A Smart Pain Management System Using Big Data Computing

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Abstract. Pain is a universal experience and there is hardly a human being who has never experienced pain at one time or another. Managing pain is of high priority for healthcare organizations given the increasing incidence of pain among patients and the costs associated with it. The current standards and practices in pain management are limited to mostly manual processes hindering innovations in this area. This paper proposes a smart pain management system based on big data computing technologies. The system devises pain management strategies based on the relevant standards and patients' data, and these strategies are identified, applied, and monitored by the system in real-time. A perpetual feedback loop is created among the system components and the outcomes are communicated to the stakeholders to enable reflections and continuous improvements in the pain management standards, strategies, and processes. The system architecture and its architectural components are described. A preliminary analysis is provided using handwritten and digital pain management related data.

Keywords: Big data computing · Apache spark · HealthCare
Pain management · Numeric Pain Rating Scale (NPRS)
Electronic Health Records (EHRs) · Patients' data

1 Introduction

Generating valuable information was always the idea behind the processing and manipulation of data. In the last many decades we have seen systems that process data to extract valuable information that sometimes is used in real-time to make right decisions. In addition, the expansion of the systems was enormous and this has resulted in the increase of amount of data and also decision making on this data has become problematic. Accordingly, big data technologies emerged to provide analysis on this large quantity and high velocity data sources. Purpose is still the same to generate valuable information and insight into the data to see what is really happening. This information is needed to set the course of actions to produce right results. Many field of science like

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economics, computer science, mathematics, and statistics have contributed in the processes of solving complex data to simplified understandable information.

Applying scientific ways to analyze data require resort to computer sciences as most of the fields like meteorology, social computing, astronomy, computational biology and bioinformatics are heavily dependent on computer sciences. In consequence, there is a number of problems but the most prominent being various resources generating huge volumes data with structures of differing nature [1]. A related example comes from the healthcare data collected in 2012 amounting to 500 petabytes which may rise to 25 exabytes in 2020 [2]. Challenges of the sort require extensive labor for being able to know more from large volumes of data.

There are various sources of data in healthcare sector. Mostly the data comes from physicians' memos, laboratory information, patients' records, Electronic Health Records (EHRs), national health registry, doctors and nurses employed, etc. Data coming from paper and other non-digital resources must be converted to digital form for enabling healthcare service providers to provide top rated health services. The data that is being collected now can be used to do analysis of different problems in healthcare. This data is sometimes too large to be analyzed so we need big data technologies to analyze data.

Analyzing huge data in healthcare is highly important because it helps to improve the level of service provided to patients by suggesting the right remedies thus avoiding any chance of error in diagnostic and prescription while at the same the process is cost effective. Moreover, such analysis can help in early detection of diseases and early prevention. In addition, a major benefit of the process is its use as a tool for quality measurement regarding different organizations and the employees therein [3].

It has been observed that due to high amount of data generated because of unexpected growth in biomedicine and the types of data being generated is not always in relational format; the storage and processing of data obtained is becoming increasingly complex [4]. For this reason, big data analytics are required to deal with enormous amounts of data. The most well-known fields include bioinformatics [5–7], health informatics [8–10], imaging informatics [11, 12], and sensor informatics [13, 14].

A branch of healthcare services is pain management and data being generated by the pain management practices is mostly stored in patient records. The patient records are stored in transactional databases and to analyze the data on a large scale, many databases should be combined to get a large enough database to do analysis of the pain management data. The improvement of the pain management practices depends on the correct analysis of the practices and their results, this combined data is too large and too complex to be placed in a simple database and the analysis has to be done through the tools and techniques used in big data analytics. Such an analysis will help develop technologies based on smart solution criteria to improve pain management through standardized assessment procedures.

