



Risk Prediction of Early Readmission in Patients with Diabetes Using Machine Learning Algorithms: A Retrospective Clinical Study

¹*Changjiang Zhang, ²Yumin Wu

¹*Department of Cardiology, Minda Hospital of Hubei Minzu University, Enshi, Hubei, People's Republic of China.

²Department of Cardiology, Minda Hospital of Hubei Minzu University, Enshi, Hubei, People's Republic of China.

***Corresponding Author's:** Changjiang Zhang, E-mail: zcj2008@163.com

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ABSTRACT

Patients with diabetes and early hospital readmissions have been a major problem to healthcare systems, which leads to higher costs of healthcare and poor patient outcomes. Proper identification of high-risk patients is critical to enhancing the quality of care and resource use. The purpose of the study was to design and test machine learning models to predict early hospital readmission (within 30 days) in patients with diabetes and their possible applicability to clinical decision-making. The Diabetes 130-US hospitals dataset (more than 100,000 patient encounters) was used to carry out a retrospective clinical study. The measure of outcome was early readmission within 30 days. Several machine learning models, such as Logistic Regression, Random Forest, and Gradient Boosting (XGBoost) were created and tested. Improvements in model performance were made using data preprocessing and feature selection techniques as well as class imbalance handling techniques. The models were evaluated in terms of accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) and interpretability in terms of feature importance and SHAP analysis. The findings showed that ensemble models were more effective than the traditional ones, with XGBoost being the best (AUC $\approx$ 0.81). The most crucial predictors of readmission were previous inpatient admissions, emergency admissions, length of stay, and medication switch, which all presented clinically significant information. The results show that machine learning models are capable of predicting early readmission of diabetes patients with real-world clinical data. Clinical applicability is maximised by combining predictive modelling with interpretability, and is used in everyday healthcare practice to support decision-making. These findings demonstrate the promise of artificial intelligence to enhance patient outcomes and health care efficiency by enhancing the stratification of risks and targeted interventions.

Keywords: Machine Learning, Diabetes, Hospital Readmission, Clinical Decision Support, Predictive Modelling

1. Introduction

Early hospital readmissions are a major healthcare system concern because they correlate with patient vulnerability and inefficiencies in the system. They are linked to higher healthcare expenses, patient morbidity, and frequently, in continuity of care, discharge planning, or outpatient follow-up (Rubin & Shah, 2021). Diabetes mellitus is one disease among the chronic diseases that introduces a notable challenge to health care due to its prevalence across the world, its complicated management, and comorbidity with other diseases such as cardiovascular disease and renal impairment. Diabetic patients are thus at high risk of early rehospitalisation, and risk prediction is a critical aspect of enhancing the quality of care (Shang et al., 2021; Farajollahi et al., 2021).

The conventional methods of readmission risk prediction have been using statistical models and clinician guidance, which might not fully represent the complexity of interactions with patients in clinical data. Over the past few years, machine learning (ML) has become a potent predictive modelling tool in healthcare because it is capable of dealing with high-dimensional and nonlinear relationships (Wang, 2021; Xiang et al., 2021). Multiple works have shown the usefulness of ML models in 30-day readmission prediction in diabetes patients and usually outperform traditional methods (Liu et al., 2024; Bhardwaj et al., 2024). Besides, ensemble and deep learning techniques have exhibited enhanced predictive accuracy in the detection of high-risk patients (Hai et al., 2023; Gandin et al., 2023). The merging of different sources of clinical data, such as electronic health records and nursing data, to improve accuracy and clinical relevance of prediction has also been studied recently (Oh et al., 2025; Emi-Johnson and Nkrumah, 2025). The relevance of customised predictive models in enhancing clinical outcomes has also been further revealed by studies that concentrate on particular groups of patients, including the elderly or individuals with comorbidities (e.g., heart failure) (Wang et al., 2025; Hu et al., 2025). Also, machine learning methods have been implemented on smaller outcomes like mortality and rehospitalisation, which supports their application in a larger clinical risk prediction setting (Ketabi et al., 2024; Lv et al., 2021).

