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M-Caemon: Modified Cloud Access Execution and Monitoring for Big Data Analytics of Health Sensor System

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Abstract

This paper aims to design and implement a flexible architectural system to analyze and access the heath sensor data with converging technologies such as Body Sensor Networks, IoT, Cloud computing and Big Data analytics. The available cloud resources enable the Body Sensor Networks to store and analyze the vast amount of data produced by them. Body Sensor Cloud is designed using IoT technology. Body Sensor Cloud operates as a facilitator for Big body sensor Data analytics. In the current application these four techniques formed as the convincing combination. Hadoop Distributed File Systems (HDFS) is proposed to be employed to store the body sensor data on to sensor cloud for further analysis. The analytics is carried out using machine learning approach on top of the MapReduce technique. This paper describes a public sensor cloud delivery model through cloud data analytics for body sensor services. The proposed architecture acts as a Modified Cloud Access Execution and Monitoring environment for body sensor systems and is able to retort to the demanded health sensor client applications (Physician) with greater flexibility.

Keywords: BSN; Big sensor Data; Cloud; HDFS; IoT; Machine Learning.

Introduction

We live in a digital environment with data spawned by organizations, health institutions, persons and equipments at a very high rate. These data are treated as "Big Data" [1] owing to their complete Volume, Variety, Velocity and Veracity. These data are heterogeneous in nature and they are classified as unstructured, quasi structured or semi structured. The present computing infrastructure requires a strategy to manage the degree and the variety of data with the speediness it is generated. In health care ambience, because of the diversity of bio sensors and health monitoring devices, the data collected from patients also have extensive distinctions. A data element in these health care environment could vary from a few bytes of numerical value (e.g. HR = 72 bpm) to several gigabytes of video stream [2].Since the data generated by variety of body sensor networks which arrive from different heath institutes would fall in Big Data, this research work is carried out to propose a flexible architectural system to manage this data efficiently by incorporating this big body sensor Data with Cloud through IoT. The diverse data formats from different body sensor networks are characterized as unstructured data [3] and are converted into a unified data format - xml, which is branded as semi structured data. This conversion is essential to integrate body sensor data to cloud. In this work four converging technologies are proposed to be used, hence xml is preferred for building the proposed flexible architectural system.

Owing to the explicit character of Big Data in Body Sensor system, it is planned to be stored up in distributed file system architectures. Inside the Hadoop framework, HDFS along with MapReduce [4] is widely used for accumulating and administering the Big body sensor Data. HDFS is a file system designed for storing very large files with streaming data access patterns such as health sensor system proposed. In this paper, it is proposed to use body sensor log files stored as HDFS in cloud and map reduced for parallel analysis. Presently, three common machine-learning use cases are supported by Mahout. They are incorporated in this proposed research: patient-based recommendations, where patient data is mined using known physician preferences and behaviors are used to predict new preferences for both patient and physician; clustering looks for similarities between patient data points, using a physician-specified metric, to identify clusters in the patient data (groups of points that appear more similar to each other than to members of other groups); classification applies discrete labels to patient data or predicts a continuous value (e.g., a body sensor output value) based on previous examples of similar patient data. The paper [5] which is our previous work called CAEMON (Cloud Access Execution and MONitoring) described an industrial sensor system based on SOA extended to Cloud based big data analytics. The proposed system is Modified CAEMON. The modification here is body sensors information is obtained through IoT and it is further deployed to cloud for big data analytics using machine learning techniques. Here, cloud is a long running background process that answers requests for body sensor services and hence it is named as modified CAEMON.

State of the Art

The health care services are provided by Pervasive healthcare [7], which offers healthcare services to individuals anytime-anywhere, has got a main focal point in the research alliances. A paper survey [8] the advances in IoT-based health care technologies. It provides reviews for state-of-the-art network architectures, platforms, applications, and trends in IoT-based health care solutions. A summary of [9] different bio marker is also given an article.

Body Sensor Networks (BSNs) [10] are developed with the help of Latest advances in miniaturized sensors, low-power electronics and wireless communications. These networks consist of intellectual communicating nodes, which are dedicated to the healthcare examination to notice and correct health problems. Wearable bio sensor system [11] is evaluated for health monitoring.

The Health Catalyst includes a Microsoft APS Appliance and a huge health system client to generate an extremely parallel data warehouse. This comprises of the Hortonworks Hadoop Cluster. From this it is concluded that a big data cluster and a traditional relational database could be run in parallel. The data processing power is increased appreciably by querying both data stores concurrently.

