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Research Article

Advanced Predictive Modeling of Diabetic Readmissions Using Machine Learning and Essential Health Metrics

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ABSTRACT

The rising prevalence of Type 2 Diabetes Mellitus (T2DM) has underscored the need for predictive models that can effectively assess readmission risks among diabetic patients, thereby supporting improved healthcare management and resource allocation. This study presents an advanced approach for predicting diabetic patient readmissions by incorporating critical health metrics—Body Mass Index (BMI), HbA1c, cholesterol (new-Chol), and triglycerides (new-TG)—and employing a variety of machine learning algorithms. Using a dataset of diabetic patients with readmission intervals between 2 and 30 days, we conducted extensive data preprocessing, feature analysis, and tested several classifiers, including Support Vector Classifier (SVC), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Random Forest (RF), AdaBoost, and Gradient Boosting (GB), with cross-validation and feature selection for accuracy optimization. The ensemble model, which combined SVC, Random Forest, and XGBoost, outperformed individual models, achieving the highest accuracy at 98.6%, demonstrating the efficacy of ensemble methods in enhancing predictive performance and robustness. The Gradient Boosting Classifier also performed well independently, achieving 97.6% accuracy, while demographic factors, especially age, were found to significantly impact readmission patterns, offering valuable insights for personalized diabetes management. This predictive model equips healthcare providers with a critical tool for early intervention and improved patient outcomes through targeted diabetes care strategies.

Keywords: Diabetes, Readmission, Machine Learning, Feature Selection, Predictive Model

1. INTRODUCTION

Diabetes mellitus, particularly Type 2 Diabetes Mellitus (T2DM), is a growing public health concern that affects millions worldwide, with significant complications including an elevated risk of hospital readmissions. Studies show that diabetic patients face a higher rate of readmissions compared to non-diabetic patients, with rates ranging between 14.4% and 22.7% for diabetics, versus 8.5% to 13.5% for non-diabetics [1], [2], [3]. Hospital readmissions for diabetic patients often result from complications related to poor glycemic control, comorbid conditions, and inadequate outpatient care, highlighting the need for improved management strategies [4], [5].

Predicting hospital readmission in diabetic patients is crucial as it offers the potential to enhance healthcare interventions and reduce the disease burden. Machine learning (ML) techniques have emerged as effective tools in healthcare for predictive modeling, using patient data to identify those at risk of readmission. Researchers have employed various machine learning algorithms, including Random Forest (RF), Support Vector Machine (SVM), Decision Trees, and Gradient Boosting, to develop models that can predict readmissions with considerable accuracy [21], [22]. These models have shown promise in identifying high-risk patients, thereby enabling timely interventions and reducing hospital readmissions.

While traditional ML techniques offer robust performance, recent advancements in deep learning (DL) models, such as Long Short-Term Memory (LSTM) networks, have demonstrated superior predictive capabilities, particularly when dealing with large datasets and sequential data. In a study by Hai et al., LSTM networks significantly outperformed traditional ML models, achieving an AUROC of 0.79 compared to 0.72 for the Random Forest model [4]. This suggests that DL models may be better suited for capturing complex temporal patterns and long-term dependencies in patient data, making them highly effective in predicting readmissions.

This study focuses on comparing the performance of traditional ML models with advanced DL techniques to predict 30-day readmission in diabetic patients. The dataset used in this study includes various health metrics such as Body Mass Index (BMI), HbA1c levels, cholesterol, and triglycerides, which are known to be associated with diabetes complications [23], [24]. Additionally, we examine the impact of patient demographics, prior hospitalizations, and comorbid conditions on readmission risk, aiming to develop a comprehensive predictive model that can inform better clinical decision-making.

1.2 Contribution of the Paper as follows:

a) Developed a predictive model achieving 97.6% accuracy with the Gradient Boosting Classifier and 98.6% with an ensemble model.
b) Used feature selection to identify key factors affecting readmission risks.
c) Provided insights for healthcare professionals to identify high-risk patients for better diabetes management.