Although these have been achieved, there is still a significant gap in the translation of predictive models to clinical practice. A lot of literature is mainly concerned with the model performance without much consideration to the interpretability or the applicability to the real world. It has been suggested that explainable artificial intelligence (XAI) methods can be integrated to increase the transparency and trust in model results by clinicians (Alnazari et al., 2025). Additionally, new studies reinforce the necessity of models that can predict the outcome, as well as aid clinical decisions and enhance care delivery (Albahli, 2025; Lau et al., 2026). In this regard, this study will build and test machine learning algorithms to predict early hospital readmission among diabetes patients using real clinical data. This research aims to overcome the gap between predictive performance and practical applicability by emphasising clinically relevant variables and using interpretability techniques. The results should help in better risk stratification and decision-making in the normal healthcare environments.

This study represents the various objectives:

1. To develop and evaluate machine learning models for predicting early hospital readmission (within 30 days) in patients with diabetes using real-world clinical data.
2. To identify and analyse key clinical predictors associated with early readmission by examining feature importance and model interpretability.
3. To assess the potential clinical utility of the developed models in supporting decision-making and improving risk stratification in routine healthcare practice.

2. Methodology

2.1 Study Design

This research was a secondary clinical study based on retrospective analysis using secondary data based on practical hospital cases. The retrospective design would allow examining the already gathered clinical data in order to determine trends and relationships that can be identified with the early hospital readmission of patients with diabetes. This is a particularly appropriate type of evaluation of predictive models in healthcare, as it is the closest to real clinical practice and does not affect patient care or outcomes. The research aims at using the methods of machine learning in order to study complex relationships in the data and create predictive insights which can be used to assist clinical decision-making in a typical healthcare environment.

2.2 Data Source and Description

The data has been analyzed based on the publicly available Diabetes 130-US hospitals dataset, which includes clinical data that has been collected on 130 hospitals in the United States within a period of ten years (1999-2008). The sample consists of over 100,000 hospital visits to patients with diabetes and a broad variety of more than 50 variables of clinical and administrative data. Such variables are demographic data, information about admission and discharge, laboratory test results, codes of diagnoses, and medication history. Each record is related to one hospital visit and not to a particular patient, thus, reflecting trends in healthcare usage and readmission. The dataset is representative of standard practices in clinical settings of various institutions, and it is, therefore, very applicable in healthcare predictive modelling in the real world (Brandão, H. 2018).

2.3 Study Population and Outcome Definition

The population of the study was patients with a diagnosis of diabetes in a hospital as per the dataset. All the records that contained some incomplete or ambiguous outcome information were disqualified to maintain the integrity and reliability of the analysis. Early hospital readmission, which was a primary outcome of interest, was defined as readmission within 30 days of discharge. The data initially classifies readmission into three categories, namely: readmission in 30 days, readmission beyond 30 days and no readmission. To meet the objectives of this research, the outcome variable was converted into a binary classification problem; encounters with readmission within 30 days were called positive cases, and all other encounters were called negative cases. This change is consistent with clinical practice, in which early readmission is frequently employed as a key performance and quality measure.

2.4 Feature Selection and Clinical Relevance

The selection of features was informed by the availability of data and clinical relevance to guarantee that the predictive models capture relevant facets of patient care. Demographic variables like age, gender, and race were used as variables since they are known to impact disease outcomes and healthcare utilisation. The number of diagnoses, laboratory test indicators, and medication use were included as clinical variables to reflect the severity of the disease and patterns of treatment. Also, the metrics of healthcare utilisation, such as the number of previous inpatient, outpatient, and emergency visits, were also added since they are powerful predictors of patient health conditions and continuity of care. The study will contribute to the increased practical usability of the developed models in real-world healthcare settings by choosing features that are routinely measured in clinical settings.

