

A Study on Explainable Inference Prediction of Diabetes Complications Based on Medical Knowledge Graph *

Shouqiang Liu¹, Mingyue Jiang², Linying Su¹

¹ School of Artificial Intelligence, Faculty of Engineering, South China Normal University, Guangzhou, China

² School of Electronics and Information Engineering, Faculty of Engineering, South China Normal University, Guangzhou, China

liusq@m.scnu.edu.cn

Abstract. This paper presents a LightGBM-SMOTE-ENN model that uses a medical knowledge graph to predict diabetes complications with improved accuracy and interpretability. In response to the public health challenge posed by diabetes, this research utilizes advanced AI to analyze medical data, integrating patient information with symptom vectors from the knowledge graph to develop a reliable classification tool. The model's effectiveness is demonstrated through superior performance metrics such as accuracy, recall, and F1 score, attributed to a SHAP value-based method for interpretability. Future directions include expanding the knowledge graph and optimizing algorithms for broader application. This work not only advances diabetes complication prediction but also leverages medical knowledge graphs for clinical support, aiming to enhance healthcare quality and patient outcomes.

Keywords: Medical knowledge graph, Knowledge graph construction, Diagnostic reasoning for diabetic complications, Interpretability.

1 Introduction

1.1 Background and Significance of the Study

Background of the Study. According to the 10th Edition of the IDF Global Diabetes Map, released by the International Diabetes Federation in December 2021, diabetes now affects 537 million adults worldwide, representing 10.5% of the global adult population, or one in every ten adults [1]. In China, the prevalence of this chronic metabolic disease is escalating rapidly, with estimates suggesting up to 114 million individuals may be affected. Diabetes mellitus, characterized by persistent hyperglycemia, can lead to various complications if not adequately managed, posing significant clinical challenges. Leveraging medical knowledge graphs could significantly enhance decision-

* Shouqiang Liu and Mingyue Jiang are the co-first authors of this paper. The corresponding author is Shouqiang Liu (email: liusq@m.scnu.edu.cn)

making in the management of chronic diseases like diabetes, providing crucial support in clinical settings.

Figure 1 from the National Health Commission's July 2023 report shows that consultations in China's healthcare institutions totaled 3.92 billion, a 5.2% increase from the previous year. Hospital visits increased by 2.8%, and primary care consultations rose by 10.6%. The expansive and diverse nature of medical data, which includes textual and visual information, presents challenges such as missing values and data imbalances. These issues necessitate advanced processing techniques to maintain the reliability of assisted diagnostic systems. Addressing these challenges is critical for enhancing diagnostic accuracy and is a key focus for researchers and industry professionals.

National healthcare institutions' medical service volume						
Classification of institutions	Number of outpatient and inpatient visits (in ten thousands)		Growth in the number of outpatient and inpatient visits (%)	Number of discharges (in ten thousands)		Growth in the number of discharges (%)
	January to July 2022	January to July 2023		January to July 2022	January to July 2023	
Hospitals	231570.2	238157.2	2.8	11790.2	14118.1	19.7
Primary healthcare institutions	122491.3	135522.3	10.6	2094.9	2611.1	24.6
Other institutions	18792.8	18498.9	-1.6	560.4	641.8	14.5
Total items for healthcare institutions	372854.3	392178.4	5.2	14445.4	17371.2	20.3

Fig. 1. National Healthcare Facility Consultation-Discharge Data.

Significance of the study. Knowledge graphs significantly enhance intelligent healthcare tasks with their robust interpretability in managing complex medical data. However, deep learning algorithms, often regarded as "black-box" models, struggle to produce interpretable outcomes, which undermines user trust in high-stakes environments such as medical diagnostics, thereby increasing operational risks. Consequently, the advancement of interpretable AI has become a critical imperative. The opacity of deep learning originates primarily from two areas: firstly, the intrinsic non-interpretability rooted in complex model architectures, necessitating external interpretation systems or expert intervention; and secondly, the inability to semantically interpret data relationships, including causality, confounding factors, and sample selection biases. Addressing these challenges, the development of interpretable mechanisms that elucidate the operational underpinnings of neural networks is essential. This progress is vital for researchers and developers to pinpoint problems and guide enhancements, fostering more transparent and trustable AI-driven solutions in healthcare.

