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Diabetic peripheral neuropathy detection of type 2 diabetes using machine learning from TCM features: a cross-sectional study

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Abstract

Aims Diabetic peripheral neuropathy (DPN) is the most common complication of diabetes mellitus. Early identification of individuals at high risk of DPN is essential for successful early intervention. Traditional Chinese medicine (TCM) tongue diagnosis, one of the four diagnostic methods, lacks specific algorithms for TCM symptoms and tongue features. This study aims to develop machine learning (ML) models based on TCM to predict the risk of diabetic peripheral neuropathy (DPN) in patients with type 2 diabetes mellitus (T2DM).

Methods A total of 4723 patients were included in the analysis (4430 with T2DM and 293 with DPN). TFDA-1 was used to obtain tongue images during a questionnaire survey. LASSO (least absolute shrinkage and selection operator) logistic regression model with fivefold cross-validation was used to select imaging features, which were then screened using best subset selection. The synthetic minority oversampling technique (SMOTE) algorithm was applied to address the class imbalance and eliminate possible bias. The area under the receiver operating characteristic curve (AUC) was used to evaluate the model's performance. Four ML algorithms, namely logistic regression (LR), random forest (RF), support vector classifier (SVC), and light gradient boosting machine (LGBM), were used to build predictive models for DPN. The importance of covariates in DPN was ranked using classifiers with better performance.

Results The RF model performed the best, with an accuracy of 0.767, precision of 0.718, recall of 0.874, F-1 score of 0.789, and AUC of 0.77. With a value of 0.879, the LGBM model appeared to be the best regarding recall Age, sweating, dark red tongue, insomnia, and smoking were the five most significant RF features. Age, yellow coating, loose teeth, smoking, and insomnia were the five most significant features of the LGBM model.

Conclusions This cross-sectional study demonstrates that the RF and LGBM models can screen for high-risk DPN in T2DM patients using TCM symptoms and tongue features. The identified key TCM-related features, such as age, tongue coating, and other symptoms, may be advantageous in developing preventative measures for T2DM patients.

Keywords Diabetic peripheral neuropathy, Type 2 diabetes mellitus, Tongue features, TCM symptoms, Machine learning

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Introduction

Type 2 diabetes mellitus (T2DM) has become a worldwide epidemic due to a complex interplay of genetic predisposition, excessive food intake, and environmental factors [1, 2]. It is estimated that around 463 million adults aged 20–79 have been diagnosed with diabetes, resulting in an alarming incidence rate of 9.3% [1]. Notably, China has the highest number of diabetic patients globally, with approximately 116 million affected adults, the majority of whom have T2DM [3]. 2DM is a chronic metabolic disorder characterized by high blood sugar levels and resistance to insulin. Poor control of blood sugar can lead to complications affecting the heart, kidneys, and nervous system [4]. Among these complications, diabetic peripheral neuropathy (DPN) is one of the most prevalent chronic conditions associated with diabetes. It often leads to sensory and motor dysfunction in the limbs along with sleep disturbances, depression, reduced quality of life, and impaired social functioning [5]. As the disease progresses, approximately half of individuals with diabetes will develop DPN making it the primary cause for foot ulcers as well as disability and amputation rates [5–7]. The significant morbidity and disability rates associated with DPN impose substantial physical and economic burdens on individuals affected by this condition [8, 9]. Unfortunately, DPN tends to manifest gradually without noticeable symptoms until it reaches an irreversible stage [10, 11]. Numerous academic studies have emphasized the importance of achieving better control over blood sugar levels in patients with T2DM in order to reduce long-term morbidity related to neuropathy [12–14]. Therefore there is an urgent need for increased awareness and early intervention strategies aimed at preventing or mitigating the debilitating consequences caused by DPN in individuals living with T2DM.

Nerve conduction studies are currently considered as highly reliable diagnostic tools for identifying DPN. These tests not only help diagnose DPN [15, 16]. However, conducting these studies can be costly, time-consuming, labor-intensive, and impractical for routine clinical care. Currently, standard clinical assessments utilize scored clinical evaluations and bedside tests to diagnose DPN in routine clinical practice. Unfortunately, by the time these basic tests detect neuropathy, it is often too advanced to reverse or halt its progression [10]. Early detection and diagnosis of diabetes and its chronic complications are crucial for effective patient treatment and recovery. The ancient Chinese medical text Huangdi Neijing documented the early diagnosis and treatment of diabetes over 2000 years ago [17]. In traditional Chinese medicine (TCM), diabetes is referred to as "Xiaoke" disease which is believed to result from "Yin deficiency", leading to excessive thirst and urination. TCM has accumulated extensive diagnostic experience with a systematic procedure and standard for diagnosing this condition [18, 19]. TCM primarily relies on tongue diagnosis to identify imbalances in Yin-Yang energy [19], which aids in early-stage disease detection. TCM stands out due to its personalized approach towards syndrome differentiation and treatment [20]. By incorporating elements of TCM into a clinical prediction model, an accurate digital risk assessment can be provided that highlights the benefits of individualized therapy. The knowledge gained from syndrome differentiation and treatment in TCM can serve as evidence-based support for preventing and treating DPN in patients with type 2 diabetes mellitus.

