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An Interactive Automated Collection and Processing of Multi-modal Health Signals Using Big Data Analytics

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ABSTRACT: Over the last five decades, information technology has advanced, and these developments are having an impact on society in all sectors that they are used, including as consumer electronics, business, healthcare, media, energy and power, and transportation. During human-technology interaction, a lot of information is immediately transferred between clients and service providers. Only substantial knowledge discovery can be used as the foundation for meaningful decision-making, understanding of the features of the collected data, performance requires accurate categorization of this large collection and effective analysis. Because its services have an impact on people's lives and a lack of service continuity might damage both the economy and people's quality of life, one important part of the infrastructure is the health care industry. The healthcare industry collects a lot of data from its patients in order to deliver health services, the information is utilized in conjunction with pharmaceutical and regulatory data, and organized into Electronic health records (EHRs). When services are provided and their effects on clients are measured afterwards, additional administering development is produced. The goal of this analysis is to develop an intelligent EHR platform that will gather and evaluate interactions between patients and doctors.

KEYWORDS: Big Data (BD), Health Care Domain, Electronic Health Record (EHR)

I. INTRODUCTION

Millions of people in India suffer from overburdened hospitals and inadequate healthcare services. It is reported that there are approximately 500,000 less doctors in India

than there are patients, with a doctor-to-patient ratio of approximately 1:1,674. In Communityhealth centers (CHCs), there is also an 83% lack of specialized medical experts.

The situation is more worse in rural areas, where there are currently, at most, 2.7 lakh doctors to care for about 870 million people, or around 3,200 doctors for 3,200 people. To satisfy World Health Organization (WHO) standards, 6 lakh more doctors are still needed in rural India Big data in medical, clinical information from doctors, prescription and comments from doctors, Magnetic resonance imaging (MRI) scans, lab results, pharmacy documents, insurance electronic patient record (EPR) records, and other information relating to administrative procedures [1].

The lack of access and understanding of medical records of patients presents a difficulty for physicians in addition to the significant limited availability of medical professionals, which may have an adverse effect on the standard of care. Although healthcare organizations have separate medical databases, there is a lack of communication between electronic health information. Analytics are required to give rapid and accurate insight into a patient's medical history, including previous clinical conditions, diagnosis, treatments, and results. Unfortunately, there aren't many medical datasets available for analytics to be performed. This application's real-time data collection capability is designed to address this problem. In light of these facts, they have developed healthcare automation solutions that lower unnecessary medical costs. The paper presents a digitalized health care model for India that could transform the people interact with health care providers and improve existing health systems. It will be essential for health promotion, prevention, and treatment.

The process of digitizing healthcare data is providing health and social care providers with new opportunities to improve patient outcomes, lower costs, and improve the quality of care. In fact, businesses may create an extensive overview of their patients' health by integrating data from several sources, including Enterprise resource planning (ERP), monitoring device data, medical records, and doctor's notes, with EHRs, many patient summaries, resulting in greater personalized social and medical services. New patterns can also be found by combining social, demographic, environmental, and behavioral data. In order to empower patients to manage their own health to foster efficiency, quality of treatment, the sustainability of health and social care systems, therefore, the analysis of all of this data will be the primary factor behind these improvements in the distribution of health and social care services. Doctors are now known to be spending an increasing amount of time recording patient encounters rather than talking and connecting with patients. While doctors appear to be spending a lot of time on Electronic Medical Records (EMR) at the expense of crucial face-to-face contact with patients, the direction of the trend appears to be incorrect. This is a crucially important area. This analysis helps doctors by providing them with the type of data that may be used to track, monitor a patient from visit to visit by providing an automated method for entering EHR records. Evaluating the patient's overall emotions and sentiment is one of these matrices. Within the international healthcare communities, this is increasingly preferred. Furthermore, there is a lack of knowledge regarding the most appropriate outline dependent on computational approaches that are necessary for this approach. Analyzing large amounts of data from numerous sources is known as bigdata analytics [2].

