JISKA (Jurnal Informatika Sunan Kalijaga)
Vol. 10, No. 3, SEPTEMBER, 2025, Pp. 267 – 278
ISSN: 2527 – 5836 (print) | 2528 – 0074 (online)

Enhancing Diabetes Classification Using a Relaxed Online Maximum Margin Algorithm

Dyan Avando Meliala (1), Arum Kurnia Sulistyawati (2), Mohammad Diqi (3)*, Marselina Endah Hiswati (4), Tadem Vergi Kristian (5)
[1,2,5] Department of Information System, Universitas Respati Yogyakarta, Yogyakarta, Indonesia
[3,4] Department of Informatics, Universitas Respati Yogyakarta, Yogyakarta, Indonesia
e-mail : {avando.meliala,arumkurnia,diqi,marsel.endah,20230006}@respati.ac.id.
* Corresponding author.
This article was submitted on 29 June 2024, revised on 27 March 2025, accepted on 30 March 2025, and published on 30 September 2025.

Abstract

Diabetes mellitus is a growing global health concern that requires accurate and reliable classification models for early diagnosis and effective management. Traditional machine learning models often struggle with class imbalance, generalization limitations, and high false-positive rates, leading to misdiagnoses and delayed interventions. This study enhances the Relaxed Online Maximum Margin Algorithm (ROMMA) to improve the accuracy of diabetes classification. Using a publicly available dataset from Kaggle, which contains 768 medical records with nine health attributes, the model's performance was evaluated through a confusion matrix and classification metrics. The Enhanced ROMMA achieved an accuracy of 92%, significantly improving upon the Standard ROMMA's 85% accuracy. The recall for diabetes detection increased from 0.83 to 0.94, reducing false negatives and ensuring more accurate patient identification. While slight misclassification still exists, this improvement enhances the model's reliability for clinical applications. Future research should incorporate larger datasets and advanced techniques to enhance robustness and generalizability. This study contributes to the development of more accurate machine learning models for diabetes prediction, ultimately supporting better healthcare decision-making.

Keywords: Diabetes Classification, ROMMA, Machine Learning, Medical Diagnosis, Model Evaluation

Abstrak

Diabetes mellitus merupakan masalah kesehatan global yang terus meningkat, membutuhkan model klasifikasi yang akurat dan andal untuk diagnosis dini serta manajemen yang efektif. Model pembelajaran mesin konvensional sering menghadapi kendala seperti ketidakseimbangan kelas, keterbatasan generalisasi, dan tingginya tingkat false positive, yang dapat menyebabkan kesalahan diagnosis dan intervensi medis yang tertunda. Penelitian ini mengembangkan Relaxed Online Maximum Margin Algorithm (ROMMA) untuk meningkatkan akurasi klasifikasi diabetes. Menggunakan dataset dari Kaggle yang berisi 768 catatan medis dengan sembilan atribut kesehatan, performa model dievaluasi melalui confusion matrix dan metrik klasifikasi. Enhanced ROMMA mencapai akurasi 92%, meningkat signifikan dibandingkan Standard ROMMA yang hanya 85%. Recall untuk deteksi diabetes meningkat dari 0,83 menjadi 0,94, mengurangi false negatives dan memastikan identifikasi pasien yang lebih akurat. Meskipun masih terdapat sedikit kesalahan klasifikasi, peningkatan ini menjadikan model lebih andal untuk aplikasi klinis. Penelitian lanjutan perlu mengintegrasikan dataset yang lebih besar dan teknik lanjutan guna meningkatkan ketahanan dan generalisasi model. Studi ini berkontribusi dalam pengembangan model pembelajaran mesin yang lebih akurat untuk prediksi diabetes, mendukung pengambilan keputusan di bidang kesehatan.