1.2 Current Status of Domestic and International Research

Medical Knowledge Mapping. Knowledge Graph is a concept first proposed by Google in 2012 to provide users with higher quality search services, which is essentially a semantic network, usually using a ternary such as (head entity, relation, tail entity)/ (h, r, t) to express the attributes of things as well as the semantic relationships between things [2]. In recent years, the research and application of large-scale knowledge graphs have attracted greater attention in various industries, and a variety of general knowledge graphs have been launched, such as Google launched Google Knowledge Graph [3] in

2012, and there are also DBpedia [4], Freebase [5], Wikidata [6], YAGO [7] etc. Meanwhile, many scholars have carried out in-depth theoretical research in this field, such as in clinical diagnosis, the use of representation models by constructing the patient's time-series knowledge graph for link prediction, so as to complete the missing information in the graph [8]. Crespo et al. [9] proposed an ontology-driven medical diagnostic system based on ontology for the diagnosis of infectious diseases by constructing ontologies for infectious diseases, medicines, and bacteria. Nie Lili et al [10] established a medical diagnostic knowledge graph with a three-layer model of "disease-symptom-feature" and applied it to a clinical decision support system; Shanghai Shuguang Hospital constructed a knowledge graph of traditional Chinese medicine, an ontology medical knowledge base SNOMED-CT [11].

Disease Prediction Models. Despite the fact that there are so much medical knowledge graph constructs available in the market, the future of the application of using deep learning-based models and medical knowledge graphs for aiding the diagnosis of diseases is still unclear because most of them are black boxes, and thus their decision-making procedures are difficult to be understood by clinicians. This limitation raises concerns about their reliability and inevitably restricts their deployment in clinical practice [12].

To address this problem, researchers have proposed a number of interpretable disease prediction models [13]. These models are usually able to generate a set of weights to indicate the contribution of each feature to the prediction of complications to be used as an explanation for the prediction. Tseng et al. used random forests to predict acute kidney injury, and they used SHAP to interpret the prediction results as a linear combination of the given features [14]; Yan et al. used convolutional neural networks (CNNs) to predict age-related macular degeneration, and they used the Locally Interpretable Model Diagnostic Interpretation (LIME) [15] to explain the prediction results [16]; Hongman Zhang and Guo He [17] used XGboost algorithm to conduct an accurate prediction study for type 2 diabetes. However, all the above methods are purely data-driven, failing to organically integrate the nervous system and symbolic system and utilize the existing medical knowledge to provide interpretable prediction results.

Interpretable Artificial Intelligence. Explainable Artificial Intelligence (XAI) [18], whose main idea is to use the facts or rules in the knowledge graph to explain the behavior of neural network training process, and then improve the interpretability of neural network. It is worth mentioning that the latest cognitive mapping proposed by Tang Jie et al. at Tsinghua University [19] is an attempt of "neural + symbolic" in explainable AI, which aims to solve the black-box problem of the deep learning solution process by using symbolic knowledge representation, reasoning and decision-making.

By providing a deeper understanding of model decisions, XAI enables non-expert users to understand model behavior. In addition to methods such as Locally Interpretable Model-Interpretation Techniques (LIME), SHapley Additive exPlanations (SHAP), and Integrated Gradients, there are a variety of other techniques and strategies that have

been developed to improve the interpretability of AI systems. One approach is through decision trees, especially their variants such as Random Forests and Gradient Boosting Decision Trees, which are considered to have good interpretability due to the fact that their decision-making process can be viewed as a series of if-then rules. While these models may not be as powerful as deep neural networks, the intuitive explanations they provide are valuable for building trust in a given application.

On the other hand, global interpretability methods, such as feature importance ranking, provide insights into model behavior by evaluating the overall contribution of individual features to model predictions. This approach is simple, intuitive, easy to understand and communicate, and is particularly suitable for scenarios where model dependencies need to be quickly assessed.

1.3 The Work and Innovations in this Paper

This study introduces a novel predictive model for diabetic complications utilizing a medical knowledge graph. This graph is constructed by aggregating clinical data and applying knowledge representation learning techniques to vectorize and establish intricate relationships among entities. Through meticulous data preprocessing and analysis, key predictor variables are identified. These are integrated with symptom vectors to form a classification model that leverages integrated learning, enhancing prediction accuracy and the reliability of assisted diagnoses. Furthermore, the study delves into model interpretability, employing a SHAP value-based method to highlight critical influencing factors, thus offering substantial decision support to clinicians. Experimental findings demonstrate that our model surpasses conventional approaches across various evaluation metrics, notably excelling in handling data imbalances with significantly enhanced performance. A case study confirms the model's effective predictive capabilities and robust interpretability. This research provides a fresh technological avenue for predicting diabetes complications and applying medical knowledge graphs. It is poised to significantly influence clinical decision-making and disease management, potentially elevating the standard of medical services and improving patient quality of life alongside advancements in medical data and algorithmic developments.

