IEEE Access
Multidisciplinary ⁝ Rapid Review ⁝ Open Access Journal

Received February 1, 2022, accepted March 9, 2022, date of publication March 22, 2022, date of current version April 1, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3161439

Secure EMR Classification and Deduplication Using MapReduce

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ABSTRACT Healthcare providers generate huge amount of data every day through registration, lab results, prescriptions, and others. This is stored in the form of Electronic Medical Records (EMR) in a central repository. A medical record data is very huge, difficult to read and understand. To give an insight to the professionals in analyzing the different domains a patient belongs to, it is necessary to get pointers to a file before classifying it to a particular department for further analysis. This study provides a EMR processing system to automatically classify EMRs based on the important medical terms using TF-IDF and topic modeling. Automatic Classification of EMRs help the healthcare professionals in taking accurate decisions, providing efficient service, and improves the time taken for processing huge amount of data and in better organizing of patient. The data stored on the cloud may contain duplicate copies of EMR on several storage systems at file level thus increasing the network bandwidth, cost, and consuming storage space. Hence, a deduplication mechanism is required to avoid or reduce the data redundancy. Adapting cloud computing for healthcare systems necessitates sharing patient data with cloud service providers, which creates security concerns as the data may contain diagnosis, medication, laboratory results and medical claims. The main aim of this work is to classify the EMRs as per the specialization using KNN algorithm, optimize storage using deduplication and protect the data using DNA encryption algorithm before uploading to Hadoop. Data redundancy is taken care by implementing deduplication techniques using MD5 hashing. Proposed methodology shows an accuracy of 90% for EMR record classification and handles duplication and security aspects. This in-turn proves the state of the art approach for health care data management.

INDEX TERMS Classification, clustering, deduplication, DNA encryption, electronic medical records, Hadoop, map reduce.

I. INTRODUCTION

During the most recent decade, there has been a huge appropriation of cloud-based Electronic Health Records (EHRs) and Electronic Medical Records (EMRs) by various clinical bodies. As indicated by National Health Record Survey 2017, the level of office-based doctors using any EHR or EMR framework is 85.9%. There has been a consistent development in the reception of public electronic well being record frameworks in recent years and 46% worldwide expansion in the previous five years as expressed by WHO.

At first, EHRs were intended for filing and getting sorted out patients' records. With time, EHR driven information bases turned out to be more extensive, dynamic, and interconnected. Health experts (physicians or nurses), health facilities (clinics, hospitals for providing medications and other diagnosis or treatment technology), and a funding institution supporting the first two are the key components of a healthcare system. Various levels of healthcare are required depending on the severity of the condition. Professionals use it for primary care, acute care that requires experienced professionals (secondary care), advanced medical research and treatment (tertiary care), and extremely rare diagnostic or surgical operations (quaternary care). Health professionals oversee many types of information at all these levels, including the patient's medical history (diagnosis and prescription data), medical and clinical data (such as data from imaging and laboratory procedures), and other private or personal medical data. A large volume of patient data has been gathered and is now accessible online, including lab tests, drugs,

The associate editor coordinating the review of this manuscript and approving it for publication was Sathish Kumar.

disease history, and treatment outcomes. Advanced clinical data analysis and data management have been developed to incorporate patient data into a database of rich longitudinal patient profiles. EMR/EHRs open previously unimagined possibilities for cohort-wide research and knowledge discovery. They are vital data sources for developing predictive models for disease diagnosis and prognosis, allowing personalized medicine to flourish. Hence, this work uses Term Frequency-Inverse Document Frequency (TF-IDF) and Latent Dirichlet Allocation (LDA) topic modeling to find relevant medical terms and topics in an EMR. LDA is used in various domains of natural processing and data mining. Each document is made up of different terms, and each topic has its own set of words. LDA's task is to identify which topics a document belongs to based on the set of words it contains.

The computing ability needed to process massive number of varieties of healthcare data rapidly can burden a system or network of servers. Thus, organizations need to adopt cloud computing to achieve sufficient processing power and speed needed to handle big data tasks. Cloud computing offers a new model for enhancing healthcare delivery and expanding medical organizations' business flexibility, allowing them to operate with greater efficiency, cost-effectiveness, and flexibility. Hence, numerous servers may often focus on Hadoop and Apache Spark's technologies, where the work is distributed among several nodes in a clustered way. To achieve such pace cost-effectively is also a challenge. Cloud computing offers users endless storage space, processing power, apps, servers, networking, and ease of access to data always. Cloud computing's primary aim is to provide services focused on virtual and decentralized computer technology.

As the use of digital medical records increases, the amount of duplicate data also increases leading to data redundancy. Redundant data need to be reduced by removing the duplicate copies of data or by avoiding the upload of redundant data. Replicate data has been identified to the point that 50% of the cloud space is filled. The expense of managing similar data sets is excessive, almost eight times higher than processing the native cloud data. Reducing management spending is very important with the rise in data submitted to the cloud and improving the use of storage. Enhancing storage performance and management expense optimization is, therefore, an urgent issue to be addressed. The cloud service providers should implement data deduplication techniques to deal with the above issue, remove duplicate data copies, optimize the use of storage, and reduce processing expenses. This can be done using various deduplication techniques. Deduplication is the method of removing duplicate data copies by means of a deduplication scanning procedure to store unique copies and then support all approved users. Deduplication is a critical component of any storage system.

Data stored in the cloud may contain personal, private, or confidential information, such as medical records, that must be protected against disclosure, breach, or misuse. Concerns about data jurisdiction, security, privacy, and compliance are impeding adoption by healthcare companies around the world. EMRs hold personal information related to patient's medical history, treatment, and other details such as medical claims, etc. Medical organizations share and manage this information for various purposes like billing, research, and storage. Hence, security is very critical in health systems to provide protection to patient data.

