International Journal of Pharmaceutical and Bio-Medical Science
ISSN(print): 2767-827X, ISSN(online): 2767-830X
Volume 02 Issue 11 November 2022
Page No: 546-551
DOI: https://doi.org/10.47191/ijpbms/v2-i11-13, Impact Factor: 5.542

Evaluating the Risk of Type 2 Diabetes Mellitus Using Artificial Neural Network

Abdulaziz Fhad Abdulaziz alsalem[1], Zaid Mohammad Alqahtani[2], Anas Ageel Alshammari[3], Hassan Rashed Alzamanan[4], Saad Mohammed Alsarhan[5], Suyuf Ahmed Alwallah[6], Rizq Saleh Alismail[7], Hassan Mohammed Atiah[8]
[1,2,3,4,5,6,7,8]Ministry of Health

ABSTRACT

To identify risk factors, neural network analysis is used to create disease prediction models, including diabetes. The goals of this study were to identify diabetes risk factors and determine their relative contribution using artificial intelligence as a mode of prediction. The current investigation was led by breaking down the dataset, as shown below. We chose a dataset from Kaggle. The diabetes dataset was from India. It has 763 female members, 497 of whom have no diabetes and 266 who have type 2 diabetes. We used neural network analysis to create mathematical models and visualize the distribution of diabetic risk factors. The significance level was set at 0.05. The current study found that the following risk factors were ranked in order of importance: Diabetes Pedigree Function, age, glucose, skin thickness, blood pressure, BMI, insulin, and number of pregnancies. When combined, neural network analysis is effective in developing mathematical models that can predict disease risk factors.

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

ARTICLE DETAILS

Published On:
23 November 2022

Available on:
https://ijpbms.com/

INTRODUCTION

Type 2 diabetes mellitus (T2DM) is a chronic, non-infectious disease [1]. T2DM can cause a variety of illnesses, including cardiovascular disease [2], stroke [3], visual impairment [4], as well as renal capacity loss [5]. Diabetes is becoming more prevalent. Diabetes affected 285 million people worldwide in 2010, compared to 422 million in 2014 [6] This figure is expected to rise to 438 million by 2030 [7] and 592 million out of2035 [8]. Diabetes is more prevalent in low- and moderate-income countries than in high-income countries [7], It also accounts for a significant portion of the mortality and incapacity rates in such networks [6]. One reason for the high prevalence of diabetes in low-income countries could be a lack of diabetes knowledge and awareness [9].

Diabetes mellitus prediction is extremely important in all networks. The first step in avoiding T2DM is to recognize its risk factors. A review of the literature revealed that variables such as 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 one of the study's most intriguing features. It detailed diabetes mellitus in relatives as well as the genetic link between those relatives and the patient. This genetic influence measurement provides insight into the hereditary risk of diabetes mellitus. Based on the findings in the preceding section, it is unclear how well this function predicts the onset of diabetes [25].

STUDY OBJECTIVES

The primary goals of this study were to identify diabetes risk factors and determine their relative contribution using artificial intelligence as a mode of prediction.

METHODS

The current investigation was led by breaking down the dataset, as shown below. We chose a dataset from Kaggle. The diabetes dataset was from India. It has 763 female members, 497 of whom have no diabetes and 266 who have type 2 diabetes. We used neural network analysis to create

mathematical models and visualize the distribution of diabetic risk factors. The significance level was set at 0.05.
The dataset focused on a few risk factors, one of which is insulin. Neural network analysis predicts risk factors, autonomous factors, or covariates on the outcome, diabetes. This cycle had three layers: the input layer (covariates), the stowed away layers, and the yield layer (subordinate variable). This cycle differs from traditional measurements in that it provides expectations that can have an impact on the reliant factors.

RESULTS

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

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

The model had three layers, as shown in table (2). The first (input layer) contained eight risk factors: the number 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 hyperbolic tangent as the activation function. The output layer had one dependent variable (the outcome, diabetes), two units, a soft max activation function, and an error function 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

A model summary was provided, as shown in table (3). In the training section, approximately 31% of diabetes predictions were incorrect. The percentage of incorrect predictions in the testing section 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 shown in table (4), the overall percent for diabetes prediction in the training part was 68.7%, while the overall percent for diabetes prediction in the testing part was 70.85.

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

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%) were the most important risk factors, as shown in table (5) and figure (1).

