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Use of Artificial Neural Network Models for Prediction of Diabetes Mellitus

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KEYWORDS

Diabetes Mellitus, Artificial Neural Networks, Multilayer Perceptrons, Convolutional Neural Networks, Feedforward Neural Networks.

ABSTRACT:

Background: Diabetes Mellitus is a chronic metabolic disease that is defined by elevated levels of blood glucose because of insulin insufficiency or insulin resistance. Around 537 million adults worldwide have diabetes, and India appears to be a diabetes hotspot, so it's critical to detect the disease early in order to manage and avoid complications.

Objective: To develop and compare the predictive performance of three Artificial Neural Network models—Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), and Feedforward Neural Network (FNN).

Methods: A study was conducted among 800 patients, including 400 diabetic and 400 non-diabetic, visiting the hospital outpatient department. Data were collected from demographic, lifestyle, anthropometric and medical history. Qualitative data have been coded and normalization has been done for the quantitative data. The dataset was divided into 80% for training and 20 % for model testing. Accuracy, sensitivity, specificity and Kappa statistics were used to compare the performance of the models.

Results: Risk factors that were found to be statistically significant included body mass index, waist circumference, neck circumference, stress score, diet, and family history of diabetes, cardiovascular disease, or parental high blood pressure. MLP demonstrated the highest accuracy (81.88%) compared to CNN (73.33%) and FNN (75.62%). The MLP was also superior in sensitivity (81.25) and kappa score (0.63) compared to the other models.

Conclusion: MLP has been shown to be the best artificial neural network model for predicting diabetes, which may demonstrate the importance of an artificial neural network for early risk detection.

Introduction

Diabetes Mellitus is a chronic metabolic condition that results in high blood glucose levels associated with insufficient insulin production or the body's inability to use insulin effectively. The World Health Organization (WHO) estimates that about 537 million adults across the

Journal of Chemical Health Risks
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globe are living with diabetes, and this number is projected to rise sharply to 783 million by 2045[1]. According International Diabetes Federation (IDF) in India, around 77 million adults had diabetes in 2021, and by 2045 this number may almost double, reaching about 134 million[2]. The worldwide prevalence of diabetes is 9.1% and prevalence of diabetes in India is 11.8% for age above 50 years according to the National Diabetes and Diabetic Retinopathy Survey report released by the health and family welfare ministry[3]. Prevalence of Prediabetes is 10.2% according ICMR-INDIAB study[4].

The prevalence of Type 2 diabetes in India is influenced by multiple factors, including urbanization, dietary shifts, sedentary behavior, and genetic susceptibility, making early detection and intervention essential to mitigate complications such as cardiovascular diseases, kidney failure, and neuropathy [5, 6].

The early prediction of diabetes is crucial for its management and prevention of long-term health risks. Recent advancements in machine learning (ML) and deep learning (DL) have revolutionized disease prediction, offering high accuracy in identifying potential diabetic patients. Among these techniques, Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), and Feedforward Neural Network (FNN) have demonstrated promising results in medical diagnosis[5]. These Artificial Neural Network (ANN) models can process vast and complex datasets, identifying intricate patterns that might not be apparent through traditional analysis[7].

MLP is a type of artificial neural network (ANN) which has several layers of neurons that back propagate the errors for learning. It is particularly useful, when analyzing medical data for example smart prediction of diabetes, because of its ability to model non-linear relationships[8]. Convolutional Neural Networks (CNN) are primarily used for image recognition tasks; however, they have also shown evidence for use in structured healthcare data. With its convolutional layers, CNN can extract relevant features from patient records which can improve the accuracy of the diagnostic prediction for diabetes[9]. The feedforward neural network (FNN) is considered one of the simplest yet powerful types of ANN. It is extensively employed for classification problems because of its data processing approach which is one-directional. Due to its architecture, it is efficient with structured data sets such as those related to assessing the risk of diabetes[10].