In our previous study, we utilized LASSO regression to screen variables and subsequently developed a clinical nomogram. The findings indicated that TCM indicators, including age, smoking, sweating, and purple tongue, demonstrated strong predictive efficacy for DPN [21]. Building upon these results, the current study employs the SMOTE algorithm to address data imbalance between the two groups. We established predictive models for DPN using four machine learning methods and evaluated their performance using the AUC. The final results indicate that the RF and LGBM algorithms exhibit superior performance, and the feature importance ranking is used to optimize the limitations of the variables in the previous study. Finally, the 5 most important features of predicted DPN were screened out and ranked.

Managing DPN should prioritize individualization; however, physicians often encounter challenges during the decision-making process due to increasing patient numbers, variations among individuals, as well as the complex nature of DPN itself. In medicine, machine learning techniques have emerged as a promising strategy for addressing these challenges effectively [22]. ML offers several advantages compared to traditional statistical methods, such as the ability to learn from multiple data sources, improved identification of variables associated with clinical outcomes, enhanced predictive performance, better modeling of complex relationships, and resilience against data noise [23]. The objective of this study is to develop a straightforward ML-based screening model for DPN that integrates clinical signs from TCM and laboratory indicators. We analyzed data from 4723 subjects in order to achieve this goal.

Materials and methods

Study Population

This cross-sectional study was conducted between January 2019 and October 2020 at the Endocrinology Department and TCM Surgery Department of The Second Affiliated Hospital of Tianjin University of TCM, Tianjin, China. Prior to inclusion in the study, all participants provided written informed consent. T2DM was confirmed based on a previous diagnosis reported at the Second Affiliated Hospital of Tianjin University of TCM, or fasting plasma glucose (FPG) levels ≥ 7.0 mmol/L and/or random plasma glucose (RPG) levels ≥ 11.1 mmol/L. DPN was confirmed based on screening methods using a 128 Hz tuning fork and 10 g monofilaments [6, 10]. Exclusion criteria for the study included the following: (1) age below 18 years old; (2) failure to complete the questionnaire; (3) pregnant or lactating women; (4) inability to cooperate with the complete tongue image collector; (5) incomplete clinical data. After rigorous data filtration, a total of 4723 subjects were included in the study. Clinical trial number: not applicable.

Data Collection

During the interview, trained investigators from the School of Health Sciences and Engineering at Tianjin University of TCM administered the standardized questionnaire (Information Record Form of TCM Clinical Four Diagnostics) developed by Shanghai University of TCM [24]. Studies related to the use of this questionnaire have been published [21]. The questionnaire included seven physicochemical indexes: age, sex, BMI, FPG, random plasma glucose, and smoking status. BMI was calculated by dividing weight in kilograms by the square of height in meters. Clinical symptom information, such as "fatigue", "sigh", "irritability", "forgetfulness", "insomnia", "sweating", "loose teeth", "dry skin", "dry mouth", "polydipsia", "thirst without drinking much", "polyuria", and "frequency of urine", was gathered using the questionnaire, which was filled out by the investigators with responses coded as "yes" (1) or "no" (0). Figure 1 illustrates the flowchart for the study.

Collection of tongue features

Two investigators identified tongue features and recorded the findings in the questionnaires. Using the Tongue Diagnosis Analysis-1 (TFDA-1) instrument developed by the national key research and development plan, tongue images were collected [25]. Tongue images were taken in the morning (8 a.m. to 9:30 a.m.) when there was no food and in a fixed light source room, where subjects were asked to rinse their mouths before they were taken. The researchers first set the shooting parameters, instructed the subjects to maintain emotional stability, rested their chin on the corresponding position on the tongue diagnostic machine, and easily stretched out their tongue to relax. The researcher then clicked on the middle of the tongue on the instrument screen to complete the acquisition. Two experienced TCM experts were invited to review the images back-to-back. In case of disagreement, the final decision would be made by a third expert. Crimson tongue, purple tongue, dark red tongue, enlarged tongue, spotted tongue, teeth-marked tongue, fissured tongue, yellow coating, less coating, thick coating, and greasy coating were the tongue variables. Crimson tongue, purple tongue and dark red tongue are the color of the tongue; enlarged tongue, spotted tongue, teeth marked tongue and fissured tongue are the state of the tongue; yellow coating, less coating, thick coating and greasy coating are the state of tongue coating.

Statistical analysis

SPSS (version 26.0), R (version 4.1.3), Python (version 3.7.3), and STATA (version 15.0) were utilized for statistical analysis. Normally distributed continuous variables were presented as means ± standard deviation. As appropriate, the chi-squared test or Fisher's exact test was used to compare differences between categorical variables. All reported statistical significance levels were two-sided, with statistical significance set at 0.05. This study used the least absolute shrinkage and selection operator (LASSO) to select the most valuable candidate variables, which were then used to build the ML models. T2DM was more prevalent than DPN, resulting in class imbalances. The synthetic minority over-sampling technique (SMOTE) algorithm was employed to address this problem. Using the area under the receiver operating characteristic curve (AUC), we compared the performance of the four constructed models. The model with the highest AUC was considered the optimal model. Finally, the variable importance ranking of the optimal model was then displayed, and a nomogram model was constructed to identify T2DM patients at risk of developing DPN.

Feature selection

The LASSO regression model was utilized to screen the final input features for ML models. This method minimizes the LASSO cost function and selects features with non-zero coefficients to produce a subset of variables for further analysis. Additionally, best subset selection was applied to all 29 variables. The SMOTE algorithm was utilized to address the class imbalance caused by the larger number of subjects with T2DM compared to DPN.

