The Application of Big Data Analytics in Healthcare: A Proactive Approach

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***Abstract* - In the recent times, advanced health information system are applied to move from the traditional record keeping method to automated electronic means for more efficient storage and maintenance of patients' records. Examples of these include electronic medical record (EMR) and personal healthcare record systems (PHR). Turning this massive amount of data into knowledge that can be used to identify needs, predict and prevent critical patients' conditions, and help practitioners to make rapid and accurate decisions is not only a desire but is of urgent and crucial necessity. Therefore, healthcare organizations must have the ability to manage and analyze their data in a rapid and efficient manner to answer several critical questions related to diseases, treatments, patients' behaviors, and care management. In this paper, we discuss the impact of big data in healthcare, big data analytics architecture in healthcare, various tools available in the Hadoop ecosystem for handling it, challenges and benefits of big data in healthcare.**

Keywords- Big Data; Data Analytics; Healthcare; Architecture; Challenges

I. INTRODUCTION

Every day, data is generated by a range of different applications, devices, and geographical research activities for the purposes of weather forecasting, weather prediction, disaster evaluation, crime detection, and the heath industry, to name a few. In current scenarios, big data is associated with core technologies and various enterprises including Google, Facebook, and IBM, which extract valuable information from the huge volumes of data collected [1–3]. An era of open information in healthcare is now under way. Big data is being generated rapidly in every field including healthcare, with respect to patient care, compliance, and various regulatory requirements. As the global population continues to increase along with the human lifespan, treatment delivery models are evolving quickly, and some of the decisions underlying these fast changes must be based on data [4].

Big Data analytics can revolutionize the healthcare industry. It can also ensure functional productivity, help forecast and suggest feedbacks to disease outbreaks, enhance clinical practice, and optimize healthcare expenditure which cuts across all stakeholders in healthcare sectors. Big data, including analytics, is a powerful tool that will be as useful in health care as it has been in other industries. Big data analytics is evolved as transformation in every sector of information.

II. RELATED WORK

A number of works have already been done by various researchers in the field of Big Data Analytics in Healthcare.

Nambiar and Thirumale [12] in their paper focused on identifying challenges to be overcome for effectively delivering efficient healthcare and to the masses.

Sun and Reddy [13] discussed about the key problems and trends in healthcare analytics research, with different applications ranging from clinical text mining, predictive modeling, survival analysis,patient similarity, genetic data analysis, and public health.

Onyejekwe and Onyejekwe [14] narrated the current status of Big Data in the healthcare industry and how the industry could derive big benefits from Big Data.

Deng and Wu [15] discussed about few current big data and predictive modeling topics in healthcare in both providers and payers market space, including the problems, current status and challenges, and opportunities for big data and future trends.

Cassavia et. al [16] proposed an architecture for supporting interoperability in healthcare systems by exploiting Big Data techniques and that is based on big data techniques to implement a nationwide system able to improve EHR data access efficiency and reduce costs.

Fang et. al [17] summarized the challenges into four Vs (i.e., volume, velocity, variety, and veracity) and proposed a systematic data-processing pipeline for generic big data in health informatics, covering data capturing, storing, sharing, analyzing, searching, and decision support.

M-Tahar KECHADI [18] discussed about all challenges and the requirements of healthcare ecosystem and descried some innovative methodologies of how to build such ecosystem to face the healthcare challenges of the next decade.

Islam et. al [19] researched based on a case of study by the incorporation of the database, mobile application, web application and develops a novel platform through which the patients and the doctors can interact.

Kayode et. al [20] highlighted the possibility of making very insightful healthcare outcomes with big data through a simple classification problem which classifies the tendency of individuals towards specific drugs based on personality measures.

Ge Zhan [21] studied; a database with 31,646 online reviews was compiled. Text mining and wordcloud analysis results indicate that the model provides an effective solution to assess the quality of doctors registered in online forum, the quality of doctor-patient online interaction, and patients' overall perception. A guideline has been provided to evaluate doctor authenticity.

