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PREDICTIONS OF DIABETIC COMPLICATIONS FOR ADULTS - CASE STUDY (RIYADH AREA)

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ABSTRACT

The World Health Organization (WHO) classified the diabetes as one of the danger disease that causing the most deaths worldwide (WHO, 2018). A lot of reasons leading to diabetes and its complication but to find solution before the complication coming, we need a confident technique that predict the patient status and help the patient in his daily life. In this research, We will focus in Data mining technique for patient of diabetes disease just for adult which is in normal case focus on patient during period of his life, (Laugesen, stergaard, & Leslie, 2015) .our target research area will be in Saudi Arabia specially in Riyadh which is the diabetes increase very fast and the patient discover its complication later (ALmorad, 2016). Our study also makes contributions to the society at large in addition to the direct support it renders at the individual level. In this research will use data mining to extract the knowledge according to the data of patient statues itself to help diabetes patients in their daily life in order to avoid any complications. The aim of this research is to inform the patient the probability on effect onthe diabetes complication in the near future. This study will effect to the society in general by creating a conscious environment about diabetes and to individual person in specific because it will prevent complications of diabetes with some patient that will affect to the social and psychological situation of the patient itself.

Keywords: LIS, KDD, Data mining, Glucose, Diabetes, WEKA

1. Introduction

Data has an enormous impact in our life. Data became the most valuable asset and the main resource in many organization because it helps the organization to create huge strategic advantages. Some organization create an individual section to manage the data. There are many companies provide you a cloud or a space in server just to manage the data. Data is produced in vast streams, not only in business but also in the field of economics, sociology, sports, education, health, civil status etc. we could not treat with any organization without data. It used in a widely range. In medical major for example,if the patient visitany medical center, the first required thing that must be presented and asked is the data. It leads to exist an environment of the Clinical and medical databases(Miroslav , 2017). "In medical fields, the Data is rich but the knowledge is poor" (V.Devedzic, 2002) . there are a lot of data we can make it useful and change it to knowledge (Kaur, 2012).

Healthcare systems like laboratory information system (LIS), electronic medical record (EMR), Radiology information system (RIS) couldn't work without data which must collect and connect with the result of the patient. we can reach to the rich data then information and knowledge. The knowledge focus on reanalysis the database and discovering the information and determine the data pattern. The important of know the knowledge is that to discover and relationships in the data to help and make the best decisions. So these data patterns used to help predict information trends then determine what shall we do about that (Sergio, 2018) (Christian & Khuri, 2018).

For knowledge discovery we can use data mining which is required and wanted in the medical filed. The data in medical filed is huge and the KDD is a fresh modern in medical filed. Using data mining will help the doctor to choose the decision and the right diagnoses which is very sensitive and critical. Data mining is one of the best solution. It is one the strong weapon we have to use it in medical major. Data mining can use to increasing efficiencies. Data mining may save patient lives or can improve patient life from disease like diabetes. (Vijayarani, 2015)

Regarding to Diabetes and its complication, during the end of 2013, the adult above 15 who effect on diabetes was 382 million in the worldwide. For children to elderly, almost half a billion people suffer from diabetes in 2013. Many people dead every year from diabetes and its complication(Kassander, 2014).

Diabetes refers to a disease that affect how the body using the glucose which is very necessary for source of energy.Patient with this disease have a risk and could be infect with number of serious health problems.CalledDiabetic complications which can lead to many diseases affecting the blood vessels, heart, foot, eyes, kidneys and nerves. In addition, patient with diabetes have a risk of developing infections. Diabetes complication may be cardiovascular disease, Nerve damage. Kidney failure, blindness, lower limb amputation or others disease we will predict it on this study (Enzo & Ralph A. , 2018)