Data imbalance processing

The SMOTE algorithm synthesizes new samples by analyzing a small number of samples and adding them to the dataset, effectively resolving the problem of model overfitting associated with random oversampling [26]. The fundamental concept of the SMOTE algorithm is to synthesize new samples by analyzing a small number of samples and adding them to the dataset [27]. This algorithm addresses the class imbalance caused by model overfitting [23].

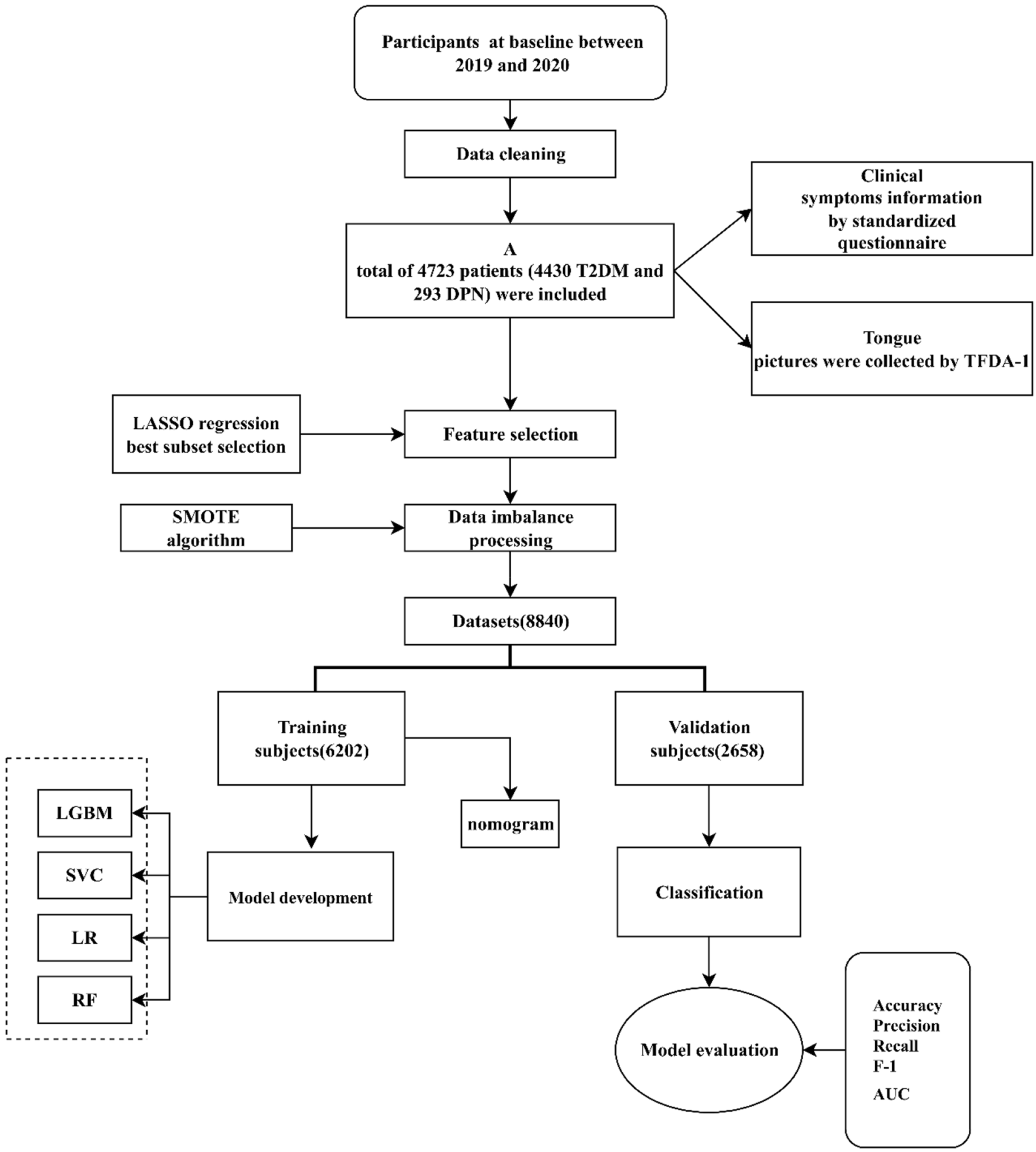

Fig. 1 The flowchart of this study. LASSO, least absolute shrinkage and selection operator; LGBM, light gradient boosting machine; SVC, supporting vector classifier; LR, logistic regression; RF, random forest

Machine learning algorithms

Four supervised machine learning algorithms, namely logistic regression (LR), random forest (RF), support vector classifier (SVC), and light gradient boosting machine (LGBM), were utilized to establish DPN prediction models. The model with the optimal performance was chosen for further analysis. LR is a classification algorithm that provides probabilities between 0 and 1 and establishes a relationship between features and outcome probabilities. In addition, it provides baseline accuracy scores relative to other non-parametric ML models [28]. LR provides baseline accuracy scores compared to other non-parametric ML models [29]. RF is an ensemble algorithm that combines multiple decision trees and can be used for regression and classification tasks [30]. SVC is used for finding hyperplanes in N-dimensional spaces and is particularly effective for distinguishing data points with a hyperplane that maximizes the edge distance [31]. Based on decision trees, LGBM is used for various ML tasks; it applies gradient-based one-side sampling (GOSS) to estimate information gain and reduce the number of data instances during training without compromising accuracy [32].