2 Medical Knowledge Graph-based Inference Prediction Model for Diabetes Complications

2.1 Basic Idea

In this study, we introduce a predictive inference model for diabetes complications, utilizing a medical knowledge graph. This model integrates the triadic relationship of the diabetes knowledge graph with processed metrics from patient cases to mine potential symptom entities. By employing integrated learning techniques, we construct a dis-

criminative model capable of identifying complications. The framework of this inference prediction model, illustrating its application in medical diagnostics, is depicted in Figure 2.

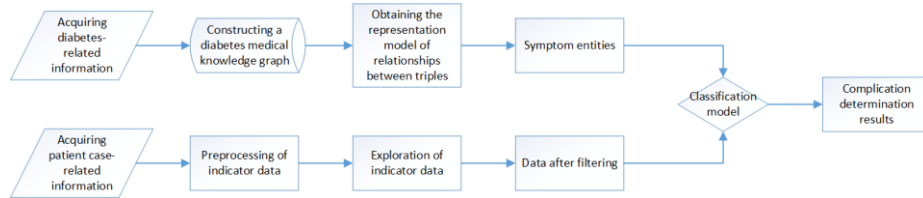


Fig. 2. Framework diagram of the inference prediction model for diabetic complications based on medical knowledge graphs.

2.2 Architecture Design

Knowledge representation of the Diabetes Knowledge Graph. By using the constructed diabetes medical knowledge map, we transformed the medical knowledge information into the form of ternary groups, such as "type 2 diabetes, complications, diabetic nephropathy" and other ternary relationships, which are stored in the map database, providing a convenient way for further querying and use. This kind of medical knowledge information transformed into ternary form will also become the basis for the development of intelligent medical system in the next step.

The next step is the knowledge representation of the constructed medical knowledge graph. Considering the complex relationships of one-to-many, many-to-one, and many-to-many in the knowledge graph, the TransR model is chosen as the knowledge representation model in this thesis. As an example, the model will give a mapping matrix $M_r \in R^{k \times d}$, to the complication \vec{r} , while the entities diabetes \vec{h} , diabetic nephropathy \vec{t} get their projection vectors \vec{h}_r, \vec{t}_r through $\vec{h}M_r, \vec{t}M_r$. The vector representation e_R^h of diabetes entity is obtained by calculating according to the formula of the TransR model.

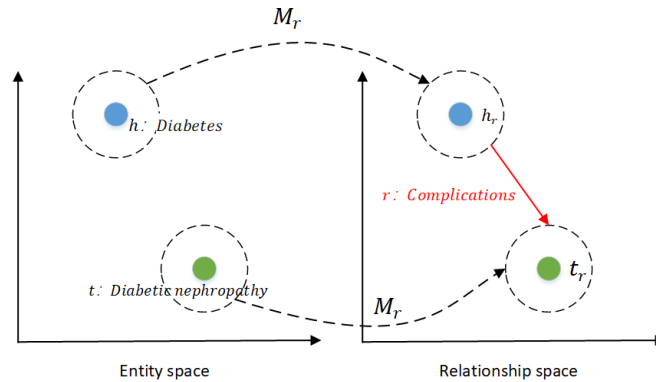


Fig. 3. Schematic of the knowledge representation model TransR model.

After the completion of knowledge representation, the matrix $E^{m \times k} = [e^1, e^2, \dots, e^m]$ of diabetes related entities can be obtained, where k is the dimension of the entity vector and m is the number of entities.

Taking the patient's entity matrix $E^{m \times k}$ as the input to the textual convolutional neural network, the results of the use of the convolutional neural network can be deduced based on the convolutional kernel to obtain features:

$$c_i = f(h \cdot e_{i:i+h-1} + b) \quad (1)$$

Where f is the activation function. The feature $c' = [c_1, c_2, \dots, c_{m-h+1}]$ of the entity matrix, the maximum pooling operation i.e. $\hat{c}_j = \max\{c'\}$ is performed for each feature mapping and the CONTACT connection is performed to obtain the representation vector of the Diabetes Knowledge Graph entities:

