Mobile Cloud Based Multistep Variable Cardiac Risk Scoring System

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***Abstract*: The use of cloud computing can help people at large in monitoring their health risks. Due to competing health standards like HL7, FHIR, there has been low adoption of mobile based applications and devices. This research work attempts accelerate the adoption of such health monitoring applications. The implements work using a hybrid model for computing heart risk of person using standard medical references on blood pressure, cholesterol etc. The validations of heart risk is one prediction by the system with the help of qualified doctors and metrics like recall and precision.**

Keywords: FHIR, Mobile application, Cardiac risk assessment, python, cloud infrastructure.

I. INTRODUCTION

Traditionally, the hospital information system is based on client-server architecture without use of cloud technology. However, the current system architecture extends to build clinical data aggregators to support third party exchange of medical data. Due to competing medical standards (HL72x/3x, FHIR) issues of interoperability crop up. The arrangement of our system support fullfeatures of data exchanges, especially when there are multiple hardware like Tabs, Smartphone, Laptops. So here a new approach is adopted in our architecture that is the incorporation of machine to machine protocols, FHIR is relatively new platform as compared to HL7; hence a better level of security protocol still need to adopted in main stream. Data collection and integration from multiple medical resources is solved over mobile, portable medical instruments, laptops. The exchange of data is supported as core functionality which is referred as Interoperability. As numerous amount of interoperable medical data models that can be shared with other industries. Rendering of data on heterogeneous devices is done by multiple resolutions and hardware configurations. Mobile application aiming at the effective management of patient's electronic personal health records (**heart**) via an easy to use interface with standard used in our work which can be accessed by multiple users. Mobile based application provides human readable wire format and exchange of information on cardiac risk of patients. It works over a simple framework for extending and adapting the existing resources on heart risk assessments frameworks.

II. LITERATURE SURVEY

In this work a Fhir standard based system is developed as mobile application that integrates with multiple health systems. In this work the web standards Fhir, Rest helped in building interoperable services. This paper solves the problems by providing the implementation based on the proposed system that works for Cardiac Risk Asseement. There are many researchers who had worked on Heart risk of health using their technologies.

P. mellilo etal.(2013) developed an automatic classifier for risk assessment in patient suffering from disease using HRV measures. Analyzed data of 12 suffering patients. Classification Regression tree tree was employed to develop the classifiers. Achieved sensitivity and specificity rate of 93.3% and 63.6%.

A.Emrich et al.(2014) presented a persuasive mobile application system for health.Parameters considered such as heart rate , blood pressure etc. Gathered data via web based or mobile clients. Requirements were mapped to analytical feature resulted in design of specific ranking functions.

Babra franz et al.(2015) Developed an HL7 standard FHIR offers a resource efficient to extend monitoring solution to support FHIR. Stated that HL7 provide interoperability b/w medical device to other health care system Exchange of data by PCD is based on ISO/IEEE 11073. Results showed the average amount of data contributed by PCD 01, FHIR-DOR and FHIR-OBS.

Alistar A.young et al.(2015) and many others described the data sharing of cardiovascular imaging as heart disease is worsening due to increase obesity. As Data sharing will help in development and validation of automated data analysis method Multivariate map constructed from PCA.

S.b et al.(2016) presented the Different programs that have attempted to increase interoperability like ONC.

III. PROPOSED METHODOLOGY

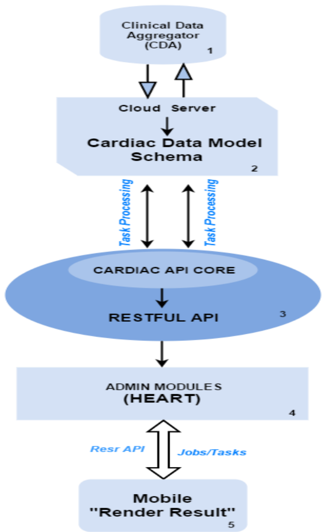

Fig-3.1 Schematic approach of Cardiac mobile system

Step1:-Clinical data aggregator server receives and sends data.
Step2:-Rest API with Cloud server does the interoperability for exchange of data.
Step3:-Restful API interacts with the mobile devices.
Step4:-A Heart risk module collects data from database and finally computes the hybrid risk assessment.
Step5:-Mobile application module takes inputs and provides output of heart statistics.