This study aims to develop and compare the performance of MLP, CNN, and FNN in predicting risk of diabetes mellitus.

Methodology

A case-control study was carried out in diabetic and healthy subjects who visited the MGM outpatient department at Chhatrapati Sambhajinagar Hospital. The 800 participants were recruited in the study which includes 400 patients with diabetes (cases) and 400 healthy participants without a history or diagnosis of diabetes (controls).

Sample Size Determination

The required sample size was determined by using following formula;

$\mathbf{n=\frac{Z^2*P*Q}{e^2}}$, P=11%, Q=89% and e = 5% n = 391

where P represents the prevalence of diabetes in India[3] 11%, Q = 100 –P, and e denotes the allowable error (5%). Based on the calculation, the minimum estimated sample size was 391. However, in order to strengthen the study and ensure sufficient power, a total of 800 participants were enrolled in the study which includes 400 patients with diabetes (cases) and 400 healthy participants without a history or diagnosis of diabetes (controls). The participants were enrolled according to predefined inclusion and exclusion criteria. Participants aged between 18 and 60 years were eligible for inclusion in cases as well as controls, whereas older participants with age above 60 years were excluded from the study. Participants were selected regardless of age and gender, while age and gender were matched for cases and controls. Pregnant women and individuals unwilling to provide consent or participate in the study were excluded. The study was approved by the Institutional Ethics Committee prior to the start of the study.

A structured case record form was prepared that included demographic data, lifestyle behavior, anthropometric measurements and medical history was used to gather comprehensive data. Control and cases were matched by considering age and gender of the study participants. The predictive models were trained using modifiable and non-modifiable risk factors, such as age (years), lifestyle

Journal of Chemical Health Risks

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(physical activity, stress score, and diet), anthropometric (body mass index, neck circumference, and waist circumference), and medical history (a history of diabetes and hypertension) variables.

Table 1: Details input variables and preprocessing of the dataset

Variable	Type	Categories / Range	Coding / Treatment
Gender	Categorical	Male, Female	Male = 1, Female = 2
Diet	Categorical	Mixed, Veg	Mixed = 1, Veg = 2
Physical Activity	Categorical	No exercise, Mild, Vigorous	No exercise = 1, Mild = 2, Moderate =3, Vigorous = 4
Smoking	Categorical	Absent, Present	Absent = 1, Present = 2
Alcohol Consumption	Categorical	No, Yes	No = 1, Yes = 2
History of Diabetes	Categorical	None, One parent, Both	None = 1, One parent = 2, Both =3
History of CVD	Categorical	No, Yes	No = 1, Yes = 2
History of Covid	Categorical	No, Yes	No = 1, Yes = 2
History of Hypertension	Categorical	None, One parent, Both	None = 1, One parent = 2, Both =3
Age in Years	Numeric	20-60 years	Normalization
BMI	Numeric	15-40	Normalization
Waist Circumference	Numeric	60-120 cm	Normalization
Neck Circumference	Numeric	30-50 cm	Normalization
Stress Score	Numeric	0-40	Normalization

The categorical variables were converted in the form of integer and the quantitative variables were normalized using standard techniques. The outcome variable of the study was the presence or absence of risk for diabetes among the participants. The diabetes was predicted using three predictive models, which included MLP, CNN and FNN and the code and model development were done using the R studio software. The dataset size was divided into 80% for the model training and 20% for the model testing to determine the performance of the models. These models' performance was compared according to accuracy, sensitivity, specificity, and the area under the receiver operating characteristic (ROC) curve.

Multi-Layer Perceptron (MLP):

An MLP is a form of artificial neural network, which has both a layer of input, one or more hidden layers, and an output layer. The neurons of one layer connect to those of the other layer. The model uses the backpropagation model that optimizes weights to minimize errors. This model was trained by using R-studio open-source software. The MLP model was trained with the neuralnet package and had two hidden layers with 10 and 5 neurons, respectively, and a logistic activation function for binary classification. The model was trained with a maximum of 10 million iterations and evaluated on a separate test set using confusion matrices, accuracy, sensitivity, specificity, and ROC-AUC. Predicted probabilities were converted to class labels using a threshold of 0.5, and ROC curves were plotted to assess performance.