$$p_{tp} = [\hat{c}_1, \hat{c}_2, \dots, \hat{c}_n] \quad (2)$$

Patient indicator data screening and vector representation. Patient's index data are the result data obtained after examination for the condition in the medical record, this thesis obtains the patient's examination data from the patient's electronic medical record, such as: patient's age, duration of diabetes, blood creatinine, LDL cholesterol, triglycerides, and fasting glucose, among 15 other indexes. In response to the lack of negligible sample size in electronic medical records, this study employed a method using normal value padding to overcome this problem. Specifically, the researcher defaulted the missing examination indicators to normal values and applied a fully-connected neural network to perform operations such as downscaling and feature extraction on the patient indicator data. The patient's indicators can be represented as:

$$u^i = [t^1, t^2, \dots, t^l] \quad (3)$$

And the process of neural network forward propagation is shown in the following equation:

$$v^i = w^i u^i + b \quad (4)$$

$$p_{zb} = \sigma(v^i) \quad (5)$$

which p_{zb} has a dimension much smaller than u^i , and the process can be repeated many times.

Vector Fusion. In order to integrate the ternary knowledge representation vectors generated by medical knowledge mapping effectively into the disease prediction model, firstly, we combine these vectors with the representation vectors of patient indicator data by direct splicing through feature fusion technique, as in Eqs. 6, and the final feature representation vector is obtained as:

$$p = [p_{tp}, p_{zb}] \quad (6)$$

In the development of our disease prediction model, feature vectors are initially weighted, with sources from the medical knowledge graph receiving higher priority due to their rich disease-symptom relationship data. These weights are dynamically adjusted based on SHAP values, ensuring they accurately reflect the true influence of features on the model's predictive performance. This iterative optimization process, validated through performance metrics on a validation set, enhances both accuracy and transparency in decision-making. The implementation of this methodology leverages the medical knowledge graph to significantly improve both the performance and interpretability of the model. Specifically, our multi-label prediction model addresses the heterogeneity of diabetic complications, grounded in extensive experimental data. While this study primarily focuses on classifiers for diabetic nephropathy, the approach sets a precedent for future research into classifiers for other complications.

Model interpretation. One important reason why machine learning is limited in security-sensitive tasks is the lack of interpretability. Especially for applications in a rigorous field like medicine, interpretability is even more critical.

The main research objective of this subsection is to analyze the application and significance of the SHAP interpretable method in the field of adjunctive diagnostic models for diabetic nephropathy. SHAP, based on game theory [20] and local interpretation [21], belongs to the classical ex post interpretive framework that can provide Shapley values to estimate the contribution of each feature. Shapley values are a method of great applied value and their main role lies in describing the weights or importance of the feature parameters of a predictive model when making data point predictions and plays a central role in SHAP. Compared with traditional feature importance methods (e.g., XGBoost's feature importance), SHAP has better consistency in presenting the positive/negative relationship of each predictor with respect to the target variable for both local and global interpretation [22, 23]. In this study, we assessed the contribution of features to the predictive outcome of diabetic nephropathy by means of Shapley values, which provided local interpretations of the features in each sample and determined their global importance by calculating the mean of the Shapley values of the features. Shapley values of ICU clinical indicators were analyzed to explore the relationship between features and diabetic nephropathy risk, and the model was interpreted in the context of

clinical findings. Using Tree Explorer, a tool designed for tree modeling, Shapley values were calculated through tree model integration and additional modeling, and an individualized heuristic SHAP method was used to score and rank the global attributes of important predictor variables to reveal their importance in prediction.

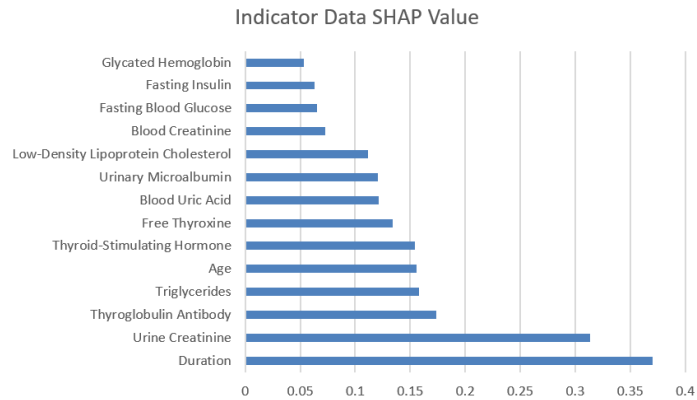


Fig. 4. Value of variable SHAP in the prediction model.