2. THEORETICAL FRAMEWORK

2.1 DATA MINING TECHNIQUE

Data mining is the process of looking at huge banks of information to generate the knowledge or useful information not existed. it is about extrapolating patterns throw some techniques which is used to make data mining happened, this technique guide us to get a new knowledge from the data you've already collected , Relying on technologies and processing and rules . There are many data mining techniques we can use to change a raw data into knowledge the below diagram explain the data mining techniques (Singh, 2005)

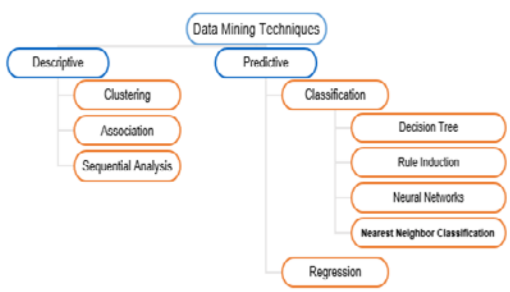

Figure 1Data Mining Techniques

2.2 WEKA

Which is the stander for Waikato Environment for Knowledge Analysis. This program is developed at Waikato University in New Zealand. It is free software license machine learning software which is written in Java program language. It contains tools and algorithms for analysis of data and predictive modeling. One of the best feature of this program is graphical user interface. Data pre-processing is also one of the best feature that is used in many research. WEKA has many algorithm technique in data pre-processing that can help the researchers to achieve his goals before the process step. It can use also in data mining Techniques like clustering, classification, regression and visualization. WEKA has a lot of number of regression and classification tools. That can be used in health section, education, research, business and in many files (Eibe, Mark , & Christopher, 2016).

3. PERVIOUS STUDY

In general, in previous studies some research has developed methods and ways depends on providing some advice or consultation for diabetics, they not focused in the condition of each patient as individual patient for period of age. Some of researches using data extraction Ways to extract knowledge from patient data without any big profit to the patients. The main objective of many researches was that to manage a systematic review of applications of the techniques of data mining in diabetes research. Many researches try to proof that the data mining is the important part in diabetes research because it can show the hidden knowledge from amount of diabetes related data.Some research use expert system and database to communicate between medical filed and IT filed and help the patient. Other research use data mining technique (Nittaya & Kittisak , 2011)(Fayyad, Piatetsky, G., & ., 1996)

Our proposed method benefits from the results get a new knowledge using data mining methods to help patient individually focus just in every status in the patient and focus on adult age from 20 to 80 years old and patient with normal case. For example, any patient his Weight is 300 will be out of our scoop, that is the also make our research a unique research.

One of the oldest researches in this major was (P. C. Jones, 1998) . In his system, he connected more than one hospital with their diabetic patient throw web application. The data was shared and provided the patient a good communication with their hospital throw electronic system , with the rapid rise of diabetes around the world , knowledge become the main target for these researchers and data mining is become the resource of doctors and patient interest (P. C. Jones, 1998).

The connection between the Information technology (IT) and medical major has played an important role in our life .Diabetic people become more interest for the technology to overcome their medical challenges that guide many research in IT and medical major to find a solution that can help the patient. Some researcher developed methods Depends on providing some general advice or same analysis, other try to use to the Knowledge Discovery algorithm with technique to help diabetic people. They used computer server, website and mobile application in there research in diabetes. They give a solution that help the diabetic people to improve their style of life but they not focused in the condition of each patient as individual patient. Our proposed is to get a new knowledge using data mining methods to help patient individually during period of lifetime, in other meaning get the knowledge and help each patient based on his or her health situation. There are a lot of research in this major but still they not focused in the states of each patient during specific age because the risk can be change according to the period of age.

