A Survey: Chronic Diseases Bigdata Mangement

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ABSTRACT

chronic diseases are the main grounds of human death and disability worldwide. Chronic diseases are ma in threat that affects million people in future, with many young age people as well as average age. The people dying by chronic diseases are more as compared to that of all infectious diseases maternal and n utritional deficiencies combined. The most of chronic disease deaths occur in poor and average income co untries and half are in women. The basic chronic diseases are heart disease diabetes; stroke; cancer and chronic respiratory diseases. This proposed paper survey some of the presented activities and opportunities related to big data for health management prediction, outlining some of the key primary risk that need to be manage and tackled.

Keywords—Big-data, chronic disease,

I INTRODUCTION

As world health organization diabetes is caused b y raised blood glucose (sugar) levels as well as be deficient in hormone insulin. The blood glucos e levels in human body controlled. The excessive weight and physical inactivity cause the most co mmon type of diabetes is type. An absolute be d eficient in insulin from childhood causes Type1 di abetic

Stroke is cardiovascular diseases this disease of th e brain caused by obstruction to the blood supply is Stroke. The heart disease is causes heart attac k. The leading cause of death globally is coronar y heart disease. The disease of the blood vessels of the heart turns into coronary heart disease.

Chronic respiratory diseases are related to lung. T he chronic obstructive respiratory disease and asth ma are due to lungs problem. That is permanent obstruction of the larger airways in the lung. The reversible barrier of the smaller airways in the l ung is turn into asthma disease.

The abnormal cells proliferate and extend out of control can turn into Cancer disease. In cancer all organs of the body can starts to damage and bo dy can convert into cancerous.

II CHRHONIC DISEASE AND ITS RISK FACTOR

The most important risk factors related to chronic disease age and heredity nonchangeable risk factor s that clarify the majority of new actions of chr onic respiratory diseases, heart disease, stroke, and some important cancers. The major modifiabl e risk factors and modifiable risk factor are simil ar in many ways around the world.

(a) infancy risk
There are many evidences found where most of c ountry, before birth where in early childhood pers uadehealth in adult life situations. In some situatio n increased rates of high blood pressure at time of birth which is symptoms of, heart disease. The stroke and diabetes are also having same feature.

(b) Risk amassing
Age is important risk factor old age signals to increase of modifiable risks for chronic disease: the brunt of risk factors increases over the life course.

(c) primary determinants
The primary determinants of chronic diseases are impact of globalization and in additional effect of urbanization and population. The major forces dr iving social change, economic conditions and cult ural change also effect on human.

(d) supplementary risk factors
A smaller proportion of disease is disease related to risk factor of chronic disease. Use of Harmful alcohol is significant provider to the global burden of disease.

(e) The foremost alcohol association to chronic di sease is more complex as compare to other risk. Therisk factor of liver cancers is infections. The environmental factors like air pollution, it leads to a rangeof chronic diseases. the chronic disease lik e asthma and other chronic respiratory diseases ca used due air pollution. Another factor such as ge netic factors participates in chronic disease.

III REVIEW OF LITERATURE

Due to unhealthy diet, physical inactivity and use of tobacco increase blood pressure. It also increas ed glucose levels. There are some abnormal blood lipids, overweight and obesity. **C. Friedmanet al. (2004)**proposed de a method based on natural lan guage processing (NLP) that automatically maps a n entire clinical document to codes with modifiers and to quantitatively evaluate the method. M. **M arcos et al. (2013)** they introduce a complete ap proach, with a set of tools as well as methodolog ical guidelines, to deal with the interoperability of CDSSs and EHRs based on archetypes. **R. Bolan d et al. (2013)** contributes a highthroughput meth od for associating epoch with universal diseases u singlinked electronic records.