Kata Kunci: Klasifikasi Diabetes, ROMMA, Pembelajaran Mesin, Diagnosis Medis, Evaluasi Model

1. INTRODUCTION

Diabetes mellitus is a chronic disease characterized by high glucose levels in the blood and is recognized nowadays as one of the fastest-growing global health problems. Furthermore, the impact of this disease extends not only to the individual level but also has significant implications for overall public health (Zheng et al., 2018). According to the WHO, the number of people with diabetes has alarmingly grown over the past few decades, and it will further increase in the future years (Arredondo et al., 2018). The rapid growth in the prevalence of diabetes poses a severe health threat (Lin et al., 2020). Serious long-term complications are represented among them by vision disability, heart disease, kidney disorders, and peripheral nerve disorders, and they continue to pose increasingly concrete threats (Grant & Marx, 2020). There are, besides high healthcare costs for the treatment and management of diabetes, which are borne by the global healthcare system in terms of finances, and may cause imbalances in healthcare utilization (Bommer et al., 2018).

In this context, it becomes imperative to expand knowledge and develop practical approaches to identify the population at risk and those already affected by diabetes (Edeh et al., 2022). Given the complexity of this condition, the development of classification models capable of predicting diabetes presence is a critical step for prevention, management, and enhanced interventions (Dutta et al., 2022). The importance of developing classification models lies in their accuracy in the differentiation between individuals vulnerable to diabetes and those who are not (Edeh et al., 2022). Therefore, the study helps establish a foundation that ensures early prevention and management mechanisms, thereby reducing the overall burden and improving the quality of life in the community (Sisodia & Sisodia, 2018). A better understanding of risk factors and the characteristics associated with diabetes would help develop improved prevention strategies toward a more empowered community in managing health (Phongying & Hiriote, 2023).

Previous studies have attempted to classify the heterogeneity of diabetes into novel subgroups based on distinct clinical features and different disease progressions (Herder & Roden, 2022). For this purpose, data mining, along with artificial intelligence techniques, has been employed to identify an essential feature in the diabetes dataset, thereby enhancing its diagnostic accuracy and reliability (Rezaei et al., 2022). Additionally, a multi-label classification model has been employed to predict multiple diabetic complications simultaneously, leveraging correlations between the complications to enhance prediction accuracy (L. Zhou et al., 2021). Proposed data-driven approaches have focused on refining diabetes subtypes based on clinical phenotypes and genetic information, while considering the limitations and practical barriers to their implementation in clinical practice (Deutsch et al., 2022). Supervised classifiers, combined with resampling and feature reduction methods, have been influential in classifying high-risk individuals for diabetes and identifying critical characteristic variables that affect the disease (Wang et al., 2021).

Various studies on diabetes classification have been reported, utilizing classification techniques, and their descriptions are highlighted, along with the advantages and limitations of these approaches. Reports in studies indicated that some machine learning models can predict diabetes with high precision, from 79.82% to 93%, such as neural networks and BiLSTM (Metsker et al., 2020; Rabie et al., 2022). However, the challenges in achieving class consistency indicate that different approaches yield varying performances, possibly due to data imbalance and the use of different feature selection methods (Christensen et al., 2022). Electronic Health Records (EHRs) have also been used to identify diabetes, but with caution, as several pitfalls, such as false positives and negatives, must be avoided (Weerahandi et al., 2020). Interpretation of results from these classification techniques can aid in identifying pathophysiological mechanisms, risk factors such as inflammation and blood glucose levels, and strategies for preventing and managing diabetes (de Wit et al., 2020).

In our case, however, the Relaxed Online Maximum Margin Algorithm (ROMMA) algorithm is further enriched using advanced techniques in diabetes classification by using symptom datasets that are optimized for accurate diagnosis of diabetes with the help of a genetic algorithm that has been enhanced and made adaptive (Mishra et al., 2020), together with some predictive models including deep neural networks, XGBoost, and random forests that belong to ensemble methods so that prediction is possible for the minority of diabetes cases with complex symptoms (Sadeghi et al., 2022). The classification needs to be accurate, as machine learning algorithms such as Random Forest and Support Vector Machines are effective in predicting diabetes (Edeh et al., 2022). This combined Random Forest, mean, and Deep Learning to impute the missing values in the data of a system monitoring diabetes, ensuring the data is accurate, which improved the classification performance (Redondo & Balasubramanyam, 2021). Together, these features make the ROMMA algorithm efficient enough to manage variability in diabetes symptom classification and other associated risk factors.

