ORIGINAL RESEARCH

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RELATIVE CONTRIBUTION OF DIABETIC RISK FACTORS AMONG WOMEN TO THE INCIDENCE AND PROGRESSION OF DIABETES: NEURAL NETWORK ANALYSIS AS A MODE OF PREDICTION

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ABSTRACT:

Neural network analysis is used to establish predicting models of disease including diabetes to identify risk factors. The objectives of this study were to identify risk factors leading to diabetes and to determine their relative contribution using artificial intelligence as a mode of prediction. The current investigation was led by breaking down dataset as depicted beneath. We chose a dataset posted at Kaggle. The dataset was about diabetes from India. It comprises of 763 female members, of whom 497 had no diabetes, and 266 with type 2 diabetes. We utilized neural network analysis to build mathematical models and to show the arrangement of diabetic risk factors. The importance was considered at $\alpha<0.05$. The results of the present study showed that the risk factors were ranked according to their relative importance in the following order: Diabetes Pedigree Function, age, glucose, skin thickness, blood pressure, BMI, insulin, and number of pregnancies. Taken together, neural network analysis is effective in establishing mathematical models that can predict risk factors of the diseases.

KEYWORDS: neural network analysis, artificial analysis, diabetes, risk factors, Kaggle.

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INTRODUCTION

Type 2 diabetes mellitus (T2DM) is a non-infectious and ongoing illness [1]. T2DM can cause numerous different sicknesses, for example, cardiovascular illness [2], stroke [3], visual impairment [4], and loss of renal capacity [5]. The pervasiveness of diabetes is expanding. Around the world, 285 million individuals had diabetes in 2010, contrasted with 422 million out of 2014 [6] and this number is projected to increment to 438 million in 2030 [7] and 592 million out of 2035 [8]. The pervasiveness of diabetes in low-pay or moderate-pay nations is higher than in top level salary nations [7], and it represents an enormous portion of the mortality and incapacity rate in such networks [6]. One reason for the high pervasiveness of diabetes in low-pay nations might be low degrees of information and mindfulness about diabetes [9].

The anticipation of diabetes mellitus is of high significance in all networks. The initial phase in the avoidance of T2DM is to distinguish its danger factors. Reviewing literature showed that variables, for example, age [10,11], sex [10,12], family background of diabetes [11, 13], hypertension [14], stoutness [10,15], stomach weight [16], stress in the working environment or home [17,18], a stationary way of life [19,20], smoking [21], inadequate leafy foods utilization [22], and active work [23,24] are hazard factors related with T2DM.

The Diabetes Pedigree Function, pedi, was a particularly intriguing feature used in the study. It included information on diabetes mellitus in relatives as well as the genetic link between those relatives and the patient. This genetic influence measurement gives us an understanding of the hereditary risk of developing diabetes mellitus. It's uncertain how effectively this function predicts the beginning of diabetes, based on the findings in the preceding section [25].

Study objectives:

The main objectives of the present study were to identify risk factors leading to diabetes and to determine their relative contribution using artificial intelligence as a mode of prediction.

METHODS:

The current investigation was led by breaking down dataset as depicted beneath. We chose a dataset posted at Kaggle. The dataset was about diabetes from India. It comprises of 763 female members, of whom 497 had no diabetes, and 266 with type 2 diabetes. We utilized neural network analysis to build mathematical models and to show the arrangement of diabetic risk factors. The importance was considered at $\alpha<0.05$.

The dataset zeroed in on a few danger factors among which is the insulin. Neural network analysis infers deciding forecasts of risk factors, autonomous factors, or covariates on the result, the diabetes. This cycle included three layers, input layer (covariates), stowed away layers, and yield layer (subordinate variable). This cycle varies from conventional measurements in giving expectations that can have effects on the reliant factors.

RESULTS

As shown in table (1), a case processing summary was provided. A total of 540 (89.3%) of cases were included in training, while a total of 65 (10.7%) of cases were included in testing. Valid cases were 605 (100%) cases.

Table 1: Case Processing Summary

		N	Percent
Sample	**Training**	**540**	**89.3%**
	Testing	**65**	**10.7%**
Valid		**605**	**100.0%**
Excluded		**163**	
Total		**768**	

Network information

As illustrated in table (2), the model included three layers. The first layer (input layer) included 8 risk factors: No of pregnancies, glucose, blood pressure, skin thickness, insulin, BMI, diabetes pedigree function, and age. The second layer(s) represented hidden layers as follows: number of hidden layers (1), number of units in hidden layer (10), and the activation function was hyperbolic tangent. The output layer included one dependent variable (the outcome, diabetes), number of units (2), the activation function was soft max, and error function was expressed as a cross-entropy.