Performance measurement

Using a balanced dataset generated by the SMOTE algorithm, we conducted a comprehensive and quantitative evaluation of the performance of our machine learning models, The dataset was randomly divided into training and validation sets for binary classification tasks. We used a confusion matrix and five standard metrics, including accuracy, precision, recall, F-1 score, and receiver operating characteristic (ROC), which were calculated using Eqs. (1)– (4) to evaluate the recognition ability of the models.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FN} \tag{2}$$

$$Recall = \frac{TP}{TP + FP} \tag{3}$$

$$F - 1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

Feature ranking algorithms

The features were independently ranked through feature ranking algorithms without using ML algorithms. The distinct and stable features were selected based on their rank scores [33, 34]. Feature ranking is a filtering method that can be affected by the classification algorithm. However, it can also generate hypotheses to gain insight into the factors influencing the prediction [34, 35].

Table 1 Baseline characteristics of the participants

Clinical characteristics N (%)	T2DM (4430)	DPN (293)	*P* value
Age			0.000
18–44	256(5.8)	9(3.1)	
45–59	1280(28.9)	66(22.5)	
60–89	2687(60.7)	185(63.1)	
> 90	207(4.7)	33(11.3)	
BMI			0.023
< 18.5	39(0.9)	6(2)	
18.5 ~ 24.5	1806(40.8)	110(37.5)	
24.6 ~ 28	1990(44.9)	124(42.3)	
> 28	539(13.4)	53(18.1)	
sex			0.000
male	2028(45.8)	168(57.3)	
female	2402(54.2)	125(42.7)	
smoke	971(21.9)	130(44.4)	0.000
fatigue	2594(58.6)	169(57.7)	0.768
irritable	1739(39.3)	113(38.6)	0.815
forgetfulness	181(4.1)	9(3.1)	0.392
insomnia	2061(46.5)	108(36.9)	0.001
sweating	1199(27.1)	45(15.4)	0.000
loose teeth	1127(25.4)	108(36.9)	0.000
dry skin	717(16.2)	86(29.4)	0.000
dry mouth	1820(41.1)	120(41)	0.966
polydipsia	701(15.8)	54(18.4)	0.238
thirst does not drink much	114(2.6)	12(4.1)	0.117
polyuria	162(3.7)	20(6.8)	0.006
frequency of urine	562(12.7)	34(11.6)	0.589
crimson tongue	700(15.8)	55(18.8)	0.179
purple tongue	329(7.4)	44(15)	0.000
dark red tongue	513(11.6)	3(1)	0.000
enlarged tongue	449(10.1)	21(7.2)	0.100
spotted tongue	285(6.4)	21(7.2)	0.621
teeth marked tongue	1119(25.3)	62(21.2)	0.117
fissured tongue	1658(37.4)	101(34.5)	0.311
yellow coating	1162(26.2)	103(35.2)	0.001
less coating	305(6.8)	23(7.8)	0.529
thick coating	1040(23.5)	55(18.8)	0.065
greasy coating	1149(25.9)	51(17.4)	0.001
FPG (mmol/L)	7.79(1.63)	7.77(1.40)	0.838
RPG (mmol/L)	11.16(2.41)	11.32(1.55)	0.273

Results

Baseline characteristics

This study included 4723 eligible diabetic participants, including 4430 T2DM patients and 293 DPN patients. Three clinical variables, including physicochemical indexes, TCM symptoms, and tongue features, were analyzed using a standardized questionnaire with categorical variables between 2019 and 2020. The participants' baseline characteristics are listed in Table 1. The DPN group had more participants aged > 60 than the T2DM group. The most common BMI range was 24.6–28 (42.3%), and the proportion of males (57.3%) in the DPN group was greater than that of females (42.7%). Significantly more

Table 2 Dataset description by SMOTE algorithm

Clinical characteristics N (%)	T2DM (4430)	DPN (4430)	*P* value
Age			0.000
18–44	256(5.8)	143(3.2)	
45–59	1280(28.9)	1069(24.1)	
60–89	2687(60.7)	2809(63.4)	
> 90	207(4.7)	409(9.2)	
smoke	971(21.9)	1668(37.7)	0.000
insomnia	2061(46.5)	1342(30.3)	0.000
sweating	1199(27.1)	403(9.1)	0.000
loose teeth	1127(25.4)	1293(29.2)	0.000
dry skin	717(16.2)	995(22.5)	0.000
polyuria	162(3.7)	99(2.2)	0.000
purple tongue	329(7.4)	382(8.6)	0.038
dark red tongue	513(11.6)	3(0.1)	0.000
yellow coating	1162(26.2)	1278(28.8)	0.006
thick coating	1040(23.5)	534(12.1)	0.000
greasy coating	1149(25.9)	510(11.5)	0.000

smokers were present in the DPN group (44.4%) than in the T2DM group (21.9%). Age, BMI, gender, smoking status, insomnia, sweating, loose teeth, dry skin, polyuria, purple tongue, dark red tongue, yellow coating, and greasy coating were significantly associated with DPN incidence ($p < 0.05$).