III. IMPACT OF BIG DATA IN HEALTHCARE

The main difference between traditional health analysis and big-data health analytics is the execution of computer programming. In the traditional system, the healthcare industry depended on other industries for big data analysis. As noted above, most of the massive amounts of data generated by this system is saved in hard copies, which must then be digitized [5]. Big data can improve healthcare delivery and reduce its cost, while supporting advanced patient care, improving patient outcomes, and avoiding unnecessary costs [6]. Big data analytics is currently used to predict the outcomes of decisions made by physicians, the outcome of a heart operation for a condition based on patient's age, current condition, and health status. Essentially, we can say that the role of big data in the health sector is to manage data sets related to healthcare, which are complex and difficult to manage using current hardware, software, and management tools. In addition to the burgeoning volume of healthcare data, reimbursement methods are also changing [7]. Therefore, purposeful use and pay based on performance have emerged as important factors in the healthcare sector. In 2011, organizations working in the field of healthcare had produced more than 150 exabytes of data[8], all of which must be efficiently analyzed to be at all useful to the healthcare system[9]. The storage of healthcare related data in EHRs occurs in a variety of forms. A sudden increase in data related to healthcare informatics has also been observed in the field of bioinformatics, where many terabytes of data are generated by genomic sequencing [9]. There are a variety of analytical techniques available for interpreting medical, which can then be used for patient care[10]. The diverse origins and forms of big data are challenging the healthcare informatics community to develop methods for data processing. There is a big demand for technique that combines dissimilar data sources [11].

Big data analytics in healthcare can contribute to:

Evidence-based medicine: Combine and analyze a variety of structured and unstructured data-EMRs,financial and operational data, clinical data, and genomic data to match treatments with outcomes, predict patients at risk for disease or readmission and provide more efficient care;

Genomic analytics: Execute gene sequencing more efficiently and cost effectively and make genomic analysis a part of the regular medical care decision process and the growing patient medical record [13];

Pre-adjudication fraud analysis: Rapidly analyze large numbers of claim requests to reduce fraud, waste and abuse;

Device/remote monitoring: Capture and analyze in real-time large volumes of fast-moving data from in-hospital and in-home devices, for safety monitoring and adverse event prediction;

Patient profile analytics: Apply advanced analytics to patient profiles (e.g., segmentation and predictive modeling) to identify individuals who would benefit from proactive care or lifestyle changes, for example, those patient s at risk of developing a specific disease (e.g., diabetes) who would benefit from preventive care [14].

IV. BIG DATA ANALYTICS ARCHITECTURE IN HEALTHCARE

Big data analytics architecture (as shown in Figure-1) that is loosely comprised of five major architectural layers: (1) data, (2) data aggregation, (3) analytics, (4) information exploration, and (5) data governance. These logical layers makeup the big data analytics components that perform specific functions, and will therefore enable healthcare managers to understand how to transform the healthcare data from various sources into meaningful clinical information through big data implementations.

1. Data layer: This layer includes all the data sources necessary to provide the insights required to support daily operations and solve business problems. Data is divided into structured data such as traditional electronic healthcare records (EHRs), semi-structured data such as the logs of health monitoring devices, and unstructured data such as clinical images. These clinical data are collected from various internal or external locations, and will be stored immediately into appropriate databases, depending on the content format.

2. Data aggregation layer: This layer is responsible for handling data from the various data sources. In this layer, data will be intelligently digested by performing three steps: data acquisition, transformation, and storage. The primary goal of data acquisition is to read data provided from various communication channels, frequencies, sizes, and formats. This step is often a major obstacle in the early stages of implementing big data analytics, because these incoming data characteristics might vary considerably. Here, the cost may well exceed the budget available for establishing new data warehouses, and extending their capacity to avoid workload bottlenecks. During the transformation step, the transformation engine must be capable of moving, cleaning, splitting, translating, merging, sorting, and validating data.