Table 2: Network Information			
Input Layer	Factors	1	Pregnancies
		2	Glucose
		3	Blood Pressure
		4	Skin thickness
		5	Insulin
		6	BMI
		7	Diabetes Pedigree Function
		8	Age
	Number of Units[a]		1069
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		10
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	outcome
	Number of Units		2
	Activation Function		Softmax
	Error Function		Cross-entropy
a. Excluding the bias unit			

Model Summary

As illustrated in table (3), model summary was provided. About 31% was the incorrect prediction of diabetes in training part. In testing part, the percent incorrect prediction was 29.2%.

Table 3: Model Summary		
Training	Cross Entropy Error	316.633
	Percent Incorrect Predictions	31.3%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:16.59
Testing	Cross Entropy Error	30.760
	Percent Incorrect Predictions	29.2%
Dependent Variable: outcome		
a. Error computations are based on the testing sample.		

Classification

As seen in table (4), in training part, the overall percent for prediction of diabetes 68.7%, while the overall percent of prediction of diabetes was 70.85 in testing part.

Table 4: Classification				
Sample	**Observed**	**Predicted**		
		.00	**1.00**	**Percent Correct**
Training	**.00**	**325**	**24**	**93.1%**
	1.00	**145**	**46**	**24.1%**
	Overall Percent	**87.0%**	**13.0%**	**68.7%**
Testing	**.00**	**43**	**4**	**91.5%**
	1.00	**15**	**3**	**16.7%**
	Overall Percent	**89.2%**	**10.8%**	**70.8%**
Dependent Variable: outcome				

Independent Variable Importance

As seen in table (5) and figure (1), the order of risk factors according to the importance came in the following order: Diabetes Pedigree Function (100%), age (92.6%), glucose (89.6%), skin thickness (87.7%), blood pressure (84.4%), BMI (83.3%), insulin (82.7%), and number of pregnancies (81.7%).

Table 5: Independent Variable Importance		
	Importance	**Normalized Importance**
Diabetes Pedigree Function	**.142**	**100.0%**
Age	**.132**	**92.6%**
Glucose	**.128**	**89.6%**
Skin thickness	**.125**	**87.7%**
Blood Pressure	**.120**	**84.4%**
BMI	**.119**	**83.3%**
Insulin	**.118**	**82.7%**
No of Pregnancies	**.116**	**81.7%**