Steps for calculating risk

Table-3.1 Blood pressure

Risk Category (B.P)	Systolic Reading (mmHg)	Diastolic Reading (mmHg)	Score Ref.
Low Blood Pressure	70-90	40-50	1
Ideal Blood Pressure	90-120	60-80	0.5
Pre-High Blood Pressure	120-140	80-90	8
High Blood Pressure	140-190	90-100	10

***Considering Score 1to5=Low Risk of B.P, 0.5=Normal/Ideal B.P, 6to8=Pre-High Risk9/10= High Risk**

According to the table[3.1] above data mentioned describes that systolic reading and diastolic reading ranges lies between 70-90 and40-50 will gives the low blood pressure scores while others ranges will so on.. Gives the specify output in the same manner. For e.g. if the patient's reading comes as 150/90 that will be equals to High Blood pressure.

Table-3.2 Age(Male)

Age Group (Years)	Height (Cm.)	Male Weight (Kg.)	Mean	Score Ref.
20-29	157-182	50-60	55	0.5
30-39	157-182	60-70	65	0.5
40-49	157-182	65-75	70	0.5
50-59	157-182	70-80	75	0.5
60-69	157-172	62-72	67	0.5
70-79	157-167	60-70	65	0.5

***Considering Score 2=Low Risk Factors, 0.5=Normal/Ideal, 10=High Risk factors**

Here in this table[3.2] score is defined according to the age factors of both males and females. The one who lie between 20-29 and having score 10 will be taken under high risk and those whose score is less than 5 or in between 3to 5 will be considered as low risk. Only 0.5 score is Normal risk factor which is an ideal risk.

Table-3.3 Age (Female)

Age Group (Years)	Height (Cm.)	Female Weight (Kg.)	Mean	Score Ref.
20-29	152-175	50-58	54	0.5
30-39	152-175	60-68	64	0.5
40-49	152-175	70-78	74	0.5
50-59	152-175	65-73	69	0.5
60-69	152-170	60-68	64	0.5
70-79	152-167	55-63	59	0.5

***Considering Score 1=Negligible/Low Risk, 0.5=Normal/Ideal, 8= Pre-High Risk**

Here in this table[3.3] score is defined according to the age factors of both males and females. The one who lie between 20-29 and having score 10 will be taken under high risk and those whose score is less than 5 or in between 3to 5 will be considered as low risk. Only 0.5 score is Normal risk factor which is an ideal risk.

Table-3.4 Active Smoking

No. of Cigarettes	Frequency (Time Slot)	Mean	Score Ref.
1-3	Daily	2	0.5
3-5	Weekly	4	0.5
5-7	Occasionally	6	0.5
0	Never-Smoker	0	0.5

***Considering Score 1/2/3=Low Risk, 0.5=Normal/Ideal, 7=Nearly High Risk, 9/10=High Risk**

Table-3.5 Passive Smoking

No. of Cigarettes	Frequency (Time Slot)	Mean	Score Ref.
1-2	Daily	1.5	0.5
3-4	Weekly	3.5	0.5
5-6	Occasionally	5.5	0.5
0	Never-Smoker	0	0.5

***Considering Score 1/2/3=Low Risk, 0.5=Normal/Ideal, 10=High Risk**

For both active and passive smoking the scores are defined as per consumption of Number of cigarettes. If one will consume cigarettes daily will have more risk than one who consume never or occasionally. So ranges of cigarettes from 0-10 (daily) will have high risk of heart attacks and others who lies between 20-25 cigarettes (occasionally/never) will be considered under low risk.

Table-3.6 Alcohol(Men)

Men (Frequency)	Alcohol Consumption (No. of drinks)	Mean	Score Ref.
Daily	1-3	2	0.5
Weekly	3-5	4	0.5
Occasionally	5-7	6	0.5
Never	0	0	0.5

***Considering 1 Drink = 30 ml**
***Considering Score 1/2/3=Low Risk, 0.5=Normal/Ideal, 9/10=High Risk**

Table-3.7 Alcohol(Women)

Women (Frequency)	Alcohol Consumption (No. of drinks)	Mean	Score Ref.
Daily	1-2	1.5	0.5
Weekly	3-4	3.5	0.5
occasionally	5-6	5.5	0.5
Never	0	0	0.5

***Considering 1 Drink = 30 ml**

For both males and females the scores are defined as per consumption of alcohol that is No. of drinks a male or females consumed. If one will consume more alcohol daily will have more risk than one who consume never or occasionally. So ranges of cigarettes from 1-2(daily) will have less risk of heart attacks and others who lies between 10-15 (occasionally/never) will be considered under pre-high risks.