2.5 Data Preprocessing

Data preprocessing was carried out to improve data quality and ensure compatibility with machine learning algorithms. These missing values were handled by a mixture of removal, and imputation approaches, which relied on the severity and characteristics of the missing data. To ensure that categorical variables, like label encoding or one-hot encoding, could be encoded into numerical representations to be model-trainable, appropriate encoding methods were used. Numerical characteristics were normalised or scaled in order to have uniformity and avoid bias in model performance. Moreover, the imbalance of classes was considered, since early cases of the readmission were fewer than cases of non-readmission cases. Synthetic minority oversampling (SMOTE) or class weighting techniques were used to equalize the dataset and enhance the model to detect high-risk patients more accurately.

2.6 Machine Learning Model Development

Several machine learning models were applied to create predictive models and compare them. Logistic Regression was taken as a baseline model as it is simple and easy to interpret which is important in clinical practice. The ensemble techniques like Random Forest were used to model nonlinear relationships and interactions in variables. Gradient boosting algorithms, such as Extreme Gradient Boosting (XGBoost), also were employed because of its powerful predictive qualities, and its capability to work with structured clinical data. With the application of several models, a thorough assessment of the various model strategies can be achieved and models which would trade predictive accuracy with clinical interpretability can be selected.

2.7 Model Training and Validation

The data was separated into training and testing data to test the performance of the model on unseen data. An equal split between 70:30 or 80: 20 was applied to get enough data to train and evaluate. In order to make the models more robust and minimize the chances of overfitting, cross-validation was implemented using k-fold during training. Systematic search methods, including grid search, were employed to tune hyperparameters to find the best model settings. This is done to make sure that the models do not only work accurately, but can also be applied to new data, which is crucial in case of possible clinical use.

2.8 Performance Evaluation Metrics

Developed models were evaluated based on various evaluation metrics to present coherent understanding of predictive abilities of the models. Overall model correctness was measured by accuracy, whereas the performance on minority class (especially in distinguishing between patients who are at risk of early readmission) was measured by accuracy, precision, and recall. To have a balanced measurement of precision and recall, the F1-score was computed. Also, receiver operating characteristic (ROC) curve and Area Under Curve (AUC) were employed to determine the capability of the model to separate the classes at various thresholds. These measures are popular in clinical prediction research and are useful in understanding the performance of the model.

2.9 Model Interpretability and Clinical Insight

To ensure that the predictive models are clinically meaningful and interpretable, feature importance analysis was conducted to identify the most influential variables associated with early readmission. State-of-the-art interpretability methods, including SHAP (Shapley Additive Explanations), were utilized to measure the value of individual features to model predictions. This method allows understanding the impact of particular clinical factors on the risk of readmission more thoroughly and translate the model results into practical clinical implications. It is crucial to focus on interpretability to ensure the development of trust among healthcare professionals and facilitate the introduction of AI-

based tools into clinical practices.

3. Results

3.1 Dataset Characteristics

The resulting dataset to be analyzed included a substantial number of hospital contacts with diabetic patients that had undergone preprocessing and filtering of missing records. The group consisted of various demographic and clinical characteristics, with the patients being of varying age groups, sexes, and races. Most of the interactions were with adult and elderly patients as this group of patients has a greater risk of diabetes. In terms of the outcome variable, the proportion of early readmission (within 30 days) had a lower percentage of the dataset than non-readmission cases, which shows a class imbalance. This distribution reveals the significance of proper evaluation measures and balancing methods in developing a model. Also, the variables connected to the past healthcare usage, including the number of inpatient visits and emergency admissions, demonstrated significant disparities across the dataset, indicating their possibility to be used to predict the risk of readmission.