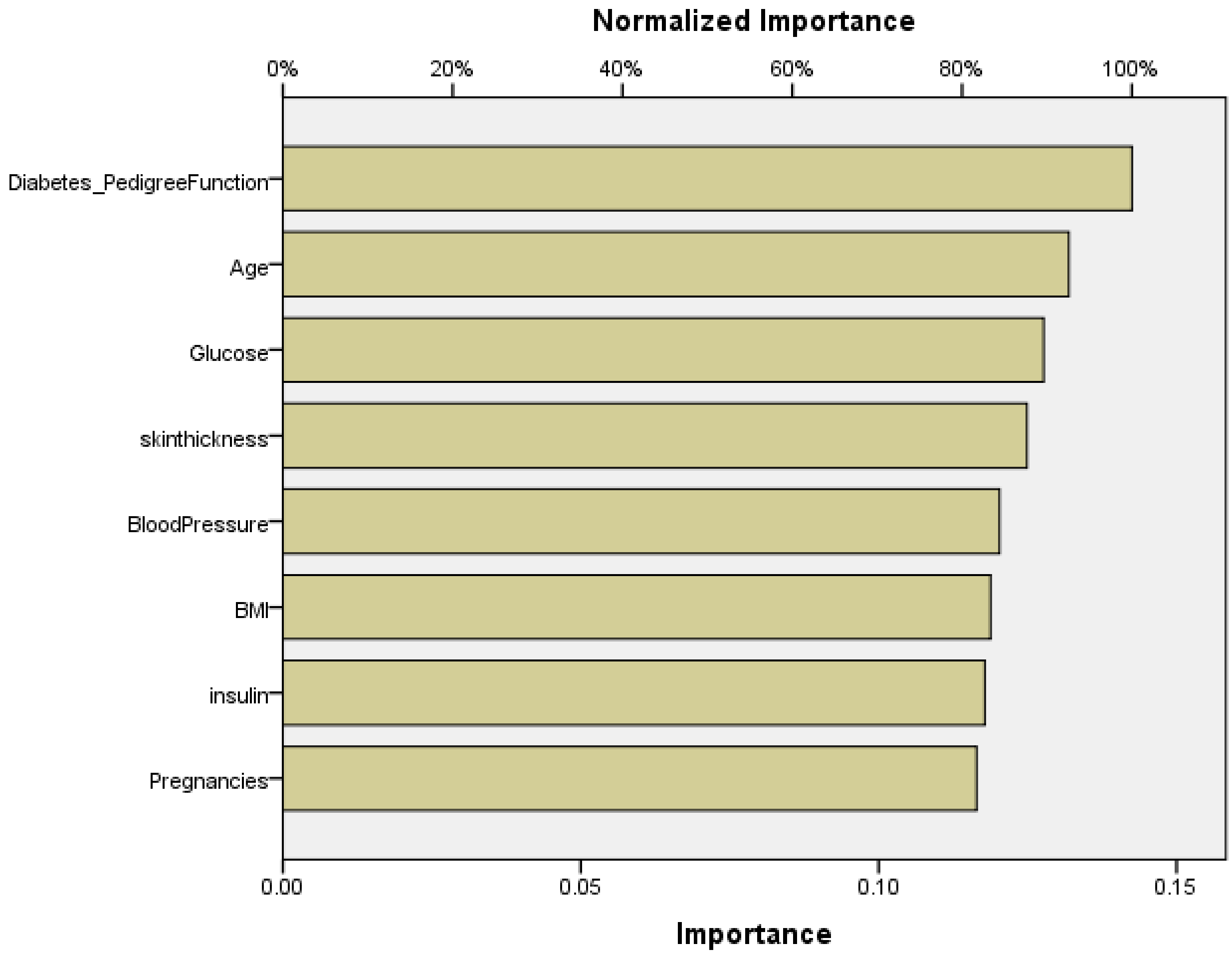

Figure 1: The importance of risk factors for diabetes

DISCUSSION:

The results of this study showed that the most important risk factor for developing diabetes is the Diabetes Pedigree Function. This implies that genetic predisposition is highly affecting the occurrence of diabetes. This was also reported by other studies in which the Diabetes Pedigree Function was one of the main causative agents for diabetes [26].

Age was shown to be the second important risk factor for diabetes. This is also in agreement with previous studies [26]. As the age increases, diabetes is likely to occur [26, 27].

The results of this study showed that the glucoselevelwas the third important risk factor for diabetes. Diabetes is measured by glucose and defined by its levels. Glucose level has been reported by other datasets as an important predicting risk factor for diabetes [26-29].

Skin thickness followed the level of glucose regarding the importance of diabetic risk factors. Skin thickness (the contact between the epidermis and the dermis), which is mostly determined by collagen content, is more evident in DM patients who have been diabetic for more than ten years [30]. This could be due to increased collagen cross-linking and lower collage turnover [31, 32]. Jain., et al. [33] undertook a study to assess skin and subcutaneous tissue thickness in type 2 diabetic patients, with the hope that this information would be useful during the insulin infusion procedure. Their findings revealed that in people with a BMI of less than 23 kg/m2, the mean skin thickness was higher in males than females at the arm and thigh (P 0.05). Males with a BMI of 19 to 23 kg/m2 had thicker skin around the middle [34].

The results showed that blood pressure predicted the occurrence of diabetes. This result confirmed previous studies in which blood pressure could be a risk factor to diabetes [26, 35]. T2D may cause hypertension, however the association between T2D and hypertension is unlikely to be causal. These findings highlight the need of maintaining a healthy glycemic profile in the general population, as well as BP screening and monitoring, particularly systolic BP, in T2D patients [36].

The results of the present study showed that BMI is one of the important risk factors of diabetes. It has been recently reported that the pre-diagnosis BMI was positively related with microvascular problems in patients with incident type 2 diabetes, although weight loss was associated with a lower risk when compared to stable weight. The links to macrovascular disease were less obvious [37].

The level of insulin was shown to be an important predicting factor for diabetes. We have previously shown that the level of insulin increases as the diabetes is progressed [38, 39].

The results of this study showed that number of pregnancies is the least important predicting risk factor of diabetes. It has been reported that pregnancy may lead to gestational diabetes [40].

CONCLUSIONS:

The present study showed that several important risk factors were associated with diabetes using neural network analysis. These risk factors were ranked according to their relative importance in the following order: Diabetes Pedigree Function, age, glucose, skin thickness, blood pressure, BMI, insulin, and number of pregnancies.

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