Convolutional Neural Network (CNN):

CNN is a deep-learning architecture that was designed to process image data, yet it has been re-used to process structured healthcare data, including the predictability of the condition of diabetes. The CNN models included two convolutional layers with ReLU activation and max-

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JCHR (2026) 16(2), 2289-2297 | ISSN:2251-6727

pooling layers, a flatten layer, a dense hidden layer with 128 neurons, and a sigmoid-activation function for the output layer of the binary classification. A sigmoid-activation function was used for output layer of binary classification. The model was compiled with binary cross-entropy loss and the Adam optimizer, trained for 50 epochs with a batch size of 32, and validated on 20% of the training data.

Feedforward Neural Network (FNN):

FNN is among the simplest types of artificial neural networks, with the flow of data flowing in one direction without creating any loops or cycles between the input layer to the output layer. The FNN was trained with two hidden layers containing 10 and 5 neurons respectively, using a sigmoid activation function which is suitable for binary classification. This model was trained by using a high iteration limit (stepmax = 1e+07) to ensure convergence.

Results:

Table 2: Independent t test for significance in risk factors of diabetes

Variable	Diabetes (Mean ± SD)	No Diabetes (Mean ± SD)	t-value	p-value
Age (years)	41.55 ± 11.79	42.22 ± 10.08	0.861	> 0.05
BMI	22.54 ± 3.39	23.14 ± 2.70	2.741	< 0.01
Waist Circumference	80.82 ± 8.91	79.17 ± 8.81	2.646	< 0.01
Neck Circumference	34.54 ± 1.96	35.16 ± 2.99	3.486	< 0.01
Stress Score	13.50 ± 3.39	16.08 ± 4.74	8.862	< 0.01

The quantitative comparison of the variables between persons with and without diabetes is made and the various parameters show that there is a significant difference in quantitative variables. The age was similar in both samples (Diabetes: 41.55 ± 11.79 years, No Diabetes: 42.22 ± 10.08 years, $p > 0.05$) which means that the age matching was done. But there was statistically significant difference in other variables. The diabetes group had a higher BMI (22.54 ± 3.39) than the non-diabetes group (23.14 ± 2.70) with $p < 0.01$ implying the possibility of existing relationship between body mass index and diabetes risk. The difference of waist circumference (80.82 ± 8.91 vs. 79.17 ± 8.81, $p < 0.01$) and neck circumference (34.54 ± 1.96 vs. 35.16 ± 2.99, $p < 0.01$) was also significant, which showed that they use them as anthropometric measurements of diabetes onset. Moreover, the group with diabetes obtained a significantly higher stress score (16.08 ± 4.74) than the non-diabetes group (13.50 ± 3.39, $p < 0.01$), which also indicates that stress is probably the cause of diabetes development. Such observations bring out the significance of lifestyle and anthropometric variables in the prediction and prevention of diabetes.

Table 3: Association of Demographic, Lifestyle, and Health Factors with Diabetes Status

Variable	Level	Type 2 diabetic patients (n=400)		No Diabetes (n=400)		Chi-Square	p-value
		n	%	n	%		
Age Group (years)	18–30	62	15.5%	62	15.5%	-	-
	30–40	102	25.5%	102	25.5%		

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(2), 2289-2297 | ISSN:2251-6727

