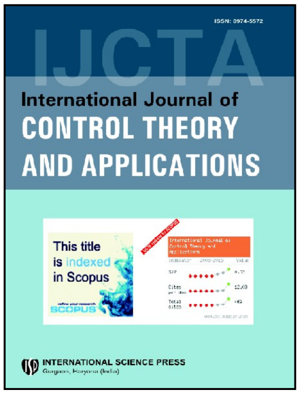

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A Methodology for Anticipating Risk Score for Congestive Heart Failure Patients

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Abstract: Now-a-days health care environment is becoming more prominent and the hospitalizations are increasing day by day. According to the surveys held by various organizations the unnecessary hospitalizations are raising and as a result the costs of care are increasing tremendously. So, this factor matters a lot to the government at the time of planning the budget [1]. So, in order to avoid the raising costs the monitoring of health care should be done. Analyzing the risk factor to particular patient will help the health status of the particular patient, continuous hospitalizations of the patient there by reducing the costs of care. This can be done by developing various predictive modeling approaches. Risk Identification and prediction is extremely challenging in healthcare informatics. Risk prediction contains the integration of various clinical parameters with socio-demographic factors, health care conditions, disease factors, hospital care and quality parameters, and a variety of factors that are constrained to each health care provider making the task increasingly difficult. Predictably, [2] many of such parameters need to be extracted individually from various sources, and integrated back to improve the quality of predictive modeling. In this paper, we propose various solutions to predict the risk rate for heart failure patients and matching suggestions to control the risk rate like the drug dosage and thereby improving the quality of life. We used a methodology to predict the risk rate and develop the scalable data mining models to predict risk of readmission. We reveal the effectiveness of the algorithm we used, describe the results of the algorithm we tested, and compare the performance against various records and differentiate the accuracy between the existing and proposed techniques.

Keywords: Healthcare; Knowledge-Discovery; Risk Prediction;

1. INTRODUCTION

Hospital readmissions are becoming more expensive and possibly preventable. Dropping the rates of readmission is measured as a key quality of care parameter that is deemed measurable. Yet, it is still thought-provoking to implement accurate predictive models to predict such risk and the importance of factors that contribute to readmission due to the diversity of data sources even within a single large hospital. Add to this the aspiration of obtaining a holistic view of cause for readmissions[3] by integrating socioeconomic parameters and external data with existing clinical data, and this problem becomes even more challenging and complex requiring significant advances in data integration, discretization[4], normalization and data organization. A diversity of factors could lead to re-admissions due to early discharge of patients, lack of proper care, and poor consideration moves, etc. Surveys have demonstrated that targetedinterventions before or after discharge can reduce the probability of readmission, especially in elderly patients, and decrease, the general restorative expenses. Legitimate pre discharge arranging and post-release arrangements like home based catch up and patient instruction can likewise lessen the readmission rates impressively and enhance the health outcome of the patients. When coming to the prediction of risk-of re-hospitalization and re-admissions for potentially critical diseases such as congestive heart failures can result in significant price savings and improvement of concern and care at many hospitals. The main question that comes when applying insight analytics is how such a data has to be managed from various heterogeneous data sources. It was very difficult to store, mine and manage large volumes of structured and semi-structured health care datasets preceding to the recent enhancements in big data analytics.

In order, to predict the risk we have to take the input parameters and run a background algorithm which visualizes the percentage and the impact of risk on various patients [5]. This can be named as a Risk Rate Predictor or risk calculator. These can be used for any of the diseases like cancer, diabetes, heart disease, and heart stroke etc. Usually these risk predictors require ample knowledge of medical terminologies which are not common to general patients. Worthwhile even to patients and healthcare providers, who are not necessarily domain experts. While the concrete prediction algorithm is developed with the analyses of composite factors, unlike existing risk calculators, it lets users to provide very simple inputs. Unlike existing risk predictors it accepts precise patient input thus offering higher flexibility. Moreover, it offers visualization of the risk of the particular patient with some graphs. Finally, along with the risk score calculation the risk predictor also suggests necessary explanation behind such prediction. We note that the proposed framework inside advanced risk predictor is generic and could be applicable to a wide variety of usual risk prediction tasks. By calculating the overall risk of the patient the re-admission rate is predicted and there by suggesting the patients about the day of re-admission.