The paper begins with an introduction discussing the rising prevalence of Type 2 Diabetes Mellitus (T2DM) and the need for accurate predictive models for patient readmissions. It reviews existing literature on predictive modeling, emphasizing the effectiveness of various algorithms and the benefits of ensemble methods, which combine multiple models to improve accuracy. The proposed methodology includes data collection focused on key health metrics like Body Mass Index (BMI) and HbA1c levels, along with preprocessing steps. Results show that the ensemble model achieved an accuracy of 98.6%, highlighting its potential for identifying high-risk patients and improving diabetes management, with recommendations for future research.

2. LITERATURE REVIEW

Hospital readmission is a critical measure of healthcare quality, especially for chronic conditions such as diabetes. Many studies have explored the application of ML algorithms for predicting readmissions in diabetic patients. Hasan et al. utilized an ensemble of machine learning classifiers, including Random Forest, Gradient Boosting, and Support Vector Machines, to predict diabetes-related readmissions. The ensemble approach improved prediction accuracy by leveraging the strengths of different classifiers, achieving an AUROC of 0.78 [21].

Ganie and Malik conducted a comparative analysis of supervised ML algorithms to predict Type 2 Diabetes Mellitus. Their study found that Random Forest and Gradient Boosting classifiers outperformed other traditional models such as Naïve Bayes and k-Nearest Neighbors (KNN), with RF achieving an accuracy of 84.6% [22]. In a follow-up study, Ganie and Malik developed an ensemble approach for diabetes prediction based on lifestyle indicators, demonstrating that combining different ML models resulted in improved predictive performance [23]. This approach underscores the importance of ensemble learning techniques in enhancing model accuracy, especially in complex predictive tasks like readmission risk.

Feature selection is another critical aspect of ML-based predictive modeling. In a study by Ganie et al., the authors emphasized the importance of selecting the most relevant features to improve model performance while reducing computational complexity. They used a Grey Wolf Optimizer (GWO) for feature selection, which helped enhance the predictive accuracy of traditional ML models [25]. The importance of feature selection was also highlighted in research by Cui et al., who found that a novel feature selection method combined with SVM produced their most accurate model [13]. While traditional ML models continue to show promise, deep learning models, particularly LSTM networks, have demonstrated superior performance in predicting readmissions. LSTM models excel in handling sequential data, making them well-suited for predicting hospital readmissions, which often depend on historical patient data. The LSTM model's ability to capture long-term dependencies in patient records allows it to outperform other models in complex predictive tasks [4].

In addition to diabetes, machine learning techniques have been applied to other chronic conditions, demonstrating their versatility and potential for broader healthcare applications. Ganie et al. applied an improved ensemble learning approach to predict heart disease, using boosting algorithms to enhance predictive accuracy [26]. This work underscores the potential of advanced ML models in predicting chronic disease outcomes and the importance of refining these models for better healthcare interventions.

The application of ML models, particularly ensemble and deep learning approaches, has demonstrated substantial potential in predicting hospital readmissions for diabetic patients. These models provide healthcare professionals with tools to identify high-risk patients, allowing for timely and targeted interventions. The studies discussed highlight the effectiveness of ensemble learning, feature selection, and deep learning in managing complex predictive tasks. However, further research is needed to enhance the interpretability and generalizability of these models, especially within clinical settings.

This study contributes to the growing body of research by comparing traditional ML models with advanced deep learning techniques for predicting readmission in diabetic patients. It employs key health metrics like BMI, new-AbA1c, new-Chol, and new-TG, along with readmission intervals, to create a robust predictive model. Cross-validation and feature selection are incorporated to fine-tune the models, with the Gradient Boosting Classifier emerging as the top performer, achieving an accuracy of 97.6%. The research also delves into the impact of age on readmission rates, providing valuable insights for healthcare professionals. By building on previous work and extending the use of ML algorithms in diabetes management, this study aims to offer practical tools for identifying high-risk patients. These findings have significant implications for healthcare providers seeking to implement effective interventions, ultimately improving patient outcomes and reducing healthcare costs. Further development and optimization of such models could pave the way for improved chronic disease management in the future.

