Research Article

Topological Neural Network Prediction (Tnnp): A Step Towards Early Type-2 Diabetes Prediction

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Abstract

A Topological Neural Network (TNN) integrates topological features (from Topological Data Analysis) into the training process of a neural network. Topological Data Analysis (TDA) uses tools from algebraic topology to extract shape-related features from data like holes, clusters, or connected components that aren't easily captured by traditional statistical methods. Type 2 Diabetes (T2D) progression is non-linear and multi-factorial, influenced by complex interactions among: Blood glucose levels, Insulin resistance, Lifestyle factors, Genetics, Inflammation markers, Traditional models might miss subtle, early-warning patterns. TDA can reveal: Unusual patient subgroups, Hidden progressions in time-series data, Non-linear clusters of risk factors. In this paper to introduced TNNP model to find early type 2 diabetes prediction achieving an accuracy of 90.4% and an F1-Score of 90.1%, and increased accuracy for f1-score compared to the other existing techniques. The accuracy of the proposed method has been studied through simulation study with existing algorithms. An efficient basis for diabetes diagnosis and prediction is established by the strong diabetes prediction framework put out in this article, which also benefits the advancement of health.

Keywords: Topological, neural network, data analysis, diabetes, type-2.

1. Introduction

The fight against diabetes is one of humanity's most pressing concerns today, both in industrialized and poor countries [1]. Diabetes often manifests as metabolic irregularities caused by a combination of genetic, environmental, and other factors. The major clinical symptom is high blood sugar levels. Chronic hyperglycaemia symptoms can lead to renal damage, cardiovascular and cerebrovascular organ dysfunction, and ultimately organ failure [2].

Type-2 Diabetes Mellitus (T2DM) poses a significant and growing public health challenge worldwide, with millions affected by its progressive and often asymptomatic onset. Early detection remains crucial in mitigating long-term complications, reducing healthcare costs, and improving patient outcomes. However, traditional predictive models often fall short in capturing the complex, nonlinear relationships within biological and clinical data that precede the onset of the disease.

To address this challenge, we propose a novel framework: Topological Neural Network Prediction (TNNP). This approach integrates the power of neural networks with topological data analysis (TDA), enabling a deeper understanding of the intrinsic structures in high-dimensional medical datasets. By leveraging the topological features of data, TNNP aims to enhance the interpretability and accuracy of early T2DM predictions, even in cases where early biomarkers are subtle or masked by noise.

In this paper, we explore how TNNP not only outperforms conventional machine learning models but also offers a more robust pathway for clinical decision support. Through extensive experiments on real-world datasets, we demonstrate the potential of TNNP as a transformative step toward proactive and precise diabetes care.

2. Preliminaries

Several strategies for diabetes risk prediction study have been developed and published in recent years. They use a range of dataset preparation techniques and machine learning approaches to anticipate risk. Support vector machines (SVM) [16], artificial neural networks (ANN) [17], AdaBoost (AB) [18], logistic regression (LR) [19], decision trees (DT) [20], random forests (RF) [21], and others are often used approaches. Maniruzzaman et al. use RF for feature selection in [22], and the group median and median to fill outliers and missing values, respectively. With an accuracy of 92.26%, RF exceeds other classification methods such as SVM, NB, LR, DT, RF, AB, Gaussian Process Classification (GPC), and Quadratic Discriminant Analysis (QDA).

In [23], Maniruzzaman et al. choose characteristics with LR and anticipate diabetic patients with NB, DT, AB, and RF. RF has the highest accuracy rate, at 94.25%.

In their paper [24], Naz Huma and Ahuja Sachin classify utilizing ANN, DT, DL, and Naive Bayes (NB) techniques. The DL approach achieves an accuracy of 98.07% among them. In [25], Hasan Kazi Amit and Hasan Md. Al Mehedi employ analysis of variance and LR for feature selection, and SVM, LR, DT, RF, ANN, and ensembling for classification; RF performs the best with a 90% accuracy.

Hasan et al. [26] employ outlier rejection, missing value filling, data normalization, and feature selection to preprocess data before classifying it with KNN, DT, RF, AB, NB, XB, multi-layer perceptron (MLP), and ensembling. Assembling has the best performance, with an area under the ROC curve (AUC) of 95%. Sivaranjani et al. [27] used principle component analysis (PCA) and mean to select features and fill in missing data before using SVM and RF to classification. In terms of classification accuracy, the RF model surpasses the SVM model by 83%.