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%

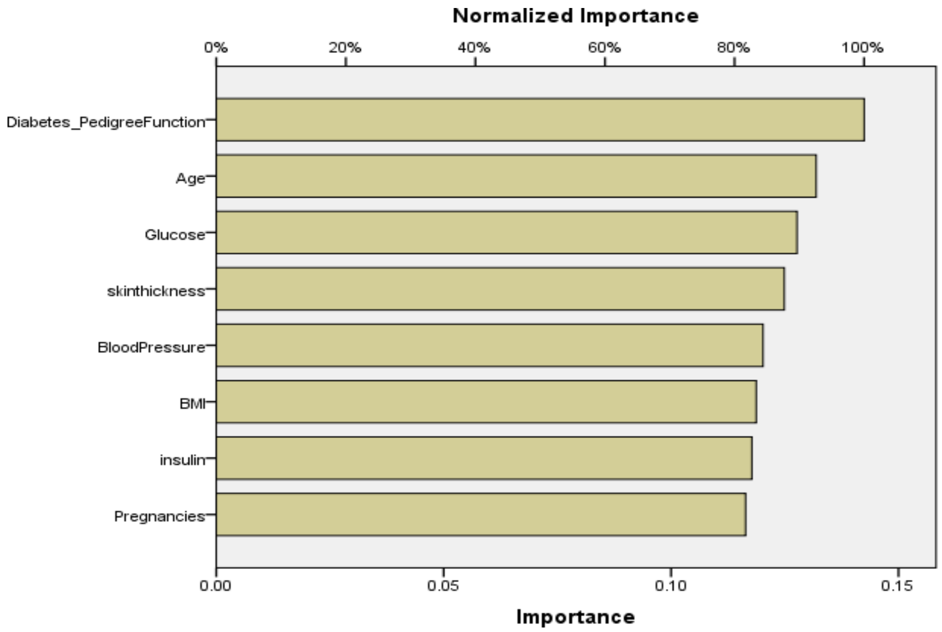

Figure 1. The importance of risk factors for diabetes

DISCUSSION

According to the findings of this study, the Diabetes Pedigree Function is the most important risk factor for developing diabetes. This implies that genetic predisposition has a significant impact on the occurrence of diabetes. This was also reported in other studies in which the Diabetes Pedigree Function was identified as one of the primary causes of diabetes [26]. Age has been identified as the second most important risk factor for diabetes. This is also consistent with previous research [26]. Diabetes is more likely to develop as one gets older [26,27].

According to the findings of this study, the third most important risk factor for diabetes is blood glucose levels. Diabetes is defined and measured by glucose levels. Other datasets have identified glucose levels as an important risk factor for diabetes [26-29].

In terms of the significance of diabetic risk, skin thickness followed glucose levels. Skin thickness (the contact between the epidermis and the dermis), which is primarily determined by collagen content, is more pronounced in diabetic patients who have been diabetic for more than ten years [30]. This could be as a result of increased collagen cross-linking and decreased collage turnover [31, 32]. Jain., et al. [33] undertook a study to assess skin and subcutaneous tissue thickness in type 2 diabetic patients, in the hope that this information will come in handy during the insulin infusion procedure. Their findings revealed that in people with a BMI of less than 23 kg/m2, males had thicker skin at the arm and thigh than females (P 0.05). Males with a body mass index (BMI) of 19 to 23 kg/m2 had thicker skin around the middle [34]. According to the findings, blood pressure predicted the occurrence of diabetes. This finding supported previous research that blood pressure may be a risk factor for diabetes [26, 35]. Although T2D may cause hypertension, the link between T2D and hypertension is unlikely to be causal. These findings emphasize the importance of maintaining a healthy glycemic profile in the general population, as well as BP screening and monitoring in T2D patients, particularly systolic BP [36].

According to the findings of this study, BMI is an important risk factor for diabetes. It was recently reported that pre-diagnosis BMI was related to microvascular problems in patients with incident type 2 diabetes, but weight loss was associated with a lower risk when compared to stable weight. The connections to macrovascular disease were less clear [37]. Insulin levels have been shown to be an important predictor of diabetes. We previously demonstrated that the level of insulin rises as diabetes progresses [38, 39].

According to the findings of this study, the number of pregnancies is the least important predictor of diabetes risk. Pregnancy has been linked to gestational diabetes, according to reports [40].

CONCLUSIONS

Using neural network analysis, the current study found that several important risk factors for diabetes were linked. Diabetes Pedigree Function, age, glucose, skin thickness, blood pressure, BMI, insulin, and number of pregnancies were ranked in the order of their relative importance.

REFERENCES:

I. Adeyemo AB, Akinwonmi AE. On the diagnosis of diabetes mellitus using artificial neural network model artificial neural network models. Afr J Comput Ict 2011; 4:1-8.

II. Tripolt NJ, Narath SH, Eder M, Pieber TR,Wascher TC, Sourij H. Multiple risk factor intervention reduces carotid atherosclerosis inpatients with type 2 diabetes. Cardiovasc Diabetol 2014; 13:95.