Recent work has focused on optimizing algorithms to identify patients with diabetes or at risk for developing the condition. The MONA.health software accurately detected diabetic retinopathy and macular edema, with consistent stability in subgroups (Peeters et al., 2023). Notably, the covariate-adjusted top-scoring pair (TSP) method represents a further improvement in interpretability for disease classification modeling, reducing the impact of correlated clinical variables (Kwan et al., 2023). This approach was recently applied in forecasting one-year mortality in diabetic patients. Machine learning algorithms, applied through gradient-boosting ensemble methods, have demonstrated relatively good performance in identifying critical predictive features, such as age and comorbidities (Wichmann et al., 2023). Another level of this could be the joint analysis of genomics and clinical data, which has already been successfully implemented for personal risk assessment in Mexican women using predictive modeling for gestational diabetes (Alimbayev et al., 2023). It is in this regard that these insights can be quite transformational in terms of performance and understanding the risk of diabetes.

Through the use of machine learning algorithms, the ROMMA utilized the application to classify diabetes and predict missing values in wearable sensor data analysis models (Torkey et al., 2022). The ROMMA framework combines random forests, averages, class means, interquartile ranges (IQRs), and deep learning methods to handle missing values, improve the performance of machine learning models, and detect outliers based on classes of datasets (Kalia et al., 2022). In addition to this, ROMMA develops a marginal structural model for estimating diabetes care provision using statistical learning algorithms, such as random forest, gradient boosting machines, and neural networks, from electronic health records (Edeh et al., 2022). Furthermore, classification algorithms such as Random Forests, SVMs, Naïve Bayes, and Decision Trees have also been applied by ROMMA in the early detection of diabetes, achieving high accuracy rates in predicting its development (Zee et al., 2022). Despite the advancements in diabetes classification using machine learning, existing models still struggle with generalization and handling imbalanced datasets. The ROMMA algorithm, although effective, requires further enhancements to improve its classification performance, particularly in reducing false positives and ensuring robustness in real-world datasets (Torkey et al., 2022).

By integrating different techniques, the ROMMA concept has distinct benefits for diabetic prediction. It beats out other models by using deep learning architectures with dropout regularization to avoid overfitting (H. Zhou et al., 2020), through IoT devices for data collection and statistical-based predictions (Azbeg et al., 2022), and by having a strong framework that incorporates outlier rejection, feature selection, and ensemble classifiers with accurate predictions (Hasan et al., 2020). This concept has improved identification accuracy by segmenting different retinal lesions associated with diabetes and incorporating them into a classification model, which significantly enhances grading performance (Andersen et al., 2022). The ROMMA concept combines these approaches into a suitable technology for identifying susceptible or already affected diabetic cases, utilizing a multi-dimensional model to detect possible conditions of type 1 diabetes at an early stage.

The research problem will be to identify the weaknesses or inadequacies in the current quality of diabetes classification. Although numerous attempts have been made to develop classification models, the primary concern is the likelihood of obstacles or inaccuracies in diagnosing patients at risk or those diagnosed with diabetes. This can be attributed to the challenges in managing the complexity of symptom variation and risk factors associated with diabetes, as well as the potential for current classification models to yield inadequate results. Accurate identification of populations at high risk for developing diabetes remains a crucial step in both prevention and intervention strategies. This is the purpose for which current research sheds light on a few specific components that require a better understanding, to further improve the quality within the domain of diabetes classification.