Insurance companies, clinical staff, doctors, patients, research and marketing organizations, health care administrators, and caregivers are the consumers of health care BD. Since each of them has a different position, each of them will make use of the health care BD in a manner suitable to their particular roles. A caregiver, will utilize the information to better provide her patients with individualized care. If the data shows that a patient needs more time to complete these necessary tasks, if the patient in issue was not taking their medication or eating at regular times, a caregiver might be able to give them more time. The research team can alert the clinical staff and doctors after the registered patients, they calculate the rate of change in the diabetic population. When different medications are prescribed or patient monitoring records are updated, these interactions result in the generation of additional data. The health care industry has well-defined role-based actions, this allows the types of interactions and data flow that take place within the system to be precisely defined. As a result, existing mathematical software libraries can be used to select or develop the tools and mathematical models required to assess the health care provided by BD. Any country health care system is an essential component of its infrastructure, and it needs to keep providing uninterrupted, high-quality service, protect patient confidentiality and safety, while maintaining costs to a minimum. To achieve these objectives, regular analyses of health care data are necessary. Precise specification of the clients, characteristics, and sources of health care BD is an essential requirement for conducting an effective analysis. To achievethat, this study offers a contribution.

LITERATURE SURVEY

Galletta Antonino, Alessia Bramanti, Lorenzo Carnevale , Maria Fazio et. al.,[3] clarifies A tool for visualizing health data is used to track a patient's condition. A person's medical state can be easily detected by looking at their color circles data.

Po-Yen Wu, Janani Venugopalan, Chih-Wen Cheng, Chanchala Kaddi D., Ryan Hoffman, Wang D May. et. al.,[4] explains that EHR and multi-omics data are used to forecast precision diseases. In order to predict diseases, molecular profiles are (the biological samples are used to identify several types of data (genomic, transcriptomic, epigenomic, proteomic, and metabolomics). The least redundancy maximum relevance approach is used in biomedical data analytics to filter the features.

Vuppalapati Chandrasekar, Santosh Kedari, Anitha Ilapakurti, et. al.,[5] The use of big data in healthcare is explained. Electronic health records, or EHRs, are databases that stores personal health information about specific people. Numerous electronic health data elements are stored in the EHR, such as demographics, medical history, current medications and allergies, immunization status, results of laboratory tests, and individual statistics like age and weight. Sanjeevani, based on (Internet of Things) IoT Patient data is handled with great availability and security due to the EHR.

Van Poucke S., Schmitz M., Zhang Z., Vukicevic M., Laenen M.V., Celi L.A., et al., [6] focused on open and visual settings in order to reduce the variation between actual and potential data utilization. By combining Hadoop, certain analytics, and a framework for the efficient use of healthcare data was developed using the MIMIC database in a RapidMiner environment.

Tawalbeh Lo'ai A., Elhadj Benkhlifa, Rashid Mehmood, Houbing Song et. al. [7] describes how big data analytics, mobile cloud computing, and networked healthcare comes to make it possible. The presentation includes the inspiration and execution of networked clinical applications, systems, along with the implementation of cloud computing in the medical field. Cloudlet-based mobile cloud computing big data applications for the healthcare sector are described. this study explores the use of big data analytics tools, resources, applications in mobile cloud computing and big data, decisions about the design of networked healthcare systems are developed. An outline of networked healthcare'sfuture is provided.

L. Wang, R. Ranjan, J. Kolodziej, A. Zomaya, L. Alem et al. [8] has produced significant data sets for use in Medical body area networks (MBANs), Health information systems (HIS), and Clinical decision support systems (CDSS), as well as Big Data applications in healthcare. Because cloud computing is suitable with machine learning techniques, programming models, semantic web, and fast communication networks, they performed big data analytics creation and implementation cloud computing infrastructures.

Ruyu Bai, Xiaoli Wang, Qiang Su et. al. [9] evaluation of the effects of HIT on the standard and security of medical care. Hospitals and other healthcare facilities used Health information technology (HIT) to improve patient care, workflow efficiency, and safety. Changes are being made in a number of areas, including patient satisfaction, care, organization collaboration, sickness treatment, nursing home administration, prescription management, and safety monitoring. The impact of HIT on healthcare consistency and safety was divided into two sections in this analysis. To gain a deeper understanding of this sector and, in turn to discover new opportunities to enhance the quality and safety of healthcare, more well planned investigation projects are required.

Fei Wang, Gregor Stiglic et. al. [10] discusses various data analytics methods and their use to enhancing healthcare quality. In the opening to the tutorials, they would set out the foundations of data analytics in the medical field. The tutorial's second section will outline specific state-of-the- art methods that can be used in healthcare informatics. The tutorial's methodologies can all be applied as standalone solutions or as components of larger health information systems, and they all have excellent translational value.

M. Vukicevic, S. Radovanovic, M. Milovanovic, M. Minovic, et al. [11] has provided a cloud-based solution for biomedical data analysis. In order to choose the best big data technologies and predictive algorithms that were accessible through open source for study, this system featured a meta-learning framework.