	40–50	110	27.5%	110	27.5%		
	50–60	126	31.5%	126	31.5%		
Gender	Female	200	50.0%	200	50.0%	-	-
	Male	200	50.0%	200	50.0%		
BMI Class	Underweight	49	12.25%	24	6.00%	57.07	<0.001, HS
	Normal	201	52.5%	293	73.25%		
	Overweight	118	45.25%	80	20.00%		
	Obese	32	5.75%	3	0.75%		
Diet	Mixed	268	67.0%	297	74.3%	5.06	<0.05, S
	Vegetarian	132	33.0%	103	25.8%		
Physical Activity	No exercise	158	39.50%	149	37.25%	32.89	<0.001, HS
	Mild	131	32.75%	202	50.50%		
	Moderate	85	21.25%	40	10.00%		
	Vigorous	26	6.50%	9	2.25%		
Smoking/ Tobaco	Absent	366	91.5%	349	87.3%	3.8	0.051, NS
	Present	34	8.5%	51	12.8%		
Alcohol Consumption	No	344	86.0%	332	83.0%	1.37	0.242, NS
	Yes	56	14.0%	68	17.0%		
History of Diabetes in Parents	None	223	55.75%	312	78.0%	72.6	< 0.001, HS
	One Parent	119	29.8%	78	19.5%		
	Both	58	14.5%	10	2.5%		
History of Cardiovascular Disease	No	358	89.5%	386	96.5%	16.3	< 0.001, HS
	Yes	42	10.5%	14	3.5%		
History of COVID-19	No	361	90.3%	372	93.0%	1.63	0.202, NS
	Yes	39	9.8%	28	7.0%		
History of Hypertension	No	225	56.25%	303	80.25%	33.89	< 0.001, HS
	Yes	175	43.75%	97	19.75%		

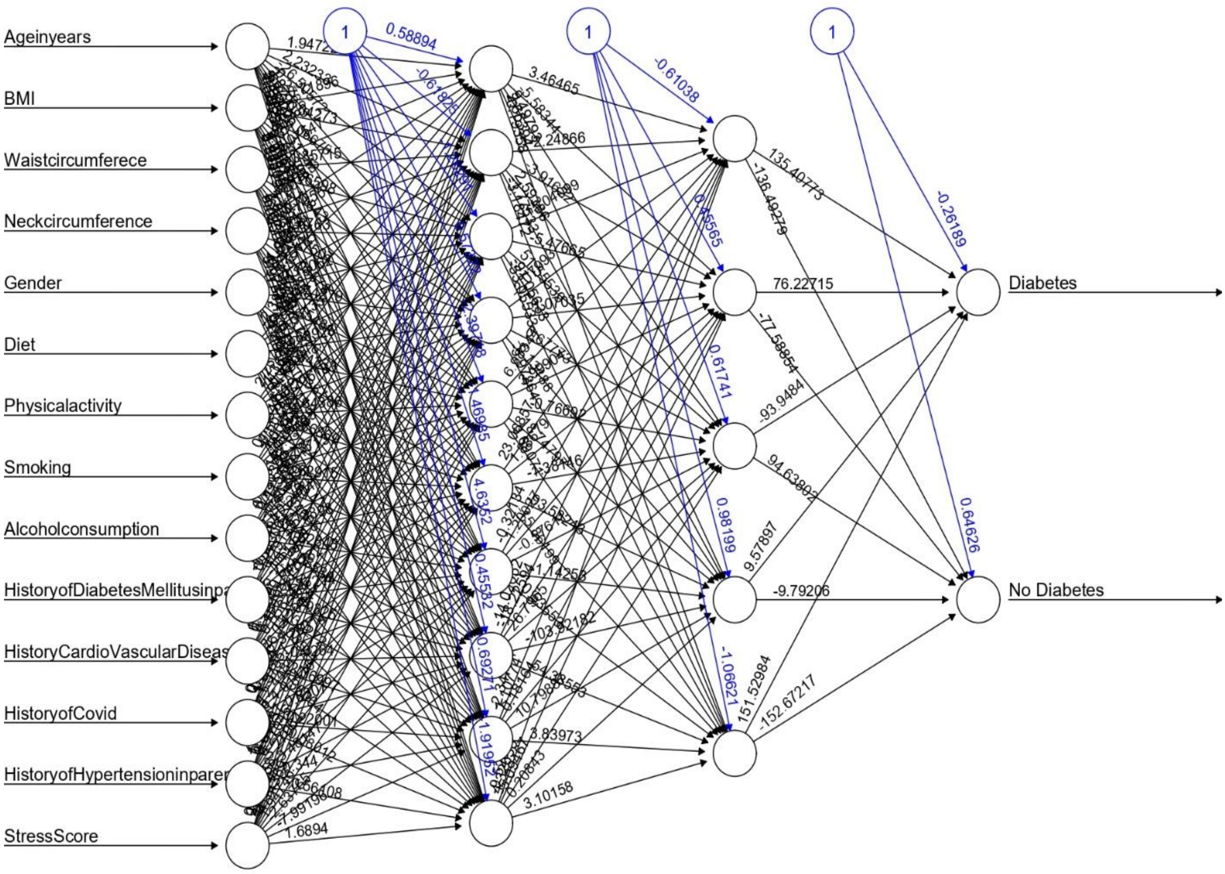
* NS-Non-significant (P-value > 0.05), HS- Highly significant (P-value < 0.01), S-Significant (P-value < 0.05),