The big data are subjected to experimentation by performing Natural Language Processing with medical notes of the doctors in Health Catalyst. Thus the big data processing in health care is slowly migrating from Symmetric Multi Processing (SMP) to Massively Parallel Processing (MPP).

Today, health care is undergoing three stages of automation through computer throughout the world and the health care data are managed by collecting the data, sharing data and analytics of health care data. Since health care is moving to data analytics stage [13] which would be exemplified by embracing the enterprise data warehouses (EDW), which has now become tantamount with the term "Big Data." The recordings of the devastating failure rate of health data interactions due to indefensible economic models are also available.

Hadoop has been called the most significant data processing platform for big data analytics in health care. IoT analytics site could be used to analyze the data sent from IoT agent. REST (Representational State Transfer)-ful web service interface would used by the client. In the present big data distributions in health care, many challenges have yet to be addressed such as technical proficiency essential to use it and the deficiencies in robust, integrated security. Hadoop is a popular open source software framework that stores large unstructured data (HDFS) and processes (MapReduce) the unstructured data and allows the distributed processing of large scale data sets [17]. Large scale data processing frameworks like MapReduce[18] have been integrated with cloud to provide powerful computation capability for applications. HDFS is the underlying file system of Hadoop.

In recent years, a significant amount of research and commercial activity has focused on integrating MapReduce and structured database technologies [19]. With fully connected multi-layer network, the data–level parallelism [20] is performed, concerning the communication cost. A Multiple Query Optimization framework, SharedHive [21] to improve the overall performance of Hadoop Hive, an open source SQL-based data warehouse using MapReduce is proposed.

Proposed System

It is proposed to converge four promising technologies to achieve a flexible architecture, which enables the body sensor system client to access and analyze the body sensor data. Figure 1 shows the overall architecture with heterogeneous body sensors, connected with IoT and Cloud integration of these body sensor data. One could arrive at a relevant data by analyzing the vast amount of body sensor data after mapping it as a distributed file system through Big Data analytics using the Hadoop framework in the cloud. These deployed body sensor data are also subjected to machine learning approach such as prediction analysis; clustering of body sensor data; and classification of body sensor data.

The body Sensors produce physical quantities such as temperature, blood pressure, endoscopy output which are unstructured data. These are converted into semi structured data such as XML, which is essential for the proposed deployment in the Cloud. With appropriate APIs they are mapped onto the cloud servers. The Cloud acts as a backbone system which integrates body Sensors obtained from IoT and Big-Data environment to analyze the body sensor data.

In this architecture, the situation takes any high level user-specific information [22] obtained directly or inferred from raw body sensor data. Usually the aggregated situations are sent to a monitoring centre (e.g. physician, nurse, hospital) for decision making about the patient's condition. To achieve the aim, one step further is taken by incorporating patient-specific intelligence that constantly learns from collected patient data and interprets new incoming patient data using that gained knowledge just as a medical expert would. This also allows doctors to make decisions with greater knowledge and to monitor chronic deterioration in a patient's condition. The identification of a patient's abnormal condition can warn the patient by activating a local device (e.g. reminder in mobile), or send an emergency message to the monitoring centre. Overall, our innovative machine learning technique on a massive volume of situation data enables reliable classification of a patient's situation for qualitative remote monitoring support, using the advantage of cloud computing. There is also a competence to connect the mobile phone directly to IoT agent through GPIO pins, the physician's mobile phone could be used to collect health data of a particular patient. Appropriate medical administration could be prearranged in case of critical health condition is detected. This leads to health care management system.