Features selected by LASSO regression

Using a balanced dataset generated by the SMOTE algorithm, the performance of the proposed ML models was evaluated thoroughly and quantitatively (Table 2). The dataset consisted of 8840 samples, evenly balanced at 1:1 for positive and negative cases, with 6202 samples used for training and 2658 samples for validation (7:3). All dataset attributes were found to be statistically significant ($p < 0.05$).

As shown in Table 2 and Fig. 2, we used LASSO regression to reduce the number of features from 29 to 12 and identify the most significant features associated with DPN incidence. Among these 12 features, age, smoke, insomnia, sweating, loose teeth, dry skin, polyuria, purple tongue, dark red tongue, yellow coating, thick coating, and greasy coating were found to be significantly associated with DPN (Fig. 2 and Supplemental Fig. 1). Using the best subset selection method, we narrowed the selection of features further, resulting in eight features, including age, smoking, sweating, loose teeth, dry skin, purple tongue, dark red tongue, and greasy coating, as visualized in the Nomogram diagram (Supplemental Fig. 2). Considering the clinical significance of TCM, we obtained a prediction model containing 12 DPN-related features.

SMOTE algorithm validation

Using the SMOTE algorithm, we obtained a dataset containing 8840 samples that was balanced in a 1:1 ratio (Table 2),

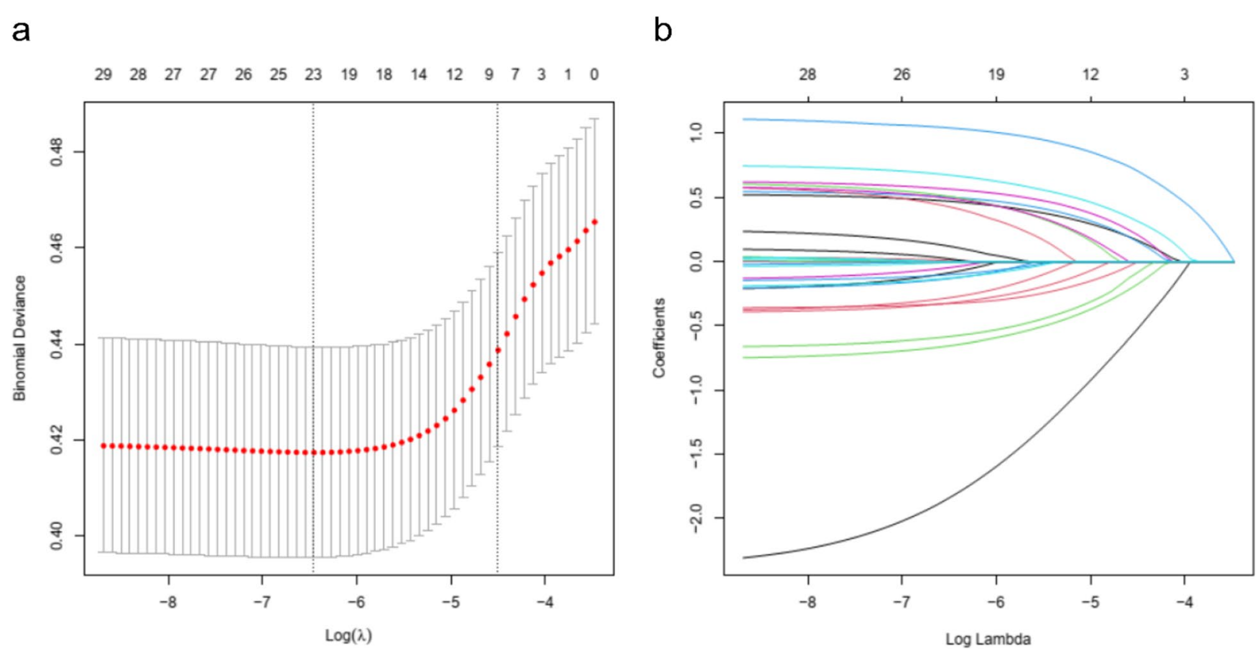

Fig. 2 LASSO for feature selection. **a** The LASSO plot was produced based on the log (λ) sequence and according to the fivefold cross-validation that resulted in 12 nonzero coefficients. **b** Dotted vertical lines were drawn at the optimal values using fivefold cross-validation using the minimum criteria and 1-SE criteria

Table 3 Performance comparison of the four ML models

Model	Accuracy	Precision	Recall	F-1	AUC
LR	0.674	0.660	0.709	0.684	0.684
RF	0.767	0.718	0.874	0.789	0.768
SVC	0.714	0.665	0.855	0.748	0.715
LGBM	0.758	0.707	0.879	0.783	0.759

with 6202 training subjects and 2658 validation subjects (7:3). All attributes were statistically significant ($p<0.05$).

Model performance comparison

As shown in Table 3, we compared the performance of four ML models, namely RF, LGBM, SVC, and LR. The RF model achieved the highest accuracy of all models with 0.767, followed by LGBM with 0.758, SVC with 0.714, and LR with 0.674. Similar trends were observed for other performance metrics, including precision, F-1 score, and AUC, except for recall, where RF consistently outperformed the other models. Regarding recall, LGBM demonstrated the highest predictive power with a value of 0.879, followed by RF with 0.874, SVC with 0.855, and LR with 0.709. The confusion matrix in Fig. 3 visually depicted the performance of the models, with darker colors indicating higher true negatives and true positives. Overall, the RF model showed the best performance, with an accuracy of 0.767, precision of 0.718, recall of 0.874, F-1 score of 0.789, and AUC of 0.77 (Fig. 4).