Kim T. W., Park K. H., Yi S. H., and Kim H. C. et. al. [12] a big data analytical approach using a universal healthcare system is presented. Their suggested system uses analysis to offer healthcare services using accelerometer-based important indicators. Continuous time series data, sometimes known as vital signs are unstructured and continuous, preventing them from being stored in regular databases. The ECG (electrocardiogram) and respiratory system provide data for vital signs. Their recommended method made advantage of an open standard platform to facilitate the impossibility of data exchange across various devices. A number of algorithms have been added to this platform to extract feature values of recent vital sign data and save them for use in real-time evaluation.

A. O'Driscolla, J.D. Roy, D. Sleator et. al.,[13] describe a few cloud-based public health management solutions. These systems are capable of maintaining and storing patient personal data through an internet platform. As a result, users can recover their data from any device, anywhere, at any time. Through utilizing these systems, they can also take care of themselves based on their current state of health. One type of Software as a Service (SaaS) platform is these services.

V. Nguyen, R. Wynden, Y. Sun et al. [14] suggested a method for processing and storing clinical data that is based on Map-Reduce programming and a web-based layer allows Apache HBase (HBase is a column-oriented, non-relational database), a NoSQL database, to parallelize compute processes.

C. Doukas, T. Pliakas, I. Maglogiannis et al. [15] proposed the development of a mobile cloud-based system that makes it possible to store, retrieve, and update electronic health records. The project established the S3 (Amazon Simple Storage Service) cloud service from Amazon, which allowed for online patient data management.

MULTI-MODEL HEALTH SIGNAL USING BIG DATA ANALYTICS

In this section, automated collection and processing multi model health signals using Big data analytics is presented. The work flow of the Multi model health signal is demonstrated in Fig.1.

Com erse elements, including government regulators, pharmacies, phar earch teams), medical device companies, hospitals with assets, psyc e health care industry. The fact that this industry combines with othe nergy, water, communications, information technology, and trans f complexity.