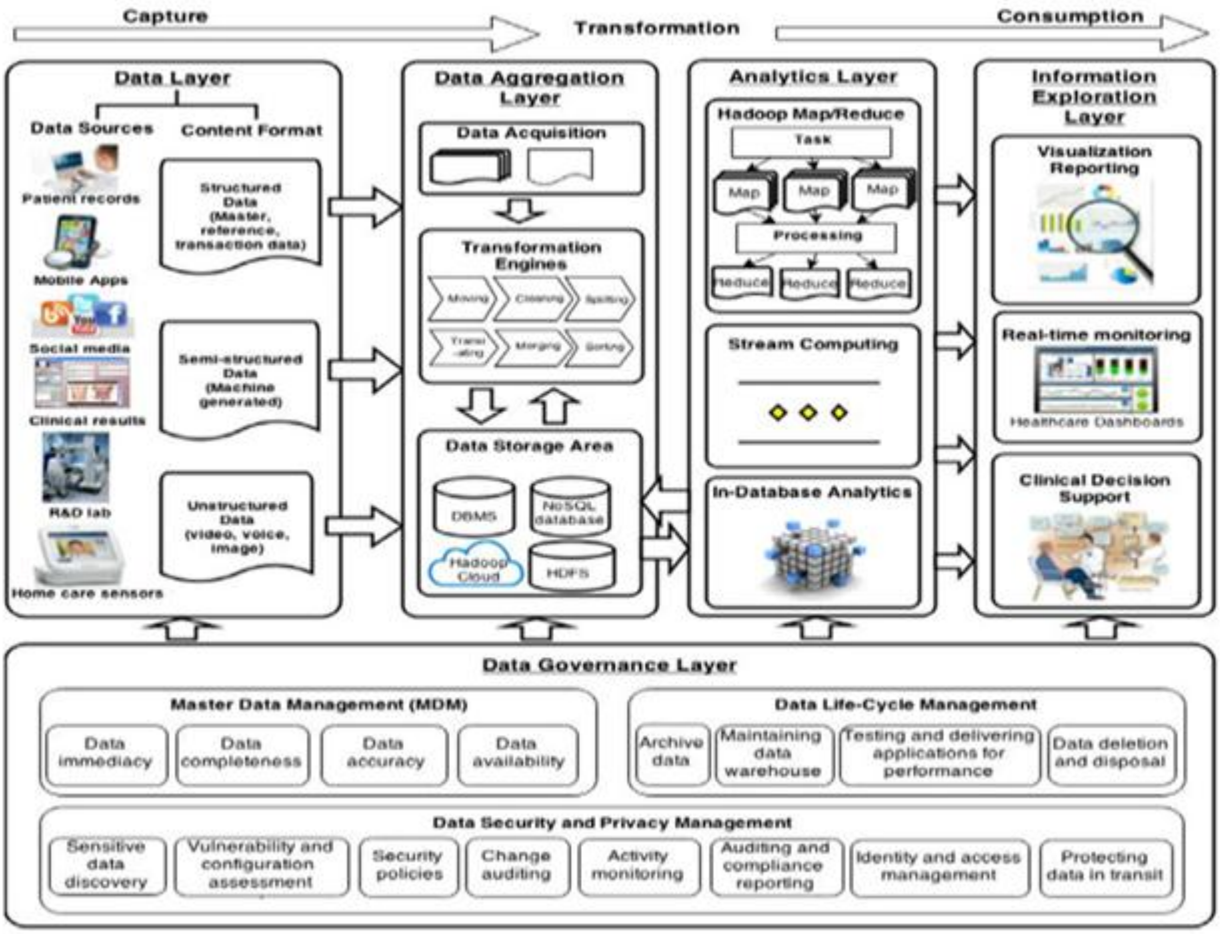

Figure-1: Big Data Analytics architecture in healthcare [12]

3. Analytics layer: This layer is responsible for processing all kinds of data and performing appropriate analyses. In this layer, data analysis can be di-vided into three major components: Hadoop Map/Reduce, stream computing, and in-database analytics, depending on the type of data and the purpose of the analysis. Map reduce is the most commonly used programming model in big data analytics which provides the ability to process large volumes of data in batch form cost-effectively, as well as allowing the analysis of both unstructured and structured data in a massively parallel processing (MPP) environment.

4. Information exploration layer: This layer generates outputs such as various visualization reports, real-time information monitoring, and meaningful business insights de-rived from the analytics layer to users in the organization. Similar to traditional business intelligence platforms, reporting is a critical big data analytics feature that allows data to be visualized in a useful way to sup-port users' daily operations and help managers to make faster, better decisions. However, the most important output for health care may well be its real-time monitoring of information such as alerts and proactive notifications, real time data navigation, and operational key performance indicators (KPIs). This information is analyzed from sources such as smart phones and personal medical devices and can be sent to interested users or made available in the form of dashboards in real time for monitoring patients' health and preventing accidental medical events.

5. Data governance layer: This layer is comprised of master data management (MDM), data life-cycle management, and data security and privacy management. This layer emphasizes the "how-to" as in how to harness data in the organization. The first component of data governance, master data management, is regarded as the processes, governance, policies, standards, and tools for managing data. Data is properly standardized, removed, and incorporated in order to create the immediacy, completeness, accuracy, and availability of master data for supporting data analysis and decision making. The second component, data life-cycle management, is the process of managing business information throughout its lifecycle, from archiving data, through maintaining data warehouse, testing and delivering different application systems, to deleting and disposing of data. The third component, data security and privacy management, is the plat-form for providing enterprise-level data activities in terms of discovery, configuration assessment, monitoring, auditing, and protection (IBM, 2012). Due to the nature of complexity in data management, organizations have to face ethical, legal, and regulatory challenges with data governance (Phillips-Wren et al., 2015).