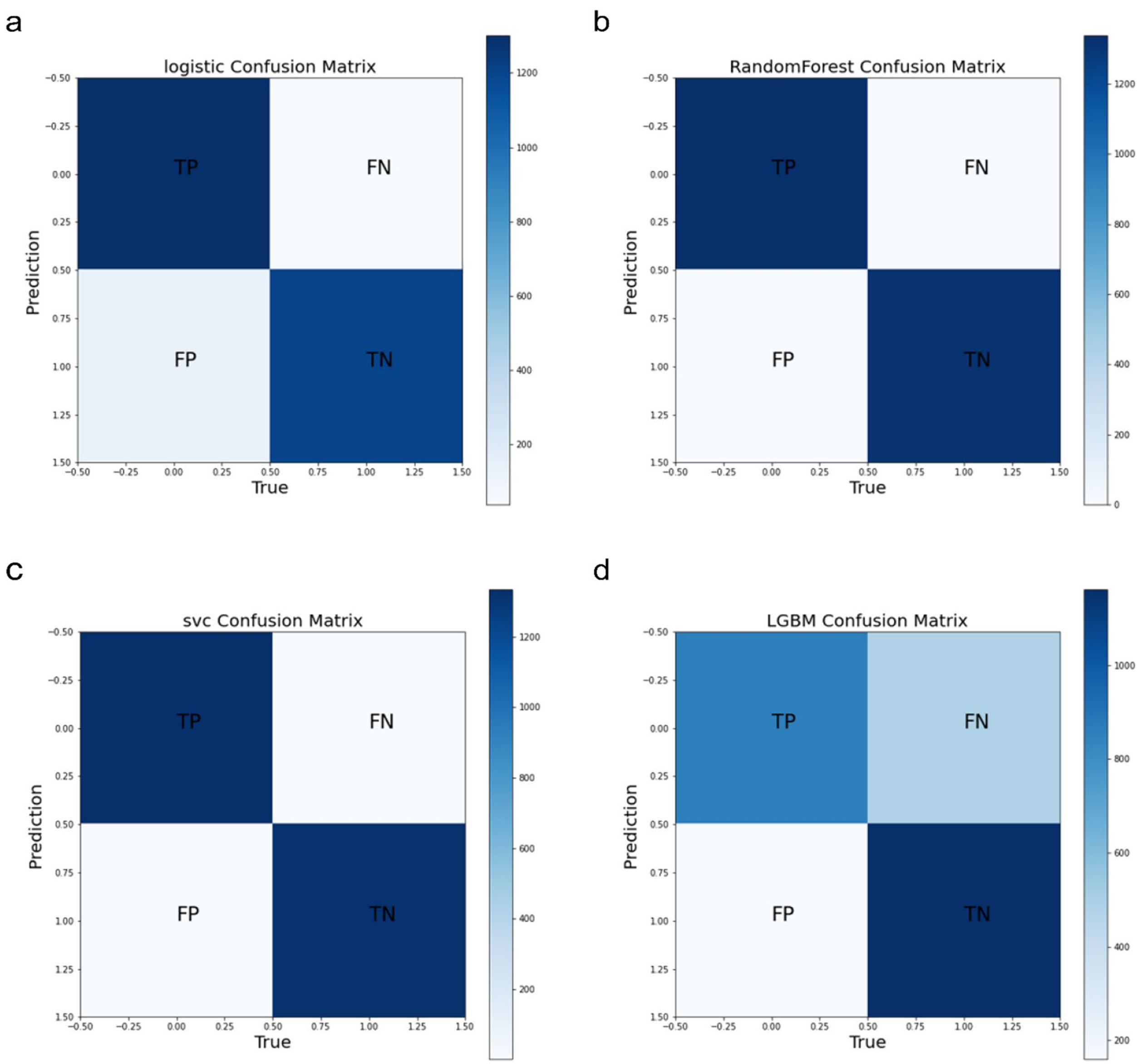

Fig. 3 The confusion matrix of the four ML models

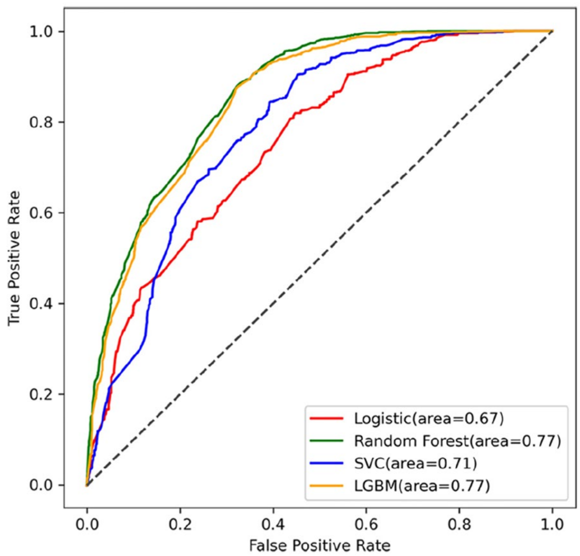

Fig. 4 The receiver operating characteristics (ROC) curves of all algorithms. Logistic, logistic regression; SVC, supporting vector classifier; LGBM, light gradient boosting machine

Feature importance

Further analysis of feature importance using relative importance value or feature importance score revealed that age, sweating, dark red tongue, insomnia, and smoking were the top five most important features in the RF model. In contrast, the top five most essential features in the LGBM model were age, yellow coating, loose teeth, smoking, and insomnia (Fig. 5). In summary, the results of this study demonstrated that the RF and the LGBM models performed the best in classification performance, with age, sweating, dark red tongue, insomnia, and smoking identified as the top important features associated with DPN in both models.