EMR is a digital record of patient information such as vital signs, medical history, treatment, diagnosis, scanning, radiology and other laboratory results, billing and medical claims maintained by healthcare organizations for improving the operations and coordination for efficient patient care. EMRs enable the doctors and physicians to extract useful information regarding medications and treatments, reduce errors and to improve healthcare. Follow-up instructions, scheduling appointments, access to lab results, and reminders for self-care can be provided to patients and thus helps in lifestyle changes to improve overall health. It also improves the quality of operation in hospitals, improves the documentation, enables the tracking and searching of patient related information in an organized and efficient manner.

Research work has following contributions:

1) Finding relevant medical topics for classification from EMR.
2) To classify the EMR's using KNN MapReduce.
3) Optimize data storage on Hadoop using deduplication techniques.
4) To provide data protection using DNA encryption.

The rest of the paper is organized as follows. The first section gives a literature review on topics like topic modeling, Hadoop, map reduce, different ways of extracting information from EMR, classification and clustering algorithms. The next section gives a detailed explanation about the proposed system. It explains the architecture of the model, KNN map reduce, DNA encryption and decryption algorithms and deduplication technique. The fourth section discusses about the results and its importance. The last section deals with the conclusion of the work and future scope.

II. BACKGROUND

In this section EMR data extraction and deduplication, big data and Hadoop technology is presented.

A. EMR DATA EXTRACTION AND DEDUPLICATION

Healthcare networks maintain clinical data registries according to their predefined enterprise-wide EMR architecture. Data is collected at different facility centers of a network and integrated into EMR system. All the facility centers must be equipped with data marts, feeding the data to EMR repository. This data can be in-turn used for disease management, quality measures, health management and health reporting. Since the data needs to be integrated from different centers, it may contain unstructured data, missing information, duplicates and inconsistencies. If we keep the duplicate data into the repository, it will increase the storage overhead. Using such data for research is challenging which may lead to inconsistencies and incorrect analysis the data. Hence the incorporating deduplication techniques before storing the data into EMR repository is significant.

B. BIG DATA

Big data refers to the large and varied data sets that are rising at ever-increasing rates. This covers the volume of data, the speed at which it is produced and gathered, and the number of data points covered. Big data is processed in computer databases using software specially designed to manage massive, complex data sets. The variety of sources, like commercial systems, customer accounts, health records, logs of online network usage, cellular phone applications, social media, scientific information, data gathered from the machine, and real-time data obtained from IoT contributes to big data. In big data analytics, using data mining techniques or data processing tools, the data can be utilized in its raw state or pre-processed to be ready for analytics use. The need to tackle the pace of big data places particular challenges on the core computing infrastructure. The computing ability needed to process massive amount of varieties of data rapidly can burden a system or network of servers. Thus, organizations need to use sufficient processing power to achieve the speed needed to handle big data tasks. Hence, numerous servers may often focus on Hadoop and Apache Spark's technologies, where the work is distributed among several nodes in a clustered way. To achieve such pace cost-effectively is also a challenge. Many business leaders, particularly those who do not run 24/7, are discreet about investing on servers capable of storing and handling the data. Therefore, nowadays, big data systems are hosted on an open cloud platform. A cloud can store up to 1015 bytes of data and step up the servers till a project is complete. The company is charged for data quantum of stored and for processing duration. Further, when the cloud is used again, its instances will be turned off. Through the service manager, the open cloud service provider offer big data capabilities which includes EMR by Amazon, Azure HDInsight by Microsoft, Cloud Dataproc by Google to service levels further. The other forms of lower-cost cloud object for storing the big data in cloud platform may comprise Hadoop Distributed File System (HDFS), Simple Storage Service (S3) by Amazon and NoSQL.Cloud computing offers users endless storage space, processing power, apps, servers, networking, and ease of access to data always. Cloud computing's primary aim is to provide services focused on virtual and decentralized computer technology.

C. HADOOP

Apache Hadoop is an open source software project for Big data analytics [6], [7]. It enables the distributed processing of large data sets across clusters. These clusters are formed using commodity servers. It is a platform that provides distributed storage and computational means. The core components of Hadoop are HDFS and MapReduce. HDFS is the storage component of Hadoop which is a distributed file system. MapReduce is a batch-based, distributed computing framework modeled after Google's paper on MapReduce [8]. It allows parallelism over a large amount of raw data such as combining unstructured or semi-structured data with relational data from an OLTP database to model the required analysis. This type of work, which could take days or longer using conventional serial programming techniques, can be reduced down to minutes using MapReduce on a Hadoop cluster.

III. RELATED WORK

Topic discovery or modelling plays a very important role in feature extraction for different domains. Bingyang *et al.* [1], studied the emotions of tourist visiting a scenic spot using LDA topic modeling to cluster the tourism dataset. An emotional dictionary is constructed separately for online reviews and micro-blogging texts. Initially Naives Bayes algorithm is used to for constructing a clear emotional parity and the LDA theme model is added to refine the errors during reclassification of another part. A Tourist corpus was selected from micro-blog and travel website. At last, the classification result of the two classifiers is combined to get the emotions of tourists.

A novel domain-oriented topic discovery was done by Xiaofeng lu *et al.* [2], to identify emerging cyber threat topics in the domain in real life to analyze open-source platforms and blogs. This Feature Extraction and Topic clustering (FETC) applied to cyber security data threat considers location of word and parts of speech. They first used web crawlers to extract data from specific labels such as vulnerability and malware. Then, the article title, body text and time are extracted and stored in a database. The authors then offer three improved feature extraction methods: a better keyword feature extraction approach, a subject word feature extraction method, and an entity feature extraction method. The obtained features are combined using feature fusion technology, and the feature vector of the article is created for use as the topic clustering module's input. Finally, an improved hierarchical clustering algorithm is implemented to cluster the feature vectors of articles in each period to identify emerging or historical topics in real time.

A knowledge base was created by Girija Attigeri *et al.* [3], for fraud detection in news related articles. Articles from news websites were collected and pre-processed by removing stop words and punctuation marks. The words with higher TF-IDF scores provide important insight about the fraud. The outcome of LDA indicates any suspicious activity that may lead fraudulent incidents. The topics derived from LDA are used to create a knowledge base ontology using which may be used for the classifying the transactions as legal or fraud.