According to Figure 4, the duration of diabetes is pivotal in predicting the risk of diabetic nephropathy. Urinary creatinine levels emerge as a crucial variable impacting renal function, with significant influence also from thyroglobulin antibodies, triglycerides, and age. The top five weighted predictors encapsulate the essential information for forecasting diabetic nephropathy.

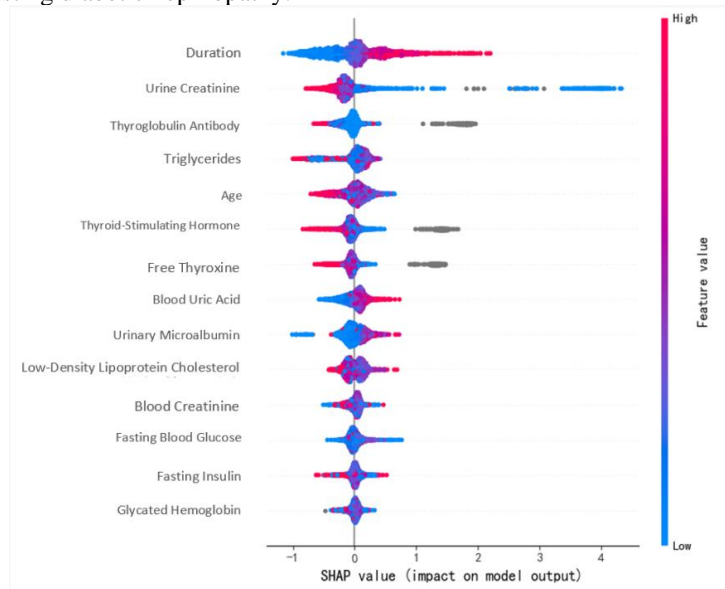


Fig. 5. Summary plot of feature variable SHAP.

Figure 5 elucidates the significance and influence of each feature within the diabetic nephropathy prediction model. Here, each point corresponds to a Shapley value, delineating the impact of individual features across various samples. Feature importance is delineated along the y-axis, while Shapley values are plotted along the x-axis, with the feature value sizes encoded in color, offering a clear, intuitive summary of the model. Variations in the vertical positioning of points illustrate the distribution of feature-based Shapley values. Notably, the duration of diabetes emerges as the most influential factor, showing a positive correlation with the likelihood of developing diabetic nephropathy. Urinary creatinine ranks as the second most impactful feature, indicating a higher probability of occurrence with elevated levels, whereas glycosylated hemoglobin and fast-ing insulin hold lesser significance in this model.

3 Findings

3.1 Data sources

In this study, we validate the predictive inference of diabetic nephropathy using the novel inference prediction model based on a diabetes medical knowledge graph, as proposed in this paper. Clinical data from diabetic patients are fed into the knowledge graph for comprehensive analysis. The data sources are twofold: firstly, the successfully constructed diabetes medical knowledge graph, which encompasses 18 types of entities and 17 types of relationships, totaling 13,032 entity nodes and 24,281 relationship pairs. Secondly, detailed clinical data from diabetic patients' consultations and examinations are extracted from the electronic medical records of three hospitals, encompassing diagnostic and treatment information of 3,182 patients. By integrating and structuring clinical data within the diabetes medical knowledge graph—through data structuring, establishing entity-attribute relationships, and other information processing steps—we enhance the diagnostic processes for identifying diabetic nephropathy complications. This structured approach provides a robust framework for leveraging extensive medical data to improve diagnostic accuracy and patient outcomes.

3.2 Experimental Design

Comparison Experiments.

Comparison with related models. The model proposed in this paper mainly adds medical knowledge graph information to the traditional integrated learning algorithms to improve the accuracy of the algorithms, and three types of integrated learning algorithms, LightGBM, CatBoost, and XGBoost, are selected in this thesis, and at the same time, the comparative experiments of classification effects are carried out together with neural networks. The overall experimental environment and equipment data are shown in the following table.

Table 1. Experimental environment.

Experimental	Name (of a Thing)	Releases Environment
programming language	Python	3.9
systems	Windows (computer)	10
editor (software)	miniconda	3
random access memory (RAM)	16G	/
CPU	Intel(R) Core(TM) i7-9750H	/

Comparison of mixed and unmixed sampling data. This paper found an imbalance in its data when predicting for diabetic nephropathy, where the number of patients with diabetic nephropathy was 786, or 25% of the total number of patients, and mixed sampling of patient information was performed to analyze the comparisons.