The table shows the association between many categorical variables and status of diabetes. The categorical variables were analyzed by applying Chi-Square test statistics for association. The data were matched during data collection for gender and age (χ^2 = 0.00, p = 1.000 for both) for Diabetes and No Diabetes participants. Body Mass Index categories showed a significant association with diabetes status (χ^2 = 57.07, p < 0.001), with diabetics having a higher representation in the overweight and obese categories, whereas normal

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(2), 2289-2297 | ISSN:2251-6727

BMI was more frequently observed among non-diabetics. Dietary pattern was associated with diabetes ($\chi^2 = 5.06$, $p < 0.05$). A highly significant association was noted between physical activity levels and diabetes status ($\chi^2 = 32.89$, $p < 0.001$). Smoking status demonstrated a borderline association with diabetes ($\chi^2 = 3.80$, $p = 0.051$), with smoking being slightly more prevalent among non-diabetics. Alcohol consumption, however, did not show a statistically significant association with diabetes status ($\chi^2 = 1.37$, $p = 0.242$). A significant association was found between family history of Type 2 Diabetes Mellitus and diabetes status ($\chi^2 = 72.6$, $p < 0.001$). Similarly, history of cardiovascular disease was significantly associated with diabetes ($\chi^2 = 16.3$, $p < 0.001$). History of COVID-19 infection did not demonstrate a statistically significant association with diabetes status ($\chi^2 = 1.63$, $p = 0.202$). A strong association was observed between history of hypertension and diabetes ($\chi^2 = 33.89$, $p = 0.002$). The stress level showed a highly significant association with diabetes status ($\chi^2 = 43.74$, $p < 0.001$). Moderate and high stress levels were more prevalent among diabetics, whereas non-diabetics predominantly reported low stress levels.

Figure 1: Network Diagram of Multilayer Perceptron



The figure1 shows visual diagram of an MLP network architecture that is used to predict diabetes and its associated hidden layer configuration is (10,5). The given model takes inputs of several variables and makes use of the network of nodes that are tied by weighted connections, which are the key to the application of this model in attaining the classification outcomes, i.e., Diabetes or No Diabetes. The structure of MLP model that received the highest prediction accuracy of 81.88% was noted to be the one of (10,5) hidden layers.

Table 4: Comparison of Performance Metrics for MLP, CNN, and FNN in Diabetes Prediction

Metric	MLP	CNN	FNN
Accuracy	81.88%	73.33%	75.62%
Kappa Score	0.63	0.47	0.51
Sensitivity	81.25%	65.25%	73.75%
Specificity	82.50%	81.15%	77.50%
Positive Predictive Value	82.28%	77.00%	76.62%
Negative Predictive Value	81.48%	70.71%	74.70%

The comparison of three neural network models—Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), and Feedforward Neural Network (FNN)—reveals that there are significant differences in the performance of each model. Comparing the performance of three neural network models, the Multilayer Perceptron model had the best accuracy rate at 81.88%, the Feedforward Neural Network model had the second highest accuracy rate at 75.62%, and the Convolutional Neural Network model had the lowest accuracy rate at 73.33%.