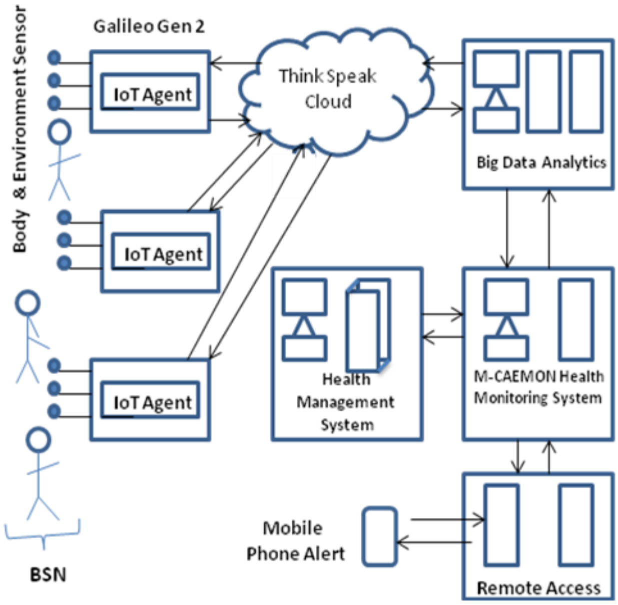

Figure 1: IoT based Health care monitoring and Management Architecture

The IoT based cloud big sensor data analytics could be understood by splitting the IoT cloud into five cloud components. The following sections discuss different components of the cloud framework in brief.

Environment Assisted Living (EAL): According to the requirements of the patient, the low level setup of system works. The sensors, devices and software services of each EAL system fabricate unprocessed data that contain low level information of a patient's health status, location, activities, surrounding ambient conditions, device status, etc.

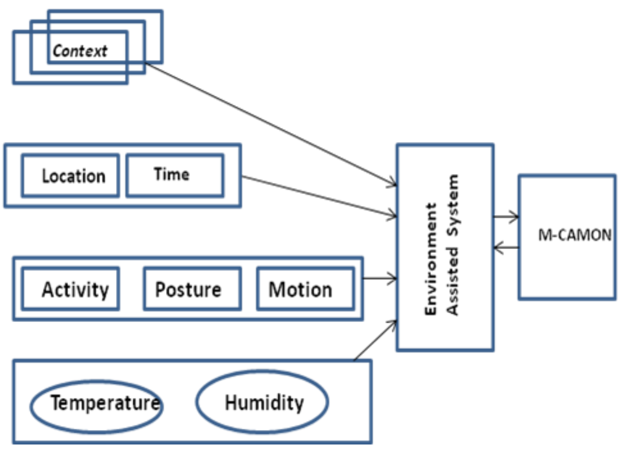

Figure 2: Environment Assisted Living

To learn the daily activity patterns of the patient and the effects of other situations on his/her medical conditions, all data need to be stored and processed. The big data scenario of a single EAL system is shown in Figure 2.

Private Cloud Servers: This stores the patterns and personalized medical rules; Body sensor Data Accumulator and Advancer which collects the body sensor data from IoT in the form of XML.

Situation Monitoring Centre (SMC): consists of a number of distributed cloud servers that hold the big body sensor data. It stores the situation histories of patients. Different machine learning techniques run inside the SMC that infer different personalized and generic rules for various user events. The SMC retains the classifier inside the model to classify new situation. After classifications, the SMC sends suitable warning to the monitoring system. With the help of obtained general behavior, the SMC is also capable of clustering similar groups of patients the same treatment plan could be adopted for them. The data flow scenario of cloud components is shown in Figure 3.

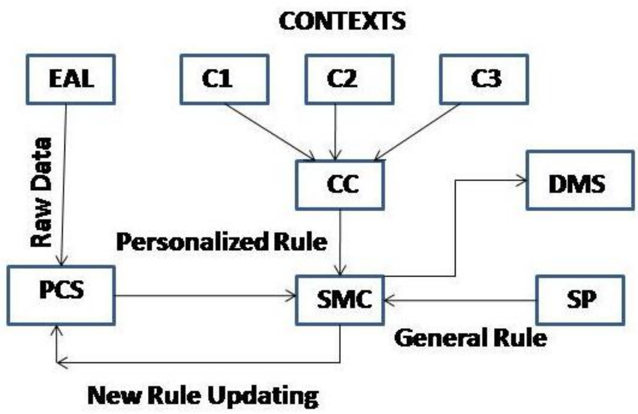

Figure 3: Data flow scenario of cloud components.

Service Providers (SP): In the proposed paper, the service providers are the public cloud servers that maintain the generic medical rules to recognize a variety of diseases and symptoms. The rules of symptoms and abnormal behaviors are constantly updated by medical experts, doctors and other medical service providers. When any new rule is discovered in the SMC it also triggers the change in the SP cloud. The SMC uses rules of SP for data filtering and classification.

Distant Monitoring Systems (DMS): When the SMC discovers any anomalous pattern in the situation for a specific user it sends appropriate notification to the DMS. For example, when the heart beat rate of a patient goes relatively high for a given situation, the SMC alerts the doctor to examine it, but if it goes unusually high then the SMC sends alerts to the emergency centre. Thus, the selection of DMS depends on situation classification. A major goal of our system is to classify a situation correctly to send proper alerts to the right DMS.

