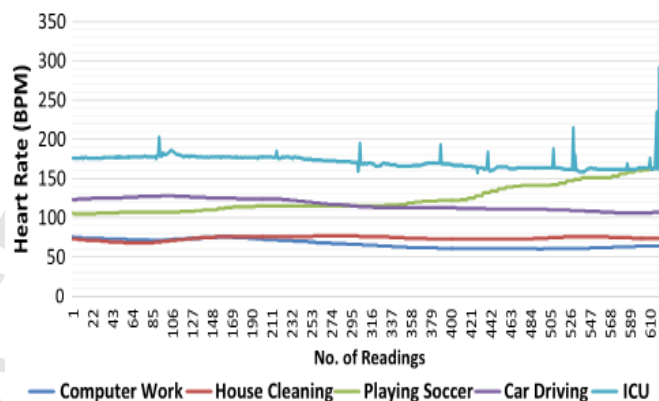


Fig. 7. Heartbeat rate of various patient

Similarly, the ECG is also measured to have user's heart monitoring shown in Fig 8. Likewise, heartbeat rate, the ECG is also analyzed and measured for various activities, such as standing, walking, sitting, jogging, cycling, etc.

During physical movements, such as cycling and jogging, the readings have extra jumps comparing with other activities.



Fig. 8. ECG of a patient while performing various activities.

We verified the proposed architecture about the efficiency and the time consumed to process large datasets. It is shown that the effectiveness of the proposed system is radically increased as compared to the existing system. We consider ECG dataset of size 227 MB, temperature dataset of size 118 MB, and heartbeat rate dataset of 1.7 GB with some attributes [25-28]. To assess the effectiveness of the proposed work, we consider the throughput and processing time, where, throughput is computed in a millisecond (ms) and processing time is computed in seconds (s) with the size. The throughput and treatment time for various datasets are revealed in Fig 9. Furthermore, different datasets of various sizes (from smaller to a larger size), are also tested using proposed system. It is observed that the overall throughput is reduced when the size of data sets is increased. This phenomenon is shown in Fig 10.

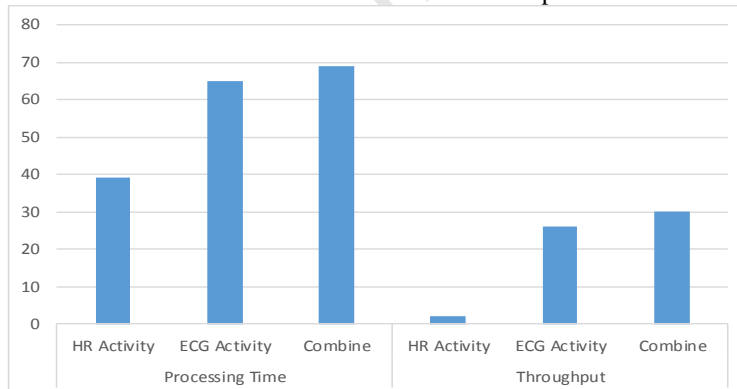


Fig. 9. Efficiency of proposed architecture

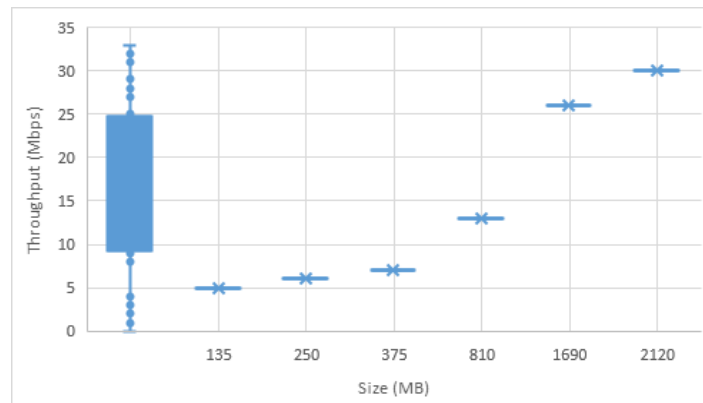


Fig. 10. Throughput of the proposed system

6. CONCLUSION AND FUTURE WORK

The notion of “health care” is believed by the widespread growth of IoT which influenced the researcher that the healthcare to be well-groomed. Though, the anxiety of healthcare is still suspicious, given the fact that the insurgency of the conventional health monitoring functions includes novelty in IoT end terminals, the ability of processing of massive data, and the networking. Therefore, the businesses and geniuses are very much keen in shaping the underpinning architecture practical healthcare. In this paper, an efficient smart health monitoring architecture is proposed using Big Data analytics. Smart decision and event management is the foremost purpose of this research. Framework for energy harvesting in IoT is proposed. The comprehensive analysis and discussion are carried out about the energy harvesting using piezoelectricity for health monitoring sensors. The Big Data analytics is performed using the Hadoop server with MapReduce mechanism. A variety of datasets is examined, evaluated, analyzed and tested, based on which it is shown that how healthcare can be performed using Big Data. Nevertheless, the proposed scheme does not reflect a generic way out; it is deliberated for explicit objectives. Furthermore, the proposed work can be extended in future.

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Authors Autobiography



Sadia Din is doing here Master's combined PhD program in Kyungpook National University since 2016 September. Her area of research is 5G networks and IoT enabled Green communication. She has published few conference paper and some journal work at the beginning of her research career.

Anand Paul



received the Ph.D. degree in Electrical Engineering from the National Cheng Kung University, Tainan, Taiwan, in 2010. He is currently working as an Associate Professor in the School of Computer Science and Engineering, Kyungpook National University, South Korea. He is a delegate representing South Korea for M2M focus group and for MPEG. His research interests include Algorithm and Architecture Reconfigurable Embedded Computing. He is IEEE Senior member and has guest edited various international journals and he is also part of Editorial Team for Journal of Platform Technology, ACM Applied Computing review and Cyber-Physical Systems (Taylor and Francis). He serves as a reviewer for various IEEE /IET/Springer and Elsevier journals. He is the track chair for Smart human computer interaction in ACM SAC 2014-2018. He was the recipient of the Outstanding International Student Scholarship award in 2004–2010, the Best Paper Award in National Computer Symposium and in 2009, and International Conference on Softcomputing and Network Security, India in 2015.

Highlights

- Smart Health Monitoring and Management Systems
 - Autonomous Wearable Sensing for IoT
 - Data Processing and Data Management for Healthcare in Big Data Analytics
 - Energy Harvesting, Data generation and Data processing architectures
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