Discussion

In this cross-sectional study involving individuals with T2DM, we employed four different machine learning algorithms to predict the risk of developing DPN. Among these models, the RF algorithm utilizing 12 features demonstrated the highest accuracy in predicting DPN incidence. Its performance metrics were as follows: accuracy = 0.767, precision = 0.718, recall = 0.874, F-1 score = 0.789, and AUC = 0.768. These results suggest that our developed predictive model can effectively screen individuals at high risk for DPN and contribute towards preventing and managing diabetes complications. This finding aligns with previous studies [36, 37] and serves as a successful application of ML in predicting DPN risk within TCM research context.

Previous research on prediction models for DPN has primarily focused on laboratory indicators while neglecting TCM symptoms and tongue features [38]. Our study stands out as the first in China to specifically target TCM-related indicators and employ machine learning techniques for building predictive models based on TCM symptoms and tongue features when it comes to DPN prediction among individuals with diabetes mellitus type 2 (T2DM). With advancements in artificial intelligence technology, unsupervised and supervised machine learning approaches have gained popularity within the medical field especially for predicting diabetes complications [39–41].

The analysis of feature importance revealed the significant contributions of various model features. The study identified age and smoking as potential risk factors for DPN. Previous research conducted in Beijing, China found that individuals aged 40 years or older were at a higher risk for DPN among diabetic patients [42]. In a Chinese cross-sectional study of diabetic patients, the prevalence of DPN increased with age [43, 44]. Similarly, a cohort study in Bangladesh demonstrated that smoking was associated with microvascular complications in diabetic patients [36]. Another study suggested that impaired sweat secretion could increase the likelihood of foot ulcers among those with diabetes and DPN [45]. Patients with DPN and abnormal sweating function had a 15-fold increased risk of foot ulcers [46]. A visual indicator plaster method has been used to diagnose DPN by assessing foot skin dryness [47]. while Sudoscan technology can quantitatively analyze sweating function to assess neurological impairment of sweat glands [48]. Patients with diabetes often exhibit oral manifestations such as periodontal disease, tooth loss, dental caries, dry mouth, delayed wound healing, and taste dysfunction [49]. The bidirectional relationship between periodontitis and diabetes mellitus is well-established [50]. Thus, it is essential to promote proper dental care and tooth retention among adults with diabetes mellitus [51]. Insomnia has been linked to an increased risk of type 2 diabetes according to observational studies and Mendelian randomization studies [52–54]. This study confirmed an association between loose teeth and insomnia in older patients with DPN. Additionally, a previous epidemiological study conducted in Japan found a correlation between yellow tongue coating and a higher prevalence of diabetes mellitus [55]. According to traditional Chinese medicine (TCM), DPN is often accompanied by blood stasis [56]. Additionally, Morita A et al. objectively evaluated the relationship between blood stasis and patients with a dark purple tongue [57]. As demonstrated by previous studies, tongue performance is crucial for detecting blood stasis [58]. Specifically, patients