This paper proposes a smart pain management system based on big data computing technologies. The standards and practice in pain management are turned by the proposed system into strategies that can be tested and improved in real-time. The system devises pain management strategies based on the relevant standards and patients' data. These strategies are identified, applied, and monitored by the system in real-time. A perpetual feedback loop is created among the system components and the outcomes are communicated to the stakeholders to allow reflections and continuous improvements in the pain management standards, strategies, and processes. The system architecture and its architectural components are described. A preliminary analysis is provided using handwritten and electronic pain management related data.

In Sect. 2 of this paper, we provide background on big data and pain management. In Sect. 3, notable related works on pain management are reviewed. In Sect. 4, we describe the architecture of our proposed smart pain management system. Section 5 provides the results and analysis. Conclusions are drawn in Sect. 6.

2 Background

2.1 Big Data, Big Data Analytics, and Healthcare

Big data has been defined in the literature differently based on the researchers' and practitioners' views of the term. For example, in [15], big data technologies are defined as *"the emerging technologies that are designed to extract value from data having four Vs characteristics; volume, variety, velocity and veracity"*. The definition refers to the four "V" characteristics of big data, which have been referred to widely in the literature.

In simple words, big data is sets of data analysis, management, and realization of which is not possible by conventional IT methods. Two implications are obvious from this definition; firstly, volume of data is increasing and changing on continuous basis and secondly, increasing data volume differs according to applications involved in analytics [16]. Another method used in defining big data is multi Vs model volume implying that generated data and its analysis has a velocity related to timeliness of big data. Variety in data signifies different data types whether structured or not. These include audio, video, webpage, text, and customary structured data. Getting value from huge volumes of data is the major objective of big data analysis and this characteristic is an important aspect of multi Vs model. The four cycles involved in life cycle of big data are; generation, acquisition, storage, and analysis.

To achieve efficiency in operations, notifying strategic route, improving customer services, developing innovative products, identifying new markets, and achieving other important objectives, big data analytics have an indispensable role to play. However, it must be borne in mind that achieving these advantages is not possible unless proper procedures are followed to benefit from big data analytics. The usual challenges appear when capturing, storage, searching, sharing, analysis, and visualization of data is to be done. Other problems include inconsistent and incomplete data, scalability, timeliness, and data security. Additionally, a critical challenge is to deal with big data of different nature that comes from a variety of sources.

The healthcare sector has adopted the developments in ICT for long. Some of the most powerful supercomputers have been commissioned for the sole purpose of healthcare research including computational grids [17]. Naturally, big data and other emerging technologies such as cloud computing and Internet of Things (IoT), have found there uses in Healthcare [15, 18–20], to provide personalized and preventive healthcare. The integration of healthcare systems with other smart city systems such as transportation and logistics have also been proposed, see e.g. [21]. The emerging technologies indeed are set to revolutionize healthcare.

2.2 Pain Management

Pain is a universal experience and there is hardly a human being who has never experienced pain at one time or another. Understanding pain and the way to manage it is essential for healthcare professionals. Managing pain is an issue of high priority for healthcare organizations and their employees given the increasing incidence of pain among patients [22]. In fact, often it is hard for doctors to comprehend the exact feelings of a patient in pain but healthcare professionals cannot ignore a patient in pain.

One of the primary objectives of any healthcare organization is preventing and managing pain. Pain is categorized according to its intensity and duration. There are two types of pain. One is acute pain which is of short duration usually not more than six months and the other is chronic pain which is permanent, continuous, and lasts for longer periods of time. Acute pain is usually sudden in onset and is better termed as a warning signal that there is something wrong with the body. On the other hand, chronic pain can be mild or severe in intensity and may develop rapidly. Moreover, pain is classified as neuropathic or non-neuropathic depending upon the comprehension of Healthcare providers (HCPs) [22].

To assess neuropathic pain, National Health Service (NHS) of UK has developed a questionnaire known as DN4 (Douleur Neuropathique 4). The DN4 questionnaire is a useful tool in diagnosing neuropathic pain with all the necessary components about assessing how much pain the patient is feeling and for how long [23]. However, health experts are expected to examine the patient and form an opinion whether pain has been reduced or increased. Moreover, it is also important to know the incidence, intensity, recurrence, duration, and level of pain. The questionnaire has proved its efficacy and validity in numerous cases of neuropathic pain and related clinical research.