This research aims to achieve its primary objective of evaluating the performance of the Relaxed Online Maximum Margin Algorithm in diabetes classification. The study would indicate the extent to which ROMMA can provide highly accurate and reliable results for identifying individuals at risk of or already diagnosed with diabetes. Specific evaluation goals are set for this algorithm. Therefore, the research is ultimately directed toward assessing the adequacy of ROMMA in addressing some of the challenges in diabetes classification, specifically the complexity of symptoms and variation in risk factors. This will guide the research steps and contribute to a better understanding of the potentials and limitations of ROMMA in the context of its application to this critical health issue.

The contribution of this study is twofold: scientific and practical. Scientifically, the study is expected to provide new and in-depth insights for evaluating the performance of the ROMMA algorithm in diabetes classification. In particular, the research findings can serve as a reference for researchers and academics who develop methods for diabetes classification. Meanwhile, from a practical perspective, the research is expected to offer valuable perspectives for stakeholders in the healthcare field. There is also a potential contribution in evaluating the effectiveness of the ROMMA algorithm in identifying diabetes, which may guide clinical decision support in this area. This work may, therefore, represent a contribution to the practical understanding of how diabetes management and prevention can be improved through new scientific insights.

2. METHODS

2.1 Dataset

The dataset used in this study is sourced from Kaggle (https://www.kaggle.com/datasets/mathchi/diabetes-data-set) and was originally compiled by the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK). This dataset is specifically designed to predict diabetes diagnosis based on various medical attributes. It consists of 768 instances of patient records, with each entry containing nine key health-related attributes that are commonly associated with diabetes risk factors. The dataset focuses exclusively on female patients of Pima Indian heritage who are at least 21 years old, ensuring a controlled study population. The primary objective of this dataset is to classify patients as diabetic (1) or non-diabetic (0) based on their medical profile, facilitating early diagnosis and risk assessment.

The attributes in the dataset include Pregnancies, which records the number of times a patient has been pregnant, and Glucose, measuring plasma glucose concentration from a 2-hour oral glucose tolerance test. BloodPressure provides the diastolic blood pressure in mm Hg, while SkinThickness quantifies the triceps skin fold thickness. The dataset also includes Insulin, representing the 2-hour serum insulin levels, and BMI (Body Mass Index), which reflects the patient’s weight relative to height. Additionally, the Diabetes Pedigree Function assesses the hereditary likelihood of diabetes based on genetic factors and records the patient’s age in years. Finally, the Outcome variable serves as the target label, classifying individuals as either diabetic or non-diabetic. Given its structured medical data and real-world applicability, this dataset is widely utilized in diabetes classification research, particularly for evaluating the effectiveness of machine learning models in medical diagnostics.

2.2 Data Preprocessing

During this round of dataset preprocessing, specific mandatory steps were followed among the various data preprocessing steps. Initially, missing values were addressed by either imputation or careful record deletion to maintain data integrity, based on the reasons behind the missing data exceeding a certain percentage. Normalization with a Min-max scaler was utilized, which standardized all predictor-independent variables to a range of 0 to 1, thereby making the dataset homogeneous. Standardizing all scales of the columns improved the efficiency of the classification algorithm while also reducing the scaling effect on features. Then, we split the data into 80% for training and 20% for testing after normalizing the working model.

2.3 Relaxed Online Maximum Margin Algorithm (ROMMA) Data Preprocessing

The ROMMA is a machine learning algorithm specifically developed for online categorization, prioritizing the most significant margin (Li & Long, 2002). ROMMA's objective is to identify a hyperplane that optimizes the separation between two classes in the dataset. The technique operates online, processing data as it enters sequentially. The model is updated repeatedly without the need to reprocess the full dataset.