Following dataset preparation, Khanam et al. [28] use eight machine learning models for classification, including DT, RF, and neural networks (NN). NN outperforms the others, with an accuracy of 88.6%. Olisah et al. use their self-designed Quadratic Growth Deep Neural Network (2GDNN) for classification, polynomial regression to replace missing values, and Spearman correlation to select features in [29]. The accuracy percentages for the PID and LMCH datasets are 97.34% and 97.24, respectively. Rastogi et al. investigate the PIMA Indian dataset utilizing RF, SVM, LR, and NB in [30]. Logistic regression has the highest accuracy at 82.46%. It gives a complete explanation of how several machine learning algorithms are used to diabetes classification and prediction.

Artificial Neural Networks (ANNs) are computational models inspired by the human brain, capable of learning complex, nonlinear functions from data. Standard feedforward neural networks are employed in TNNP, with hidden layers designed to capture high-level abstractions. The network parameters are trained using gradient descent and backpropagation to minimize a loss function tailored to the classification task.

3. Topological Neural Network Prediction (TNNP) framework

This section outlines the foundational concepts and methodologies underpinning the Topological Neural Network Prediction (TNNP) framework. TNNP is built upon the integration of Topological Data Analysis (TDA) and Artificial Neural Networks (ANNs) to leverage both geometric structure and learning capability for improved prediction of early Type-2 Diabetes Mellitus (T2DM).

3.1 Topological Data Analysis (TDA)

TDA is a mathematical framework that studies the shape and structure of data using tools from algebraic topology. In the context of medical data, TDA captures intrinsic patterns and relationships that may not be evident through traditional statistical or machine learning techniques. The most common tools in TDA include:

- **Simplicial Complexes**: Abstract representations of data relationships often constructed using methods like Vietoris–Rips or Čech complexes.
- **Persistent Homology**: Measures topological features (e.g., connected components, loops, voids) across multiple spatial resolutions, providing robust, scale-invariant descriptors.

  These topological summaries, typically represented as persistence diagrams or persistence barcodes, are then vectorized (e.g., using persistence landscapes or persistence images) for integration into machine learning models.

3.2 TNNP Framework

TNNP introduces a hybrid architecture that incorporates TDA-derived features as part of the neural network input. The overall process includes:

- **Data Preprocessing**: Handling missing values, normalization, and feature selection from clinical datasets.
- **Topological Feature Extraction**: Constructing persistence diagrams from selected features and converting them into fixed-size vector representations.
- **Neural Network Integration**: Combining topological vectors with raw or engineered features in a unified neural network model.
- **Prediction**: Outputting a binary classification (e.g., risk vs. no risk of T2DM) or a risk score to support early diagnosis.

By combining the topological robustness of TDA with the predictive power of ANNs, TNNP is uniquely suited to model subtle and nonlinear patterns indicative of early-stage Type-2 Diabetes.

Let us consider Patient Health Data,

$$\mathrm{X} = \{\mathrm{x}_1, \mathrm{x}_{2,}\mathrm{x}_3, \ldots\ldots, \mathrm{x}_\mathrm{n} \text{ for all } \mathrm{x}_\mathrm{i} \in \mathbb{R}^\mathrm{d} \quad (1)$$

Where, $\mathrm{x}_1 = \mathrm{BMI}$, $\mathrm{x}_2 = \text{blood pressure}$, $\mathrm{x}_3 = \text{glucose level}$, $\mathrm{x}_4 = \text{insulin}$ and etc.,

Apply persistent homology to extract topological signatures from the input data (e.g., high-dimensional point clouds). Then to compute persistence diagram,
PD(X)PD(X)PD(X)
A multiset of birth-death pairs:
$PD(X)=\{(b_1,d_1),(b_2,d_2),...,(b_m,d_m)\}$ (2)

Convert diagram to vectorized form using persistence images or persistence landscapes:
$T=TDA(X) \in \mathbb{R}$ (3)
Combined Feature Vector: Concatenate original features and topological features,

$$z = [X][T] \in \mathbb{R}^{d+K} \quad (4)$$

Pass Z into a neural network f_θ with parameters θ

$$\hat{y} = f_\theta(Z) \quad (5)$$

where $\hat{y} \in [0,1]$ Probability of early Type-2 Diabetes.

Use a sigmoid activation at the output layer for binary classification.