4. METHODOLOGY

4.1 COLLECT THE DATA

The data collected in Saudi Arabia, Riyadh from medical laboratory as XLS files. We export the data from Laboratory Information system. We collected all the data related to a patient from 2016 until 2019. The data contains patients information in general , medical history, disease type, Follow-up data, treatment types and risk factors like age ,gender , smoking, patient statues , family history, and many data related to the medical statues . The data consists late complications that caused problem and effect on the patient. We have many attribute but we focused on attribute below that show on table 1 to start to preprocess the data

Name	Weight
Gender	HBA1C
Title	Activity
Age	Bad-habit
Blood-pressure	Body-mass
Length	LDL
Late-Complication	Family-history

Table 1 attribaute that collected to be factor risk

4.2 PREPARE THE DATA

After we collected the data for patient, we prepare the data because it is not fully completed and still raw data.In this level our target is prepare the data to make the data more clearly and almost completely for applying the data mining. We used many strategy to clean the data starting with Organize the data correctly, Delete unwanted data, replace a missing value, check the values and solve the problem of data .we used also four level to make our data completely, which is data cleaning, data integration, data reduction and data transformation (Salvador, Julián , & Francisco , 2015). There were some bugs in data and some data was not complete and missed. We used several algorithm of data cleaning, data integration, data reduction and data transformation throw WEKATools .Wealso filtered the data to beready to apply the data mining (Kubat, 2017)(David , Heikki , & Padhraic , 2001).

4.3 APPLY THE DATA MINING

This step is the main aim to get and extract data patterns and new knowledge. Apply the data mining is required after the data process. I used the classification strategy, decision tree (J48) algorithm which is a clever technique that help me to get a new extract patterns and to predict the probability effect on Diabetes Complications which is mention in table 2 (Enzo & Ralph , 2018)

Cardiovascular disease.
Nerve damage.
Kidney damage.
Eye damage.
Foot damage.
Skin conditions.
Hearing impairment.
Alzheimer's disease.
Depression.

Table 2Diabetes Complications

In applying the data mining, I used WEKA tools throw the steps blew:

1. Select thedata:select the data from repository which late-complication equal to one of the Diabetes complication which is mention in table 2. I started to choose cardiovascular disease to apply the steps below then same steps with other diabetes complication changing in every time the data set and the class to the specific disease that I want to predict its result.The risk factors that are used is (”Gender” , ”Age” , “Blood-pressure” , “Body-mass” , “family-History” , “Activity” , “Bad-habit ” , “HBA1C” , “LDL” , “Cardiovascular-disease”) .the Age of patient will selected from 20 to 80 years old. And body mass will calculate from patient who is length between 0.6 to 2 Meter and weight from 40 to 200 Kilogram.

2. Convert the file: in this step, I used WEKA program and converted all file to CSV file type.

3. Clear the data: in this stage I used some technique for cleaning the data. Replacing data used to replace any missed or similar values. In some records, the missed data will be replaced with value from same group. We used replaces the miss values figure part of the process. We used also Standardize the data. Checking for categorical and missed data also used.

4. Discretize: In this step, discretize will be applied, the selected numerical attributes discretize into user specified classes. Discretize function in data has been used.

5. Data transformation : In this step we convert some attributes from there orginal format to anther format. we change some date and kept just for the year of the attribute to

reduce the time of apply the final step .The body mass is organized rounded to a decimal point.

6. Apply risk factors values number: apply equationabout attribute calsssification.each risk factor has diferent Measurable score for example , If LDL of the patient less than 100 mg/dl then LDL risk factor will be 0 . and If the

LDL of patient between 100 mg/dl and 129 mg/dlthen LDL risk factor will be 1 . or it will be 2 if the LDL is more than 129 mg/dl and less than 190 mg/dl .

7. Calculate the Risk Values and make Aggregation**:** In this step we will make the Aggregation and calculate the total Risk value attribute , We will categorize the value into 3 group

- LOW RISK: If the total of Risks factors between 0 and 7 .
- Moderate RISK: If the total Risk value between 8 and 11.
- HIGH RISK: If the total Risk value above 11.

8. Select attribute as class: in this stage I select the attribute as a class. This stage help us to predict if the patient will effect on the one of the nine diabetes complication.