Table-3.8 Cholesterol

Category (Cholesterol)	Cholesterol Readings (mg/dL)	Mean	Score Ref.
Total Cholesterol Level	0-200	100	0.5
HDL Level	35-70	52.5	0.5
Triglycerides Level	50-160	105	0.5
LDL Level	08-30	19	0.5

***Considering Score 1=Low Risk, 0.5=Normal/Ideal, 10=High Risk**

Cholesterol table[3.8]is depends upon the type of categories like total Cholesterol level, HDL level, Triglycerides Level and LDL level. So our scores are calculated on the basis of these factors. As cholesterol readings range is between 0-200(Total Cholesterol Level) but according to my own test reading from the hospital my total cholesterol reading comes as 140 so that mean it's a normal risk. But if it increases above<=200 then that will be consider as high risk. Same will be for the other cases.

Table-3.9 Diet

Category (Diet)	No. of Calories (Kcal.)	Mean	Score Ref.
Balance Diet	1500-2000	1750	0.5
Nearly Balance Diet	1000-1800	1400	0.5
Obese Diet	2500-3000	2750	10
Deficient Diet	500-1000	750	10

***Considering Score 1=Low Risk, 0.5=Normal/Ideal, 10=High Risk**

In this above table[3.9] of diet all the scores are obtained according to the type of diet one maintained in their life. A balance diet obtained score as 0.5 which is equals to Ideal Risk that is No risk, Nearly balance diet with score 1 is also comes under low risk, persons with obese diet is considered as high risk with score 10.

Table-3.10 Hormonal Activity

Category (Hormonal Complications)	Age (Years)	Mean	Score Ref.
Heart disease	40-50	45	0.5
Mood Disorders	30-40	35	0.5
Insomnia	20-30	25	0.5
Adrenal fatigue	50-60	55	0.5
Osteoporosis	60-70	65	0.5
Thyroid	50-60	55	0.5

***Considering Score 1=Low Risk, 0.5=Normal/Ideal, 10=High Risk**

According to the table[3.10] of hormonal activity the scored are computed on the basis of complication occur naturally by age wise. So if an age lies in range of 40-50 can consider under heart diseases. Age of 30-40 can have complications of Mood disorders. Insomnia type of complication occurs mostly the age of 20-30 teen age So all these complication factors as per age wise will automatically calculate the score of the patients. Lesser the score lesser will be the Risk and vice versa.

Table-3.11 Physical Activity

Category (Physical Activity)	Time Period(min)	Mean	Score Ref.
Meditation	30-40	35	0.5
Physical Exercise	20-30	25	0.5
Cycling	60-90	75	0.5
Yoga	30-40	35	0.5
Walk/Jogging	60-90	75	0.5

***Considering Score 1=Low Risk, 0.5=Normal/Ideal, 10=High Risk**

According to the data of this table[3.11] following physical activities are described with the number of frequency and times slots. In table frequency of 50-60% for time period in between 30-40 min is considers as score 10 while in case of cycling the frequency is 15-20% with 60-90 min obtained score 6. That concludes score 10 is of high risk and score 6 is pre-high risk.

Table-3.12 Weight

Category (Weight)	Range (BMI)	Mean	Score Ref.
Underweight	10-15	12.5	10
Ideal Weight	20-25	22.5	0.5
Overweight	25-30	27.5	10
Obese	30-40	35	10

***Considering Score 1=Low Risk, 0.5=Normal/Ideal, 10=High Risk**

Underweight category of BMI range 10-15 obtained score 6(pre-high risk), ideal weight with 20-25(pre-high risk), overweight of BMI 25-30 results with 6 score and In the case of Obese category BMI range is 30-40m with High Risk of score 10.