Another effort in assessment of pain is the development of Numeric Pain Rating Scale (NPRS) with the purpose of measuring intensity of pain in adults with chronic pain. NPRS is a numeric form of visual analog scale (VAS) where respondent has to select between 0 and 10 to inform the intensity of pain being felt [24]. As in the case of VAS, NPRS is a description of pain severity. The digit is the reference point of no pain and the digit 10 is for expressing the extremity of pain. Patients are to respond on the basis of pain intensity felt in the last 24 h on an average basis [24].

The administration of NPRS can be verbal, through telephone, or by a graphic portrayal. Patient has to respond by attaching a numeric value to the questions being asked indicating the intensity of pain. Patient responses help clinicians in choosing best remedies from the available ones to manage pain [24]. NPRS is a speedy and easy way to assess the condition of patients no matter the language or cultural belonging of the patients. It has proved its reliability and validity in measuring intensity of pain. The measuring method of NPRS is advantageous over VAS because it can be used in writing or through verbal communication. Moreover, NPRS is simple as regards scoring and analysis of the results is concerned. However, one obvious weakness of NPRS is its inability to give a complete picture of pain experiences [24]. Moreover, it cannot handle the fluctuations in intensity of pain and the variable nature of pain.

3 Related Work

Every healthcare organization works for welfare of patients striving to provide the best of care with continuous attempts for improvements. To make it possible various models and theories have been proposed in the last few decades [25]. The emphasis during the last decade has been on "personalized medicine" whereby each patient is dealt with individually with the purpose to provide efficient and personalized healthcare on priority basis [26]. In 2009, Hood and Friend proposed the P4 model where P4 stood for personalized, predictive, preventive, and participatory [27]. The intent of P4 model is to focus on patients by doing away with reactive care methods to be replaced with proactive treatment methods and also reduce healthcare expenses [27]. Of recent, a new model has been proposed named "precision medicine." This model extends personalized medicine model with emphasis on classifying patients according to subgroups of diseases categorized on biological basis [28, 29]. The essential requirement of precision medicine model is utilizing data right from the start till the application of analytic techniques [30].

In 2005, for examining the complexity of human body through collaborative efforts using established methods and technologies, the phrase virtual physiological human (VPH) was coined [31]. VPH is explained as follows. For simplifying the study of living beings, the necessary parts such as cells, tissues, organs, and organ systems can be isolated and studied independently for better understanding. In this way, a specialist will examine one part and the other expert will study the part related to personal expertise. On the contrary, such a method will be an impediment towards diseases related to multi-organs or systemic diseases. Further, it will be difficult to know how genotype-phenotype interacts with treatment methods related to multiple diseases treatment. A proposed solution to overcome this challenge is to use computer models for rearranging the known data and related information to see how body parts interact with each other and then observe the final results.

The above-stated understanding of VPH may appear simple but developing an efficient and effective mathematical model for the accurate understanding of biological systems is a massively complicated task. For the purpose of overcoming problem involved, extensive research is required in knowing medical imaging and sensing technologies so that quantitative information is obtained regarding anatomy and physiology of a patient. To know the unknown information, it is imperative that all the available data should be processed. In the end, biomedical modeling is the reliable way to develop predictive models using known information with aid from computational skills and related engineering sciences for simplifying huge volumes of data.

Analyzing big data is vital in understanding of VPH applications and plays a key role in enabling this approach to handle complex issues in clinical applications. The purpose is better achieved if researchers working on big data devise appropriate methods in the field of computational biomedicine and propose problem solving methods to deal with emerging issues in the field. Moreover, a proposition to give a research platform for future needs is urgently needed.