Judging Criteria. For classification problems, the confusion matrix is an important evaluation tool that can be used to calculate the model's recall, precision, F1 value and other indicators. The confusion matrix of this study is shown in Table 5.2, which can intuitively reflect the classification performance of the model and provide a strong reference for subsequent studies.

Table 2. Confusion Matrix.

	The model predicts a positive	The model predicts a negative
The actual result is positive	TP	FN
The actual result is negative	FP	TN

3.3 Experimental results

Comparison with related models. In this thesis, the experimental results of four types of models, LightGBM, CatBoost, XGBoost and Neural Networks, were compared on the prediction of complications and the results are shown in Table 3.

Table 3. Comparison of experimental results of different models.

	LightGBM	Cat Boost	XGBoost	Neural network
Accuracy	0.83	0.81	0.82	0.79
Precision	0.82	0.80	0.75	0.83
Recall	0.36	0.32	0.38	0.21
F1 Score	0.49	0.45	0.50	0.34
AUC	0.75	0.74	0.73	0.69
Gini	0.50	0.49	0.47	0.38
KS Value	0.37	0.36	0.35	0.31

From this table, the LightGBM model has the best classification performance as it ranks first in all four dimensions of accuracy, AUC, Gini coefficient and KS value, and the model also ranks second in the other three dimensions (precision, recall and F1 value).

The individual parameters of the LightGBM model are analyzed next. Shown in Figure 6 is the AUC curve of the LightGBM model, usually the value of AUC ranges from 0.5 to 1. The closer the AUC is to 1, the better the classifier performance. In general, an AUC greater than 0.7 represents a good classifier. This shows that the model performs well in terms of effectiveness.

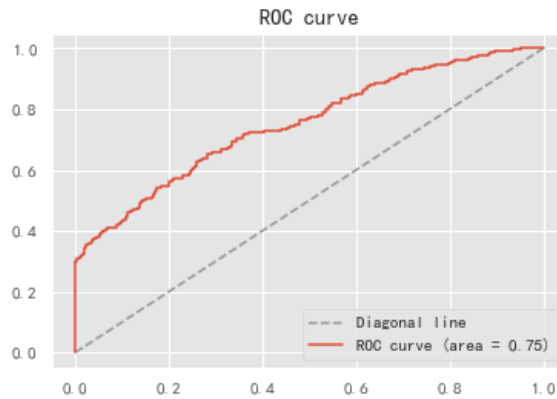


Fig. 6. AUC curve for the LightGBM model.

And the confusion matrix for the whole model is shown in Figure 7.

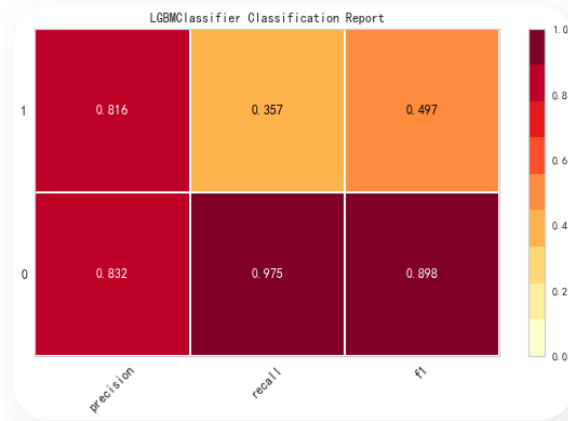


Fig. 7. Confusion matrix for the LightGBM model.

Comparison of Mixed and Unmixed Sampling Data. Through the in-depth analysis of the patients' disease conditions in the e-cases, it is found that the proportion of patients with diabetic nephropathy is low, accounting for only about one-third of the total number of patients, and this unbalanced data distribution will have certain impacts and challenges on the training and prediction of the model. We cite a mixed-sampling unbalanced data processing technique based on LightGBM integration tree algorithm to fully utilize the advantages of oversampling and undersampling and balance the disadvantages of oversampling and undersampling. In the hybrid sampling algorithm, a new sample is synthesized by SMOTE by selecting each sample in turn from a small number of samples as the root sample, and the noise samples are eliminated by using ENNs when generating the SMOTE process. The hybrid sampling process is shown below in Figure 8.