IV. DATA SETS OF USERS

S.NO	NAME	AGE	GENDER	D.O.B	MARITAL STATUS	EMAIL ID	CONTACT
1	Shubam Sharma	23	Male	31.03.1993	Single	Shubam.sharma67@gmail.com	07837413224
2	Neeraj Jasrotia	23	Female	23.05.1993	Single	Neeraj.rajput@gmail.com	08716824539
3	Mona Pathania	25	Male	04.11.1991	Single	Pathaniamona786@gmail.com	08716835928
4	Rahul Sharma	24	Female	21.08.1992	Single	Rahulsharma55@yahoo.com	8713087446
5	Puneet Arora	42	Male	31.12.1974	Married	puneet@ecologic.co.in	9872856485

Table 4.1 User's DataSets

This is the table[4.1] of data sets with the patients details regarding age, gender, date of birth, email id and contact numbers. These data sets of patients are further used in obtaining the results of an each individual on basis of their risks. These are the true and actual biodata of the patients which are taken through the survey.

Medical data of shubam Sharma

Risk Factors	Systolic Reading (mmHg)	Years	BMI (Kg/m^2)	No. of Calories (K cal.)	Active/Passive +frequency+Cigarettes	No. of drinks	Chl. Reading (mh/dL)	Complications	Time (Min)
Blood PressureReadings	110/70								
Age		23Y							
Weight			20.11						
Diet				700					
Smoking					No				
Alcohol						No			
Total Cholesterol							140		
Hormonal Activity								No	
Physical Activity									0

Table 4.2

In the above table[4.2] of the User Shubam Sharma here is the list of risk categories with their readings are mentioned above which actually gives the value and the type of risk a person is suffering from. These reports can actually helps in calculating the final scores which is given on behalf of these report results only. The factors which are mentioned in above table are Blood pressure, age, weight, diet alcohol, smoking, total cholesterol, hormonal activity and physical activity, so we have collected the detail medical data of an each patient.

V. RESULTS OBSERVATION

In context of our research work , random sampling method has been considered best to validate the Risk Assessments Reports being created by the proposed system , it is also one of the best method to evaluate the accuracy of the system when the system is used by large number of people or in simple words "samples" . In this method a subset of cardiac risk assessment reports samples have been chosen from a larger set or the full population of samples being assessed for cardiac risk. Each individual sample for validation is chosen randomly and entirely by random probability, such that each individual sample assessment has the same probability of being chosen at any stage during the sampling process, and each subset of k individuals has the same probability of being chosen for the sample as any other subset of k individuals. Following are the outcomes of this type of sample testing and evaluation.

The "line" graph (Figure 5.1) shows that with an increase in number of evaluation samples, the precision remains in range bounds (0.93, 1). This range bound seems to be tight and reflects that the standard deviation is low (0.02). From this it can be interpreted that system behaviour is consistent for the aforesaid purpose of checking heart risk of a person. The mean precision is 0.958 and its curve is more or less plateau with a slope close to zero, i.e. a nearly horizontal curve with downward trend. This reflects that the precision slightly decreases when number of samples increases after 50. However, when the recall curve is observed, a linearly increasing trend can be seen. The rate of change or the slope of the recall curve is positive. From this it can be interpreted that as the size of the evaluation data-set increases the recall also increases linearly. The recall shows the number of correct answers that have been retrieved from the full evaluation set. The small value of the standard deviation shows that results remain consistent and there is not much difference in worst case and best case of accuracy evaluation.

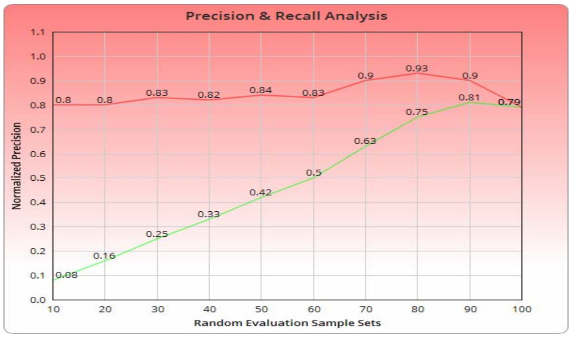

Fig-5.1 Recall and Precision Analysis

From the "recall-precision" line graph (Figure 5.1), it can be observed that initially the precision is 90%, when the sample size is 10. But as the sample size increases, the precision values drop as low as 0.79. The minimum of 0.83 values is also fairly good score in terms of accuracy. In this case, the mean precision provided by the system is 0.93. The recall and precision curves meet at point when sample size is becomes 100, showing that both statistics are in concordance. These value ranges are lowest amongst all the seven types of Punjabi questions. The recall values also maintain the lowest level i.e. 0.8.