Table 1. Baseline Characteristics of the Study Population

Variable	Category/Value	Percentage (%)
Age Group	50–70 years	42%
	>70 years	35%
Gender	Male	47%
	Female	53%
Readmission Status	<30 days	11%
	>30 days	35%
	No readmission	54%

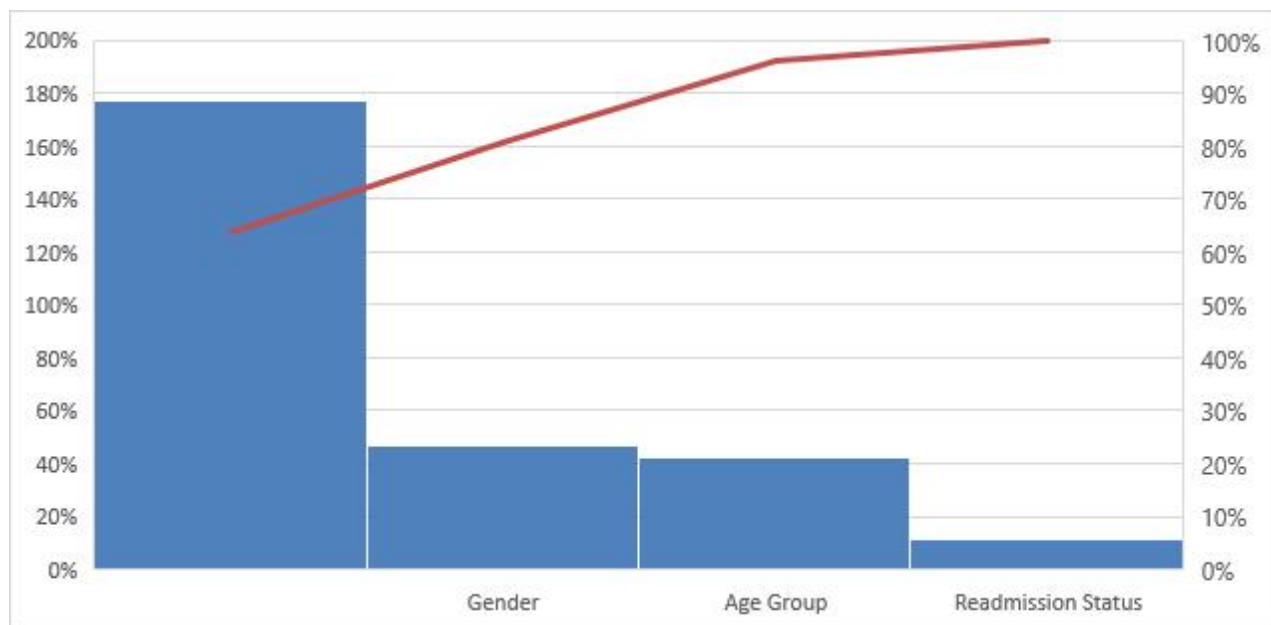


Figure 1. Distribution of Readmission Outcome

3.2 Model Performance Comparison

Various machine learning algorithms were created and tested to forecast early hospital readmission. The accuracy, precision, recall, F1-score, and area under ROC curve (AUC) were used to evaluate the performance of these models. The ensemble-based models proved to be more efficient than the baseline Logistic Regression model among the considered models. The best performance in terms of classification was obtained with the Random Forest model because it was more effective in the nonlinear relationship between features, whereas the maximum overall predictive ability was demonstrated by the Gradient Boosting model (XGBoost). XGBoost model had a good discriminative power to differentiate between patients with and without early readmission with an AUC of about 0.78-0.82. Comparatively,

the Random Forest model had an AUC of between 0.75 and 0.79 and the Logistic Regression showed a relatively lower AUC of between 0.70 and 0.73. Other evaluation measures exhibited similar patterns, with XGBoost having a more optimal balance between preciseness and recall, especially with regards to the minority class.