III. Tuttolomondo A, Maida C, Maugeri R,Iacopino G, Pinto A. Relationship between diabetes and ischemic stroke: analysis of diabetes-related risk factors for stroke and of specific patterns of stroke associated with diabetes mellitus. J Diabetes Metab 2015; 6:544.

IV. World Health Organization. Prevention of blindness from diabetes mellitus: report of a WHO consultation in Geneva, Switzerland, 9-11 November 2005; 2006 [cited 2018 Mar 26]. Available from: http://apps.who.int/iris/handle/10665/43576.

V. Nasri H, Rafiean-Kopaei M. Diabetes mellitus and renal failure: prevention and managment. J Res Med Sci 2015; 20:1112- 1120.

VI. World Health Organization. Global report on diabetes; 2016 [cited 2018 Mar 26]. Availablefrom:http://apps.who.int/iris/bitstream/10665/204871/1/9789241565257_eng.pdf

VII. Rawal LB, Tapp RJ, Williams ED, Chan C, Yasin S, Oldenburg B. Prevention of type

VIII. 2 diabetes and its complications in developing countries: a review. Int J Behav Med 2012; 19:121-133.

IX. Olaniyi EO, Adnan K. Onset diabetes diagnosis using artificial neural network. Int JSci Eng Res 2014; 5:754-759.

X. Soltanian AR, Borzouei S, Afkhami- Ardekan M. Design, developing andvalidation a questionnaire to assess generalpopulation awareness about type II diabetes disease and its complications. Diabetes MetabSyndr 2017;11 Suppl 1: S39-S43.

XI. Adhikary M, Chellaiyan VG, ChowdhuryR, Daral S, Taneja N, Kumar Das T. Association of risk factors of type 2 diabetes mellitus and fasting blood glucose levels among residents of rural area of Delhi: a cross sectional study. Int J Community Med Public Health 2017; 4:1005-1010.

XII. Binh TQ, Nhung BT. Prevalence, and risk factors of type 2 diabetes in middle-aged women in Northern Vietnam. Int J Diabetes Dev Ctries 2016; 36:150-157.

XIII. Lee YH, Shin MH, Nam HS, Park KS, Choi SW, Ryu SY, et al. Effect of family history of diabetes on hemoglobin A1c levels among individuals with and without diabetes: the dong-gu study. Yonsei Med J 2018; 59:92-100.

XIV. van Zon SK, Snieder H, Bültmann U, Reijneveld SA. The interaction ofsocioeconomic position and type 2 diabetes mellitus family history: a cross-sectional analysis of the Lifelines Cohort and Biobank Study. BMJ Open 2017;7:e 015275.

XV. Zhang N, Yang X, Zhu X, Zhao B, Huang T, Ji Q. Type 2 diabetes mellitus unawareness, prevalence, trends and risk factors: National Health and Nutrition Examination Survey (NHANES) 19992010.J Int Med Res 2017; 45:594-609.

XVI. Suhail Khan M, Kumar Singh A, Bihari Gupta S, Saxena S, Maheshwari S. Assessment of risk factors of type 2 diabetes mellitus in an urban population of district bareilly. Indian J Forensic Community Med 2016; 3:5-9.

XVII. Mi SQ, Yin P, Hu N, Li JH, Chen XR, Chen B, et al. BMI, WC, WHtR, VFI andBFI: which indictor is the most efficient screening index on type 2 diabetes in Chinese community population. Biomed Environ Sci 2013; 26:485-491.

XVIII. Hackett RA, Steptoe A. Type 2 diabetes mellitus and psychological stress: a modifiable risk factor. Nat Rev Endocrinol2017;13: 547-560.

XIX. Pan KY, Xu W, Mangialasche F, Fratiglioni L, Wang HX. Workrelated psychosocial stress and the risk of type 2 diabetes in later life. J Intern Med 2017; 281:601-610.

XX. Bertoglia MP, Gormaz JG, Libuy M,Sanhueza D, Gajardo A, Srur A, et al. The population impact of obesity, sedentary lifestyle, and tobacco and alcohol consumption on the prevalence of type2 diabetes: analysis of a health populationsurvey in Chile, 2010. PLoS One 2017;12: e0178092.

XXI. Gao Y, Xie X, Wang SX, Li H, Tang HZ,Zhang J, et al. Effects of sedentary occupations on type 2 diabetes and hypertension in different ethnic groups in Northwest China. Diab Vasc Dis Res 2017; 14:372-375.

XXII. Maddatu J, Anderson-Baucum E,Evans-Molina C. Smoking and the risk of type 2 diabetes. Transl Res 2017; 184:101- 107.

