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Development of Score Based Smart Risk Prediction Tool for Detection of Type-1 Diabetes: A Bioinformatics and Machine Learning Approach

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Abstract: In this study, a smart risk prediction tool has been demonstrated along with the algorithm, which works as a backend of the tool to detect Type-1 Diabetes. The algorithm was contrived by the weightage values that are articulated by analyzing the risk factors of Type-1 diabetes. The analysis takes place with a machine learning and statistical approach. Data were collected from a number of cases and control groups, which was preprocessed to be fit for the analysis. Risk factors were extracted by comparing two different approaches one is machine learning, and another is the statistical approach. A common regulatory pattern was found that leads to the design of an algorithm that gives a predictive result of the risk level of any user for Type-1 Diabetes. Elaborated results of different approaches have also been shown in this paper, which gives clear excogitation about risk factors and their ranking.

Keywords: Risk Factors; Type-1 Diabetes; Risk prediction tool; Data mining; Machine learning.

1. Introduction

In recent years, there are several diseases that are pernicious for human life. Among those diseases, diabetes is mostly found. The abnormality of the exuberant level of sugar in the human blood assuredly produces very well-known diseases diabetes. It is a chronic condition and is directly associated with blood sugar levels. According to medical science and advanced research in this specific arena, diabetes is mainly classified into two major groups, one is type-1, and another is type-2. Type-1 diabetes is one of the major causes of death in worldwide people.Type-1 diabetes is not only a disease but also a cause of occurring different kinds of diseases like eye problems, thyroid problems, liver problems, heartbeat problems, Thalassemia, skin problem, and affect to heart problems with respect to Bangladesh. Recently dataset based research on Type-1 diabetes has been implemented [1]. Type-1 Diabetes is especially can happen for lower age groups like children [2]. Different factors like obesity, growth rate, education, age, hypoglycemic cause Type-1 Diabetes [3,4,5]. Type-1 diabetes is in every year, increasing at a rate of approximately 3% (2013 year) per year in different countries around the world [6]. Type-1 diabetes means insulin deficiency due to pancreatic β cell damage [7]. Insulin means move sugar or glucose in the full body. When a person failed to make insulin in his body, then he is affected by type-1 diabetes. People are affected in type-1 diabetes in 30 million in 1985 to 150 million in 2000 and then to 246 million in 2007, according to the International Diabetes Federation. It expects this number to hit 380 million by 2025 [8]. They are more than many child are suffering from type-1 diabetes. Nowadays, many people are hesitant about their future life. As a result, the child can not continue his/her study properly. Day by day, many children are lost his/her good health. Type-1 diabetes also affects to foot or leg Disruption, and risk of infections, heart diseases in the human body. Type-1 diabetes patients are generally affected before age 25 years, and autoantibodies are present in 85–90% of individuals when fasting hyperglycemia is initially detected [9]. 20 years of age, 5–8% of the offspring of diabetic men, and only 2–5% of the offspring of diabetic women have been found to be affected [11]. Generally realized to increase young children are at-risk, especially females are more risk in type-1 diabetes [10]. Approximately 90% of cases are sporadic, occurring in individuals, and no family history of type-1 diabetes in Japan [12]. The island of Sardinia has the second-highest incidence of type-1 diabetes in the world (45/100,000), right after Finland (64.2/100,000) [13]. Type-1 diabetes is affected by worldwide people. Like as, Madeira Island was 7.2/100,000 per year, Portiere was 21.1/100,000 per year, New Zealand was 21.9/100,000 per year, Auckland was 12.3/100,000 per year, China was 0.1/100,000 per year [14]. The risk of type 1 diabetes in the offspring of diabetic fathers is high than in the offspring of diabetic mothers [15]. In addition, a lot of works are presented on diabetes in recent times [16, 17, 18].

In this paper, a detailed analysis of risk factors of Type-1 Diabetes has been done and shown. The results show that 13 risk factors are highly significant and associated with Type-1 Diabetes. An algorithm and App was developed to detect the risk level of Type-1 Diabetes of any random person.

2. Materials and Methods

2.1. Data collection and preprocessing.

Data collection is a crucial factor in any survey-based research. In this research, data were collected by a questionnaire. The questionnaire was designed by the study of numerous research papers [1-7] related to Type-1 Diabetes and by discussing with medical persons. To collect data, the required sample size has been determined using the sample size determination process [20]. Data of 306 persons were collected from different diagnostic and medical centers at Dhaka in Bangladesh. Among them, 152 was the case, and the rest 154 was a control group of both male and female persons. Type-1 Diabetes occurs at an early age, so at the time of data collection, it was accounted for early age groups (details in Figure 1).