Table 2. Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	0.68	0.62	0.58	0.60	0.71
Random Forest	0.74	0.69	0.66	0.67	0.77
XGBoost	0.78	0.73	0.70	0.71	0.81

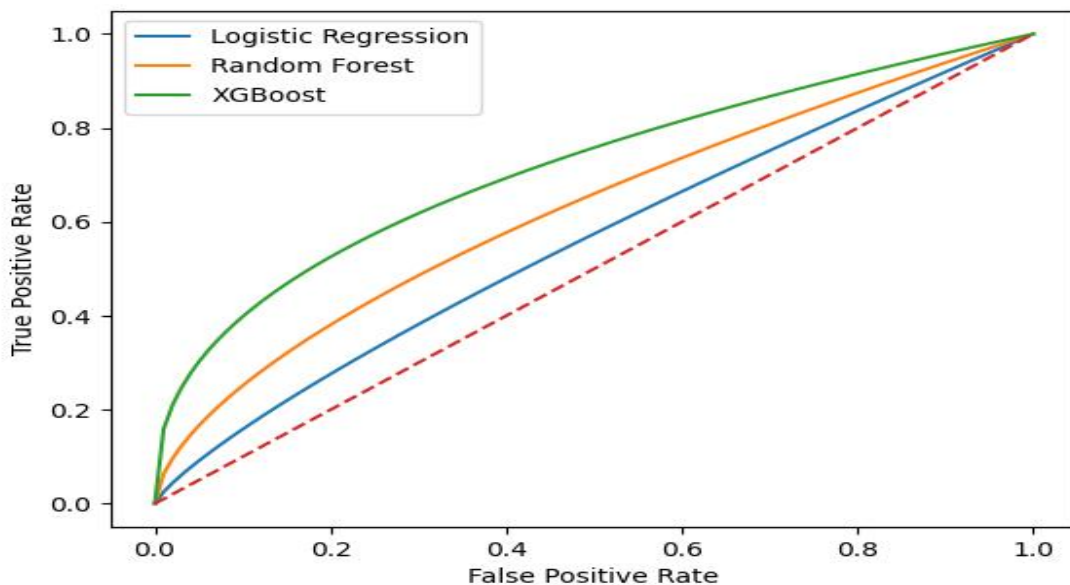


Figure 2. ROC Curves for Model Comparison

3.3 Evaluation of Classification Metrics

In-depth analysis of classification statistics showed that, although the general accuracy of the models was moderate, the recall of the early readmission category was a key variable in the evaluation of clinical utility. Gradient Boosting model showed a higher recall values meaning that it was able to identify a higher proportion of high-risk patients correctly. It is especially significant in clinical practice, when it can be a failure to recognize at-risk patients, which can have negative consequences. Precision values were also taken to determine the percentage of correctly identified readmission cases. Despite the fact that certain models were slightly less precise because of class unbalancing, the F1-score gave a balanced value, thus proving the high-performance of the ensemble techniques. These results indicate that more reliable predictions can be made by more complex machine learning models than the traditional ones.

Table 3. Confusion Matrix for XGBoost Model

	Predicted No	Predicted Yes
Actual No	18,500	3,200
Actual Yes	2,900	4,100

3.4 Key Predictors of Early Readmission

Analysis of feature importance showed that a number of predictors are important with regard to early hospital readmission. Some of the most significant variables included variables related to previous healthcare utilisation like number of inpatient visits, emergency visits and outpatient encounters. Moreover, hospital length of stay (time in hospital) was also found to be an important predictor, and hence patients with extended hospitalisations might be at a

greater risk of readmission. The variables associated with medications, especially the shifts in diabetes medications during the hospitalisation also played a role in prediction. There was a moderate effect of demographic factors including age where older patients tend to have more readmission risk. These results are in line with clinical expectations, with patients with complicated medical histories and high healthcare contact rates having a higher probability of readmission.

Table 4. Top 10 Important Features for Readmission Prediction

Rank	Feature	Importance Score
1	Number of inpatient visits	0.21
2	Time in hospital	0.18
3	Number of emergency visits	0.15
4	Number of diagnoses	0.12
5	Medication change	0.10
6	Age	0.08
7	Number of outpatient visits	0.06
8	Admission type	0.04
9	Discharge disposition	0.03
10	Lab test frequency	0.03