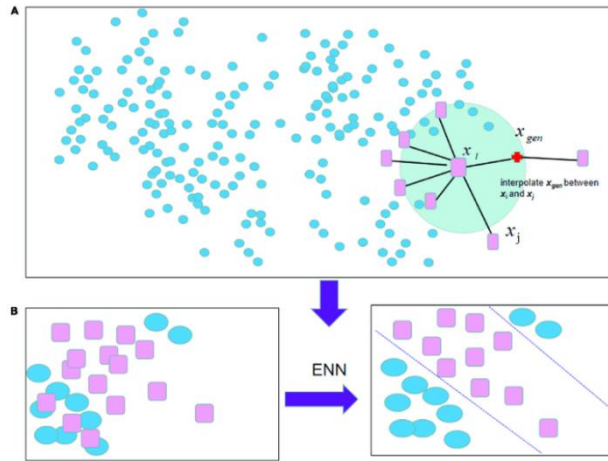


Fig. 8. Mixed sampling flow.

In this thesis, the experimental data were processed by oversampling of SMOTE algorithm and hybrid sampling of SMOTE-ENN based on LightGBM integration tree algorithm, and the results are shown in Table 4.

Table 4. Comparison of experimental results of different models after resampling.

	LightGBM	LightGBM-SMOTE	LightGBM-SMOTE-ENN
Accuracy	0.83	0.82	0.90
Precision	0.82	0.82	0.97
Recall	0.36	0.64	0.71
F1 Score	0.49	0.72	0.82
AUC	0.75	0.86	0.91
Gini	0.50	0.72	0.82
KS Value	0.37	0.57	0.73

As can be seen from the table results, the LightGBM-SMOTE-ENN algorithm has improved the data of all the metrics. For the LightGBM model without mixed sampling, the KS value, recall and F1 value of the LightGBM-SMOTE-ENN algorithm are improved by 97.3%, 97.22% and 67.35%, respectively; for the LightGBM-SMOTE model with separate sampling oversampling treatment, the KS value, accuracy, and Gini coefficient are improved by 28.07%, 18.29% and 13.89%, respectively. Among them, the accuracy, precision, and AUC of the mixed sampling model are improved to more than 0.90.

3.4 Analysis of experimental results

This subsection delves into the interpretability of the experimental outcomes, utilizing predicted data from randomly selected patients to exemplify this analysis.

Figure 9 presents the SHAP waterfall plot for the third patient, illustrating that the final prediction outcome value is $f(x) = 4.665$. Given that this value exceeds 0, it indicates a positive prediction for diabetic nephropathy. This visual representation not only underscores the predictive accuracy but also enhances our understanding of the contributing factors leading to the diagnosis, thereby facilitating a deeper insight into the model's decision-making process.

The graphical representation in the SHAP waterfall plot effectively visualizes the impact of different features on the predicted outcomes. In this visualization, blue bars illustrate the extent to which specific characteristics decrease the predicted value, while red bars indicate how certain features contribute to an increase in the predicted value. For instance, a red bar for urinary creatinine, marked as +2.65, signifies that this variable significantly increases the likelihood of a diabetic nephropathy prediction. Conversely, a blue bar for triglycerides, noted as -0.3, demonstrates that this variable tends to lower the predicted risk of diabetic nephropathy. This method of visualization provides a clear and intuitive understanding of the influence and importance of various features within the prediction model, enhancing interpretability and aiding in more informed clinical decision-making.

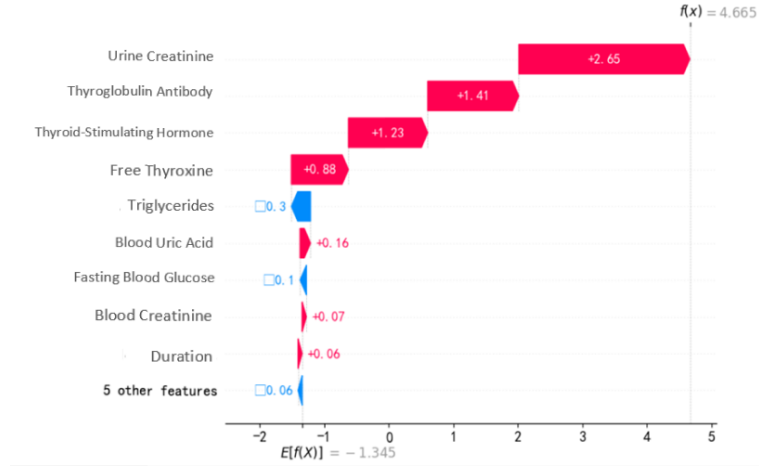


Fig. 9. SHAP waterfall diagram for patient 3.