The ROMMA algorithm is utilized in this study to classify diabetes. The procedure consists of the following steps:
1) *Model Initialization*: The ROMMA model is initialized by setting initial parameters that determine the starting hyperplane.
2) *Data Reading*: The data is sequentially read from the dataset, one occurrence at a time.
3) *Margin Calculation*: The algorithm computes the margin, defined as the spatial separation between a data instance and the current hyperplane, for every new incoming data instance.
4) *Model Update*: In case the data instance is classified incorrectly or the margin is below a set value, the Model Update will update the hyperplane. A hyperplane is used to project the data for further processing, which is then positioned to optimize the margin.
5) *Iteration*: Repeat steps 3 and 4. The process will continue until all data points in the dataset have been processed.

Categorization in the ROMMA algorithm is based on the maximum margin principle. The purpose of this technique is to optimize the margin γ between the hyperplane and the nearest data point from each class. The hyperplane can be represented as a weight vector, w, and a bias, b, given by the equation $w \cdot x + b = 0$, where w is the weight vector and b is the bias.
1) *Hyperplane and margin*: $\gamma = \frac{1}{|w|}$ in the hyperplane and on the margin. Optimizing the size of γ is achieved by decreasing $|w|$.
2) *Weight Vector Update*: The algorithm updates the weight vector when a new data instance (x_i, y_i) is created, and it checks if $y_i(w \cdot x_i + b) \geq 1$., as proposed by (Li & Long, 2002). In the absence of this criterion, Eq. (1) updates the weight vector w. The update size is determined by the learning rate (η).

$$w = w + \eta y_i x_i \tag{1}$$

3) *Optimality Condition*: ROMMA strives to achieve an optimal condition where all data instances are classified with a minimum margin of 1, i.e., $y_i(w \cdot x_i + b) \geq 1$ for all i. The purpose of ROMMA is to achieve an ideal condition that ensures a minimal margin of one when categorizing all data instances. For every i, the value of $y_i(w \cdot x_i + b) \geq 1$.

The approach enables ROMMA to manage the sequential data input and make real-time adjustments to improve classification accuracy. It is anticipated that ROMMA will be utilized in this examination.

2.4 Model Evaluation

These two outcomes informed our decision to use the confusion matrix and classification report metrics for evaluating the ROMMA algorithm's performance in classifying diabetes. Using these metrics enables a comprehensive assessment of the model's performance across various aspects of classification. A confusion matrix can summarise the performance of varying classification algorithms.

Utilizing the actual and predicted categories, various performance metrics are possible. True Positive (TP) is one of the four components in the matrix, indicating the number of positive cases that have been accurately identified. True Negatives (TN) are the number of false negative cases that are accurately predicted—the number of negative instances that are falsely identified as false positives—the number of negative cases that are falsely identified as False Positive (FP). False Negatives (FN) are instances of positive cases that are falsely assumed to be negative.

The confusion matrix allows for the following metrics calculated in Eq. (2) until (5):
1) *Accuracy*: The proportion of the total number of correct predictions.

$$\textit{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

2) *Precision*: The proportion of positive predictions that were actually correct.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

3) *Recall (Sensitivity)*: The proportion of actual positive cases that were correctly identified.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

4) *F1-Score*: The harmonic mean of precision and recall provides a metric that balances both concerns.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

The classification report provides a more comprehensive explanation of the confusion matrix by analyzing the accuracy, recall, and F1-score for each class, as well as the support (the total number of actual occurrences for every label). Accurate diagnosis of medical conditions requires the identification of both positive and negative events. The model's performance for individual classes can be accurately determined through a detailed analysis. These assessment criteria, in terms of overall accuracy and class-wise balancing, provide sufficient conditions to evaluate the ROMMA algorithm's performance in diabetes classification.