Discussion

The Kappa score that measures the agreement above chance was highest with MLP (0.63) followed by FNN (0.51), and CNN (0.38), which means that MLP achieved the most reliable classification. Sensitivity which indicates the ability to accurately identify diabetic patients was also the best in MLP (81.25%), and CNN was the worst (65.25%), indicating that it is missing more cases of diabetes. Specificity that quantifies the capacity to categorize the non-diabetic individuals correctly was 82.50% with MLP, a little higher than CNN (81.15%) and a lot better than FNN (77.50%). Regarding Positive Predictive Value (PPV) that measures the accuracy of the predictions about diabetes, MLP scored the highest with 82.28, and it outperformed CNN (77.00) and FNN (76.62).

In the same direction, MLP was also the most predictive model in terms of Negative Predictive Value (NPV) (81.48%), and thus it was the most dependable in the elimination of diabetes. CNN possessed the least NPV (70.71%), which means that it misclassifies more diabetic patients as non-diabetic. In this study, MLP was the best predictive model (81.88%), then followed by FNN (75.62%) and CNN (73.33%). FNN had the highest Kappa (0.51), then MLP (0.63) and CNN (0.47) meaning that FNN and MLP had moderate agreement.

Some of the studies have compared performance of ANN models in predicting diabetes which have produced a mixed-up performance with respect to the nature of the datasets and model parameters. Our results are consistent with the previous studies on artificial neural network in the prediction of diabetes. Partially, these findings are in line with the available literature. In Pima Indian case, Butt et al. achieved an MLP accuracy of 86.08 %, which is larger than the accuracy in this study, but nonetheless claimed the strength of MLP in structured datasets[11]. On NHANES, Zhao et al. obtained an accuracy of 94.12 % with an attention-oriented CNN but the accuracy declined to 89.47 % on Pima, which highlights the reliance of CNN accuracy on data set size and diversity[12]. The reduced CNN accuracy in the current research (73.33) is consistent with other research that has used Pima data where CNN had an average accuracy of about 89.47% [13] and this fact has supported the idea that CNN can be ineffective in small datasets and feature-limited datasets. An FNN accuracy in the study of 75.62 is lower compared to the 88 % reported by Hatmal et al. with a Jordanian clinical cohort that had genetic and biochemical markers[13]. This difference could be attributed to a more elaborate set of features in their study, where it is possible to assume that FNNs require multidimensional clinical and genetic data.

The comparison together reveals that MLP and FNN models are effective when working with structured and tabular data, whereas CNNs may outperform these

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JCHR (2026) 16(2), 2289-2297 | ISSN:2251-6727

models in case they receive feature-engineered or high-dimensional data. It seems that the difference in the input variables and the preprocessing method used in different studies is the most important factor affecting the variation in performance. Future studies must thus focus on the hybrid models which integrate clinical, biochemical and genetic aspects and feature augmentation methods to improve the accuracy of prediction in the classification of diabetes.

Conclusion

The study suggests that MLP is consistently better in all the main measures of performances than CNN and FNN, which is why it is the most efficient model to predict diabetes in the present research. The low was the lowest in terms of sensitivity and NPV, which implies that CNN did not identify enough cases of diabetes. Although FNN was superior to CNN, it was still lower in comparison to MLP as far as the overall accuracy and specificity, and the predictive values. Since MLP shows better performance, it is the most appropriate model that can be used in predicting diabetes, whereas CNN needs more optimization and adjustment to achieve better results.

Conflict of interest

The authors declare that there is no conflict of interest.

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Journal of Chemical Health Risks

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