V. BIG DATA TOOLS FOR HEALTHCARE ECOSYSTEM

Big data tools for healthcare ecosystem (as shown in Table-1) comprised of five major tasks: (1) data integration, (2) searching and processing,(3) machine learning, (4) stream data processing, and (5) visual data analytics. The task, tool and merits and applications for them are specified in the table categorically.

Table 1. Big Data Tools for Healthcare Ecosystem

Task	Tools	Merits & its applications
1. Data Integration	Pentaho (2017)	Tool for performing knowledge discovery process from a scalable environment in a robust and flexible manner.
	Palantir (2017)	Assist decision makers for highlighting the process insights by uncovering treatment options and improving the standard of patient care.
	Ayata (2017)	Performs exclusive prescriptive analytics from large amount of data towards helping organizations for making smarter decisions.
2. Searching and processing	Apache Lucene (2017)	High performance, full-featured text search engine for performing full-text search across different platforms.
	Google Dremel Melnik et al. (2010)	Complements Map/Reduce based computations supported by Hadoop for processing nested data with high scalability.
	Cloudera Impala (2017)	Executes low latency and high concurrency analytical queries
3. Machine Learning	Apache Mahout (2017)	Offers distributed machine learning library for processing scalable mining algorithms.
	Skytree (2017)	Tool for performing machine learning and advanced analytics of massive data sets at high speed.

4. Stream Data Processing	Apache Storm (2017)	Scalable and flexible real-time computation system for processing massive amount of data.
	S4 Neumeyer et al. (2010)	Tool for processing unbounded stream data in a distributed, scalable and fault-tolerant manner.
	SQLstream Blaze (2017)	Supports creation of distributed streaming applications that deliver data ingestion, integration, and analytics in real time.
5. Visual Data Analytics	Jaspersoft (2017)	Provides interactive visual analytics at large scale by extracting information from one or more data sources.
	Tableau (2017)	Provides faster, highly interactive dashboards to project extracted patterns.
	Qlik (2017)	Explores clinical and operational data through visual analytics for discovering insights.

VI. CHALLENGES ASSOCIATED WITH HEALTHCARE BIG DATA

Methods for big data management and analysis are being continuously developed especially for real-time data streaming, capture, aggregation, analytics (using ML and predictive), and visualization solutions that can help integrate a better utilization of EMRs with the healthcare. For example, the EHR adoption rate of federally tested and certified EHR programs in the healthcare sector in the U.S.A. is nearly complete. Nonetheless, we can safely say that the healthcare industry has entered into a 'post-EMR' deployment phase. Now, the main objective is to gain actionable insights from these vast amounts of data collected as EMRs. Here, we discuss some of these challenges in brief.

Storage

Storing large volume of data is one of the primary challenges, but many organizations are comfortable with data storage on their own premises. It has several advantages like control over security, access, and up-time. However, an on-site server network can be expensive to scale and difficult to maintain. It appears that with decreasing costs and increasing reliability, the cloud-based storage using IT infrastructure is a better option which most of the healthcare organizations have opted for.

Cleaning

The data needs to cleansed or scrubbed to ensure the accuracy, correctness, consistency, relevancy, and purity after acquisition. This cleaning process can be manual or automatized using logic rules to ensure high levels of accuracy and integrity. More sophisticated and precise tools use machine-learning techniques to reduce time and expenses and to stop foul data from derailing big data projects.

Unified format

Patients produce a huge volume of data that is not easy to capture with traditional EHR format, as it is knotty and not easily manageable. It is too difficult to handle big data especially when it comes without a perfect data organization to the healthcare providers. A need to codify all the clinically relevant information surfaced for the purpose of claims, billing purposes, and clinical analytics. Therefore, medical coding systems like Current Procedural Terminology (CPT) and International Classification of Diseases (ICD) code sets were developed to represent the core clinical concepts. However, these code sets have their own limitations.

Accuracy

Some studies have observed that the reporting of patient data into EMRs or EHRs is not entirely accurate yet [25, 26, 27, 28], probably because of poor EHR utility, complex workflows, and a broken understanding of why big data is all-important to capture well. All these factors can contribute to the quality issues for big data all along its lifecycle. The EHRs intend to improve the quality and communication of data in clinical workflows though reports indicate discrepancies in these contexts. The documentation quality might improve by using self-report questionnaires from patients for their symptoms.