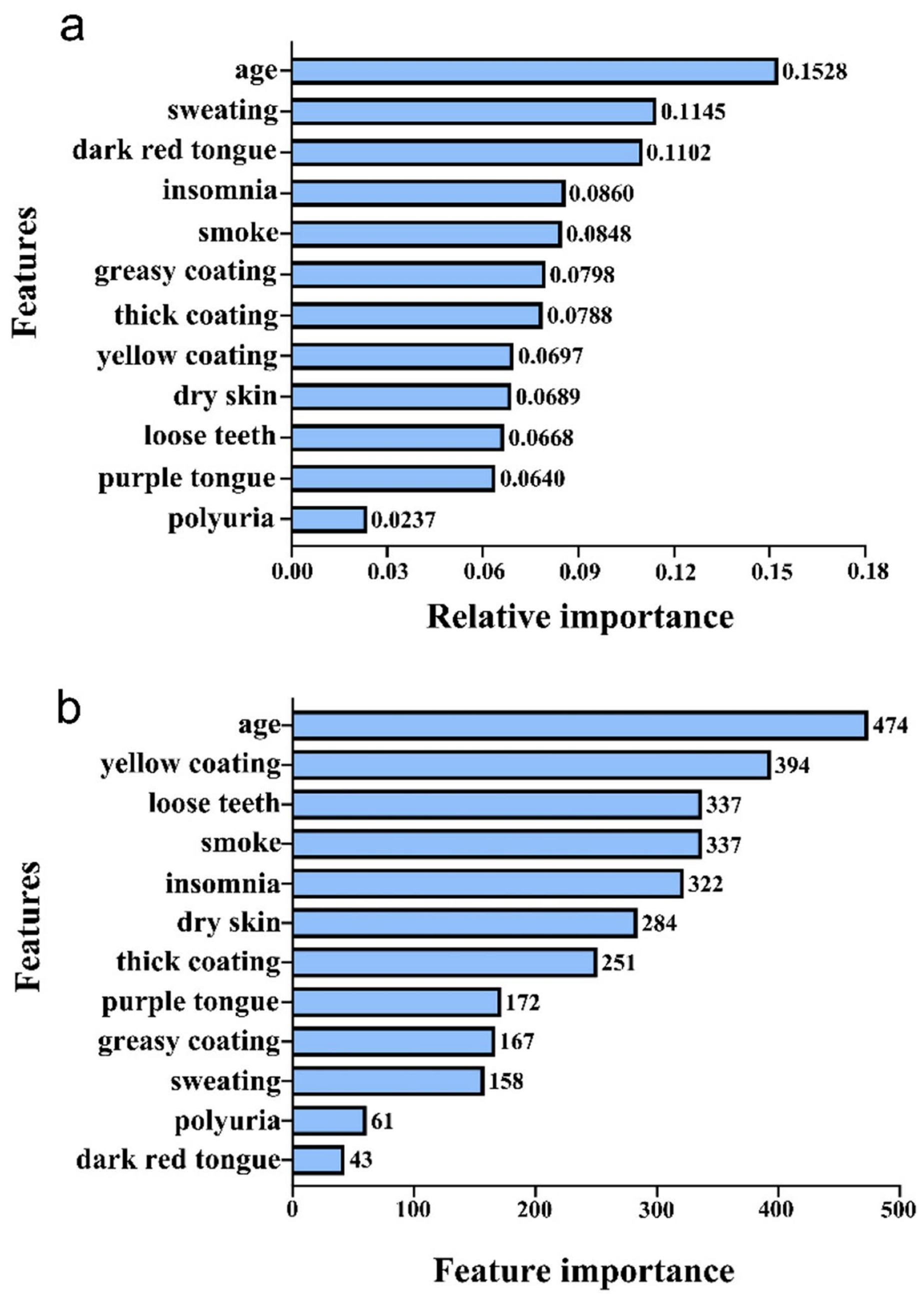

Fig. 5 The importance rankings. **a** The relative importance ranking of RF; the top ten were age, sweating, dark red tongue, insomnia, smoke, greasy coating, thick coating, yellow coating, dry skin, loose teeth, purple tongue, and polyuria. **b** The importance ranking of LGBM; the top ten were age, yellow coating, loose teeth, smoke, insomnia, dry skin, thick coating, purple tongue, greasy coating, sweating, polyuria, and dark red tongue

with T2DM exhibit increased tongue manifestations of blood stasis associated with severe arterial stiffness [59]. Consistent with previous findings, we observed a preference for dark red tongue color and yellow coating in patients with DPN in our study. Our study is the first to develop four classical machine learning methods for predicting DPN using TCM-related features. Xia et al. compared three classical ML methods and found that the RF model best diagnosed metabolic syndrome [60]. Some Traditional Chinese Medicine (TCM) indicators, such as chest constriction, spontaneous sweating, wiry pulse, and tongue coating with a greasy appearance, have also demonstrated improved diagnostic accuracy for metabolic syndrome. The RF algorithm employs random samples and variables to generate decision trees, where the final prediction of its model is based on the category predicted by these decision trees [61]. In our study, we established an RF prediction model that exhibited favorable performance as well. This model could assist TCM practitioners in identifying individuals with type 2 diabetes at a heightened risk of developing diabetic peripheral neuropathy (DPN). Our study identified TCM-related characteristics that encompassed not only physicochemical indicators but also TCM symptoms and tongue features. These findings can effectively contribute to the development and implementation of TCM-based strategies aimed at preventing DPN in individuals diagnosed with type 2 diabetes.

Strengths and limitations

There are certain limitations to our study that should be acknowledged. Firstly, the generalizability of our findings to other cities or countries may be uncertain as the study population was recruited solely from a single center in Tianjin. Secondly, it is important to note that our study employed a cross-sectional design and further research is required to validate the reliability of the established prediction models. In future investigations, we aim to incorporate additional indicators in order to enhance the predictive accuracy of these models. Thirdly, due to insufficient data availability, significant risk factors such as low-density lipoprotein cholesterol (LDL-C) and glycosylated hemoglobin (HbA1c) were not included in our prediction model. Lastly, while our study focused on analyzing tongue features alone, we believe that incorporating data on specific tongue flora and integrating information from various dimensions will contribute towards developing more advanced prediction models for diabetic peripheral neuropathy (DPN) in future studies.

Supplementary Information

The online version contains supplementary material available athttps://doi.org/10.1186/s12911-025-02932-w

Supplementary Material 1.

Supplementary Material 2.

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Authors' contributions

Conception, design, and manuscript reviewing: ZT, HW. Data collection and sorting: ZT, XS, DW, JZ and XL. Data analysis and manuscript drafting: ZT, YF,GL and HW. All authors contributed to the article and approved the submitted version.

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Data availability

The data used for the modelling in this study belongs to the National Key Research and Development Program of China and restrictions apply to the availability of these data.

Declarations

Ethics approval and consent to participate

This study reporting adheres to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines and only anonymous data was used in the analysis. This study was approved by the institutional ethics committee of Tianjin University of TCM (No: TJUTCM-EC20190004), and all participants were required to sign an informed consent form before the study's initiation. We had obtained informed consent from all participants in this study.This study adhered to the tenets of the Declaration of Helsinki.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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