9. Numerical to Binominal: In WEKA program, there is predictable attribute we can use it .I changed from numerical to binominal which is one of the important process. I will change the attribute of cardiovasculardiseasetobinominal value.

10. Select the technique: in this stage we will build classifier what we need .I chose decision tree is predict tools .I chose a J48 which is "an algorithm that used for generating a decision tree developed by Ross Quinlan mentioned earlier" (Croce & Roberto, 201) . figure 2 show the algorithm that I have used.

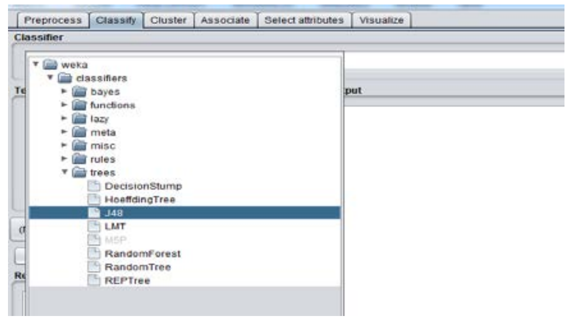

Figure 2choosing a decision tree as the classify

11. Split process: TheDecision Tree used for classification. I will use the training set which is 70% from the whole selected data and select 30% to be our test set. Figure 3 show the split process in WEKA program.

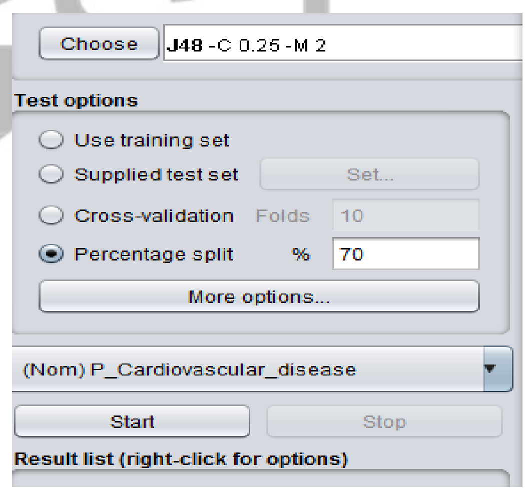

Figure 3 choosing the training set

12. Apply classify: I applied the model to get predict of other 30 %. I have now predict of 30 % for the patient who will effect with one of the nine of Diabetes complication**.**

13. Performance evaluation: Confusion Matrix has been used for evaluation. the Detailed Accuracy show the evaluation of the

test set which we will discuss it in the next part.

14. Make interface: I chose a web application as a sample interface for the patient. So, the patient can fill the data to get the result of diabetes complication. Our web application is like a friendly user interface with a sequence of questions that allow the patient to insert his own information then give him the result. I write this web application with html and java codes using the rules and the data mining technique. I use some interfaces to make the interface looks good, then uploaded to local server hosting (Leon & Richard, 2003).

5. THE EXPERIMENTS AND THE RESULTS

Our result is to predict the expected complications of the diabetes which is mention on table 2 .

Cardiovascular disease:

The table 3 show the rules that could probability effect on diabetes patient and led to cardiovascular disease

If the Total Risk is greater than 3
If the Total Risk is equal to 3 and the LDL Risk is greater than 1
If the Total Risk is equal to 3 and the LDL Risk is less or equal to 1 and the Age Risk is less than 2 and the family Risk is greater 1
If the Total Risk is equal to 3 and the LDL Risk is less or equal to 1 and the Age Risk is more than 1 and the Blood Pressure Risk is more than 1
If the Total Risk is less than 3 and the LDL Risk is greater than 1 and Bad-Habit is more than 1 and the age is less or equal 1 and the body-mass is more than 1
If the Total Risk is less than 3 and the LDL Risk is greater than 1 and Bad-Habit is more than 1 and the age is more than 1 and the Blood-Pleasure is more than 1

Table 3 Rules that led to Cardiovascular disease

Nerve damage

The table 4 show the rules that could probability effect on diabetes patient and led to Nerve damage.