Materials and Methods

The proposed health monitoring and management system consists of different Health Monitoring sensor for health care data collection. Blood pressure sensors and heart beat rate sensors are considered in this paper. The Health Monitoring sensors are touched or worn by the patients to sample the physiological signals. In addition, it is possible to capture medical images (Radiology such as ultrasound, magnetic resonance, tomography, and angiography Printed signals and waves such as electro encephalograph, electro Cardiograph and Electromyography, microscopic images) using appropriate cameras interfaced with IoT. Intel Galileo is officially registered device under IBM Internet of Things Foundation. Hence it is chosen for implementation in this proposed research. The sensor values are recorded using the Arduino programming for Intel Galileo Gen2. It is also possible to interface the physical world such as I2C, GPRS/GSM and sensors with IOT proxy (Intel Galileo Gen2).

Efficient processing of the large volume of medical data using computational power of cloud infrastructure, finding the correlations among different situations for inferring knowledge, and prediction of a state using those inferred observations to deliver proper situation-aware services, clustering of data to identify the data groups which are more similar and classification to predict a continuous sensor output value to take critical decisions are considered in this research work. Different modules of the entire process are shown in the following figure 4.

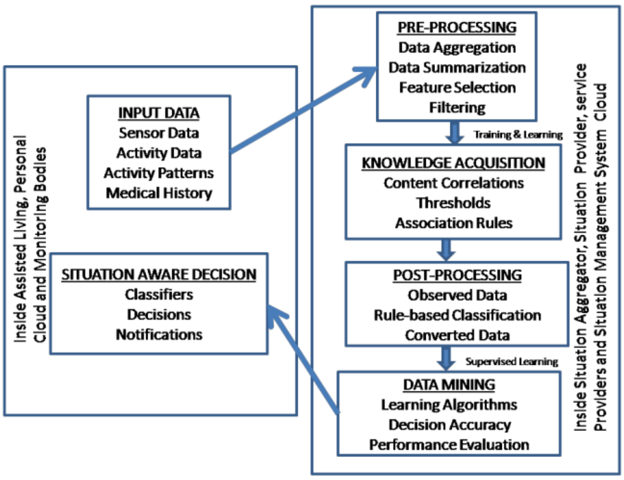

Figure 4: Process of modules

Data collection and situation-aware actions happen inside the EAL system and personal cloud. Situation processing, knowledge acquisition, data mining are performed in distributed cloud components.

Situation conversion: The body sensor data accumulator module runs in the local server that collects the raw data from an EAL system and forwards them to the SA cloud. To make the computation simpler, each situation attribute is converted to an xml file. Some situation attributes already have numeric values (e.g. HR, BP, room temperature).

Situation Aggregation: For a single EAL system, after converting the entire situation attributes to xml described above, the situation information for each of the domain are generated. Then they are converted to a situation state. This is the aggregated information of all situation domains at a specific time of the EAL system. Some attributes have discrete time intervals (e.g. BP measured in time interval t and some have time duration (e.g. activity x starts at ts and end at te). To represent everything in a single time (t) slot, a standard time interval is chosen. That is, a situation state is sampled in interval. Such sampling process satisfies the velocity property of big data for our model, as each situation state is generated and made available using a fixed time interval. A MapReduce process [23]which runs in multiple clusters inside the SA cloud does this aggregation task for every EAL system. Table 2 shows an example dataset that is generated after aggregation step.

Trend Analysis : All generated situation states and situation information are sent to the SMC cloud. The SMC stores those inside its cloud repository. One of the roles of the SMS is to detect the trend in the dataset. Some of the patterns are detected using statistical analysis. For example, by summing up the duration of sleeping activity it is possible to summarize how many hours the user usually sleeps in one night. Using this statistic, the daily mean of sleep hours can be measured say, from the observation of 1 month's data. So, for any new data if there is a large deviation of sleep hours from the mean, then it is considered as less sleep symptom.