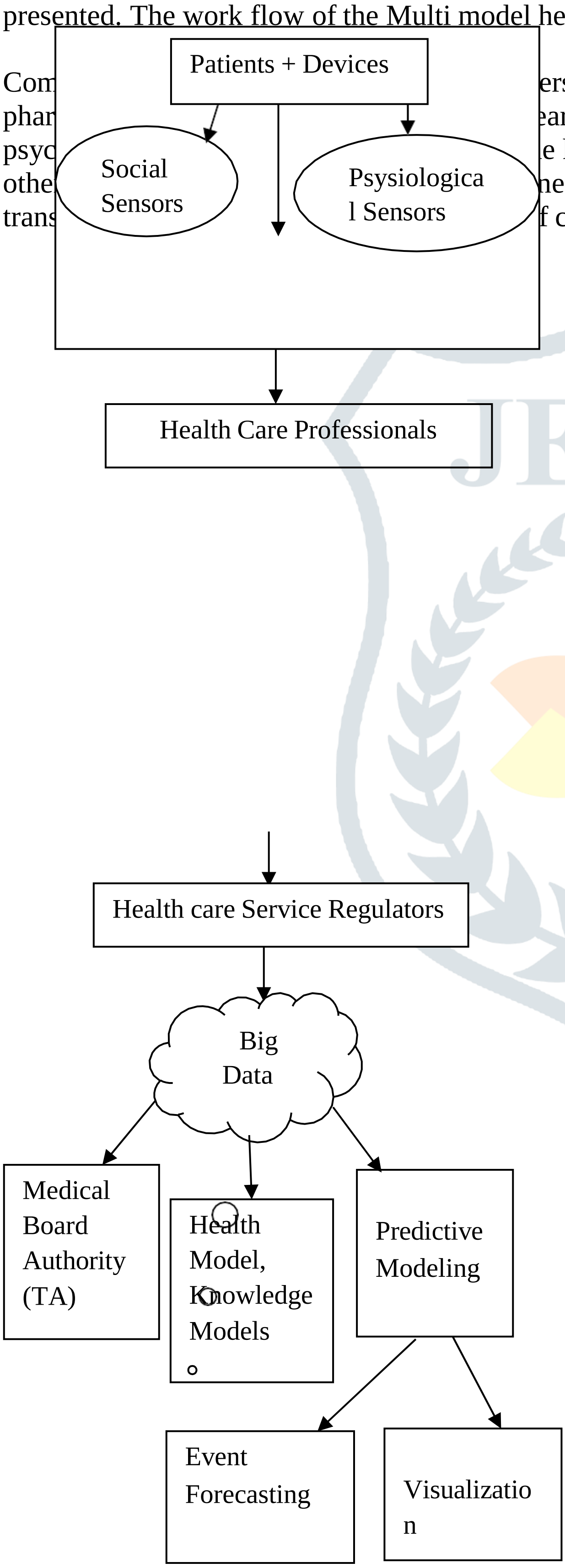

Fig.1: The Work Flow of the Multi Model Health Signal Using Big Data Analytics

Data from one sector quickly interacts and impacts data from another industry. The health care sector's trust will be impacted by any uncertainty or inaccuracy in any of its support sector assets. An uncertified medical equipment or a virus attack on an asset used in the communications business, could make it more challenging for elderly patients with chronic illnesses to receive medical care. Another illustration is the challenge of identifying the origins of some diseases and the routes by which they distribute to new areas. The overall health care system suffers when a sensor is unable to locate the beginning of the disease or when the statistical model that predicts the possibility of an area becoming infected is not updated frequently with accurate data. In clinics, information is gathered directly from

patients as detected through sensors. To ensure the reliability of data, context-dependent data policies must be applied to each type of data. Information gathered from client profiles, observed data, and the specifications of the devices connected to the patients must be examined for dependencies and consistency. The system can be receiving data continuously, thus a one-time study is insufficient. Dataand information layers must be cycled.

Professionals who offer health care services are referred to as Health care providers (HP). Physicians (PH), Emergency care professionals (EC), Pharmacists (PA), and Clinical staff (CL) are the only professions mentioned. While providing care for patients whose data flow in, they have certain regulations that they must conform. They create additional patient data, such as their current medical state, clinical data (such as charts and photographs), and prescriptions, based on these two types of data. Physicians are required to manage patients personal health information in accordance with professional regulations, the patient's set privacy limits in their personal health record, in addition to any federal and provincial privacy regulations that could be relevant. Any doctor may be granted access to transmit diagnostic data immediately to a Clinic (CL) and medication lists directly to a patient-trusted pharmacy. After consulting CC for the patient record, the patient may get the medication in an EH from a PH, that will only give the PA security-filtered data.

GR is the primary resource for health policy and information distribution with the purpose of enhancing the healthcare system in the country. Additionally, health surveys carried out in different countries may be distributed by the GR, in order to inform the medical community on worldwide developments that affect national health profiles. Publications from this source typically contain alerts and warnings presented as charts or images, statistical data in table forms, and plain language descriptions of regulatory processes including service administration, security and safety verification. Consider combining the best elements of the traditional and traditional methods, approaches, and art with the modern EHR. The doctors can focus on what matters most talking and examining patients if important data can be automatically entered into the EHRs also the process of collecting, recording, evaluating the doctor-patient encounter can be mostly automated. In such a system, they predict methodologies and approaches that allow they to follow and maintain historical data while incorporating several sensory modalities, so successfully capturing and nonverbal patient communication with the clinician.

The TA will (consume the data from GR, and monitor CC to ensure no data policy (as announced by GR).As soon as GR announces a data policy, after receiving the data from GR, to make sure that CC is being followed, the TA will keep a watch on. While monitoring on Cloud Cyberspace (CC), Technical Assistance (TA) is an expert that determines information from the information receives and makes decisions by using his expertise. Data that can be utilized by other model actors is not often produced by TA.

This is necessary to combine knowledge from multiple domains. For the purpose of validation, the application domain knowledge needs to be moved up to the information layers. Extracting knowledge from data sources requires analysis of the data that is pumped up to the knowledge layer. That is, information that is pushed down may need to be externalized (shared with environmental entities), whereas knowledge that is pumped up must be internalized. Wisdom Knowledge must be combined to become Wisdom (W) in order to project intelligence. Acquiring and understanding actual information more than information knowing the processes for accurately and properly extracting information from facts and data, understanding when and how to take the lead, being able to evaluate the impact of starting, and looking at the process from a position of developing an intelligent health care system, decision-making based on ethical concerns that affect the safety and privacy of every creature in the environment are all essential features. Health care quality can be enhanced and medical

errors can be decreased with the use of Clinical decision support systems, or CDSS. The use of evidence is essential to CDSS. There are three types of evidence: Patient-directed evidence (PDE), Practice-based evidence (PBE), and Literature-based evidence (LBE). Therefore, three databases of information to enable

CDSS, the health care network should have one for each type of evidence.