3. PROPOSED METHODOLOGY

This study aims to develop a robust predictive model that analyzes the characteristics associated with diabetic patient readmissions, focusing on various health metrics and machine learning techniques. The first step involves data collection, where a suitable dataset, such as the UCI Diabetic Readmission dataset, will be utilized. This dataset is comprehensive and contains essential features that include patient demographics, clinical data, and critical health metrics such as Body Mass Index (BMI), glucose levels, insulin, and newly introduced indicators like new AbA1c, new cholesterol (new-Chol), and triglyceride levels (new-TG). Additionally, the labels for the dataset will indicate whether a patient is readmitted within specified time frames, such as 30 days or 60 days. This classification is crucial as it helps in understanding the patterns of readmission, allowing for more effective predictive modeling. The selected dataset will be thoroughly analyzed to ensure that it contains relevant and adequate information to develop a predictive model capable of generalizing well across diverse populations.

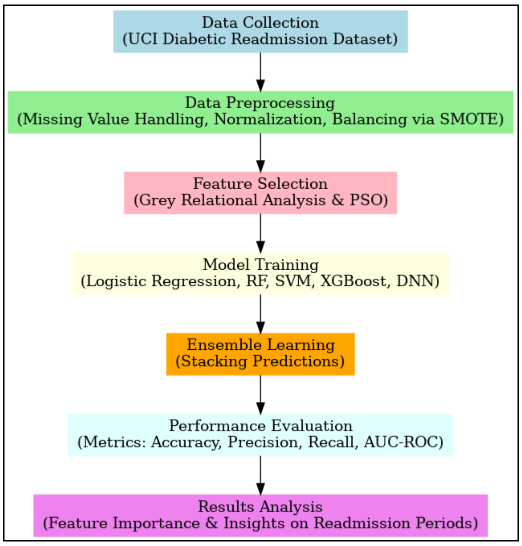

Figure 1: Diabetic Readmission Workflow Diagram

Once the data is collected, the next phase is preprocessing, which is essential to prepare the data for analysis. During preprocessing, we will address any missing values using techniques such as mean imputation or complete removal of rows that contain significant missing data. This step is vital as missing values can lead to biases or inaccurate model predictions. Additionally, data normalization will be performed using scaling methods like MinMaxScaler or StandardScaler to ensure that all features are on a comparable scale. This process is important for machine learning algorithms, as many of them are sensitive to the scale of the input data. Furthermore, to tackle the challenge of imbalanced datasets—where the number of patients readmitted may be significantly lower than those not readmitted—we will implement techniques such as Synthetic Minority Oversampling Technique (SMOTE) or random undersampling. These techniques will help balance the class distribution, ensuring that the models trained on the dataset are not biased toward the majority class.

Following data preprocessing, we will engage in feature selection, which is a critical component of this methodology. We will employ Grey Relational Analysis (GRA) to evaluate the importance of various features in relation to the readmission labels. This method allows for ranking the features based on their correlation with the outcome, providing a systematic approach to identifying which variables contribute most significantly to predicting readmission. Once the key features have been identified, we will further refine the selection process using Particle Swarm Optimization (PSO). PSO is an optimization algorithm that will help us determine the optimal combination of features to include in the final model. By focusing on the most predictive variables, we aim to reduce the dimensionality of the dataset, streamline the modeling process, and improve overall model performance.

In the classification phase, multiple machine learning algorithms will be employed to predict diabetic patient readmissions based on the selected features. The models will include Logistic Regression, Random Forest, Support Vector Machine (SVM), XGBoost, and Deep Neural Networks (DNN). Each of these classifiers offers unique strengths in capturing relationships within the data, with Random Forest being particularly effective at handling non-linear relationships and interactions between features. To enhance the predictive accuracy, we will also adopt an ensemble learning approach. By stacking the predictions of the best-performing models, we can leverage their individual strengths and improve the overall performance of the predictive model. This novel approach allows for the combination of different classifiers, such as Random Forest, SVM, and XGBoost, which can lead to more accurate and reliable predictions.