Designing of clinical systems and their support is done very effectively when data mining procedures are used. The procedure has been found capable of finding the requisite non-obvious patterns and related relationships that are highly relevant in healthcare data. To analyze heart related issues, data mining techniques and their classification are in use in recent times. As a follow up, clustering data mining techniques of diverse nature are proposed for predicting the incidence of heart disease [32]. Of these techniques, k-mean, EM, and the farthest first algorithm are well known. The most important one among all the known algorithms is the farthest first algorithm with clustering properties.

Ramia et al. [33] aim to describe the intensity of acute pain felt by patients. The assessment involves patients' description of pain, management of pain, and to see whether patients are satisfied with their treatment procedures.

For the purpose of research, three medical centers in Lebanon were chosen and patients were to answer a questionnaire prepared on the basis of cross-sectional study. The period of study was between October 2014 and March 2015. Once answered, excel sheets were used to codify the patients' reply and analysis of data was done through SPSS version 21 software. Specific steps were taken not to mix up the data collected from different units thus assuring accuracy of records and simplifying the analysis procedures. All relevant variables such as demographic information, intensity of pain, and patients' reaction about pain management were summed up through descriptive statistical procedures.

The noteworthy fact is that cases of acute pain must be treated with extreme care in accordance with the expectation of patients. The quality of treatment requires proper assessment of pain following proper treatment procedures which includes complete patient participation. The intent is to administer treatment in a way that patients feel thoroughly satisfied. In cases where patients have been through surgery, the condition of pain before and after is a serious issue requiring special attention. There should be remedies to handle known issues in treatment of pains.

The major objective of the research in [34] is to see the effect of using big data in reducing problems of healthcare systems. The known issues in this regard include: accurate diagnosis, selection of correct treatment method, improving healthcare systems, and many more. The methods used provides general impressions about applying big data in healthcare and studying the challenges as well as opportunities involved in the usage of big data for public and private healthcare systems. The authors conclude that there are positive indications for applying big data to determine and solve healthcare issues for all interested parties. In fact, the use of big data by public or private healthcare systems can enable them to excel the health service provision. What is needed is the careful analysis of essentials.

Kononenko [35] present an outline of advances in the analysis of intelligent data especially where machines are involved. Such analyses are of concern where medical diagnosis has to be done. In historical perspective, the focus is on Bayesian classifier, neural networks and decision trees. Herein, a comparison of modern systems and various aspects of machine learning are given when emphasis is on medical diagnosis. Two case studies are illustrative of future tendencies. The first study depicts good prospects for analysis of intelligent data through a method showing consistent decisions by classifiers. With second study, the verification of complicated occurrences in complementary medicine through machine learning is attempted though there are reservations by medical community. However, in future, such an approach can be fruitful for diagnostic purposes.

4 The Proposed System and Its Architecture

In this section, we discuss our proposed system using its architecture depicted in Fig. 1. The system is composed of three layers: Big Data Computing layer, Data Integration layer, and Pain Management Strategy Improvement layer. These layers interact with the stakeholders and various databases to acquire and provide data and feedback related to pain management.