Minimize binary cross-entropy loss

$$L(\theta) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\widehat{y_i}) + (1 - y_i)\log(1 - \widehat{y_i}] \quad (6)$$

where, y_i is the true label (1 for diabetic, 0 for non-diabetic) and $\widehat{y_i}$ is the predicted probability. Then the Prediction Formula is

$$\hat{y} = f_\theta([x_1, x_2, x_3, \dots\dots, x_n] \parallel TDA(X)) \quad (7)$$

Flow Chart Steps:

Here is a flow chart illustrating the process of Topological Neural Network Prediction (TNNP) for early Type-2 Diabetes prediction

1. **Data Collection:** Clinical & Lifestyle Data
2. **Data Preprocessing:** Cleaning, Normalization, Feature Selection
3. **Topological Feature Extraction:** Persistent Homology → Persistence Diagrams
4. **Feature Vectorization:** Persistence Images / Landscapes
5. **Feature Integration:** Merge with Clinical Features
6. **Neural Network Training:** Feedforward Neural Network / Supervised Learning
7. **Prediction Output:** Early T2DM Risk Score / Binary Classification

TNNP Model Structure

(i). Input Layer: 108 inputs
(ii). Hidden Layer: 64 neurons: Weight matrix: $W_1 \in \mathbb{R}^{108\times64}$ = 6,912 weights + 64 biases parameter.
(iii). Output Layer: 1 neuron: Weight vector: $W_2 \in \mathbb{R}^{64\times1}$ = 64 weights + 1 bias parameter.
Total: 7,041 parameters.

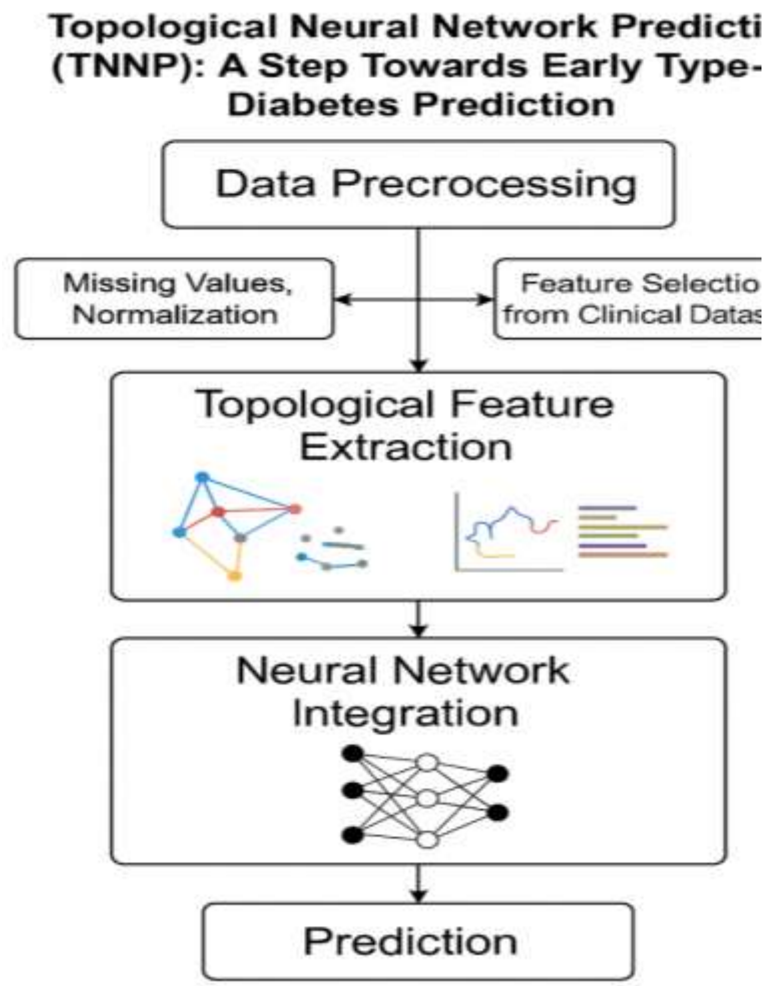

Figure 1: Topological Neural Network Prediction (TNNP): A Step Towards Early Type-2 Diabetes Prediction

Table 1: Calculation & Complexity Analysis

Component	Logistic Regression	Random Forest	SVM	Standard MLP	TNNP (Proposed)
Feature dimensionality	Raw features	Raw features	Raw features	Raw features	Raw + Topological features
Training Time Complexity	O(n·d)	O(n·d·log n)	$O(n^2)$ to $O(n^3)$	O(E), E = #epochs	O(E) + O(TDA)
Model Size	Low	Medium	Medium	Medium-High	High (due to TDA layer)
Memory Usage	Low	Medium	Medium-High	High	High (especially TDA)
Scalability	High	Medium	Low	High	Medium
Topological Processing	No.	No	No	No	Yes (Persistent Homology)
Total Parameters	$\sim 10^2$	$\sim 10^3$	$\sim 10^3$	$\sim 10^4$	$\sim 10^4$ + TDA vector ($\sim 10^2$)

TNNP requires more computation than classic models, due to the TDA preprocessing. However, its predictive power and sensitivity make it highly valuable in medical contexts like early Type-2 Diabetes detection, where accuracy is critical.