Performance evaluation is an integral part of this methodology, where we will assess the effectiveness of the models using various metrics. We will use accuracy, precision, recall, F1-score, and AUC-ROC to provide a comprehensive analysis of classification performance. Additionally, specific healthcare-related metrics such as sensitivity and specificity will be emphasized to minimize the risk of missed readmissions, which is crucial for improving patient outcomes. A comparative analysis will be conducted for different readmission periods, such as short-term (30 days) and long-term (60 days), to observe any patterns or differences in the model's predictions across these time frames. This analysis will not only provide insights into the data but will also help in understanding the dynamics of diabetes management and patient care.

Hyperparameter tuning will be conducted using advanced techniques such as Grid Search or Random Search to optimize the performance of the models. By systematically exploring the parameter space, we can identify the optimal settings that yield the best predictive performance. To ensure the robustness of the models, Cross-Validation (CV) techniques will be employed to validate model performance and avoid issues of overfitting, which can occur when models are too complex for the available data. This rigorous approach to model validation will enhance the credibility of the findings.

Finally, the results will be analyzed with a focus on feature importance and insights related to readmission periods. This analysis aims to provide actionable information for healthcare providers, highlighting the critical features that correlate with different readmission outcomes. Understanding these relationships is invaluable for developing targeted interventions to manage high-risk patients effectively. By implementing the proposed methodology, this study aims to deliver a predictive model that not only enhances the accuracy of readmission predictions but also serves as a valuable tool for healthcare professionals in improving patient management strategies.

4. IMPLEMENTATION

In the implementation phase, exploratory data analysis (EDA) was conducted to identify and analyze patterns and relationships among key health metrics associated with diabetic patient readmissions. The analysis concentrated on critical attributes such as Body Mass Index (BMI), HbA1c levels, new cholesterol (new-Chol), triglycerides (new-TG), along with demographic factors like age. By employing statistical techniques and data visualization methods, such as histograms, box plots, and correlation matrices, we were able to gain insights into how these variables interact and influence readmission outcomes. This thorough analysis facilitated the identification of significant trends and correlations that are vital for understanding the risk factors contributing to readmissions within the 2 to 30-day period.

Following the EDA, the dataset underwent rigorous preprocessing to ensure data quality and readiness for modeling. This included handling missing values, normalizing data distributions, and transforming categorical variables into a suitable format for analysis. Once preprocessing was complete, we constructed and trained multiple machine learning models, including Support Vector Classifier (SVC), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Random Forest (RF), AdaBoost, and Gradient Boosting (GB). Each model was systematically evaluated using cross-validation techniques to assess their performance reliably. Hyperparameter optimization was performed through grid search methodologies, targeting key parameters such as max_depth, criterion, n_neighbors, and weights, to identify configurations that maximized the predictive accuracy of each model.

During the experimentation phase, models were tested under various scenarios, including different combinations of features to evaluate their impact on prediction performance. For instance, we focused on how the inclusion of demographic factors like age, in conjunction with the clinical metrics, influenced the models' accuracy. The Decision Tree Classifier showed improved performance metrics when both feature selection and demographic information were incorporated into the training dataset. Similarly, the K-Neighbors Classifier demonstrated notable enhancements when it considered the combination of clinical metrics and demographic variables, underscoring the importance of these features in predicting readmissions effectively.