To ease the problem of sparsity in short texts, a sentence based LDA was set up by Fan Zhang *et al.* [4]. A single topic is used for generating the short text words. To do this, a word embedding model with replacement is used to recognize the relationship between the words. This relationship plays an important role in determining the relevance or importance of a word. In practice, a health-care decision-making system assesses whether a patient has an illness based on a set of symptom indexes and physical characteristics; disease diagnosis is, in essence, a classification problem. Data mining technology can assist healthcare by grouping patients with similar ailments so that healthcare providers can give them with better treatment [5].

A. EMR DATA EXTRACTION AND DEDUPLICATION

Due to the expanding number of health records and complexities associated with the health business, several challenges will be met by the healthcare data managers. The burden on e-health data managers can be reduced by automating their work. Heath [6], described the distribution of scanned documents at their institution. The author developed a system that categorizes the EMRs based on the design. The author evaluated the text classification models that were trained on documents through optical character recognition. The author made use of previously manually classified documents to determine the accuracy of their system, Thus, their system could classify the documents based on the clinical relevancy. Thus, using machine learning and OCR approach they were able to classify the documents into clinically relevant documents.

Policy-makers and other key stakeholders will use the key organizational, human, and technical factors described in this analysis to make evidence-based decisions during the implementation of a completely inter-operable EHR across primary, secondary, and long-term care. Orna Fennelly *et al.* [7], aimed at identifying the key factors that impact on successful implementation of EHR at different levels of e-healthcare. They concluded that the efficient implementation of these variables, however, requires careful consideration of the contextual influences. End-users, current technical requirements, and policies, as well as developments in technology and research in the field, will all influence how these factors communicate dynamically during EHR implementation and affect performance. Segura-Bedmar *et al.* [8], explored different techniques that automatically classify EMRs. They also compared various ways of representing EMR and applied some efficient text classifiers to identify clinical records describing anaphylaxis (an allergic reaction) cases. Their experiments revealed that the prediction of anaphylaxis cases is a linear problem that thus they can be efficiently solved by using linear classifiers such as Linear SVM or Logistic Regression and the BoW (Bag of Words) representation. A simple CNN architecture achieves the top F1, but it takes about 50 minutes to train the network. High F1 (91–94%) and low training times are given by k-NN, Linear SVM, and Logistic Regression (less than 20 s). The fastest algorithm is k-NN, which takes less than a second to learn.

Different analytic tools can be adapted in various stages of implementing EHR. Fadoua Khennou *et al.* [9] studied the challenges in implementing the EHRs and their association with different health systems. They could successfully implement an OpenEHR model to study the intermediate steps involved in it. A processing technique that involved in depth study of different steps of processing EMRs like data cleaning, integrating, transforming and privacy protection was proposed by Wencheng Sun *et al.* [10], reviewed different approaches of extracting information from EMRs that involved structured and unstructured data. Unstructured data in clinical notes can be processed to help doctors arrive at certain important decisions. Wencheng Sun *et al.* [11], have discussed the current state of data mining technology research in EMR and the obstacles that EMR research is currently facing. The Electronic Medical Record (EMR) is used by medical institutions to keep track of a range of medical operations, including diagnostic details (diagnosis codes), procedures performed (procedure codes), and admission records. Due to the growing social value, it creates, it has become a hotspot for experts and academics.

The inherent characteristics of electronic medical records were examined by Yuan Zhang [12] from real-world electronic health (eHealth) systems, finding that, first, multiple patients produce many duplicate EMRs, and second, cross-patient duplicate EMRs are produced in large numbers only when patients visit doctors in the same department.They proposed effective and stable encrypted EMRs deduplication scheme for cloud-assisted e-Health systems (HealthDep). HealthDep enables the cloud server to effectively conduct EMR deduplication, resulting in a 65 percent reduction in storage costs while maintaining EMR confidentiality.

Parallelism was implemented by Dongzhan Zhang *et al.* [13], by using MapReduce technique and HBase to accelerate the deduplication process. However, one among the critical challenges faced by file service providers is that they often need to contain duplicate copies of file contents as data are being accumulated. A new file aggregation scheme supported MapReduce is proposed and therefore the recent SHA-3 standard KECCAK is employed for hash computation. Shahid Munir Shah *et al.* [14], have analyzed various ways of mining data from EHRs. Healthcare providers produce massive quantities of clinical data on a regular basis in today's technological age. As a central data repository for hospitals, generated clinical data is stored digitally in the form of an Electronic Health Record (EHR). The information stored in EHR is used for a variety of secondary purposes, including clinical testing, automated disease monitoring, and clinical audits for quality improvement. Individuals' privacy may be jeopardized if confidential personal information stored in EHR is leaked or revealed to the public. Data breaches may result in financial damages, and if a person's medical condition is revealed in public, he or she can face social boycott. Different privacy laws exist to safeguard patients' personal data from certain risks, such as the General Data Protection Regulation (GDPR), the Health Insurance Portability and Accountability Act (HIPAA), and My Health Record (MHR). However, as state-of-the-art techniques in Machine Learning (ML), Data Analytics (DA), and hacking continue to evolve, it is becoming very difficult to fully protect a patient's privacy. They have thoroughly analyzed various uses of EHR in the article with the aim of highlighting how the secondary analysis impact patients' privacy. However, the current work emphasizes on better security using MD5 hashing and DNA Encryption. Further our work is implemented by considering distributed data storage on Hadoop, handling duplicate data, classifying data based various diseases of different departments, which is hybrid approach suitable for healthcare data management.

A list of the benefits, implementations, research methods, and challenges of Big Data for health care were reviewed by Liang Hong *et al.* [15]. Heterogeneity, incompleteness, timeliness and persistence, anonymity, and ownership are all characteristics of Big Data in health care. These characteristics present several difficulties in terms of data storage, mining, and sharing to advance health-related science. To address these issues, research methods based on Big Data in health care must be created, as well as laws and regulations governing the use of Big Data in health care. From the standpoint of the patient, Big Data analysis may result in better care and lower costs. The government, hospitals, and research institutions, in addition to patients, could benefit from big data in healthcare.