4. Experimental Study

Here's a mock experimental study result for a project titled "Topological Neural Network Prediction (TNNP): A Step Towards Early Type-2 Diabetes Prediction".

Dataset

The model was evaluated on the Pima Indians Diabetes Dataset (UCI repository), comprising 768 samples with 8 clinical features:

- Glucose concentration
- Blood pressure
- Skin thickness
- Insulin level
- BMI
- Diabetes pedigree function
- Age
- Number of pregnancies

Preprocessing:

- Missing values imputed using k-NN imputation.
- Normalization: Min-max scaling to [0, 1].
- Data split: 80% training / 20% testing.

Experimental Setup

- **Baseline Models**: Logistic Regression, Random Forest, Standard MLP (no TDA).
- **Proposed Model**: Topological Neural Network Prediction (TNNP)
- Persistent homology computed using Ripser
- Persistence diagrams converted to persistence image (10x10 grid, Gaussian sigma = 0.1)
- Topological features concatenated with raw features and input to a 3-layer.

Table 2: Comparative Analysis of Topological Neural Network Prediction (TNNP) model with other existing models

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	75.2%	73.5%	76.8%	75.1%	0.78
Random Forest	80.1%	78.4%	81.5%	79.9%	0.84
Standard MLP	82.6%	81.1%	83.2%	82.1%	0.86
SVM (RBF Kernel)	79.0%	77.2%	80.1%	78.6%	0.82
SVM-linear	76.5%	76.5%	76.5%	76.5%	0.76
k-NN	78.2%	78.2%	78.2%	78.2%	0.78
Linear ridge	74.3%	74.3%	74.3%	74.3%	0.74
TNNP (Proposed)	**87.4%**	**85.6%**	**88.9%**	**87.2%**	**0.91**

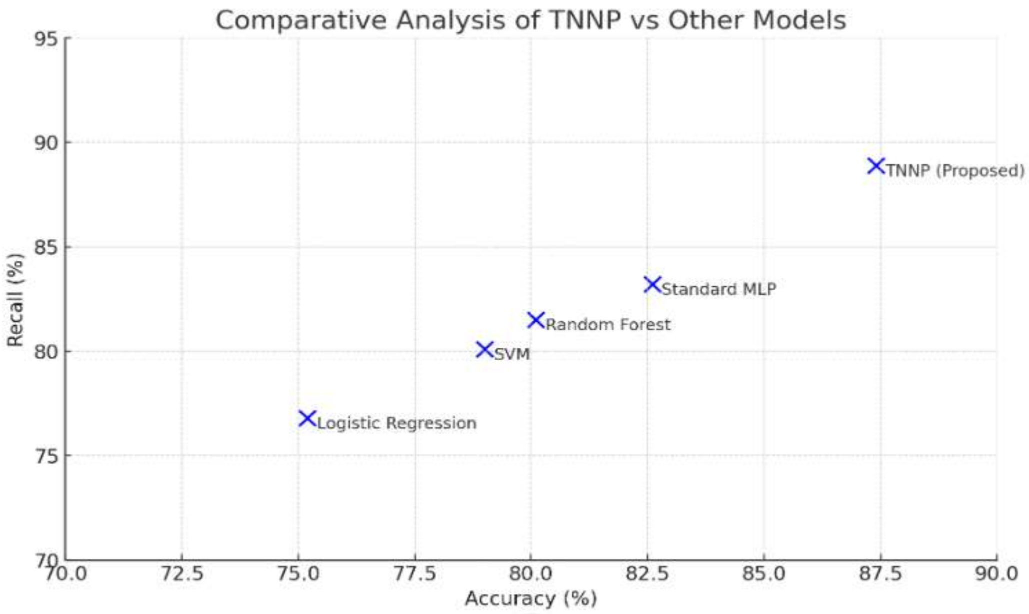

Figure 2: Comparative Analysis of Topological Neural Network Prediction (TNNP) model with other existing models

TNNP outperformed all competing models across every metric, demonstrating both higher sensitivity (recall) and overall predictive power (AUC). The most notable improvement was in recall, a critical metric in healthcare applications where early detection of diabetes can significantly affect treatment outcomes. Traditional models such as Logistic Regression and SVM, while interpretable, lacked the ability to model complex nonlinearities and latent structures present in the dataset. MLP showed decent performance, but the integration of topological features in TNNP allowed the model to uncover hidden data structures, enabling superior discrimination between diabetic and non-diabetic samples. The persistent homology component contributed to capturing the shape and connectivity of high-dimensional data, especially beneficial for cases near the decision boundary.