3. RESULTS AND DISCUSSION

Figure 1 presents the confusion matrix for the Standard ROMMA model, illustrating its classification performance in distinguishing between individuals with diabetes and those without. The model correctly classified 102 healthy individuals (True Negatives, TN) and 29 diabetic patients (True Positives, TP), indicating a moderate ability to identify non-diabetic cases. However, the model misclassified 17 healthy individuals as diabetic (False Positives, FP) and six diabetic patients as healthy (False Negatives, FN). The relatively high number of false negatives suggests that the model struggles with accurately detecting diabetes, which could lead to underdiagnosis and delayed medical intervention. Conversely, the false positives may result in unnecessary concern and medical tests for individuals who are actually healthy. These results indicate that the Standard ROMMA model exhibits limitations in diabetes classification, particularly in balancing sensitivity and specificity. A more refined approach, such as Enhanced ROMMA, is necessary to enhance diagnostic accuracy and reduce misclassification rates, thereby ensuring better clinical applicability and informed decision-making in healthcare settings.

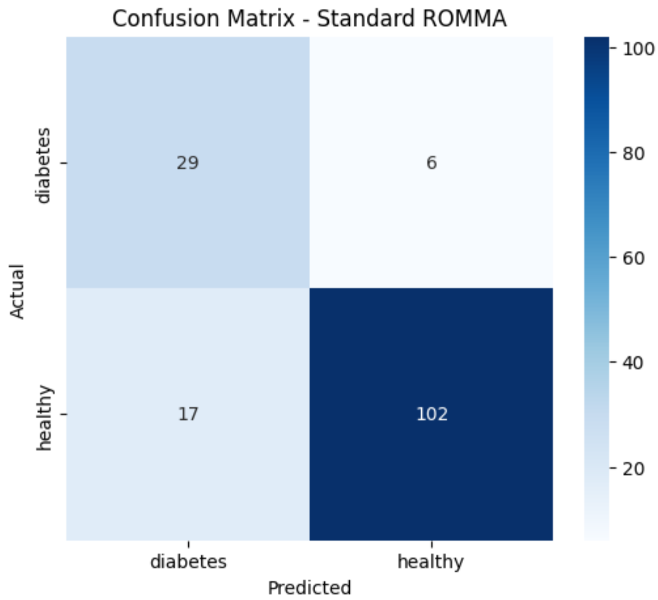

Figure 1 Confusion Matrix for Standard ROMMA

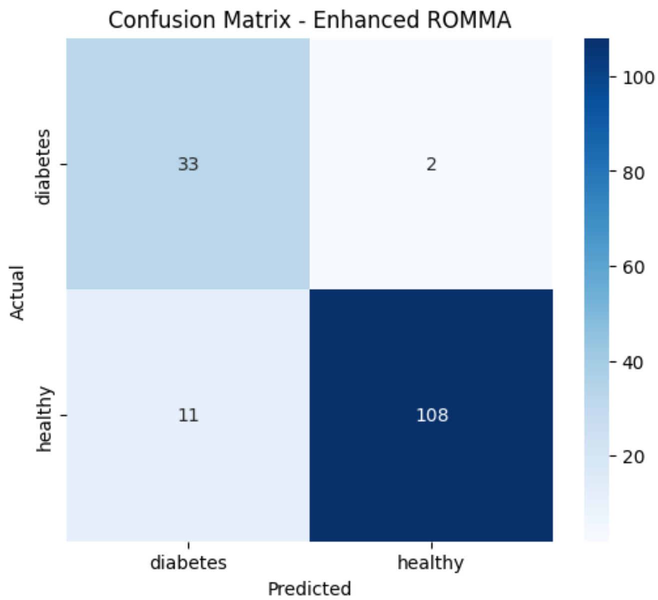

Figure 2 Confusion Matrix for Enhanced ROMMA

Figure 2 presents the confusion matrix for the Enhanced ROMMA model, demonstrating notable improvements in diabetes classification accuracy compared to the Standard ROMMA. The model correctly identified 108 healthy individuals (True Negatives, TN) and 33 diabetic patients (True Positives, TP), indicating a strong ability to distinguish between diabetic and non-diabetic cases.