This strategy's primary concept is that a smart room that includes audio, video, and other signal- gathering tools can be extremely helpful in obtaining and extracting, evaluating high clinical signals that can be used for follow-up, predicting, therapy, and rehabilitation of patients in the end. The ultimate goal is to create an intelligent, fully automated electronic health record (EHR) system that can help physicians by removing them from the burden of data entry, which is currently done in clinical settings by human dictation helpers or transcript makers.

The first step in the process is to record these sessions with an outstanding video camera, following HIPAA (Health Insurance Portability and Accountability Act) regulations and with the patient's express consent. After that, these movies can be instantly examined to extract and evaluate important data for use in clinical decision-making, such as emotion, gesture, posture, gracefully, and movement. Excellent audio is another crucial source of information. The secret of recoding speech. Speech recognition is important for two reasons. One is that text can be extracted from this using speech-to- text technology, and then a number of relevant data can be extracted by natural language processing, include sentiment analysis, vocabulary, speech quality, and other significant clues that may be beneficial for medical diagnosis or rehabilitation. The other, more analytical reason is that speech can be processed and examined to detect patterns in speech, such as slurred speech, a number of other purposes, to identify breathing patterns or lung capacity.

Other sources of data that can be gathered include signals, which can be obtained using a number of modern devices. By using wearable sensors, such as BioStamp, these can be more traditional ECG, heart rate, oxygenation, pulse, temperature, etc., or more aggressive and in some cases previously invasive signals like blood sugar, blood flow rate, skin moisture, etc.

IV. RESULTS

In this section, automated collection and processing multi model health signals using Big data analytics is presented. The result analysis of the Multi model health signals using Big Data Analytics (BDA) performed best efficiency compared to health signals.

Fig. 2 shows Efficiency Comparison of health signals and health signals using Big data analytics with various thresholds. X-axis shows classification and Y-axis represents percentage (%). The Multi modal health signals using Big data analytics has a high efficiency.

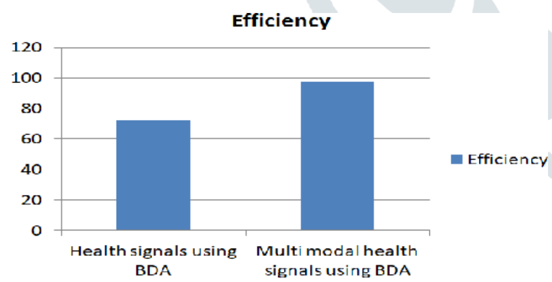

Fig.2: Efficiency Comparison Graph

The Fig. 3 shows the processing time comparison between health signals using Big data analytics and Multi model health signals Big data analytics. The Multi model health signals using Big data analytics

takes less time compared to health signals using Big data analytics. The Y-axis represents the time in ms (milliseconds) and X-axis represents the systems.

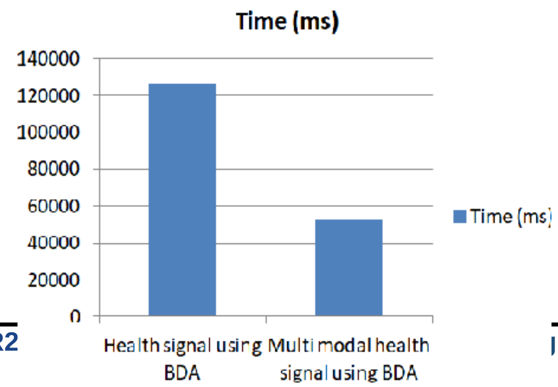

Fig.3: Processing Time Comparison Graph

V. CONCLUSION

In this section, automated collection and processing multi model health signals using Big data analytics is presented. The result analysis of the Multi model health signal is demonstrated. This analysis's primary goal is to highlight the different aspects of hybrid authority (HBD), their origins, and the factors that drive dataflow in a health care model among the many actors. Every data flow process's objectives, the connections amongst participants in the health care sector, and the data sources all point to the natural categorization of HBD. In other words, this categorization offers an extensive overview of all dataflow within the HBD-conceptualized health care paradigm. A platform called "Wired Room" was used to evaluate and better manage healthcare results from consultations between physicians and patients, and this analysis is a part of an ongoing research and development program in health analytics. Their next attempt is to develop a sentiment analysis technique to compare the sentiment collected from the textual content with the study of facial expressions.

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