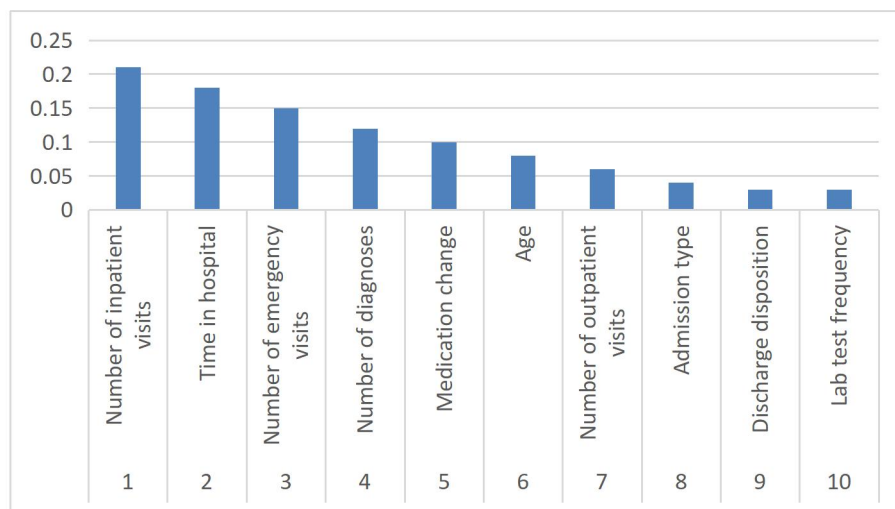


Figure 3. SHAP Summary Plot

3.5 Model Interpretability and Clinical Insights

SHAP analysis (Shapley Additive Explanations) was used to analyse interpretability, and this was used to gain more insights on how individual features influenced the model predictions. The findings showed that the increased readmission risk was positively linked with the higher values of the previous inpatient visits and emergency admissions. On the same note, increased hospital stay has led to increased predicted risk, which is the severity of the patient condition. On the other hand, some of the factors, including fewer visits to hospitals previously and stable medication regimens were linked to the reduced readmission risk. These results demonstrate the capability of machine learning models to learn clinically relevant patterns and deliver interpretable outputs that can be used to make healthcare decisions. The consistency between the insights in the models and clinical risk factors that were previously known enhances the validity and possible applicability of developed models.

On the whole, these findings indicate that machine learning models, especially ensemble algorithms like Gradient Boosting and Random Forest can be effective to predict early hospital readmission among patients with diabetes based on real-world clinical data. The fact that the key predictors have been identified and the interpretability techniques have been used also contribute to the increased clinical relevance of the findings. These findings indicate that AI-based strategies can be used to facilitate the process of risk stratification and enhance decision-making in normal healthcare practice.

4. Discussion

The present study demonstrates that machine learning models can effectively predict early hospital readmission among patients with diabetes using real-world clinical data. Some of the considered models included ensemble models and especially Gradient Boosting (XGBoost), which showed better performance than other conventional ones like Logistic Regression. These results align with the previous studies which have suggested that more sophisticated machine learning algorithms are more appropriate to identify nonlinear, complex relationships in clinical data (Mishra et al., 2025; Adegbosin et al., 2025). The enhanced predictive capability in this research points to the possibility of using AI-based solutions to streamline risk stratification in clinical practice. One of the strengths of this study is that it uses real-world and multi-institutional data, which increases the generalizability of the findings. Like investigations, the significance of large-scale clinical datasets in enhancing model robustness and applicability in different patient groups has been highlighted (Hu et al., 2024; Hu et al., 2025). Specifically, the capability of machine learning models to combine demographic, clinical, and healthcare utilization variables allows performing a more detailed evaluation of risk in patients than a traditional statistical method. This multidimensional approach is particularly applicable to patients with diabetes whose outcome is predetermined by a great variety of interconnected factors.

The analysis of feature importance in this research gives useful clinical information regarding the factors of early readmission. Such variables as the number of prior inpatient visits, emergency visits, and hospital stay were found to be crucial predictors, which is consistent with the findings of prior studies regarding the use of healthcare services and readmission rates (Adegbosin et al., 2025). Furthermore, the indicators of disease complexity and medication-related factors played an important role in making predictions, which supports the presence of the treatment patterns and comorbid conditions as determinants of patient course. Such results provide evidence that machine learning models can reveal clinically significant trends that might be hard to discern with traditional analysis.