Image pre-processing

Studies have observed various physical factors that can lead to altered data quality and misinterpretations from existing medical records [29]. Medical images often suffer technical barriers that involve multiple types of noise and artifacts. Improper handling of medical images can also cause tampering of images for instance might lead to delineation of anatomical structures such as veins which is non-correlative with real case scenario.

Security

There have been many security breaches, hackings, phishing attacks, and ransom ware episodes that data security is a priority for healthcare organizations. After noticing an array of vulnerabilities, a list of technical safeguards was developed for the protected health information (PHI). These rules, termed as HIPAA Security Rules, help guide organizations with storing, transmission, authentication protocols, and controls over access, integrity, and auditing. Common security measures like using up-to-date anti-virus software, firewalls, encrypting sensitive data, and multi-factor authentication can save a lot of trouble.

Meta-data

To have a successful data governance plan, it would be mandatory to have complete, accurate, and up-to-date metadata regarding all the stored data. The metadata would be composed of information like time of creation, purpose and person responsible for the data, previous usage (by who, why, how, and when) for researchers and data analysts. This would allow analysts to replicate previous queries and help later scientific studies and accurate benchmarking. This increases the usefulness of data and prevents creation of “data dumpsters” of low or no use.

Querying

Metadata would make it easier for organizations to query their data and get some answers. However, in absence of proper interoperability between datasets the query tools may not access an entire repository of data. Also, different components of a dataset should be well interconnected or linked and easily accessible otherwise a complete portrait of an individual patient’s health may not be generated. Medical coding systems like ICD-10, SNOMED-CT, or LOINC must be implemented to reduce free-form concepts into a shared ontology. If the accuracy, completeness, and standardization of the data are not in question, then Structured Query Language (SQL) can be used to query large datasets and relational databases.

Visualization

A clean and engaging visualization of data with charts, heat maps, and histograms to illustrate contrasting figures and correct labeling of information to reduce potential confusion, can make it much easier for us to absorb information and use it appropriately. Other examples include bar charts, pie charts, and scatter plots with their own specific ways to convey the data.

Data sharing

Patients may or may not receive their care at multiple locations. In the former case, sharing data with other healthcare organizations would be essential. During such sharing, if the data is not interoperable then data movement between disparate organizations could be severely curtailed. This could be due to technical and organizational barriers. The biggest roadblock for data sharing is the treatment of data as a commodity that can provide a competitive advantage. Therefore, sometimes both providers and vendors intentionally interfere with the flow of information to block the information flow between different EHR systems [30].

VII. BENEFITS OF BIG DATA IN HEALTHCARE

The benefits of big data analytics in different aspects like IT infrastructure, Operational, Organizational, Managerial and Strategic are shown in Figure-2.

Potential benefits of big data analytics	Elements
IT infrastructure benefits	Reduce system redundancy Avoid unnecessary IT costs Transfer data quickly among healthcare IT systems Better use of healthcare systems Process standardization among various healthcare IT systems Reduce IT maintenance costs regarding data storage
Operational benefits	Improve the quality and accuracy of clinical decisions Process a large number of health records in seconds Reduce the time of patient travel Immediate access to clinical data to analyze Shorten the time of diagnostic test Reductions in surgery-related hospitalizations Explore inconceivable new research avenues
Organizational benefits	Detect interoperability problems much more quickly than traditional manual methods Improve cross-functional communication and collaboration among administrative staffs, researchers, clinicians and IT staffs Enable to share data with other institutions and add new services, content sources and research partners
Managerial benefits	Gain insights quickly about changing healthcare trends in the market Provide members of the board and heads of department with sound decision-support information on the daily clinical setting Optimization of business growth-related decisions
Strategic benefits	Provide a big picture view of treatment delivery for meeting future need Create high competitive healthcare services

Figure-2: Benefits of big data analytics in healthcare [12]

VIII. CONCLUSION

Big data will facilitate healthcare by introducing prediction of epidemics (in relation to population health), providing early warnings of disease conditions, and helping in the discovery of novel biomarkers and intelligent therapeutic intervention strategies for an improved quality of life.

In this paper, we have discussed about the impact of big data in healthcare, big data analytics architecture in healthcare, various tools available in the Hadoop ecosystem for handling it, challenges and benefits of big data in healthcare and it will definitely provide a quick guidance to researchers who do their research in big data analytics in healthcare industries.

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