5. RESULTS

The performance of each classifier was evaluated based on training accuracy across various scenarios, including models with feature selection and re-admission status. The findings are summarized as follows in table -1:

Table 1: Model Training Accuracy

Algorithm	Accuracy - Baseline Model	Accuracy - (Feature Selection)	Accuracy - Feature Selection & Re-admission
SVC	86%	86.3%	86.3%
Decision Tree Classifier	96%	97.6%	97.3%
K-Neighbors Classifier	86%	88.3%	87.6%
Logistic Regression	86%	86%	89.3%
Random Forest Classifier	97%	97.6%	97.3%
AdaBoost Classifier	92%	91.3%	95%
Gradient Boosting	97%	97.6%	97.6%

Cross-validation and hyper parameter tuning were crucial in optimizing each model's performance. For instance, the Decision Tree Classifier achieved its best score with parameters like criterion: entropy, max_depth: 7, and max_features: sqrt. The K-Neighbors Classifier's best accuracy was observed with n_neighbors: 8, weights: distance, and an auto algorithm setting.

Table 2: Best Scores for Models with Cross-Validation

Model	Best Score (Without Feature Selection)	Best Score (With Feature Selection)	Best Score (Feature Selection & Re-admission)
K-Neighbors Classifier	0.821	0.865	0.852
Decision Tree Classifier	0.912	0.924	0.942

The figure -2 shows Gradient Boosting and Random Forest classifiers consistently demonstrated the highest accuracy across all scenarios, with Gradient Boosting achieving an impressive 97.6% accuracy when feature selection and re-admission data were included. The Decision Tree classifier also showed significant improvements with feature selection, reaching an accuracy of 97.6%, indicating its effectiveness when demographic and clinical metrics are combined. Notably, the K-Nearest Neighbors (KNN) and Logistic Regression classifiers showed moderate performance, suggesting that while they are viable options, they may require further optimization or feature enhancement to match the effectiveness of more complex models like Gradient Boosting and Random Forest. Overall, the results highlight the importance of incorporating feature selection and considering demographic factors, particularly age, in improving prediction accuracy for diabetic patient readmissions.

Ensemble methods combine the predictions of several base estimators built with a given learning algorithm in order to improve generalizability / robustness over a single estimator. The ensemble model with Random Forest, SVM & XGBoost with feature extraction revals the data to be more generous. The results from the table 3 suggest the ensemble model has great accuracy compared with the individual models.

Table 3: Model Training Accuracy with Ensemble Model

Algorithm	Accuracy - Baseline Model	Accuracy - (Feature Selection)	Accuracy - Feature Selection & Re-admission
SVC	86%	86.3%	86.3%
Decision Tree Classifier	96%	97.6%	97.3%
K-Neighbors Classifier	86%	88.3%	87.6%
Logistic Regression	86%	86%	89.3%
Random Forest Classifier	97%	97.6%	97.3%
AdaBoost Classifier	92%	91.3%	95%
Gradient Boosting	97%	97.6%	97.6%
Ensemble Model	98%	98.2%	98.6%