2. EXISTING SYSTEM

2.1. Framingham Risk Assessment Tool - Men and Women

This risk assessment tool uses information from the Framingham Heart Study to predict the risk of developing a myocardial infarction (heart attack) or death from coronary disease in the next 10 years. This tool is designed for people aged 20 years and older without

Known heart disease and who do not have diabetes.

The risk factors included in the Framingham calculation are age, cigarette smoking, total cholesterol, HDL cholesterol, systolic blood pressure measurement and treatment for hypertension (high blood pressure). Point values are calculated based on each of these risks. In this algorithm the attributes are segregated and score values are given independently. If we consider the attribute age then the ranges are classified from 20-79 with interval range 4.In the same way the factors like smoking, cholesterol and blood pressure are also calculated. Depending on the medical literature survey they have taken the values for all the attributes. Limitations were given for each attribute i.e. less than 200 mg/dL indicates the lower risk of heart disease. A cholesterol level of 200 mg/dL or greater increases the risk. Similarly the limitations for remaining attributes were given and the risk score was calculated. The risk factor was classified into High Risk, Intermediate Risk and Low Risk. A more noteworthy than 20% danger will come about a heart attack or kick the bucket from coronary sickness in the following 10 years.

3. RECOMMENDED SYSTEM

3.1. Risk Assessment Algorithm Overview

Cardiovascular absolute risk assessment is a simple tool that can enhance the clinical judgment, and improve the ability to educate and motivate patients. Single risk factors (like cholesterol level) provide a poor estimate of a patient's CVD risk. Absolute risk (not coping with the incomplete defined data [6]) assessment provides a more accurate estimate of overall, individualized CVD risk, thereby allowing the clinician to best tailor pharmaceutical and lifestyle management to the patient.

As shown in the figure 1, Absolute risk is the numerical probability of an event occurring within a specified period, expressed as a percentage. For example, if your patient's risk is 15%, there is a 15% probability that they will experience a cardiovascular event within 5 years i.e. readmission rate will be delivered.