XXIII. Beidokhti MN, Jäger AK. Review of antidiabetic fruits, vegetables, beverages, oils and spices commonly consumed in the diet. J Ethnopharmacol 2017; 201:26-41.

XXIV. Joseph JJ, Echouffo-Tcheugui JB, Golden SH, Chen H, Jenny NS, Carnethon MR, et al. Physical activity, sedentary behaviors and the incidence of type 2 diabetes mellitus: the Multi-Ethnic Study of Atherosclerosis (MESA). BMJ Open Diabetes Res Care 2016;4: e000185.

XXV. Smith AD, Crippa A, Woodcock J, Brage S. Physical activity and incident type 2 diabetes mellitus: a systematic review and dose response meta-analysis of prospective cohort studies. Diabetologia 2016; 59:2527- 2545 https://machinelearningmastery.com/case- study-predicting-the-onset-of-diabetes-within- five-years-part-1-of-3, retrieved in 17-9-2021.

XXVI. Rabindra Nath Das. Determinants of Diabetes Mellitus in the Pima Indian Mothers and Indian Medical Students. The Open Diabetes Journal, 2014, 7, 5-13.

XXVII. Knowler WC, Nelson RG, Saad MF, Bennett PH, Pettitt DJ. Determinants of diabetes mellitus in the Pima Indians. Diabetes Care, 1993; 16: 216-27.

XXVIII. Dort A, Ballintine EJ, Bennett PH, Miller M. Retinopathy in Pima Indians relationships to glucose level duration of diabetes age at diagnosis of diabetes and age at examination a population with a higher prevalence of diabetes mellitus. Diabetes 1976; 25: 554-60.

XXIX. Pettitt DJ, Knowler WC, Lisse JR, Bennett PH. Development of retinopathy and proteinuria in relation to plasma-glucose concentrations in Pima Indians.Lancet 1980; 4: 1050-2.

XXX. Collier A., et al. Change in skin thickness associated with cheiroarthropathy in insulin- dependent diabetes mellitus. British Medical 292 (1986): 936.

XXXI. Brownlee M., et al. non-enzymatic glycosylation and the pathogenesis of diabetic complications. Annals of Internal Medicine101 (1984): 527-537.

XXXII. Kennedy L and Baynes JW. Non- enzymatic glycosylation and the chronic complications of diabetes: an overview. Diabetologia 26 (1984): 93-98.

XXXIII. Jain SM., et al. Evaluation of skin and subcutaneous tissue thickness at insulin injection sites in Indian, insulin naïve, type-2 diabetic adult population. Indian Journal ofEndocrinology and Metabolism 17 (2013): 864-870.

XXXIV. Ahed J Alkhatib., et al. “Skin Thickness can Predict the Progress of Diabetes Type 2: A New Medical Hypothesis”. EC Diabetes and Metabolic Research 4.8 (2020): 08-12.

XXXV. Lee Y, Nelder JA, Pawitan Y. GeneralizedLinear Models with Random Effects (Unified Analysis via H-likelihood). London: Chapman & Hall 2006.

XXXVI. Sun D, Zhou T, Heianza Y, Li X, Fan M, Fonseca VA, Qi L. Type 2 Diabetes and Hypertension. Circ Res. 2019 Mar 15;124(6):930-937. doi: 10.1161/CIRCRESAHA.118.314487. PMID:

30646822; PMCID: PMC6417940.

XXXVII. Polemiti, E., Baudry, J., Kuxhaus, O. *et al.* BMI and BMI change following incident type 2 diabetes and risk of microvascular and macrovascular complications: the EPIC- Potsdam study. *Diabetologia* **64,** 814–825 (2021). https://doi.org/10.1007/s00125-020-05362-7.

XXXVIII. Alkhatib AJ. Insulin as a predictor of diabetes type 2: a new medicalhypothesis. *Adv Obes Weight Manag Control*.2021;11(1):1-3. DOI: 10.15406/aowmc.2021.11.00328.

XXXIX. Ahed J Alkhatib, New Insights of Diabetes: is it Rational to Initiate Insulin Treatment for Diabetes Type 2 Patients J Diabetes and Islet Biology 2(1) Doi: 10.31579/ 2641-8975/013.

XL. Mdoe MB, Kibusi SM, Munyogwa MJ, et al. Prevalence and predictors of gestational diabetes mellitus among pregnant women attending antenatal clinic in Dodoma region, Tanzania: an analytical cross- sectionalstudy. BMJ Nutrition, Prevention & Health 2021;0. doi:10.1136/ bmjnph-2020-000149

 Corresponding Author: Abdulaziz Fhad Abdulaziz alsalem