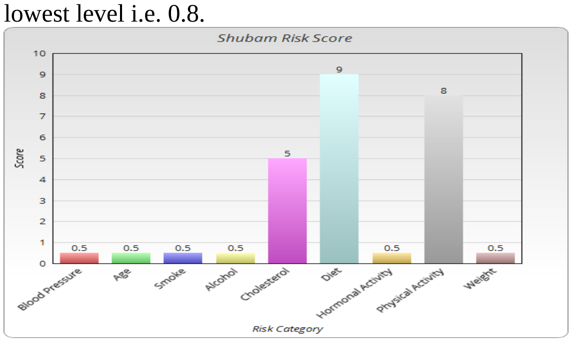

Fig 5.2 Risk score of user Shubam Sharma

In this table [5.2] of Shubam, the bar graph [5.2] of his output shows the values of score for every risk factors taken in the graph. This bar chart shows how rewards are depicted in above graph according to their risks where as in Y-axis there is score column and in X-axis Risk factor Block is in the horizontal manner.

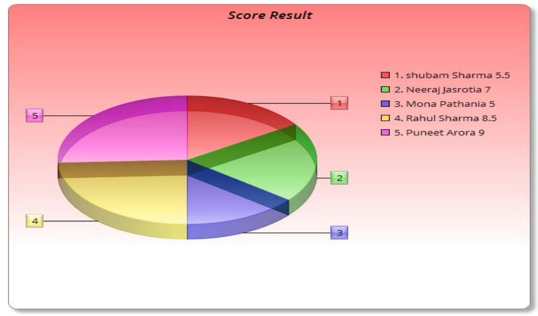

Fig 5.3 Score Results of 5 Users

The final result of this figure[5.3] is represented in the form of pie-chart comparing their overall results on the basis of *SCORE*. A score is computed by the risk factors, more the score means more the patient is under risk category.

SCORE CARD

NAME	Blood Pressure	Age	Smoke	Alcohol	Cholesterol	Diet	Hormonal Activity	Physical Activity	Weight
Shubam Sharma	0.5	0.5	0.5	0.5	5	9	0.5	8	0.5
Neeraj Jasrotia	0.5	5	0.5	8	6	9	0.5	0.5	0.5
Mona Pathania	8	0.5	0.5	0.5	0.5	0.5	8	0.5	0.5
Rahul Sharma	5	5	10	6	7	0.5	8	6	0.5
Puneet Arora	10	8	0.5	0.5	0.5	9	6	0.5	8

Table 5.1 Overall Score Card

Here in this table[5.1] of score card the overall score has been calculated on the basis of the outcomes received by the risk factors. These results are originally depends upon the personal medical data report of an each patients. From the medical data of each patient our result is computed. Score system of this table is done by the rule as if higher the risk field more will be score and vice-versa. So those patients who obtained more score=10 will be considered under an high risk. Risk score=0.5 is condition of an ideal case.

VI. CONCLUSION AND FUTURE SCOPE

The current work ,basically is based on FHIR standards for sending and receiving data form and points in cloud. The system need the concept of restful API to start the information of the users, the algorithm used for computing heart risk is based on hybrid approach. It uses the concepts both from Framingham and Reynolds risk model. The outcome of the user's heart risk assessments reports have been validated using experts. And computed by using evaluation parameters Recall & Precision.

VII. EXPERIMENTAL SETUPS

Software Requirements:

Operating System	Software Packages
Linux / Window Ubntu Or Window 7	1. Java 2. Python 3. Pycharm 4. JavaScript 5. GitHub 6. Digital Ocean

Hardware Requirements:

Processors	Disk Space	RAM	Graphics
Intel CORE i5	500 GB	4 GB	32 bit OS

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