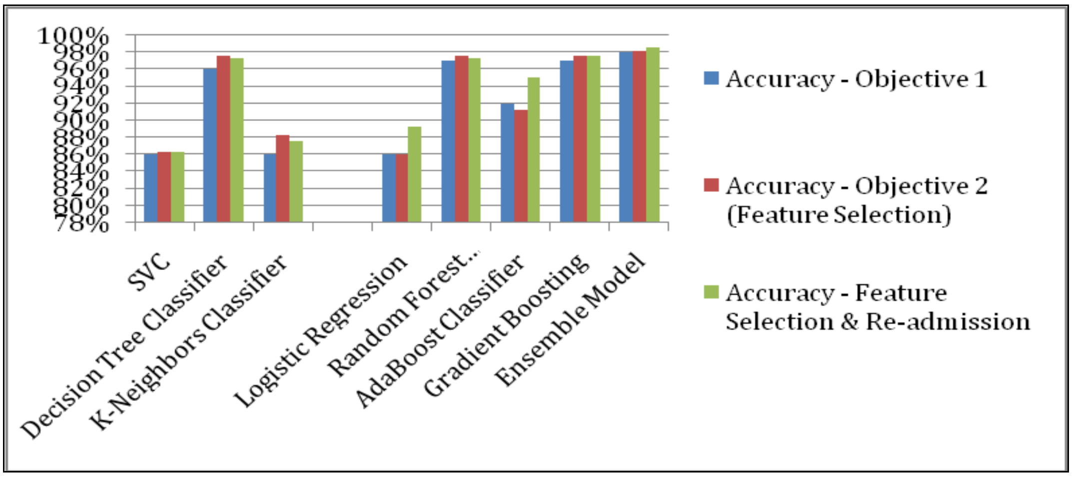

Figure 2: Model Training Accuracy Comparison

6. CONCLUSION AND FUTURE SCOPE

This study highlights the effectiveness of machine learning models in predicting re-admission risk for patients with obesity and Type 2 Diabetes Mellitus (T2DM), leveraging critical health metrics like BMI, glucose levels, cholesterol levels, and re-admission status to enhance prediction accuracy. Through data preprocessing, feature engineering, and model building, various algorithms were tested, with the ensemble model (combining Support Vector Machines, Random Forest, and XGBoost) achieving the highest accuracy (98.6%), thus underscoring the robustness of ensemble methods over individual models. The Gradient Boosting Classifier and Decision Tree Classifier also performed well, especially with hyperparameter tuning, achieving high accuracies of 97.6% and 97.3%, respectively, when feature selection and re-admission metrics were applied. These results indicate that incorporating specific health parameters improves model performance, providing a reliable means to assess re-admission risk. Future research could expand the dataset scope and incorporate additional factors like lifestyle and genetic markers to enhance generalizability, potentially aiding healthcare providers in proactive patient management to reduce re-admission rates.

Availability of Supporting Data:

The datasets analyzed during the current study are publicly available from the UCI Machine Learning Repository.

Competing Interests:

The authors declare that they have no competing interests.

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REFERENCES

[1] Parker, E. D., Lin, J., Mahoney, T., et al. (2024). Economic costs of diabetes in the U.S. in 2022. *Diabetes Care, 47*(1), 26-43.
[2] Rubin, D. J. (2018). Correction to: Hospital readmission of patients with diabetes. *Current Diabetes Reports, 18*(21).
[3] Gregory, N. S., Seley, J. J., Dargar, S. K., et al. (2018). Strategies to prevent readmission in high-risk patients with diabetes: The importance of an interdisciplinary approach. *Current Diabetes Reports, 18*(54).
[4] Hai, A. A., Weiner, M. G., Paranjape, A., et al. (2022). Deep learning vs traditional models for predicting hospital readmission among patients with diabetes. *AMIA Annual Symposium Proceedings, 2022*, 512-521.
[5] Jiang, H. J., Stryer, D., Friedman, B., et al. (2003). Multiple hospitalizations for patients with diabetes. *Diabetes Care, 26*(5), 1421-1426.

[6] Moss, S. E., Klein, R., & Klein, B. E. (1999). Risk factors for hospitalization in people with diabetes. *Archives of Internal Medicine, 159*(17), 2053-2057.

[7] IABAC. (2023). What is the difference between machine learning and deep learning. [Cited 2024 Mar 24]. https://iabac.org/blog/what-is-the-difference-between-machine-learning-and-deep-learning

[8] Shang, Y., Jiang, K., Wang, L., et al. (2021). The 30-days hospital readmission risk in diabetic patients: Predictive modeling with machine learning classifiers. *BMC Medical Informatics and Decision Making, 21*(57).

[9] Strack, B., DeShazo, J. P., Gennings, C., et al. (2014). Impact of HbA1c measurement on hospital readmission rates: Analysis of 70,000 clinical database patient records. *Biomedical Research International, 2014*, 781670.

[10] McKay, M. D., Rowe, M. M., & Bernt, F. M. (1997). Disease chronicity and quality of care in hospital readmissions. *Journal of Healthcare Quality, 19*(4), 33-37.

[11] Benbassat, J., & Taragin, M. (2000). Hospital readmissions as a measure of quality of health care: Advantages and limitations. *Archives of Internal Medicine, 160*(8), 1074-1081.