SA S. (2013) build model for heart disease predi ction system is developed using three data mining classification modeling techniques. **J. Sun et al. (2014)** developed personalized hypertension manage ment plans. **R. Eriksson (2014)** used techniques f or temporal data mining of EPRs in order to det ect ADRs ina patient- and dose specific manner. **D. W. Bates et al. (2014)** big data, including analytics, is a controlling tool that willbe as valuable in health care. EHRs describing patient treatments and outcomes are rich but unde rused information. Traditional health data centres c apture and store an enormous amount of structure d data concerning a wide range of information in cluding diagnostics, laboratory tests, medication, and ancillary clinical data. **M. R. Eriksson, et al .(2014)** the systematic analysis to individual patien t reports, the use of natural language processing p lays an essential role

TABLE 1
DATA OF VARIOUS VARIABLES EXTRACTED FOR THE OVERVIEW OF CHRONIC DISEA SE MODELS

Study location	Data was collected on the location of the studies including U.S. versus non U.S. b ased and whether or not the studies were done in rural or urban settings.
Study design	Data was also collected if the studies were randomized controlled clinical trials and if they were interventional or not.
Studies follow up	The period of the studies was also accessed to examine the force of the chronic models on longitudinal
Disease studied	The survey is focused on diseases including Diabetes, Chronic Obstructive Pulmonar y Disease and Cardiovascular diseases because of their predominance in resulting de ath and disability worldwide.
Chronic disease model and its cl ements	Data was recorded on the specific chronic disease models and their elements that were described and evaluated across all these studies
Outcomes assesse d	Data was also recorded about the various outcomes that were measured in these st udies.

Fig.1 Discovered by Ashoo Grover1 and Ashish Joshi(2014)

IV CHRONIC DISEASES BIGDATA MANAGEMENT

According to **WHR (2015)** BigData can be transf ormed an actionable asset rather than a siloed bu reaucratic nightmare with its potential for solving big healthcare problems at both the population and personal level.

(a) verdict what's working
Medicitynews(2018) Big Data opens up real oppor tunities for solving big healthcare problems at bot h the population and personal level. When someo ne is diagnosed with diabetes, they are asked to check their blood sugar at least once a day. This simple act creates hundreds of data points per ye ar, per person. This data has the potential to pro vide some of the richest insights about specific c hanges to behaviour and therapies that can improv e quality of life and overall health outcomes.

(b) Summarizing, and presenting results autom atically
Savvy algorithms can rapidly analyze patient gluco se data, for example, to determine a patient's best day. Combining results from Big Data sets can go further, providing the content and context to both summarize and present information in terms best suited for individual physicians and patients. Rather than spend precious time on data analysis, people can focus on making the most of what they've learned.

(c) Enabling decision support
Data drives the creation of valuable decision supp ort tools. It answers to questions like when to ch angesettings on a medical device, if a medication dose should be changed, or if a patient needs mo ral support can all be garnered from machine lear ning algorithms that use past behaviors and perso nal data to recommend decisions. Doctors are start ing to access algorithms results and use them dur ing appointments more frequently.

(d) Predicting when changes are coming
Is a person's glycemic control, blood pressure, or weight trending in the wrong direction? Is a pers onlikely to decline in health? Big Data forms the basis for predictive algorithms that can give patie nts and their doctors' early warning about real is sues that may be on the horizon.

(e) Knowing where to ask more questions
Often, data analysis uncovers more questions. In diabetes, for example, knowing a person's glucose level is only step one. This data uncovers questi ons about diet and exercise habits, stress, or othe r healthproblems. With new, patientgenerated healt h data (PGHD) flowing in from wearable and sm art phone, gathering the data required to answerth

ese questions is closer than it has ever been before

V CONCLUSION

The Big data can provide to boost theapplicability of clinical research studies into realworld scenarios ,where population heterogeneity is problem. It equ ally provides the opportunity to enableeffective and precision medicine by performing patient strati fication. This is indeed a key task toward persona lized healthcare. A better use of medical resources by means of personalization can lead to wellmana ged health services that can overcome the challen ges of a rapidly increasing and aging population. Thus, advances in big data processing for chronic disease model input data, health informatics, bioinf ormatics and sensing will have a great impact on future clinical research.

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