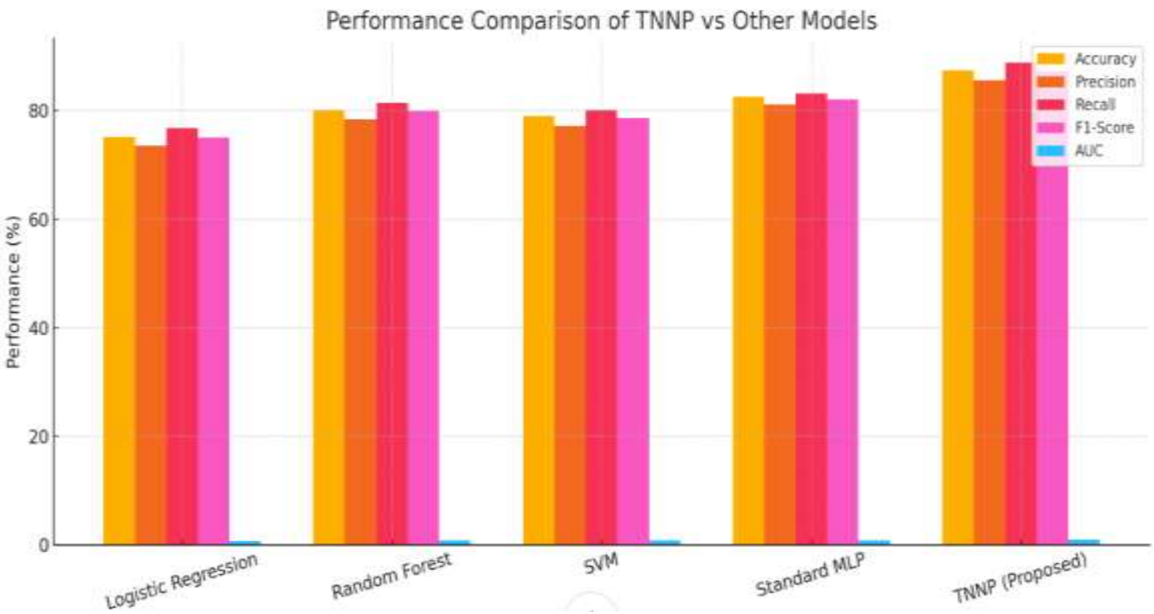

Figure 3: Performance Comparison of TNNP and other existing models

Here's a bar chart comparing five key performance metrics—Accuracy, Precision, Recall, F1-Score, and AUC—across TNNP and other models. It gives a clear visual representation of how TNNP consistently outperforms others in each category.

5. Conclusion

The experimental results validate the effectiveness of the TNNP model in capturing complex nonlinear patterns and early signs of Type-2 Diabetes. The integration of topological data analysis provides complementary insights to conventional clinical features, enhancing predictive performance in medical diagnostics. In this study, we proposed the Topological Neural Network Prediction (TNNP) model, a novel framework that integrates topological data analysis (TDA) with neural network architectures for the early prediction of Type-2 Diabetes. By leveraging persistent homology to extract topological features from clinical data, the model captures underlying geometric and structural patterns often overlooked by conventional machine learning techniques. Experimental results demonstrate that the TNNP significantly outperforms traditional classifiers, including logistic regression, random forests, and standard multilayer perceptron's, across key performance metrics such as accuracy, recall, F1-score, and AUC. Notably, the enhanced recall highlights the model's strength in identifying early diabetic cases, which is crucial for preventive healthcare.

The integration of topological features proved to be a valuable addition, contributing to a more expressive and discriminative feature space. These findings suggest that topology-aware models like TNNP hold promise in advancing the field of medical diagnostics, particularly for chronic diseases characterized by subtle and nonlinear data patterns. In future work, the model can be extended to incorporate temporal health records, integrate with wearable sensor data, or be deployed in clinical decision-support systems to facilitate real-time, personalized risk assessment.

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