If the Total risk is more than 2 .
If the Total Risk is less than 3 and the HAB1C Risk is equal or more than 2 and the age risk is more than 2 .
If the Total Risk is less than 3 and the HAB1C Risk is equal or more than 2 and the age risk is less or equal than 2 and the gender is male.

Table 4 Rules that led to Nerve damage.

Kidney damage

The table 5 show the rules that could probability effect on diabetes patient and ledto Kidney damage

If the Total risk is more than 3
If the Total risk is equal to 3 and the body mass risk is greater than 2 and the blood pressure risk is more than 2
If the Total risk is less than to 3 and the blood pressure is more than 2 and HBA1C Risk is more than 2
If the Total risk is less than to 3 and the blood pressure more than 2 and HBA1C risk is equal or less than 2 and bad-habit Risk is more than 2

Table 5 Rules that led to Kidney damage

Eye damage

The table 6 show the rules that could probability effect on diabetes patient and led to Eye Damage

If the Total risk is more than 3 and the HBA1C risk is more than 1 and the age risk is more than 2 and family – history is more than 1

Table 6 Rules that led to Eye Damage

Foot damage

The table 7 show rules that could effect on diabetes patient and led to Foot Damage.

1. If the Total Risk is greater than 3
2. If the Total Risk is equal to 3 and the LDL Risk is greater than 1
3. If the Total Risk is equal to 3 and the LDL Risk is less or equal to 1 and the Age Risk is more than 1 and the activity Risk is more than 1
4. If the Total Risk is less than 3 and the Age Risk is greater than 1 and Bad-Habit is more than 1 and the LDL is less or equal 1 and the body-mass is more than 1
5. If the Total Risk is less than 3 and the age Risk is greater than 1 and Bad-Habit is more than 1 and the LDL is more than 1 and the Blood-Pleasure is more than 1

Table 7 Rules that led to Foot Damage

Skin conditions

The table 8 show The Rules that could probability effect on diabetes patient and led to Skin Conditions.

1. If the Total Risk is greater than 3.
2. If the Total Risk is equal to 3 and the HBA1C Risk is greater than 1
3. If the Total Risk is equal to 3 and the HBA1C Risk is less or equal to 1 and the Family-history Risk is less than 2 and the blood-pleasure is greater than 1 and the bad-habit is more than 1
4. If the Total Risk is equal to 3 and the HBA1C Risk is less or equal to 1 and the Family-history Risk is more than 1 and the age Risk is more than 1
5. If the Total Risk is less than 3 and the Age Risk is greater than 1 and Family-history is more than 1 and the HBA1C is less or equal 1 and the Bad-habit is more than 1.
6. If the Total Risk is less than 3 and the Age Risk is greater than 1 and Family-history is more than 1 and the HBA1C is more than 1.

Table 8 Rules that led to Skin Conditions.

Hearing impairment

The table 9 show The Rules that could probability effect on diabetes patient and led to hearing impairment .

1. If the Total risk is more than 3 and the history of family risk is more than 1 and the age risk is more than 2 and HAB1C is more than 1

Table 9 Rules that led to Hearing impairment

Alzheimer's disease

The table 10 show TheRules that could probability effect on diabetes patient and led to hearing impairment.

If the Total risk is more than 3 and the Family History risk is more than 1 and the age risk is more than 2 and bad habit is more than and the activity is more than 1

Table 10 Rules that led to Alzheimer

Depression

The table 11 show TheRules that could probability effect on diabetes patient and led to Depression.