Correlations learning and Association Rule Mining: This is the knowledge acquisition phase as shown in Figure 3 and the major part of the learning process of our model. Once m numbers of situation states are gathered in the cloud storage of the SMC for an EAL system, it starts this learning process. In this phase, the associations between situations attributes are measured. To find the correlations among situation attributes and the threshold values of vital parameters, Apriori-based association rule mining approach is adopted. MapReduce version of Apriori [23] is used for this paper which is a more efficient technique for mining association rules from big data that utilizes the computational resource of multiple dedicated clusters of distributed cloud model. In typical MapReduce process there is a Map function that processes a key-value pair to generate a set of intermediate key-value pairs. The reduce function then merges all intermediate values associated with same intermediate keys.

Learning using the Association Rules: After discovering the knowledge of every EAL system, the next step is to verify the validity of this learning process using a new set of big data.

When a new situation state arrives in the SMC cloud, it classifies the state according to the rules and thresholds. When a large number of such instances is available, the SMC uses that big dataset for building a classifier model. The classifier is used for future classification.

Data Mining: The dataset generated in the previous phase is used to build classifiers for EAL system and so any new situation state can be classified accurately and immediately. The dataset is subdivided into training and test set. Different data mining algorithms (e.g. Multi Layer Perceptron, Decision Table, J48 Decision Tree, Radial Basis function, Bayes Network) are applied over training data and the accuracy of classification is obtained using test data. Comparing the accuracies of different classifiers, the SMS picks the best classifier for decision support. The training and classification process run in distributed clusters inside the SMC.

Situation-aware Decision Support: The SMC uses the classifier generated in the data mining step to classify forthcoming situation states and make situation-aware decisions. Based on the classification the SMC performs following actions.

- If a situation is normal then do nothing.
- If a situation is abnormal but not dangerous then sends a warning to the user.
- If any vital situation attribute has abnormal value then send alert to doctor.
- If two or more situation attributes are abnormal or anyone is extremely abnormal then notify to emergency.

A situation state will not always be same. It can change due to the change of a patient's condition or low level sensor setup of the EAL system, etc. So the SMC needs to adapt its behavior every time with these changed situations. The SMC iteratively runs all the phases to become up-to-date with any altered conditions. Being cloud-based model, the SMC has sufficient storage and processing capability to run the whole process iteratively.

Experimental Results

The purposes of this implementation are: (i) discover knowledge of BP and HR changes on different situations [24] for different patients; (ii) find association rules for specific patient situations using a distributed cloud model, and (iii) classify an unknown situation based on the learned model. The continuous BP level of a patient is determined by examining systolic BP (SBP) and diastolic BP (DBP) values in mmHg using a body worn BP sensor, and HR is measured in bpm using the ECG sensor [25]. BP is high during eating [26], [27]. The variations are also common from patient to patient for other factors. The learning process utilizes large historical data of multiple patients and generates personalized knowledge for each patient. The knowledge generation and abnormality detection cases are run in a cloud platform. Some general medical rules [28], [29] for identification of patient situation based on these two vital signs (HR and BP) are described in Table 1. The dataset is generated using MATLAB and stored in multiple files.

Table 1: General medical rules to identify different diseases related to the variation in BP and HR

Category	Heart Rate (bpm)	SysBP (mmHg)	DiaBP (mmHg)
Hypotension	-	90	60
Pre-Hypertension	-	121-139	81-89
Hypertension	-	140	90
Normal	61-100	91-120	61-80

Data taken over 1 year for 3 patients are generated using 15 minutes sampling intervals that results in 35,040 samples per patient. So, the generated data satisfy variety property. The dataset will be very large if millions of patients are considered (instead of 3) and thus it satisfies volume property. A java worker thread is implemented to simulate an EAL system. Multiple threads run in parallel that simulate the scenario of many EAL systems simultaneously send data to the cloud. In our simulated environment, 1 minute is normalized to 1 millisecond (ms). To simulate the velocity of big data, the java worker thread reads one sample of synthetic data from local files every 15 ms and sends it to the Public Cloud Storage. The use of MapReduce techniques in the proposed system for generating rules also satisfies the velocity criteria, as MapReduce has the streaming paradigm that deals with velocity. After data aggregation and trend analysis steps the situation space with 8 situations attributes is obtained. A small part of the generated situation space is shown in Table 2. This data sample is from a hypertensive patient whose average BP is always high.