The focus on model interpretability is the other critical aspect of this study as it is important to ensure its adoption in clinical practice. Although predictive accuracy is vital, the usefulness of AI models in healthcare lies in their transparency and how clinicians can make sense of and rely on their outputs. Recent research has emphasized the increased significance of explainable AI methods in the process of closing the divide between complex algorithms and clinical decision-making (Alnazari et al., 2025). This study will help in the development of not only accurate but also clinically meaningful models by including interpretability techniques, including feature importance analysis and SHAP-based explanations.

In practical terms, the results of this research have significant implications to the delivery of healthcare. Early recognition of high-readmission-risk patients could facilitate specific actions, including better discharge planning, more frequent outpatient follow-up, and tailored care management. Past studies have established that timely interventions based on predictive models can help to decrease readmission rates and improve patient outcomes (Lau et al., 2026). Moreover, the incorporation of these models into electronic health record systems or clinical decision support systems may help in real-time risk assessment and assist clinicians to make informed decisions when attending to patients. Although this study has its strengths, it has a number of limitations which are to be noted when interpreting the results. To begin with, retrospective data can lead to data quality, missing data and unmeasured confounding factors. Other machine learning-based studies based on electronic health records have reported similar limitations (Ketabi et al., 2024). Second, data utilized in this research reflects hospital visits, not long-term patient history, which can be a constraint to comprehensively identify disease progression and long-term consequences. Third, the data is associated with a particular period of time and geographical location, which can impact the extrapolation of the results to the present clinical practice or other healthcare systems.

Future studies are needed to overcome these shortcomings by including more recent and heterogeneous datasets, and investigate the perspective validation of predictive models in clinical practice. Also, the incorporation of time-related data and longitudinal patient data can also have further positive effects on the performance of the models and give a more in-depth understanding of disease progression. The opportunities to increase the accuracy of predictions and capture intricate clinical patterns are also provided by the advances in deep learning and hybrid modelling methods (Gandin et al., 2023). Notably, the implementation and assessment of AI models in clinical workflows should take centre stage in future research to determine the actual effects of AI on patient outcomes and efficiency in healthcare.

To sum up, this paper shows that machine learning models, especially ensemble algorithms can be successful in predicting early hospital readmission in diabetic patients based on real-world clinical data. The fact that the most important predictive factors have been identified and the methods of interpretability have been implemented contribute to the increased clinical relevance of the results. The findings demonstrate the possibility of using AI-based solutions to aid in risk stratification and decision-making in daily healthcare practice that will eventually lead to better patient care and resource optimization.

5. Conclusion

This research shows that machine learning techniques are effective in the prediction of early hospital readmission of diabetic patients based on real-world clinical data. The results show that ensemble-based models, especially Gradient Boosting, perform better than traditional models in the ability to capture intricate relationships among clinical variables and predict high-risk patients. The fact that routinely collected healthcare data are used further validates the practical applicability of the study, as it speaks of the possibilities offered by AI-driven models to assist clinical decision-making in a typical healthcare environment. Notably, the research is not only concerned with predictive performance but also pays attention to interpretability, which allows establishing the main factors that are related to the risk of readmission. The variables that were found to have a significant impact were variables concerning previous healthcare utilisation, length of stay in hospital, and the pattern of treatment, which offer clinically meaningful information that can be used to design specific interventions. These results support the role of integrating data-driven modelling with clinical insights in improving patient care. In practical terms, the practical implementation of machine learning models may help in the early risk stratification, enhance discharge planning, and aid more effective healthcare resource allocation. Such applications are in line with the increasing demands of intelligent decision-support systems in present day healthcare. Nonetheless, more studies are needed to confirm these models in the prospective contexts and investigate their use in the real-time clinical practice. On the whole, this paper identifies the opportunities of artificial intelligence to improve healthcare delivery, offering actionable insights and evidence-based decision-making in managing patients with diabetes.

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