Caifeng Zhang *et al.* [16], have emphasized on efficient adoption of EHRs in medical field. The China government issued the Electronic Health Record Architecture and Data Standard in 2009 as a guide for hospitals with the aim of enhancing treatment quality through the meaningful use of electronic health records (EHRs). The Chinese EHR Standard defines EHRs as "A full set of digital clinical information recording the clinical treatment given to a person". EHRs have been recommended for over two decades to improve the quality and efficacy of healthcare services, but these do not guarantee that implementing the EHRs scheme would result in such benefits. To know the payback, healthcare professionals must make the EHR a part of their everyday work routine. As a result, the Health Information Technology for Economic and Clinical Health (HITECH) Act establishes "meaningful use" of electronic health records as a target for adoption. Act's key goal is to develop meaningful and usable digital medical records, including electronic health records (EHRs) entry and storage, as well as to maximise the use of EHRs.

Using deterministic record linkage algorithms, a stable protocol for deduplication of horizontally partitioned data sets was developed by Kassaye Yitbarek Yigzaw *et al.* [17]. They have found various techniques for computing statistics on distributed data sets without disclosing any personal data other than the statistical results. In a distributed data set, however, duplicate records can lead to incorrect statistical results. As a result, safe deduplication is an essential pre-processing step for improving the accuracy of statistical analysis of a distributed data set. They targeted on the reuse of health records horizontally partitioned among records custodians, such that every records custodian presents the equal attributes for a fixed of patients. Reusing records from more than one records custodian presents sufficient patients who satisfy the inclusion standards of a selected study. The variety of patients at a single records custodian can also additionally offer inadequate statistical power, especially for research on uncommon exposures or outcomes. When records are acquired through more than one source, the records of a heterogeneous blend of sufferers may be reused.

B. HADOOP MapReduce

Due to the rising number of health records, there will be many problems to overcome. And the problems that come with working in the health-care sector as a result, it is critical to convert the data size and quality into a crucial nominal value using all available solutions. In terms of safety and efficiency problems, detailed research need to be made. An attempt to meet the requirements of privacy, reliability, and accuracy separately was made by Jiawei Yuan *et al.* [18]. They first proposed a privacy-preserving algorithm based on clustering using K-means for handling extensive dataset on public cloud domain. Centered on the hard problem of Learn with Error (LWE), a new encryption method was discovered, which achieved privacy-preserving calculation of data object similarity upon cipher-texts. With the help of their encryption program, they built the entire K-means clustering scheme in a privacy-safeguarding mode, wherein cloud servers having access to encrypted data performed all operations without any decryption. In this way, along with creating a new method in cloud computing, they also achieved better performance compared to the K-means clustering without security. Considering the support of large-scale datasets, they integrated the MapReduce system into the new architecture, and it was highly appropriate for parallelized environmental analysis for cloud computing.

An agglomerative fuzzy algorithm based on K-means with the MapReduce technique was implemented by Ruixin Zhang *et al.* [19]. In this algorithm, an initial centre is selected to improve the convergence speed of the k-means algorithm. Then, to improve scalability for large datasets, a MapReduce implementation based on Apache Hadoop is presented. Though K-means is a simple algorithm, determining the initial centroid is very difficult and if the data set is very large all the variables have the same effect and it may lead to dimension trap. To solve this dichotomous method is used in which two objects which are far are selected as initial centroids as explained by Qingyuan *et al.* [20]. Yurong Zhong *et al.* [21], focused on integrating both property and location of K-means clustering on Hadoop platform. The new cluster will be calculated based on Map function. They also analyzed the time complexity of the algorithm. A distributed environment and parallel processing of data was proposed by Wooyeol Kim *et al.* [22] to process the KNN joins using MapReduce for Bigdata. This KNN-MR algorithm identifies the data that need to be eliminated by using non-KNN points that utilizes vector projection pruning. This approach reduces the computational and network costs across the machines.

The problem of discovering knowledge and making decisions from rapidly rising voluminous big data is a difficult one, K. Sharmila *et al.* [23]. In developing countries like

India, diabetes mellitus (DM) is a major health concern. The acute essence of diabetes mellitus is linked to long-term complications and various other ailments. Based on their findings, they propose an effective predictive approach, the MRK-SVM hybrid algorithm, for identifying diabetes types and predicting diabetes complications at an early stage. For big data analysis, a real-time dataset was generated by replicating records from five districts in Tamilnadu, and big data analysis was performed using Hadoop MapReduce, Spark, and in the cloud.

Srikanth Bethu *et al.* [24] have inferred that the pursuit of knowledge and its application in computationally intensive activities with a wide variety of applications, data mining plays a critical role. A theoretical and experimental comparison of the approaches for computing KNN on MapReduce is done. Each stage of data pre-processing, data partitioning, and computation is examined for load balancing, accuracy, and complexity. The experiment results are produced from a variety of datasets. Each dataset's time and space complexity are examined on a regular basis, yielding new benefits and drawbacks that are addressed for each algorithm. Finally, they have discussed various ways of dealing with KNN-based problems in the context of Big Data MapReduce.

Shaobo Du, Jing li *et al.* (cite23 have proposed Hadoop-based parallel processing of an improved KNN text classification algorithm. They state that the network has become a significant platform for people to share information due to the rapid growth of mobile Internet. The study of text classification is useful in the real world. The Hadoop platform can be used to parallelize the KNN classification algorithm, which can easily and accurately classify text. However, when measuring the similarity or distance of sample points, the KNN algorithm will increase as the sample data grows, increasing the algorithm time. The CLARA (Clustering Large Applications) clustering algorithm is used to take out samples in the dataset that have low similarity, and the sample distance measurement in the dataset is reduced. Subsequently, to identify the network public opinion data, parallel KNN MapReduce program is designed. The results of the experiments show that the improved parallel KNN algorithm improves text classification accuracy and speed.