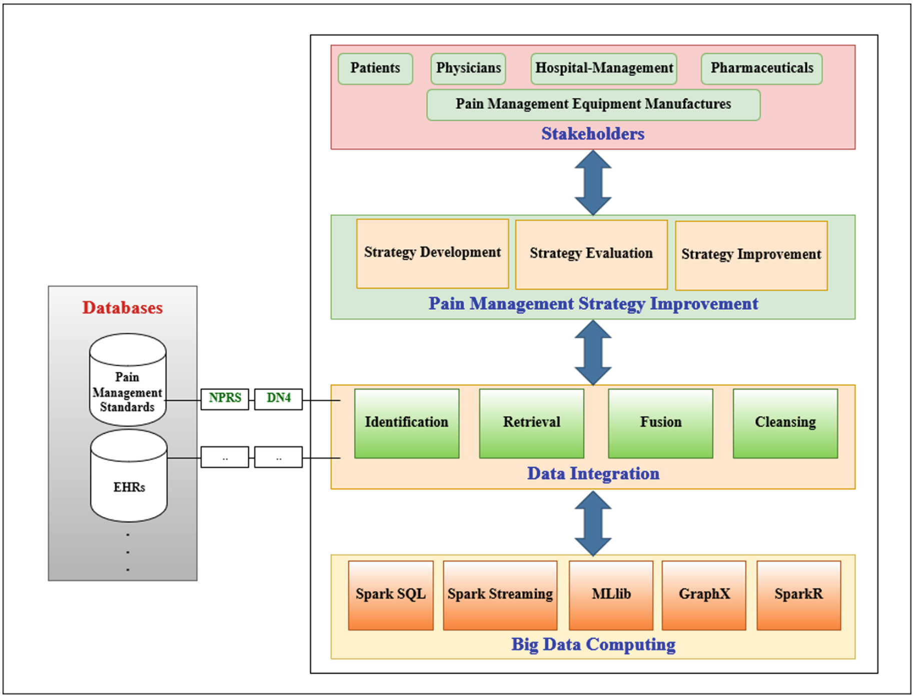

Fig. 1. The proposed system architecture.

The Big Data Computing layer comprises Apache Spark platform and tools. These include Spark SQL for performing SQL queries, Spark Streaming to enable live processing streams of data, MLlib which is a library of different machine learning algorithms, GraphX library to manipulate graphs and perform parallel computation, and SparkR that enables using spark within R. The Data Integration layer compromises of some components to identify and retrieve a suitable pain management strategy and do some data cleansing functions. The Pain Management Strategy Improvement layer focuses on developing strategies of pain management and considers any required improvement based on the evaluation process.

The system interacts with the various stakeholders to acquire and provide feedback about various pain management standards, strategies and processes. The stakeholders include pain management standards bodies, patients, physicians, hospital management, pharmaceuticals, manufacturers of pain management equipment, etc. The stakeholders could use the outcomes of the proposed systems to improve pain management standards, which then can become part of the proposed system databases. Additionally, the various databases that our system acquired data from include patient health records databases and pain management standards databases.

4.1 Improvements in Pain Management Standards, Strategies, and Processes

The system we propose here should have an evaluation criterion to measure the change in the effectiveness and efficiency in managing the pain. There are many ways to establish a criterion to measure this. We will discuss some ideas here. One way is to perform analysis on data about different types of methods for pain management, like DN4 and NPRS methodology. These types of comparative studies will provide a basis for many types of analyses with the proposed architecture.

With the proposed system, we are able to monitor the outcome for the changes in the pain management standards. The architecture allows the system to get new data as it arrives, as it imports data from different transactional data sources.

The evaluation mechanisms would be included in the system as workflows, which will communicate with the Big Data Computing Layer, Data Integration Layer, and the stakeholders. This will allow the developed analysis tests to be included automatically into the processes of evaluation of the architecture and system. The analysis provides the basis for the changes in the methodologies being applied to the pain management techniques. This way evaluation of the system can also be automated.

The usage of the apache spark layer also requires us to evaluate the performance of the system, the system can be evaluated on the basis of amount of data and value it generates from the analysis. The measurement of the pain score that the system generates can be elaborated by the health sector and uploaded into the Identification and Retrieval functions within the Data Integration Layer, from the pain management standards.

In summary, the system workflow for the evaluation and improvement of a pain management strategy can be summarized as follows. The system receives a patient for pain management. In addition to the current symptoms of the patient, the system acquires any data related to the patient, such as EHRs, from the associated databases. Based on the patient information and circumstances, the system identifies and retrieves an appropriate pain management strategy (including pain management standards) to be executed. The patient's condition is monitored and alternative strategies are used if the patient's condition does not improve. These strategies are selected and all decisions are made based on machine learning intelligence. The outcomes of the patient management workflows are updated in the databases resulting in the improvements of the pain management strategies. These outcomes are also made available to the stakeholders through textual and graphical interactive reports to allow discussion and improvements in the standards and processes for pain management.