In a survey-based study, raw data may be inappropriate, inconsistent, missing, etc. So data preprocessing is much needed before analysis. In this research, a brute force approach is used to make inconsistent data consistent and missing values to proper values. Data preprocessing was also done by WEKA, a data mining tool that resets and retrieves the missing values. Targeted parameters and other parameters are organized for analysis. “Affected by Type-1 Diabetes” was the targeted value for the research.

2.2. Analysis.

The whole analysis was done by using two data mining tools (Orange and WEKA) and a Statistical tool (SPSS). In recent years this type of risk prediction analysis has been done by both data mining [19,20] and the Statistical approach [21-23]. The main intention was to examine the risk factors by comparing it with two different approaches. In this research, data were collected for 22 different variables where few variables were numeric values. K-Means clustering algorithm was used by WEKA to make the category of the numerical factors (BMI, Age, Height, Weight, HBA1c).

Probability can be defined as the likelihood of an event that can happen from different events [8].

$$P\ (H/D) = \frac{P(D/\ H)P(H)}{P(D)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where P (D/H) is the likelihood function, and it causes the probability of the observed data from the hypothesis. P (H) is prior knowledge before learning about D, P(H/D) is the posterior probability of H after learning about D and P(D) obtained by integrating, which is sometimes called normalizing constant.

Chi-square (χ2) Test is another important test to measure whether the factor is significantly associated or not.

$$\chi^2 = \sum \frac{(Observed\ Value - Expected\ Value)^2}{Expected\ Value} \quad \ldots\ldots\ldots(2)$$

A low value of chi-square means there is a high association between two sets of data. If observed and expected values were equal (no difference), then the chi-square value would be zero, which is rare in practical life. A high chi-square value indicates there is little or no association between two variables.

In the hypothesis test, the p-value is used to check the significance of results. Hypothesis tests can be used to test the validity of the claim that is called the null hypothesis. For ($p \leq 0.05$), these null hypotheses can be omitted, whereas for ($p \geq 0.05$), the null hypothesis cannot be omitted.

Ranker Algorithm has been used to find the significance level of risk factors. Significant factors are extracted from 22 factors using comparative analysis. Ranker algorithm gives ranking with a weightage value of significant factors.

2.2.1. Algorithm design and tool implementation.

A comparative analysis takes place on both data mining (WEKA) and statistical (SPSS) approaches. Among 22 factors highly significant and correlated, 13 risk factors are chosen. P-Value and Chi-square tests are used to find the highly associated factors and level of significance among them.

Ranker algorithm analysis and probability analysis are also used to detect the significance among the significant factors. By comparing all the analysis, a final table (Table 3) has been implemented along with corresponding weightage values. By these weightage values, an algorithm has been designed that shows the probability of Low/Middle/High risk of Type 1 Diabetes. The minimum sum of weightage values is 33, and the highest weightage value is 63. So, the difference is 63-33=30. Interval is 30/n= 30/3=10 (Here n=3 as total three risk level). By designing an algorithm, an android based App was developed, which can be used to detect the risk level of any person.

3. Results and Discussion

All the factors and subfactors are evaluated in such a way. Figure 2 shows the distribution of different age groups. The figure illustrates the correlation between age group and affected three dimensions of height, weight, and BMI.

Table 1. P-value and χ2- Test of different factors.

Factors	P-value	95% C. I for Odds ratio		χ^2- Test
		Lower	Upper	
Age Less than 5 Less than 11 Less than 15 Greater than 15	0.000 *	0.2633	0.4884	92.146
Sex Male Female	0.000 *	0.1111	0.2235	11.843
Area of Residence Rural Urban Suburban	0.000 *	0.1489	0.3162	45.003
Height	0.665	0.245	0.0384	----------
Weight	0.996	1.88	0.1.89	----------
BMI	0.996	0.70	0.70	----------
Adequate Nutrition Yes No	0.008	0.0173	0.1163	16.361
Education of Mother Yes No	0.999	0.0544	0.0544	18.491
Standardized growth-rate infancy Lowest quartile Middle quartile Highest quartile	0.999	0.251	0.251	2.741
Family History in Type-1 Diabetes Father Mother Father's Heredity Mother's Heredity	0.000 *	0.4522	0.5550	9.081
Family History in Type-2 Diabetes Father Mother Father's Heredity Mother's Heredity	0.000 *	0.1864	0.2986	4.434

The probability of different factors with their sub-factors along with ranking from the ranker algorithm has been shown in Table 2. The factors are placed according to their significance level. The higher value has the probability of the higher the risk [24]. Table 1 and Table 2 are used to find the significance values, and finally, Table 3 was demonstrated. Table 3 illustrates the weightage value of the factors and subfactors. The weightage values are given based on the analysis result from both Table 1 and Table 2. Ranking of the factors and their values, Probability, and its values, p values were considered to give the weightage values of the significant factors. Among 22 factors, 13 factors were identified as significant by the Statistical and Data mining approach.

