HEALTHCARE DATA ANALYTICS

1.TITLE & AUTHOR:

Analysis of research in healthcare data analytics **&** Alkhatib, mohammad and talaei-khoei, amir and ghapanchi, amir.

2. YEAR:

2017

3. TECHNIQUE:

Healthcare, data analytics, clinics, systematic review, tools and techniques.

4. FINDING /PROBLEMS/CONTENT:

4.1 BIG DATA STORAGE AND MANAGEMENT:

The traditional methods of storing and retrieving such data are not efficient anymore, since it was structured and stored in data warehouses and relational databases, after extracting and loading it from different outside sources.

4.2 HEALTHCARE PREDICTIONS AND DECISION SUPPORT SYSTEM:

Healthcare prediction is another data analytics method focusing on reducing future medical costs.

4.3 HEALTHCARE DATA ANALYTICS PLATFORMS AND TOOLS:

Comparing between traditional analytics and advanced analytics, traditional analytics is focusing on business intelligence, operational research and data mining. However, advanced analytics is focusing on descriptive, predictive and optimization.

4.4 Research Approaches:

Out of 81 studies included in this systematic review, 50 studies have adopted qualitative research approach, 19 studies used quantitative methods, and finally 12 studies used a mixture between qualitative and quantitative research approaches.

1.TITLE & AUTHOR:

Big healthcare data analytics: challenges and applications **&** Lee, chonho and luo, zhaojing and ngiam, kee yuan and zhang, meihui and zheng, kaiping and chen, gang and ooi, beng chin and yip, wei luen james.

2. YEAR:

2018

3. TECHNIQUE:

Healthcare · data analytics · big data · machine learning.

4. FINDING /PROBLEMS/CONTENT:
4.1 DATA ANALYTICS AND MODELLING:

We have proposed a healthcare analytics framework is composed of four phases which can give a better representation of medical features, and exploit the intrinsic information in ehr data and therefore, benefit further data analytics performance.

4.2MEDICAL FEATURE REGULARIZATION:

After regularizing EHR data into a more suitable format for analytics and representing features to reveal underlying relationships, we now turn to re-weight medical features for better analytics results.

4.3HEALTHCARE APPLICATIONS:

Computational Phenotyping has become a hot topic recently and has attracted the attention of a large number of researchers because it can help learn robust representations from sparse, high-dimensional, noisy raw EMR data.

4.4Healthcare Systems:

Instead of solving individual problems, a number of healthcare systems have been designed and built to serve as platforms for solving the problems described above. Now we shall discuss several representative healthcare systems.

1.TITLE & AUTHOR:

On delay-sensitive healthcare data analytics at the network edge based on deep learning & fadlullah, zubair md and pathan, al-sakib khan and gacanin, haris.

2. YEAR:

2019

3. TECHNIQUE:

Medical services, healthcare fraud detection,senior citizens,sensors,aging.

4. FINDING /PROBLEMS/CONTENT:
4.1 SENSOR DATA ANALYSIS:

Sensor data [2] is ubiquitous in the medical domain both for real time and for retrospective analysis. Several forms of medical data collection instruments such as electrocardiogram (ecg), and electroencaphalogram (eeg) are essentially sensors that collect signals from various parts of the human body [32]. These collected data instruments are sometimes used for retrospective analysis, but more often for real-time analysis.

4.2 PRIVACY-PRESERVING DATA PUBLISHING:

In the healthcare domain, the definition of privacy is commonly accepted as "a person's right and desire to control the disclosure of their personal health information" [25]. Patients' health-related data is highly sensitive because of the potentially compromising information about individual participants.

4.3 HEALTHCARE FRAUD DETECTION:

Healthcare fraud has been one of the biggest problems faced by the United States and costs several billions of dollars every year. With growing healthcare costs, the threat of healthcare fraud is increasing at an alarming pace.

4.4 Resources for Healthcare Data Analytics:

There are several resources available in this field. We will now discuss the various books, journals, and organizations that provide further information on this exciting area of healthcare informatics.

1.TITLE & AUTHOR:

Using machine learning applied to real-world healthcare data for predictive analytics: an applied example in bariatric surgery & johnston, stephen s and morton, john m and kalsekar, iftekhar and ammann, eric m and hsiao, chia-wen and reps, jenna.

2. YEAR:

2020

3. TECHNIQUE:

Prediction,machine learning,type 2 diabetes,metabolic surgery,antihyperglycemic medication.

4. FINDING /PROBLEMS/CONTENT:

4.1 SOURCES OF DATA:

We trained the model in the ccae database and externally validated the model in the optum database. The ccae database comprises health insurance claims and encounter records for commercially insured employees and dependents in the united states and is the largest database for privately insured patients with longitudinal follow-up in all 50 states.

4.2 TARGET POPULATION:

The target population comprised patients meeting all following criteria: underwent laparoscopic metabolic surgery (either roux-en-y gastric bypass or sleeve gastrectomy) between january 1, 2007, to october 1, 2013 (first observed surgery during this period = index); aged ≥18 years at index; continuous observation (ie, insurance enrollment) of 180 days before (baseline) to 730 days after index; ≥1 baseline condition occurrence of t2d; and ≥1 baseline prescription fill for antihyperglycemic medication. Above, these criteria are defined in terms of the omop cdm nomenclature, but what underlies these criteria are sets of codes lists which are native to given databases and data sources.

4.3 STATOSTICAL ANALYSIS METHODS:

We trained a lasso logistic regression model, a type of machine learning, within the ccae database using one repetition of 10-fold cross-validation.

1.TITLE & AUTHOR:

An iot based healthcare data analytics using fog and cloud computing & nandankar, praful and thaker, rukhsana and mughal, shafqat nabi and saidireddy, malgireddy and linda, anusha and kostka, je and nag, ma.

2. YEAR:

2021

3. TECHNIQUE:

Hadoop clusters, iot, heterogeneous,big data analysis,fog computing, cloud systems.

4. FINDING /PROBLEMS/CONTENT:

4.1 SENSOR DATA ACQUISITION LAYER:

The iot revolution has brought rapid growth and improvement in the medical devices (and telehealth) market. According to the 2014 berg insight report, the revenue from telehealth equipment and services reached $4.5 billion, almost doubling by 2017.

4.2 MEDICAL RESOURCE MANAGEMENT LAYER:

The reliability of its classifier is the cornerstone of every health analysis method. As the data collected can be large, unlimited or unbalanced, classification becomes increasingly complex. In addition, the distribution of data can be unbalanced, leading to a class that contains more samples than other classes.

4.3 HEALTHCARE SECURITY LAYER:

The health care safety layer plays an important role in confirming that admission privileges using predefined policies are correct. The information of the cloud system is secured by an iot broker that accepts or refuses access. The next layer is then mapped to registered and authenticated requests. Anomaly identification and privacy preservation in data mining ensure data protection and privacy.

4.4 PERSONALIZED NOTIFICATION/DECISION LAYER:

Finally, via the customised notification/decision layer, the overall input of the health system is directed towards one person. Patients, surgeons, hospitals, data analysts, paramedics, pharmacists and decision-makers are device stakeholders.