5 System Analysis and Results

This section provides a preliminary analysis of the proposed system. We have collected some data related to pain management in both electronic forms and handwritten notes on paper. We converted the paper notes to digital form before the analysis.

One of the most important challenges that has hindered the implementation of the proposed architecture is that most of the patients' data that has been collected are paper documents. These data need to be digitized to fulfill the requirements of the proposed architecture. Some of the patients' information that will be considered as a pain management case includes *Case Number, History, Exam, Numeric Pain Score Before Treatment, Treatment,* and *Numeric Pain Score After Treatment*.

Table 1 shows statistics found from original data for few patients following with some descriptive charts. Column 1 in the table gives six different patient cases with different pain types. Columns 2 to 4 give details related to patients, their age, gender, and the effected body part. Columns 5 and 7 list the numeric pain score before and after the treatment. Column 6 gives the particular treatments offered to each patient such as Occipital nerve block for the first patient in the second row.

Figures 2, 3 and 4 depict patients pain related data in a graphical form. The aim here is to show that our proposed system can provide reports in tabular form and the visualization of data for quick insights. Figure 2 provides age and gender wise diseases distribution. The chart shows that the Males have major issues in their middle and lower body parts, as they grow older, while females in their 30's get lower body problems.

The chart in Fig. 3 shows that the oldest age people were involved in two major diseases cerebral facet join osteoarthritis and peripheral neuropathy. Chronic abdominal pain and Discogenic low back pain were the most common diseases found in middle-aged patients.

Figure 4 shows that the Numeric Pain Score after treatment was dramatically lower than the Numeric Pain Score before treatment. The remarkable downfall in the upper body and the middle body Numeric Pain Score can easily be seen. The decreased value in the lower body is also visibly low from the 7 points down to 2.

We have also used a sample of pain management data for Queensland Ambulance Service to reflect how big data analytics can benefit pain management field [36]. Figures 5, 6, and 7 depict the results from this data. The figures plot different types of patients that have used various pain management strategies and their responses against these strategies.

Table 1. A sample of pain management data

Case #	Age	Gender	Effected body part	Numeric Pain Score before treatment	Treatment	Numeric Pain Score after treatment
1- Occipital neuralgia.	45	Female	Upper body	9/10	Occipital nerve block	2/10
2- Cerebral facet join osteoarthritis	65	Male	Upper body	8-9/10	Nonsteroidal anti-inflammatory drugs (NSAIDs) - Celebrex 200 mg P.O B:D	3-4/10
3-Discogenic low back pain	38	Male	Middle body	10/10	- Lumbar Epidural - Steroid injection	3/10
4- Chronic abdominal pain	35	Female	Middle body	9/10	Celiac plexus block	0/10
5- Chest wall pain	52	Male	Middle body	10/10	- Intercostal nerve block - pregabalin 150 mg P.O B:D	3/10
6- Peripheral neuropathy	58	Male	Lower body	7-8/10	- Pregabalin 150 mg P.O B:D - Tramadol 50 mg P.O B:D	2/10