Doreswamy *et al.* [25] have suggested a k-means clustering algorithm that scales up to a large dataset of about 8 million items. Each object is a five-attribute vector. To find the maximum value of inter-cluster density and the minimum value of intra-cluster measurements, inter and intra cluster measurements were computed. Dillon Chrimes *et al.* [26] developed a HBDA (Healthcare Bigdata) platform for health applications was built using a Hadoop/MapReduce framework. Only a few works have used big data tools for analyzing hospital patient data for healthcare applications. This solution removes the need to move data in and out of the storage system while parallelizing the computation. This problem is very relevant in healthcare due to the growing number of sensors and data produced. Furthermore, making a stand on using the Apache software needs usability goals-based end user computing of Big Data technology and leveraging existing tools from a data warehouse at a health authority. A stable medical big data ecosystem on top of the Hadoop big data platform to increase the intelligence of the medical system was implemented by Xiangfeng Zhang *et al.* [27]. It was created in response to the current security medical big data ecosystem's increasingly serious trend. Authors emphasized utilizing block-chain as it has been a successful breakthrough point for innovation in medical data interchange since it is a distributed accounting system for multi-party maintenance and backup information security. The customized health information system for stroke has been built to deliver personalized care for patients and to promote the management of patients by medical professionals by using the advantages of the Hadoop big data platform.

C. DATA SECURITY

Prasanna Balaji Narasingapuram *et al.* [28], suggested a new form of cryptography to detect and remove malicious users to improve security at the user level to prevent the entry of malicious users into cloud applications. Various cryptographic approaches, algorithms, and strategies for user verification for data access have been proposed in their research. But malicious user activities are still growing day by day in the cloud. This approach focuses on eradicating malicious cloud user behavior. In-order to do this, the device uses the method of DNA cryptography to produce a strong user key and the decryption process for data encryption. The findings are analyzed with the method's current outcomes and have shown that the proposed DNA outperforms other cryptographic techniques. In-order to reduce the burden on network bandwidth and improve storage R. Shiny Sharon *et al.* [29], proposed a deduplication technique. In terms of encryption and decryption, File Hierarchy-ABE is used, which has a low storage cost and computational complexity. Privacy preserving technique was also implemented for securing the PHI (Personal Health Information) such as the Layered Model of Access Structure, which addresses the issue of sharing multiple hierarchical files. In-order to improve the efficiency on the cloud, Huiqi Zhao *et al.* [30] proposed that convergent encryption be applied to the medical cloud, with the convergent key's hash value being used as a repeat detection label and Bloom filter search to improve the medical cloud's efficiency, and the practicality of medical data be improved by introducing fuzzy keywords to address the problem of resource waste caused by the repeated storage of medical data. At the same time, the identity token authorization access methodology was to be used to achieve multi-function access to the medical cloud based on the real application of diverse medical data.

IV. METHODOLOGY

First the EMR is processed by removing the stop words, lemmatized by changing verbs in past and future tense to present tenses. Words are then stemmed by using corresponding root words. A dictionary containing the most frequent words with their number of appearances is created using genism package.

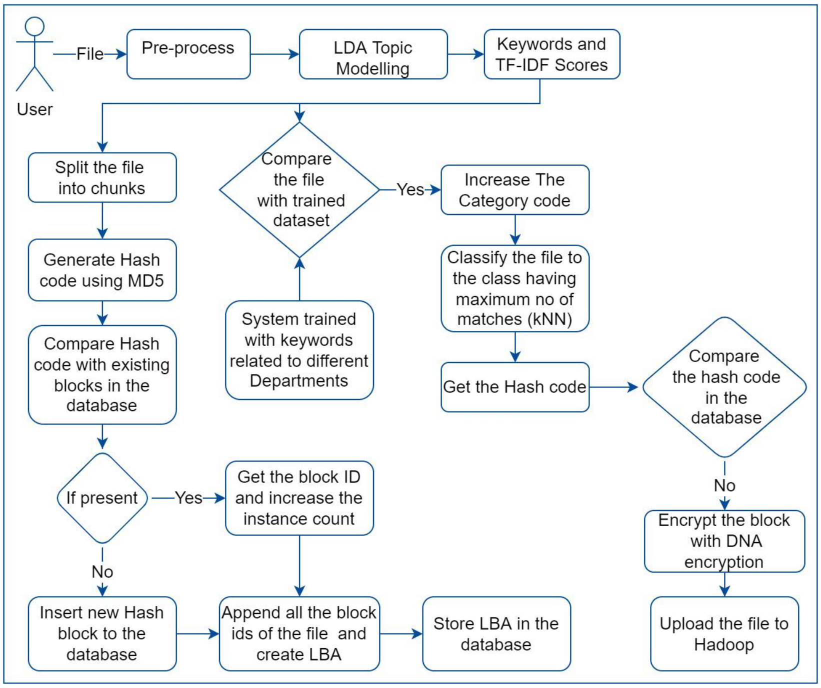

User
File
Pre-process
LDA Topic Modelling
Keywords and TF-IDF Scores
Split the file into chunks
Compare the file with trained dataset
Yes
Increase The Category code
Generate Hash code using MD5
Classify the file to the class having maximum no of matches (kNN)
System trained with keywords related to different Departments
Compare Hash code with existing blocks in the database
Get the Hash code
Compare the hash code in the database
If present
Yes
Get the block ID and increase the instance count
No
No
Encrypt the block with DNA encryption
Insert new Hash block to the database
Append all the block ids of the file and create LBA
Store LBA in the database
Upload the file to Hadoop

FIGURE 1. **Process flow diagram of the system.**

LDA model is then trained with the key phrases and their weights to obtain the topics related to medical terms along with their TF-IDF scores. TF-IDF scores indicate the significance of a term in a particular EMR. Thus, the knowledge obtained from this algorithm is used for classifying the EMRs to the most significant department. For the Map Reduce technique, the proposed work utilizes optimized KNN method on large Dataset on Hadoop. A distributed file system has the benefit of Hadoop and provides fast file access. The architecture diagram shown in Figure 1 depicts the different components of the proposed system. Database is used to store the hash codes of the blocks generated from MD5 and to store the Logical Block Addressing of respective files. Hadoop HDFS is used to store the blocks related to the user files. The file will be classified based on the resemblance to the trained dataset class labels.