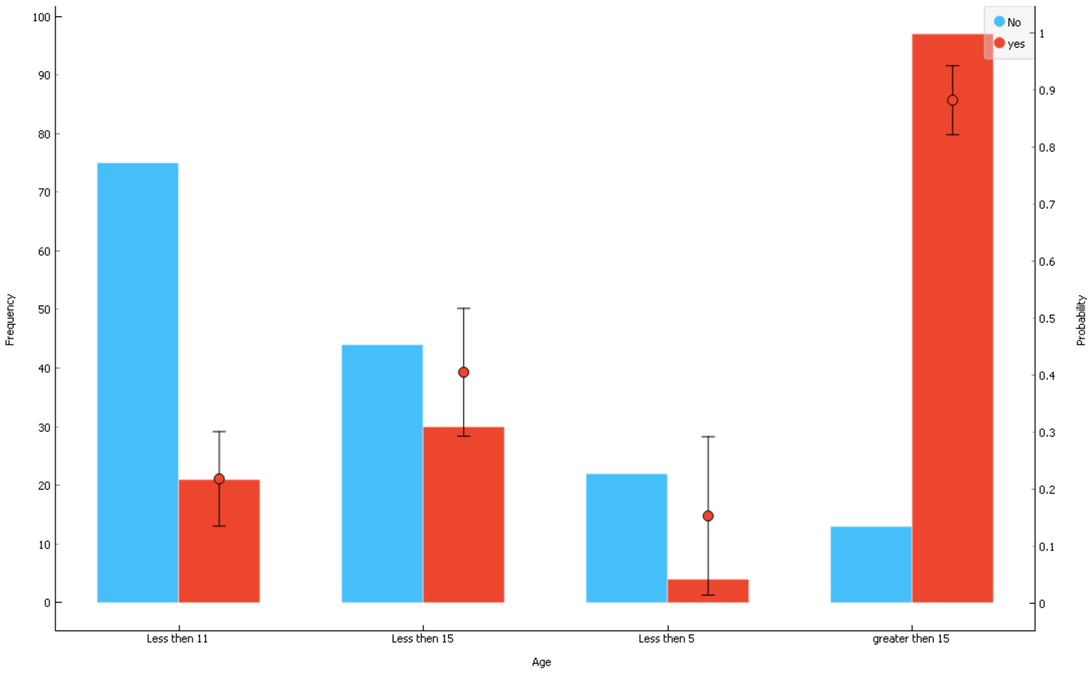

Figure 1. Frequency distribution along with probability with respect to different age groups.

Table 2. Probability Distribution and Significance ranking of different factors and sub-factors.

No	Factors	Sub-factors	Probabilities	Ranking
1	Age	Greater than 15	0.88	4
		Less than 15	0.42	
		Less than 11	0.2	
		Less than 5	0.18	
2	HBA1c	Less than 7.5	0.21	2
		Greater than 7.5	0.72	
3	Hypoglycemis	Yes	0.69	2
		No	0.27	
4	Pancreatic Diseases diagnosed in affected childs	Yes	0.5	
		No	0.31	
5	Area of Residence	Rural	0.82	3
		Suburban	0.65	
		Urban	0.22	
6	Adequate Nutrition	No	0.86	2
		Yes	0.36	
7	Autoantibodies	No	0.4	2
		Yes	0.38	
8	Sex	Female	0.65	2
		Male	0.36	
9	Family History type 1 Diabetes	Yes	0.68	2
		No	0.41	
10	Family History type 2 Diabetes	Yes	0.59	2
		No	0.44	
11	Standard Growth Rate	Lowest	0.96	3
		Height	0.72	
		Middle	0.45	

A smartphone-based risk prediction tool was developed by research on Heart Attack risks prediction [25], appendicitis Patients risk prediction [26]. In our research, a smart risk prediction tool is also designed for predicting the risk of Type-1 Diabetes. Figure 3 and Figure 4 shows the results of the research. Figure 3 shows the flowchart of the designed algorithm. The flowchart was designed by the weightage values of Table 3. From Figure 3, it can be illustrated that by giving a choice among the Factors of Table 3, all the sum of weightage values implies the risk level low or middle or high risk. Figure 4 shows the Implemented Apps using the flow chart of Figure 3. By using the App, one can easily detect the risk level of his/her Type-1 Diabetes.