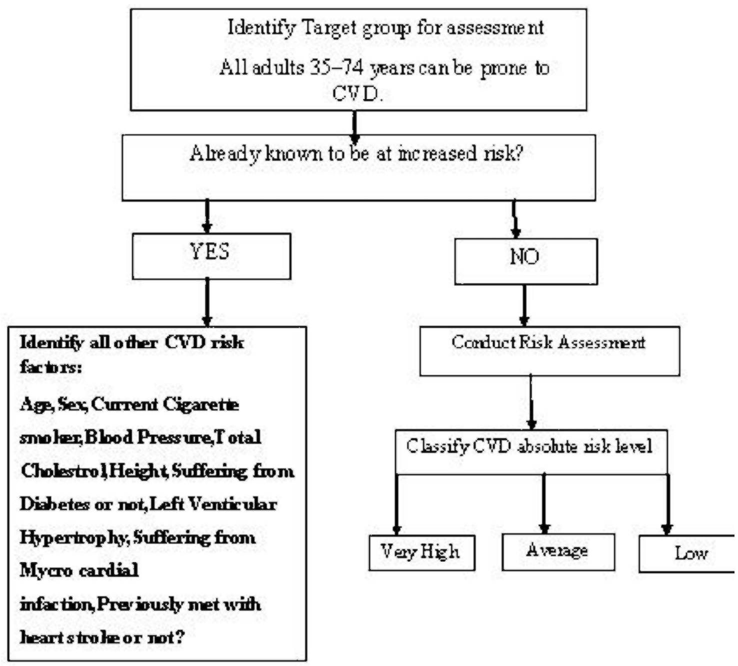

Figure 1: Archtecture for Prediction score Algorithm

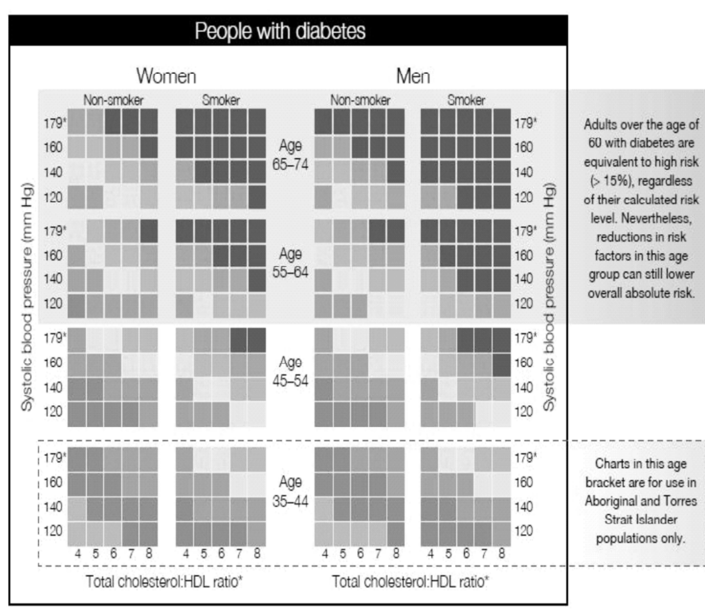

Figure 2: Analysis of without Diabetes patients with various age ranges missed

As shown in the figure.2 In accordance with Australian guidelines, patients with systolic blood pressure ≥ 180 mm Hg, or a total cholesterol of > 7.5 mmol/L, should be considered at increased absolute risk of CVD. Adults with any of the following conditions are known to be at increased risk of CVD.

Diabetes and age > 50 years

Suffering from Left Ventricular Hypertrophy

Suffering from chronic kidney disease

Systolic Blood pressure Range should be 90 to 250mm Hg

Cholesterol Range should be 3 to 14 mmol/l (or) 100 to 550 mg/dl

Creatinine Range should be 30 to 200 umol/l (or) 0.3 to 2.3 mg/dl

Height Range should be 120 to 210 centimeters (or) 45 to 85 inches

3.2. Classification

Initially in our proposed system we have taken all the attributes which can be used to calculate the risk factor. The classification is done among the sex and age attributes. The number of possible combinations are considered and the mapping [7] is done accordingly. The age attribute is divided into 8 regions i.e "35-39","40-44","45-49","50-54","55-59","60-64","65-69","70-74".If the age is 37 then the age falls in the range 35-39.Here raises a new scenario. Analysis is done separately for both male and female. Though a common calculation is done from our side, variation can be clearly shown for both type of patients. Unlike with the existing algorithms the risk score is calculated if and only if all the input attributes [8] are given. The attributes that we have considered were found very crucial in our survey. Instead of coping up with the missing values, the attributes that we considered can work effectively as they are key parameters for the heart patients. The stepwise explanation can be done as follows:

- a user can provide the parameters like age(=71), gender(=M), Cigarette Smoker(=Yes), the history of diabetes(=yes), and the blood pressure(<130/80) etc.;
- When the "Calculate Risk" button is clicked the corresponding risk score is displayed.
- Outputs the risk score and the corresponding suggestions that will be required for the respective patient.
- Visualizes the risk score of the patient in the form of a bar graph.

3.3. Data Visualization

A fundamental goal of data visualization is to give information evidently and profitably to users through the information outlines like tables and charts. Good visualization helps users in analysing and pondering data. This assumes a crucial part in health care informatics. We used bar graphs for displaying the risk score of the particular patient. The graphs are displayed with the min risk factor and max risk factor value for a patient and the existing risk score that a patient has at the time of hospitalization. As shown in the figure.3 initially the data that we have is numerically transformed into the values which are used to plot the graph i.e. X-Axis and Y-Axis [10]. Then the graph is interpreted visually which will fetch as a user friendly interface for the users and patients.

4. TESTS AND RESULTS

The outcome for the project can be illustrated in the following figures 4 and 5. The patient risk profile is generated with the parameters sex, age, smoker, SBP, Cholesterol level, Creatinine level, Height and whether the patient suffering from Diabetes, Micro Cardial Infaction and left ventricular hypertrophy or not.