1.	If the Total Risk is greater than 3
2.	If the Total Risk is equal to 3 and the Activity Risk is greater than 1
3.	If the Total Risk is equal to 3 and the Activity Risk is less or equal to 1 and the bad_habit Risk is less than 2 and the blood_pleasure is greater than 1 and the body mass is more than 1 .
4.	If the Total Risk is equal to 3 and the Activity Risk is less or equal to 1 and the bad-habit Risk is more than 1 and the age Risk is more than 1 .
5.	If the Total Risk is less than 3 and the Age Risk is greater than 1 and Bad-Habit is more than 1 and the Activity is less or equal 1 and the body_mass is more than 1
6.	If the Total Risk is less than 3 and the age Risk is greater than 1 and Bad-Habit is more than 1 and the LDL is more than 1 and the Blood_Pleasure is more than 1 .

Table 11 Rules thatled to Depression.

6. THE EVALUATION RESULTS

We used Confusion matrix to get the average of accuracy, recall, precision, and f-measure which recorded in table below table below describe number of test case for the result study which is total 938 cases.

Classifier	No of case	(TP)	(TN)	(FP)	(FN)
Cardiovascular disease	91	55	25	8	3
Nerve damage (neuropathy)	102	29	63	7	3
Kidney damage (nephropathy)	162	80	74	0	8
Eye damage (retinopathy)	99	49	41	3	6
Foot damage	121	53	66	2	0
Skin conditions	122	74	39	4	5
Hearing impairment	92	49	37	3	3
Alzheimer's disease	12	7	4	1	0
Depression	137	73	46	5	13
TOTAL	938	469	395	33	41

Table 12 analysis the Confusion matrix

From the above table we can consider that number of total test case is 938 and total number of true positive is 469, the total number of True negative is 395, the total number of false positive is 33, finally the total number of false negative is 41. Now we can get the average of accuracy, recall, precision, and f-measure on each of the classifier and we can use the equation of confuse matrix to get the result. The table below explain the summary of it.

Classifier	Accuracy	Mean Recall	Mean Precision	F-Measure
Cardiovascular disease	94.82	87.30	90.90	87.91
Nerve damage	90.62	80.55	85.29	90.19
Kidney damage	90.90	100	95.23	95.06
Eye damage	89.09	94.23	91.58	90.90
Foot damage	100	96.36	98.14	98.34
Skin conditions	93.67	94.87	94.26	92.62

Hearing impairment	94.23	94.23	94.23	93.47
Alzheimer's disease	100	87.5	93.33	91.66
Depression	84.88	93.58	89.02	86.86
TOTAL Average	91.96	93.42	92.68	92.11

Table 13 evaluate the Confusion matrix

EVOLUTION OF WEB APPLICATION

We Used LIKERT scale way. We make the questioners for 50 diabetes patient with different age from 20 until 80 years old to know the satisfy form medical laboratory patients. The highest ratio was for strongly agree which is was 81.25% and second ration was also for satiety agree which is 12.25 %. If we calculate agree and strongly agree result, we will get 93.52% which is satisfy from this knowledge. We will improve to reach more than this percentage in the future. (Wuensch, 2005)

7. CONCLUSION

Medicine and Technology have gone hand and hand for many years , but still the use of technology in medical center is very poor especially in Saudi Arabia . Using the technology in medical major can saved millions of lives and improved many others . In our research we try to offer technology which is data mining technique to offer a knowledge in medical filed. We focused in helpping the diabetic patient for predict the competition of the diabetes. Our research focus on patient during period of life according to his or her status, his activity for example between dialy and weekly can efect on the predict result . that's make our research more accurate . I start to collect the data from Medical laboraotry, then I prepare the data before I apply the data mining. In data mining I use a decion tree algorthim and usin Weka Tools . after that I discuse the result and finally evalute this study, I discused and discovered that The results of this study indicates that the average accuracy of the data mining system is 92.25%, and the average acceptance rate of participants is equal to 92.5%. Finally I hope that this research apply in wide range and help the patient ,the heath care center , government and the whole socity.

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