A. DATASET

The input data will be the patient EMR (text document). It consists of patient's history, detailed explanation consisting of the vital signs of patient along with the treatments suggested by the doctor. The vital signs or the medical terms related to a particular department play a major role in classifying the patient EMR. Before testing the system, it is trained with the data related to each department. The following departments related to medical field are considered: Cardiology, Physiology, Pathology, Pediatrics, Obesity, Histology, Gynaecology, Oncology, Neurology, Forensic, Dental, Digestive, Opthomology, Orthology, Respiratory, Surgery, Micrology, Otorhinolarynygology, Nephrology.

The system is first trained with datasets related to different medical departments. The file selected by the user must be saved in that category. The selected files will be split into blocks and hash code is generated using MD5 algorithm. If the hash tag matches, we will not upload the block to Hadoop, we will increase the number of instances of that block in the database table. Subsequently hash blocks compared with the current hash tag from the database. If the hash tag is not matched, we will add the information of the block hash to the database and upload the block to Hadoop.The technique of Logical Block Addressing (LBA) is used to define which blocks in a file are present. The process flow is shown in the Figure 1.

First, for each distinct class label (department) that is linked to medical knowledge, we upload a qualified data collection. Each keyword is associated with a weight based on the number of occurrences in the data set. The words in the user file are compared with the trained data set. Each class has a center data point, and the keyword is compared with the data point in the trained data. If it matches, the weight-age of the word is calculated using Euclidean distance. The keyword and its weight-age are stored as key value pair and used by the MapReduce algorithm to recalculate the weight-age of words.

Based on the combined weight of the words, and its distance with the user file, the file is given a class label. The class with maximum of matches will be chosen using the single nearest neighbour KNN classification. After that, the file is stored in the respective class directory in the eclipse.

The blocks that are already stored in the database are not uploaded to the HDFS. After that, DNA encryption is applied to the blocks of data created to make it secure before storing it on the Hadoop HDFS. To write data to HDFS, the client must first contact with the name node to ensure that the file can be written, and the data node that will receive the file block. The client then sends the file in order, block by block, to the associated data node, and is responsible for ensuring that the data node receives each block.The file upload algorithm steps are explained in the algorithm 1.

Algorithm 1 File Upload Algorithm

```
1) Read File F form the perspective.
2) Based on the packet size file chunks will be formed
3) for I= 0 to N do Generate the hash code for each chunk
   using MD5 algorithm.
4) Compare the hash code with the existing hash code in
   the database.
5) if exists then
     • get the block id of the identical hash code from the
       database.
     • increase the Instance by Map Reduce Technique
       (Mapping to the existing Block)
6) else
     • Insert the new hash code to the database and get the
       id of the inserted hash code for the LBA process.
     • Upload the block to the HDFS storage end if end
       for Append all the block ids of the file and cre-
       ate the Logical Block Addressing store it in the
       database.
```

Algorithm 2 File Download Algorithm

```
1) Select the file in download list.
2) Get the LBA based on file id.
3) Each encrypted blocks must get decrypted by using
   DNA algorithm.
4) Using LBA, find the block numbers which are in
   selected file.
5) check if all the blocks required for the file are available,
6) if all the blocks are available in Hadoop storage space
   then download blocks,
7) the encrypted blocks will get decrypt by using DNA
   algorithm then merge the blocks and give it to the user.
```

When the file needs to be downloaded, Logical Block Address of the file is obtained from the file id as explained in the algorithm 2. The blocks are downloaded from the HDFS, and the encrypted blocks will get decrypt by using DNA algorithm then merge the blocks and give it to the user. Because of its reliability and simplicity, the k-Nearest Neighbor classifier is one of the most well-known data mining approaches. This model enables us to categorize many previously unseen cases (test instances) against a huge (training) dataset at the same time. To do so, the map phase will find the k-nearest neighbors in various data partitions. Following that, the reduce stage will compute the definite neighbors from the map phase's list. subsequently, it will use the k-NN model's majority voting technique to predict the resulting class. The numeric vector represents the input document dataset after pre-processing and these vectors are stored in the register. The number of the vector values is taken at random from the dataset.

This model enables us to categorize many previously unseen cases (test instances) against a huge (training) dataset at the same time. To do so, the map phase will find the k-nearest neighbors in various data partitions. Following that, the reduce stage will compute the definite neighbors from the map phase's list. After that, it will use the k-NN model's typical majority voting technique to predict the resulting class. The numeric vector represents the input document data-set after pre-processing the data-set and the vectors are stored in the register. The number of the vector values is taken at random from the data-set. The Algorithm 3 provides the implementation of the KNN Map-Reduce:

Algorithm 3 KNN Algorithm

```
1) Extract the keywords with their weightage and store it
   in an array.
2) Let N be the number of classifications and M the num-
   ber of extracted words.
3) Initialize an array – weight[N]
4) For I=1 to M, J=1 to N Check the presence of K word
   in classification keywords,
5) if it is present, weight[J]=weight[J]+ K word Next J,
   Next I.
6) Fetch the next highest weight value and index, add the
   index in classification array.
7) W = W + Fetched class weight. If W >=Threshold,
   goto step 7
8) Print all the categories in the classification array.
```

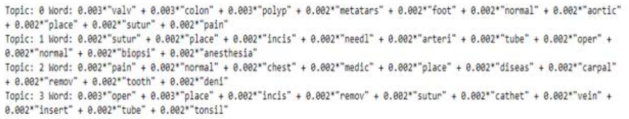
The DNA carries the genetic instructions used in the growth, development, functioning and reproduction. Nucleotides are composed of DNA and RNA, which in turn are composed of four nucleotide groups: cytosine(C), guanine(G), adenine(A) or thymine(T), deoxyribose and phosphate. The hydrogen bonds and nucleobases form double-stranded DNA to store biological information according to the base pair law. As a key for the encryption algorithm, this knowledge is used. 1021 bases, equal to 108 terra-bytes, are contained in a gram of DNA. One gram of DNA contains 1021 bases of DNA, corresponding to 108 TB of data. Hence, in a few milligrams, all the data in the world can be stored. Cryptography based on DNA is the technique of using biological structure to hide data and details. The DNA algorithm works as explained in the algorithm 4. The decryption algorithm is reverse of encryption.