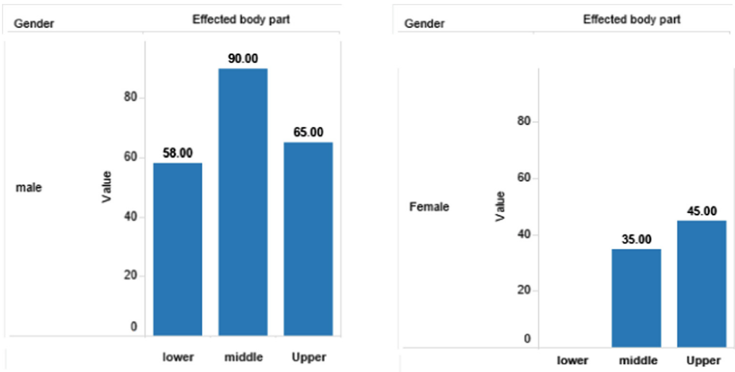

Fig. 2. Age/gender wise diseases distribution

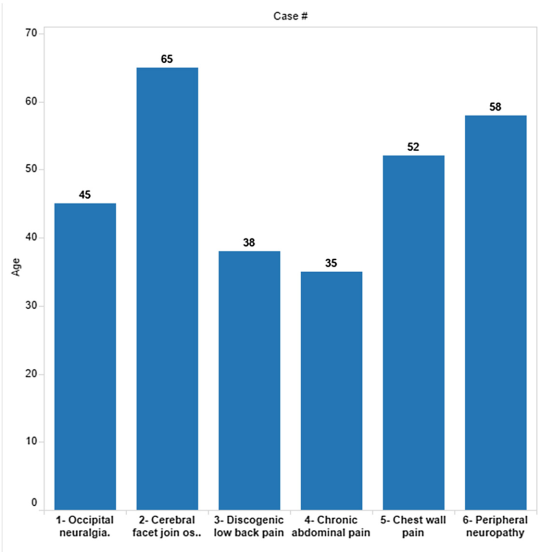

Fig. 3. Disease wise age statistics

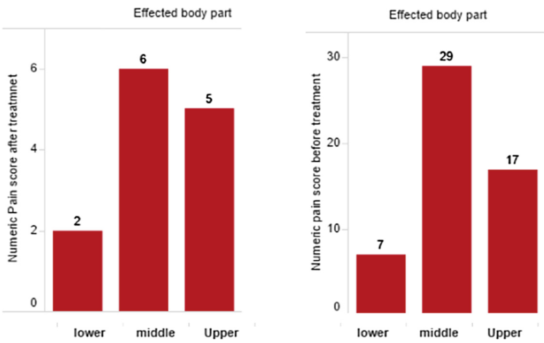

Fig. 4. Stats before and after the treatment

Figures 5 and 6 indicate proportion of patients who report a clinically meaningful decrease in pain rating, while Fig. 7 depict total patients with a lower last pain value than first recorded pain value.

For the future work, we are working to convert the data that have been collected to the digital format and use our Spark architecture to analyze such large-scale data, which will help to automate the process of data collection and analysis.

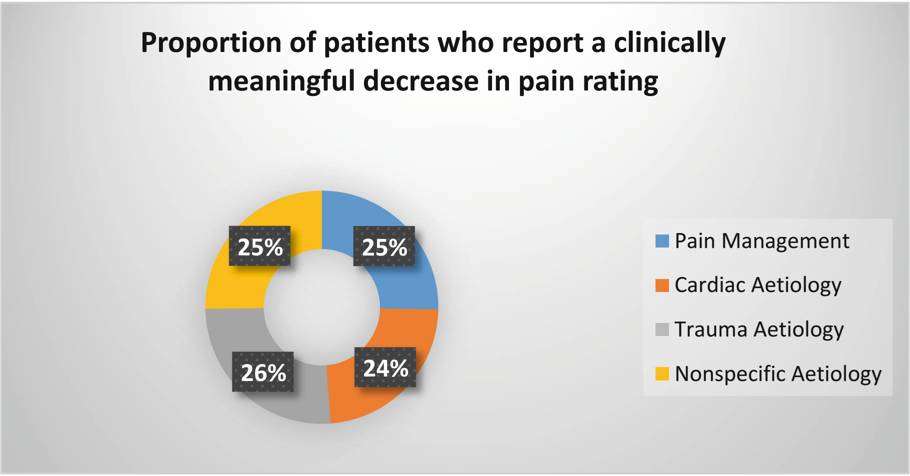

Fig. 5. Proportion of patients who report a clinically meaningful decrease in pain rating.