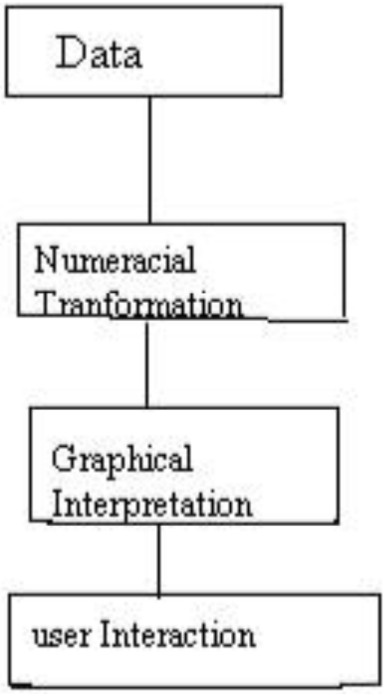

Figure 3: Mechanism and Data Visualization diagram before the tests and results

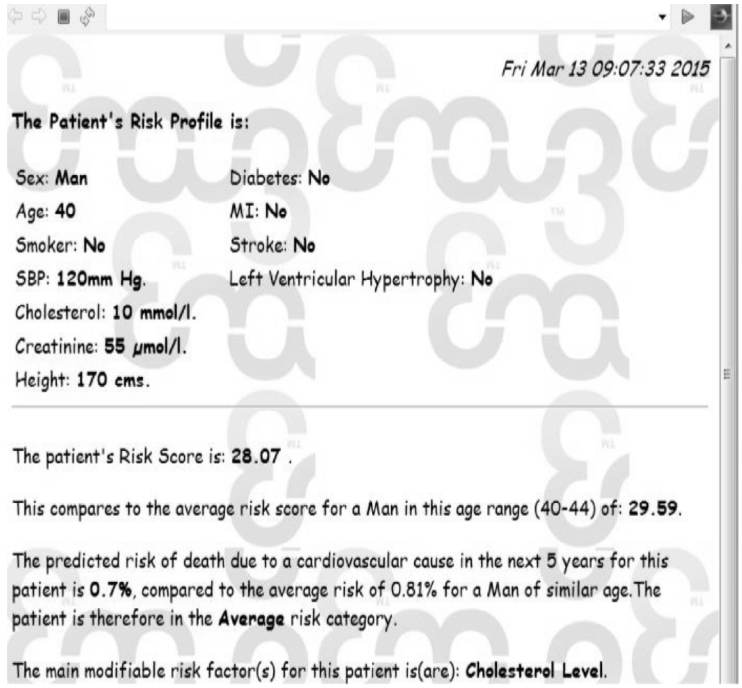

Figure 4: Patient's Risk Profile

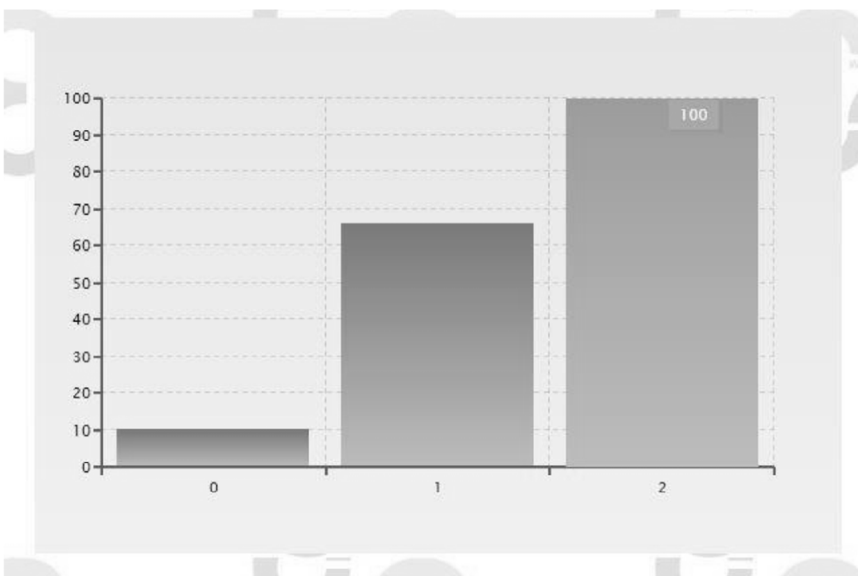

Figure 5: Bar Chart for Level of Risk and Re-admission

5. CONCLUSION AND FEATURE EXTENSION

The risk assessment in health care analytics [9] has a crucial part which helps to avoid the repeated re-admissions and hospitalizations. The overall risk factor concludes the patient risk rate, the chances of readmissions and improvements in lifestyle. As our future work this project can be extended to the patients who suffers with the heart disease with the age group less than 30.

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