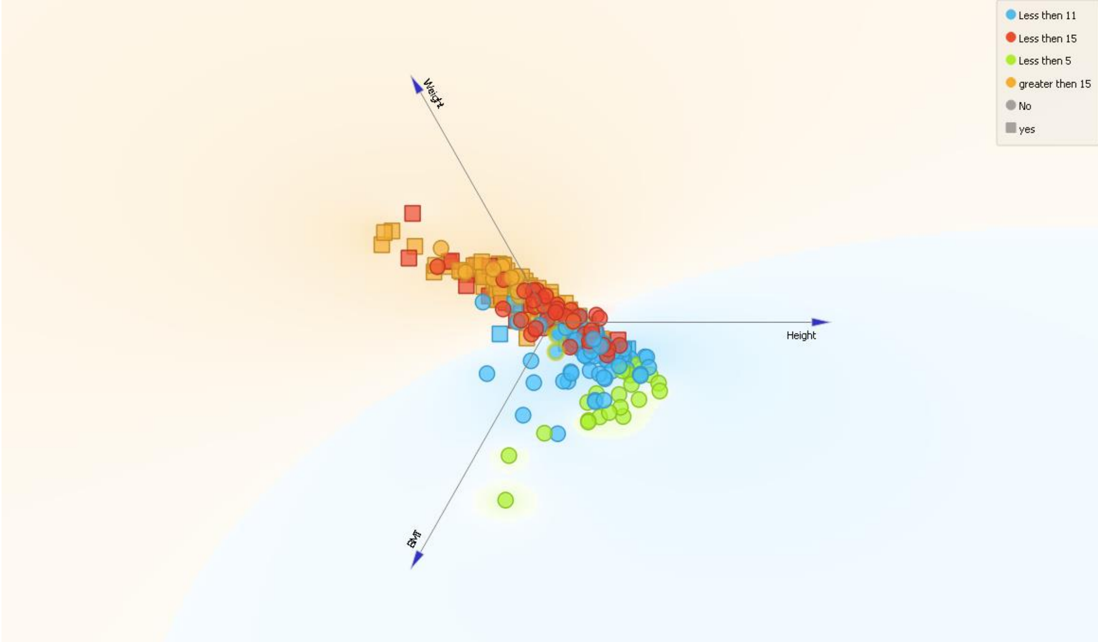

Figure 2. Affected and Non-affected density distribution of different age groups.

Table 3. Weightage value of different factors and sub-factors.

No	Factors	Sub-factors		Weightage value
1	Age	Greater than 15		8
		Less than 15		6
		Less than 11		5
		Less than 5		4
2	Standard Growth Rate	Lowest		6
		Height		5
		Middle		3
3	Area of Residence	Rural		6
		Suburban		5
		Urban		3
4	HBA1c	Less than 7.5		2
		Greater than 7.5		4
5	Hypoglycemis	Yes		6
		No		4
6	Pancreatic Diseases diagnosed in affected childs	Yes		6
		No		4
7	Adequate Nutrition	Yes		2
		No		4
8	Autoantibodies	Yes		3
		No		4
9	Sex	Female		4
		Male		2
10	Family History type 1 Diabetes	Yes	Mother	4
			Father's Heredity	3
			Mother's Heredity	2
			Father	1
		No		1
11	Family History type 2 Diabetes	Yes	Mother	4
			Father's Heredity	3
			Father	2
			Mother's Heredity	1
		No		1
12	Education of Mother	Yes		2
		No		1
13	Symptoms	Frequent Urination		5
		Increased thirst		4.5
		Fatigue and Weakness		4
		Unintended weight loss		3.5
		Extreme Hunger		3

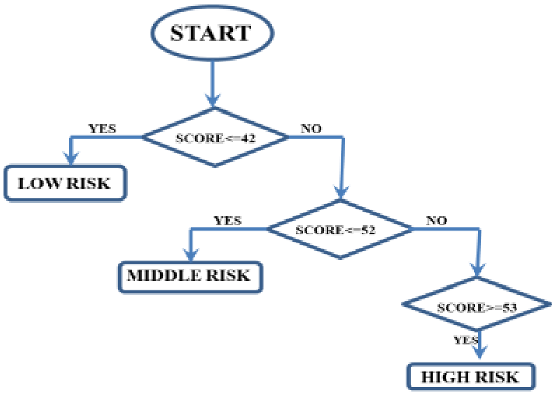

Figure 3. Flow chart of risk prediction algorithm.