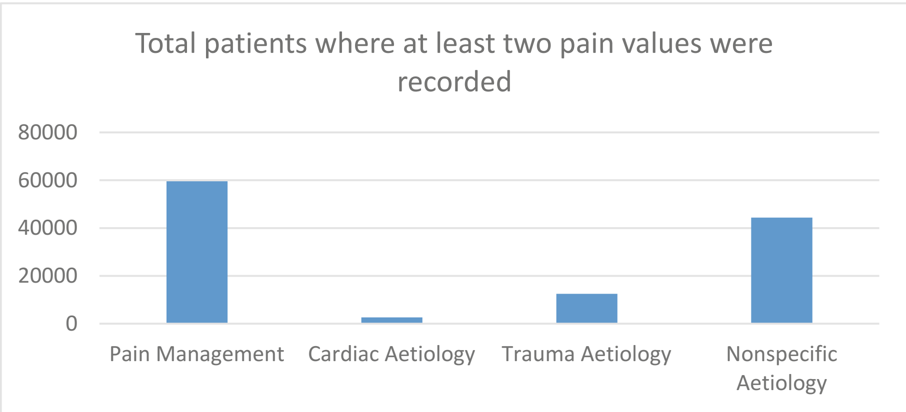

Fig. 6. Proportion of patients who report a clinically meaningful decrease in pain rating.

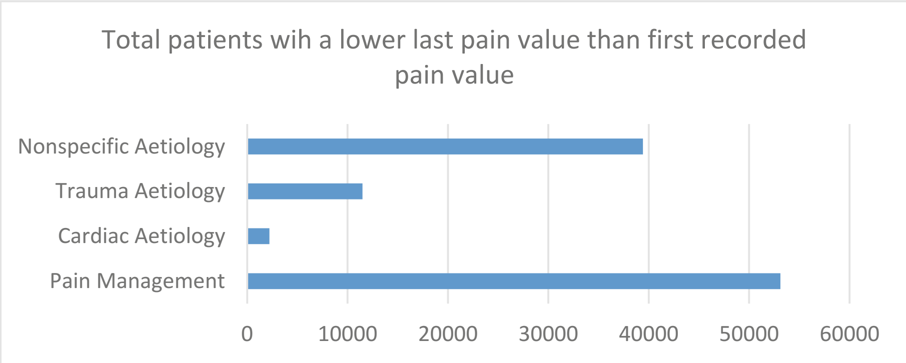

Fig. 7. Total patients with a lower last pain value than first recorded pain value.

6 Conclusion

The Proposed smart pain management system may provide insight into the management practices, their efficiency and their effectiveness. The goal of the paper is to provide smart way of managing patients' pain. The current systems that are in place can only provide pain management on standards that are developed by many organizations, but their effectiveness and efficiency cannot be monitored at microscales. We provides a way of solving problem that the pain management practices are facing in terms of data management and feedback handling. The standards that are being developed to manage the patient's pain are only limited to the patient record management, the proposed system will collect these data and provide a way to analyze this data so that the practices can be categorized and analyzed. Furthermore, the system will be able to monitor the change in the records of patients if any of the standards are changed in the pain management practices. This will enable the healthcare community to make more efficient standards for pain management.

The paper provides overview and details of the architectural components involved in the proposed system and makes use of Apache Spark components for storage, manipulation and analysis of data. In addition, it provides other components that will interact with external entities and Apache Spark to make use of the resources that are already under use in the healthcare industry.

To conclude, the system can provide a basis for testing the pain management standards and the results from the practice of these standards, and the data then can be analyzed in comparison with the standards and the results using large quantities of different types of data from different sources. The standards and practice are turned by the proposed system into strategies that can be tested and improved in real-time. The strategies and their outcomes are also made available to the stakeholders through textual and graphical interactive reports to allow informed discussion and improvements in the standards and processes for pain management. Future work will focus on a detailed implementation and analysis of the proposed system using real-life big data.

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