V. RESULTS AND DISCUSSIONS

- Relevant medical topics for classification from EMR: The topics obtained from the LDA algorithm along with their TF-IDF scores is shown in Figure 2. This score

Algorithm 4 DNA Algorithm

```
1) Get the block to be encrypted.
2) Change it to ASCII value
3) Convert it to binary (0's and 1's)
4) Change it to DNA code.
5) A random key is generated between 1-256
6) 256 index values are created using permutation of 4 letters A,T,C,G (stored in a table )
7) Change it to DNA code
8) convert to binary and to corresponding numbers
9) Numbers - output
```



```
Topic: 0 Word: 0.003*"valv" + 0.003*"colon" + 0.003*"polyp" + 0.002*"metatars" + 0.002*"foot" + 0.002*"normal" + 0.002*"aortic"
+ 0.002*"place" + 0.002*"sutur" + 0.002*"pain"
Topic: 1 Word: 0.002*"sutur" + 0.002*"place" + 0.002*"incis" + 0.002*"needl" + 0.002*"arteri" + 0.002*"tube" + 0.002*"oper" +
0.002*"normal" + 0.002*"biopsi" + 0.002*"anesthesia"
Topic: 2 Word: 0.002*"pain" + 0.002*"normal" + 0.002*"chest" + 0.002*"medic" + 0.002*"place" + 0.002*"diseas" + 0.002*"carpal"
+ 0.002*"remov" + 0.002*"tooth" + 0.002*"deni"
Topic: 3 Word: 0.003*"oper" + 0.003*"place" + 0.002*"incis" + 0.002*"remov" + 0.002*"sutur" + 0.002*"cathet" + 0.002*"vein" +
0.002*"insert" + 0.002*"tube" + 0.002*"tonsil"
```

FIGURE 2. LDA topics generated.

indicates the importance of a word in the EMR document. The first topic 0 indicates the words related to cardiac. The next topic 1 recognizes the words related to operation, topics 2 and 3 dental and respiratory topics.

- classifying the EMR's using KNN Map Reduce:
  EMRs are classified using KNN. The experiments have been carried out on 4 nodes in a cluster: a master node and 3 compute nodes. Each one of these compute nodes has an Intel Core i7 4930 processor, 3.4 GHz and 64GB of RAM. In terms of software, we have used the open-source Apache Hadoop distribution (Hadoop 2.5.0-cdh5.3.2).
  The performance of the classification system is evaluated by calculating the accuracy, F1 score,Kappa, Recall and Precision values depicted in Figure 3. The classification algorithm was evaluated for 5 classes and the true labels vs predicted labels are shown in Figure 3. Accuracy is the number of EMRs correctly classified to a particular department to the total number of EMRs. F1 score represents the harmonic mean of precision and recall.The accuracy is above 85% for all the classes and the F1 score is above 69%. The graph shows a good recall and precision values. The Kappa value generated is more than 0.60 indicating moderate inter reliability. The Figure 4 shows calculations related to kappa statistics. Also training and testing accuracies are almost same, hence the model is correct fit over the data. However model fit can be validated though cross validation approaches.
  The Figure 5 and explains the sensitivity and specificity ratios of the model.The positive and negative RCE indicate how likely an EMR belongs to a particular department. Positivity tells us how much to increase the probability of belonging to a particular department and negativity explains how to much probability to decrease. The values of positive and negative likelihood ratios are shown in the Figure 6.

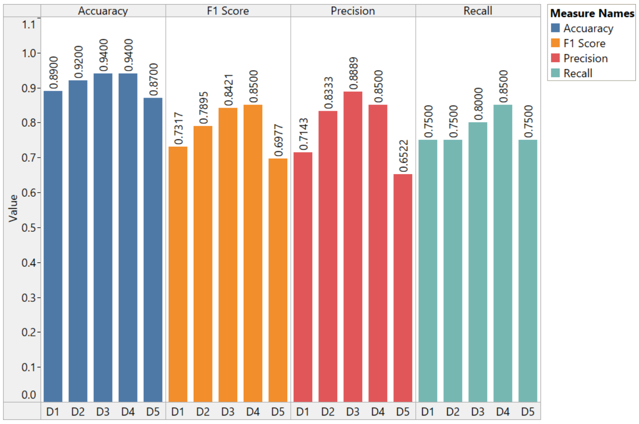


FIGURE 3. Evaluation metrics.

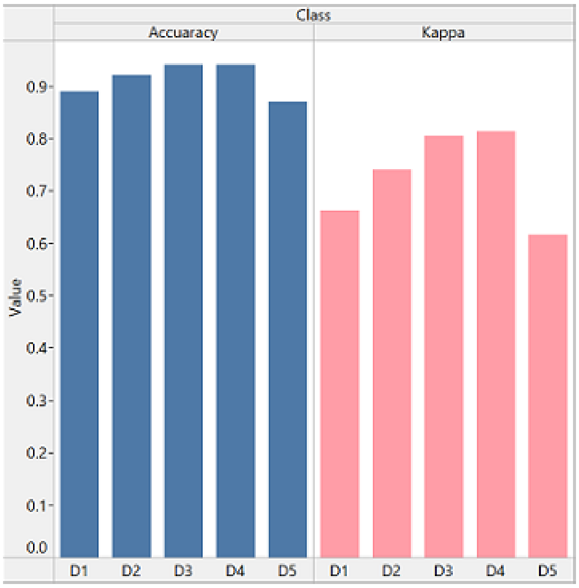


FIGURE 4. Accuracy and kappa.

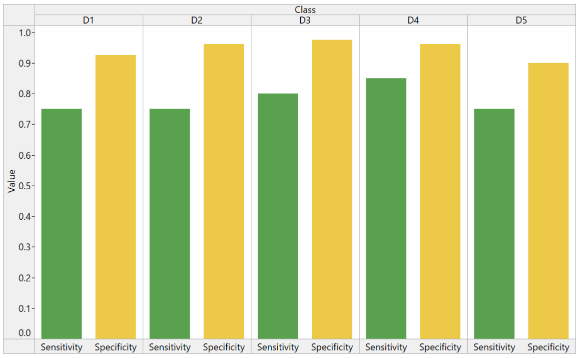


FIGURE 5. Specificity and sensitivity.