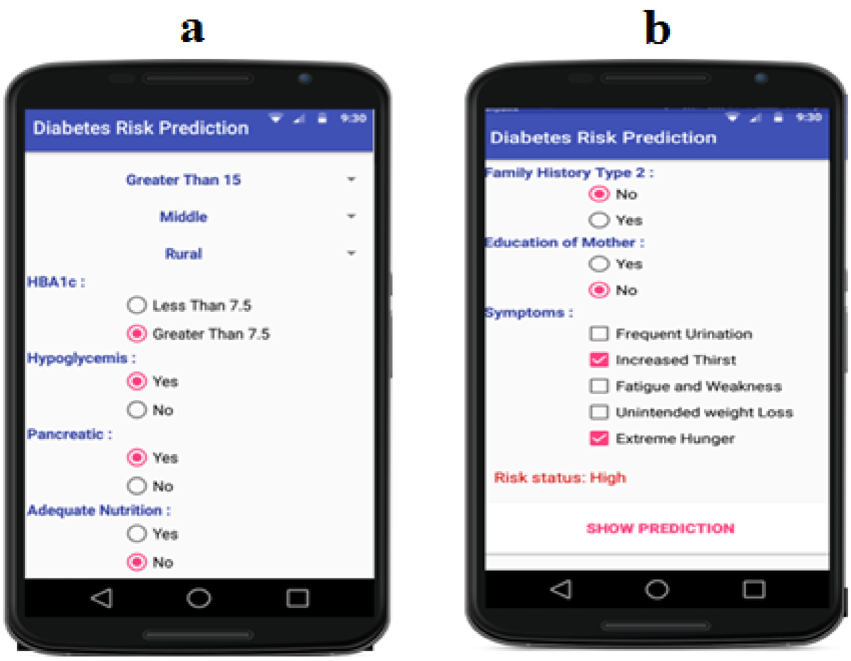

Figure 4. Smart risk prediction tool for type-1 diabetes.

Diagnosis and Prognosis by analyzing the risk factors have been made in recent research on medical science. This kind of research has drawn the attention of the new researchers. Risk analysis, risk prediction, and implementing device/tool to diagnosis the disease has been a common trend nowadays [27, 28]. In this section, the detailed result analysis has been shown. Table 1 shows the p-value and the Chi-square test of the factors. Among the factors, age has a p-value of 0.000<0.05 and $\chi2$- Test value of 92.146. Figure 1 shows the frequency distribution with the probability of each subfactor for both case and control groups. Comparing $\chi2$- Test value with the other factors age is most significant. From Table 2, it can be defined that among the subfactors, "Greater than 15" has the most probability (0.88) to be affected by Type-1 Diabetes. On the other hand, other subfactors have the probability (Less than 15 is 0.42), (Less than 11 is 0.2), (Less than 5 is 0.18). A worldwide study showed that approximately the same number of boys and girls are affected by type-1 diabetes, and the incidence peak of type-1 diabetes is at puberty [29]. This result is slightly different from our findings as our result has shown that the probability of affecting by type-1 diabetes between ages 11 to 15 is 0.42. Sex, Area of residence, Family history of both Type-1 and Type-2 Diabetes are some of the significant factors with p-value ≤0.05, which indicates that the factors are highly significant. A family history of type-1 diabetes is one of the significant risk factors, which is quite similar to the findings of a study of Germany [30]. Type-1 Diabetes has a significant relationship with pandemic COVID-19 [31] and changing epidemiology [32-34]. So, our proposed model will also be helpful for the early detection of Type-1 Diabetes patients. It will also be highly favorable for COVID-19 patients.

4. Conclusions

A risk prediction tool and detailed risk factor analysis have been done in this article. Statistical analysis like p-value, Confidence Interval, Chi-square test has been done to find the risk factors. Data mining approach like ranking and probability of risk factors has also been made to find out the risk level among the factors. By analysis, a weightage value is given to each factor and subfactors by which a flow chart was designed. The flow chart or so-called decision tree may give the decision whether the person is affected and how much possibility to be affected by Type-1 Diabetes.

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Conflicts of Interest

The authors declare no conflict of interest.

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