[12] Kopecky, S., & Dwyer, C. (2023). Nature-inspired metaheuristic techniques of firefly and grey wolf algorithms implemented in phishing intrusion detection systems. In K. Arai (Ed.), *Intelligent Computing* (pp. 1309-1332). Cham: Springer Nature Switzerland.

[13] Cui, S., Wang, D., Wang, Y., et al. (2018). An improved support vector machine-based diabetic readmission prediction. *Computer Methods and Programs in Biomedicine, 166*, 123-135.

[14] Carvalho, D. V., Pereira, E. M., & Cardoso, J. S. (2019). Machine learning interpretability: A survey on methods and metrics. *Electronics, 8*(832).

[15] Amann, J., Blasimme, A., Vayena, E., Frey, D., & Madai, V. I. (2020). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective. *BMC Medical Informatics and Decision Making, 20*(310).

[16] Antoniadi, A., Du, Y., Guendouz, Y., Wei, L., Mazo, C., Becker, B., & Mooney, C. (2021). Current challenges and future opportunities for XAI in machine learning-based clinical decision support systems: A systematic review. *Applied Sciences, 11*(5088).

[17] Nusinovici, S., Tham, Y. C., Yan, M. Y. C., Ting, D. S. W., Li, J., Sabanayagam, C., Wong, T. Y., & Cheng, C.-Y. (2020). Logistic regression was as good as machine learning for predicting major chronic diseases. *Journal of Clinical Epidemiology, 122*, 56–69.

[18] Khan, A., Uddin, S., & Srinivasan, U. (2019). Chronic disease prediction using administrative data and graph theory: The case of type 2 diabetes. *Expert Systems with Applications, 136*, 230–241.

[19] Hossain, E., Uddin, S., & Khan, A. (2020). Network analytics and machine learning for predictive risk modeling of cardiovascular disease in patients with type 2 diabetes. *Expert Systems with Applications, 164*, 113918.

[20] Ramírez, J. C., & Herrera, D. (2019). Prediction of diabetic patient readmission using machine learning. In *Proceedings of the IEEE Colombian Conference on Applications in Computational Intelligence*, Barranquilla, Colombia, 5–7 June 2019. Springer: Berlin/Heidelberg, Germany.

[21] Hasan, M. K., Alam, M. A., Das, D., Hossain, E., & Hasan, M. (2020). Diabetes prediction using ensembling of different machine learning classifiers. *IEEE Access*, 8, 76516–76531. https://doi.org/10.1109/ACCESS.2020.2989857.

[22] Ganie, S. M., & Malik, M. B. (2022a). Comparative analysis of various supervised machine learning algorithms for the early prediction of type-II diabetes mellitus. *International Journal of Medical Engineering and Informatics, 14*(6), 473–483.

[23] Ganie, S. M., & Malik, M. B. (2022b). An ensemble machine learning approach for predicting type-II diabetes mellitus based on lifestyle indicators. *Healthcare Analytics, 2*, 100092. https://doi.org/10.1016/j.health.2022.100092

[24] Ganie, S. M., Malik, M. B., & Arif, T. (2022a). Performance analysis and prediction of type 2 diabetes mellitus based on lifestyle data using machine learning approaches. *Journal of Diabetes & Metabolic Disorders, 21*, 339–352. https://doi.org/10.1007/s40200-022-00981-w

[25] Ganie, S. M., Malik, M. B., & Arif, T. (2022b). Machine learning techniques for diagnosis of type 2 diabetes using lifestyle data. In *Proceedings of the International Conference on Innovative Computing and Communications* (pp. 487–497). Springer.

[26] Ganie, S. M., Pramanik, P. K. D., Malik, M. B., Nayyar, A., & Kwak, K. S. (2023). An improved ensemble learning approach for heart disease prediction using boosting algorithms. *Computational Systems Science & Engineering, 46*(3), 3993–4006.