Table 2: Sample aggregated data of Patient P1 for rule mining

HR	SBP	DBP	Room Temp.	Activity	Last Activity	Medication	Symptom
67	166	83	1	2	5	0	2
79	153	86	0	1	2	1	0
88	143	73	1	3	1	0	1
77	155	91	0	5	4	0	4
82	166	81	0	1	3	1	0
93	111	85	1	5	2	0	16
79	162	86	1	4	2	1	0
81	169	87	1	1	1	0	8
56	114	93	0	2	3	1	0
62	163	101	1	3	5	0	3

To evaluate the sensibility, we compared the situation classification of our model with generalized clinical classification based on medical rules [29]. Table 3 shows the result of such comparison.

Table 3: Comparison of modified CAEMON generated rule-based classifications with generic rule-based classification and BDCaModel

Generic Rules			
Patient	**Total Data**	**Normal**	**Abnormal**
P1	33400	25321	8079
P2	34390	26424	7966
P3	35270	27845	7425

BDCaModel					
Patient	**Total Data**	**Normal**	**Warnings**	**Alert**	**Emergency**
P1	33400	24918	6543	1856	83
P2	34390	24911	7980	1360	139
P3	35270	25420	7220	2509	121

Modified CAEMON architecture					
Patient	**Total Data**	**Normal**	**Warnings**	**Alert**	**Emergency**
P1	33400	25061	6485	1786	68
P2	34390	25122	7912	1244	112
P3	35270	22607	7154	2412	97

In general, the rule is that when SBP and DBP value go above/below a certain threshold (e.g. SBP above 135and DBP below 85 for hypertension) then the situation is classified as abnormal. An emergency state is not identifiable; it is the doctor’s responsibility to manually analyze the values and then make a decision. The term general medical rule is adopted because this is the current manner in which traditional situation-aware [24] systems process vital signs data. In contrast, the system [30] learns these patient-specific thresholds [30] and quickly adapts to new changes. From the results of Table 3, we can summarize that the modified CAEMON architecture performs extremely well to find a true normal situation of a patient. Hence, it can reduce the generation of false alerts at receiver’s end.

The new situation space is tested with different classifiers using 10-fold cross validation. The classification results obtained for 3 patients are presented in Table 4. The accuracy of J48 decision tree classifier is very high in comparison with others because the training data are generated using association rules. To guarantee an unbiased result we tested the dataset with other classifiers. As shown in Table 4, Bayes Network (BN) and Radial Basis Function (RBF) do not have good accuracy. The performance of Multi Layer Perceptron (MLP) is better other than J48 and decision table.

Table 4: Anomaly detection accuracy and false positive rate for 3 different types of patient over 1 year data

Classifier	**Classification Accuracy**			**Avg. False Positive Rate**		
Patient	P1	P2	P3	P1	P2	P3
J48 Decision Tree (J48)	99.12%	98.73%	98.37%	0.003	0	0.005
Decision Table (Dtable)	96.72%	98.18%	96.73%	0.068	0.03	0.062
Multilayer Perceptron (MLP)	92.36%	96.65%	91.37%	0.116	0.024	0.085
Bayes Network (BN)	85.58%	95.41%	87.45%	0.223	0.032	0.170
Radial Basis Function (RBF)	82.42%	83.73%	83.67%	0.324	0.274	0.225

CONCLUSION

A flexible architectural system to analyze the body sensor data with converging technologies such as IoT, body Sensor Networks, Cloud computing and Big Data analytics is implemented and the result analysis are examined. Hadoop Distributed File Systems (HDFS) is implemented to store the streaming body sensor data on to sensor cloud for further analysis using MapReduce technique along with machine learning. Modified CAEMON presents a generalized framework for personalized healthcare, which leverages the advantages of situation-aware computing, remote-monitoring, cloud computing, machine learning and big data. The architecture also simplifies the tasks of healthcare professionals by not inundate them with false alerts. The system can precisely differentiate critical from normal conditions. The data used to validate the proposed system are obtained via data derived from real patients, preserving the correlation of a patient’s vital signs with different activities and symptoms. The stronger relationship between vital signs and situational information will make the generated data more dependable and the system will be more accurate for validation. The experimental evaluation of the system in cloud model for patients having different HR and BP levels has demonstrated that the system can predict correct abnormal conditions in a patient with great accuracy and within a short time when it is properly trained with large samples. This paper described a public sensor cloud delivery model through cloud data analytics for sensor services. The proposed architecture acts as a modified Cloud Access Execution and Monitoring environment for body sensor systems. Further the modified

CAEMON runs constantly in the background and handles all the complexities, and the system is able to react to the requested sensor client applications with simple security credentials such as user name and password. This feature also provides flexibility to the proposed system.

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