- Optimizing data storage on Hadoop using deduplication techniques. While storing the EMR each time in the data store, it is checked for duplication.For detecting duplicated blocks, indexing is used to compare existing hash values with new fingerprints. If any two data blocks have the same hash value, it means they are the repeated blocks that need to be removed, and only one block will

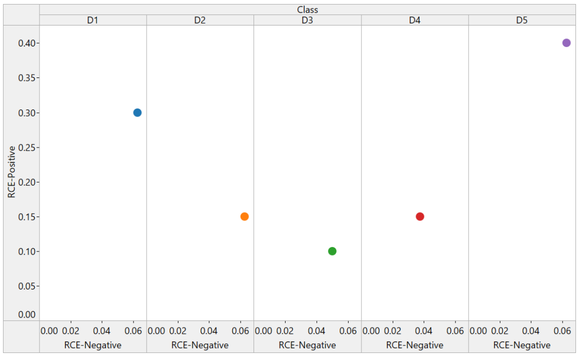
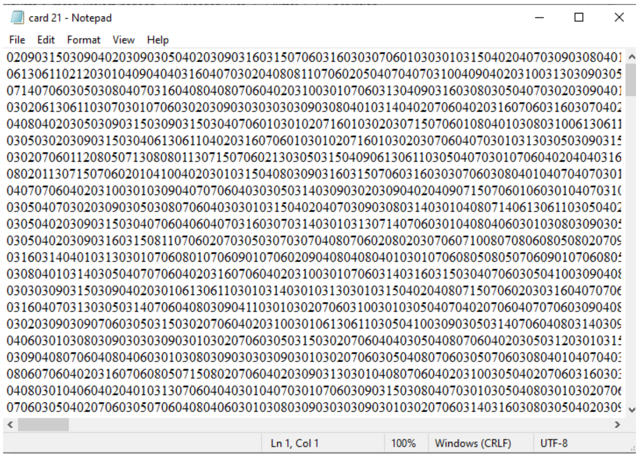


FIGURE 6. RCE positive and negative.



```
0209031503090402030903050402030903160315070603160303070601030301031504020407030903080401
0613061102120301040904040316040703020408081107060205040704070310040904020310031303090305
0714070603050308040703160408040807060402031003010706031304090316030803050407030203090401
0302061306110307030107060302030903030303030903080401031404020706040203160706031603070402
0408040203050309031503090315030407060103010207160103020307150706010804010308031006130611
0305030203090315030406130611040203160706010301020716010302030706040703010313030503090315
0302070601120805071308080113071507060213030503150409061306110305040703010706040204040316
0802011307150706020104100402030103150408030903160315070603160303070603080401040704070301
0407070604020310030103090407070604030305031403090302030904020409071507060106030104070310
0305040703020309030503080706040303010315040204070309030803140301040807140613061103050402
0305040203090315030407060406040703160307031403010313071407060301040804060301030803090305
0305040203090316031508110706020703050307030704080706020802030706071008070806080508020709
0316031404010313030107060801070609010706020904080408040103010706080508050706090107060805
0308040103140305040707060402031607060402031003010706031403160315030407060305041003090408
0303030903150309040203010613061103010314030103130301031504020408071507060203031604070706
0316040703130305031407060408030904110301030207060310030103050407040207060407070603090408
0302030903090706030503150302070604020310030106130611030504100309030503140706040803140309
0406030103080309030303090301030207060305031503020706040403050408070604020305031203010315
0309040807060408040603010308030903030309030103020706030504080706030507060308040104070403
0806070604020316070608050715080207060402030903130301040807060402031003050402070603160303
0408030104060402040103130706040403010407030107060309031503080407030103050408030103020706
0706030504020706030507060408040603010308030903030309030103020706031403160308030504020309
```

FIGURE 7. Encrypted file.

TABLE 1. Deduplication testcase.

File No	File Name	LBA
1002	Patient 1	1-2-3-4-5-6-7
1007	Patient 2	1-2-3-4-5-6-7

be stored on the disk. when the user chooses to upload a file, the file is divided into data chunks using MD hashlib in python, hash code is generated using MD5 algorithm. The algorithm takes data of arbitrary length as input, divides it into 16 blocks each of 32-bit length and produces a 128-bit length output as message digest. The number of instances of that block is also updated if it is already present in the table.

In order to test this, two EMRs named Patient1 and Patient2 with same contents were uploaded. The first file Patient1 was uploaded successfully. But when the second file with the same content was given for upload, it was not allowed to upload on HDFS, and the logical addressing of the blocks was stored in the database as shown in the table 1. Hence, by not allowing the upload of similar files, deduplication is achieved.

- Data protection using DNA encryption. In the proposed system, DNA encryption and decryption functions are implemented in python script before the file is uploaded to the Hadoop system, it is encrypted. The algorithm converts the value to ASCII representation and calculates the binary value of the data to convert it into DNA code, the encrypted file is shown in the Figure 7.

VI. CONCLUSION

In today's healthcare systems, digitization of all clinical evaluations and medical information has become a regular and widely accepted procedure. The huge amount of data that gets generated through various devices, need to be analysed to provide efficient service by reducing the errors. Because the MapReduce engine and HDFS can process thousands of terabytes of data, Hadoop technology is successful in tackling the above issues faced by the healthcare business. In this work, a Map Reduce based KNN classification is proposed to classify large amounts of patient EMR into different departments of medical using the vital signs of patient as data points. To do so, the map phase will find the k-nearest neighbors in various data partitions. Following that, the reduce stage will compute the definite neighbors from the map phase's list. The suggested approach enables the k-Nearest neighbor classifier to classify the patient EMR to different departments of medical effectively. The DNA algorithm provides the necessary security to the data and deduplication reduces the storage cost and the number of transactions to the cloud is reduced by uploading the blocks that are unique.

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