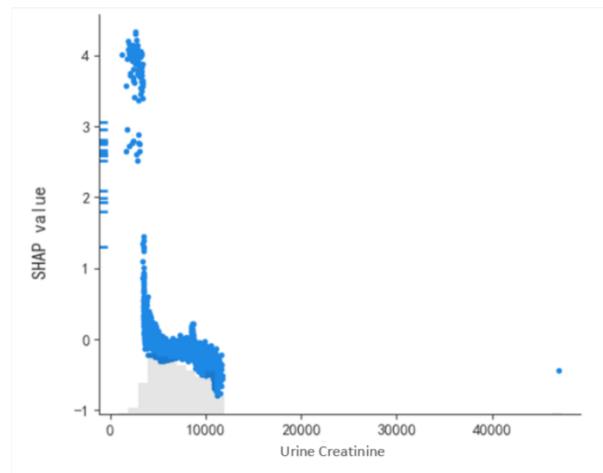


Fig. 10. Effect of urinary creatinine on model outputs.

The SHAP waterfall plot, while insightful, is limited to illustrating the impact of variables on a single sample value. To address this limitation and observe the dynamic changes of variables, we employ a scatter plot. As depicted in Figure 10, a discernible trend emerges: lower urinary creatinine levels correlate with higher SHAP values, indicating an increased probability of disease presence. Conversely, higher levels of urinary creatinine correspond to lower SHAP values and a decreased likelihood of disease. This pattern is corroborated by real clinical data, where patients with diabetic nephropathy often exhibit chronic inflammation and renal impairment, coupled with reduced

urinary creatinine excretion. Such findings are consistent with observed clinical conditions, enhancing our understanding of the disease's progression and aiding in the predictive accuracy of the model.

4 Conclusions

4.1 Summary of the work in this paper

This study introduces a novel model for predicting diabetes complications, utilizing a medical knowledge graph. This graph is constructed by aggregating diabetes-related clinical data and employing knowledge representation learning techniques for vectorization. This process helps identify key predictor variables, which are integrated with symptom vectors to form a classification model. The aim is to enhance prediction accuracy and the reliability of assisted diagnoses. The model incorporates a SHAP value-based approach to bolster interpretability and support clinical decision-making. Experimental validation confirms that this model surpasses traditional methods in accuracy, AUC, and other evaluation metrics, particularly in handling data imbalances with significantly improved outcomes. Case studies demonstrate the model's efficacy in predicting complications and providing explanatory guidance. This research paves a new avenue for the application of medical knowledge graphs in diabetes complication prediction, potentially elevating healthcare service quality and improving patient outcomes.

4.2 Outlook

In this study, we investigated the utility of medical knowledge graphs in assisting the diagnosis of diabetic complications. By compiling extensive clinical data, we constructed a comprehensive diabetic medical knowledge graph, which we then analyzed using advanced representation learning and integrated learning techniques. Our findings highlight the significant role of mining implicit disease features from patients' chief complaints recorded in electronic medical records, facilitated by natural language processing techniques. This approach proved crucial for enhancing diagnostic accuracy. However, experiments revealed discrepancies between the entities of the medical knowledge graph and actual patient examination indices, primarily due to the diversity of natural language, which impacted entity representation consistency, information matching, and ultimately, the accuracy of the knowledge graph.

Future research will focus on developing entity alignment techniques to refine the performance of the knowledge graph and the accuracy of the inference model by analyzing and integrating heterogeneous data sources more thoroughly. Additionally, this study underscores the critical importance of adhering to medical ethics and protecting personal privacy to ensure the safety and fairness of data processing, which is essential for fostering technological advancement in the field of medical AI.

In real-world scenarios, Large Language Models (LLMs) tend to encounter domain-specific pragmatics that require a combination of domain expertise and complex reasoning capabilities [24]. In this context, the application of LLMs in healthcare is a research topic of interest. As large-scale language models (LLMs) have achieved breakthroughs in general-purpose domains such as natural language processing, their potential application in healthcare is attracting extensive attention from both academia and industry [25]. It is foreseen that in the near future, with the continuous deepening and optimization of LLMs technology, the research results in this field will be more deeply integrated with LLMs, which will contribute to the further development of personalized medicine and precision medicine, especially providing more efficient and precise treatment strategies and management plans for patients with diabetes mellitus and other chronic diseases, which will fundamentally enhance the overall quality of healthcare services, and greatly improve the quality of life of patients. This will fundamentally enhance the overall quality of healthcare services and greatly improve the quality of life of patients.

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