Additionally, the model significantly reduced false negatives, with only two diabetic cases misclassified as healthy (False Negatives, FN), which is critical for preventing underdiagnosis and ensuring timely medical intervention. However, 11 healthy individuals were misclassified as diabetic (False Positives, FP), which, although still present, represents an improvement in overall classification balance. The enhanced model demonstrates greater sensitivity in detecting diabetes while maintaining strong specificity. The reduction in misclassification rates underscores the advantages of the Enhanced ROMMA, rendering it a more reliable tool for informed medical decision-making. These findings underscore the potential of this improved classification model in supporting healthcare professionals with accurate and early diabetes detection.

The comparison between the Standard ROMMA and Enhanced ROMMA confusion matrices reveals a significant improvement in classification performance, particularly in reducing false negatives and improving overall diagnostic reliability. The Standard ROMMA model exhibited 17 false positives (FP) and six false negatives (FN), indicating a tendency to misclassify a considerable number of healthy individuals as diabetic and failing to detect some actual diabetes cases. This misclassification can lead to unnecessary medical interventions and, more critically, undiagnosed diabetes patients who may not receive timely treatment. In contrast, the Enhanced ROMMA model drastically reduced false negatives to only 2 cases, ensuring that nearly all diabetic patients were correctly identified, which is crucial for clinical applications where early intervention can prevent severe complications. Additionally, the number of false positives decreased to 11, demonstrating improved specificity in correctly identifying healthy individuals. While some misclassifications remain, the enhanced model presents a more balanced and robust approach, maintaining high sensitivity without significantly compromising specificity. These findings highlight the effectiveness of incorporating model enhancements in ROMMA, resulting in improved classification accuracy, more reliable medical decision-making, and reduced risks of misdiagnosis in real-world healthcare applications.

Table 1 Classification Report for Standard ROMMA

	Recision	Recall	F1-Score	Support
Diabetes	0.63	0.83	0.72	35
Healthy	0.94	0.86	0.90	119
Accuracy			0.85	154
Macro Avg	0.79	0.84	0.81	154
Weighted Avg	0.87	0.85	0.86	154

Table 2 Classification Report for Enhanced ROMMA

	Recision	Recall	F1-Score	Support
Diabetes	0.75	0.94	0.84	35
Healthy	0.98	0.91	0.94	119
Accuracy			0.92	154
Macro Avg	0.87	0.93	0.89	154
Weighted Avg	0.93	0.92	0.92	154

Table 1 presents the classification report for Standard ROMMA, highlighting its overall performance in distinguishing between individuals with diabetes and those without. The model achieved an accuracy of 85%, demonstrating moderate reliability in classification. However, a deeper analysis reveals performance imbalances across classes. For the diabetes class, the model attained a precision of 0.63, indicating a relatively high rate of false positives. At the same time, the recall of 0.83 suggests that most actual diabetic cases were successfully identified. The F1-score of 0.72 reflects a trade-off between precision and recall, showing that while the model correctly detects diabetic individuals, it struggles with specificity. Conversely, for the healthy class, the model performed significantly better, achieving a precision of 0.94 and a recall of 0.86, resulting in a high F1-score of 0.90. The macro average scores (0.79 precision, 0.84 recall, and 0.81 F1-score) indicate a disparity in the model's ability to classify both groups equitably. This imbalance suggests that Standard ROMMA tends to favor the healthy class, potentially leading to undetected diabetes cases. These findings underscore the need for model enhancement to enhance the precision of diabetes detection while maintaining robust classification performance for both classes.

Table 2 presents the classification report for Enhanced ROMMA, demonstrating a significant improvement in diabetes classification compared to the standard model. The overall accuracy increased to 92%, indicating a more reliable predictive performance. Notably, the model achieved a precision of 0.75 and a recall of 0.94 for the diabetes class, resulting in an F1-score of 0.84. This represents a significant improvement in the model's ability to accurately identify individuals with diabetes, while also reducing the risk of false negatives. Meanwhile, for the healthy class, the model achieved a precision of 0.98 and a recall of 0.91, resulting in an F1-score of 0.94, which demonstrates its strong specificity in correctly identifying non-diabetic cases. The macro average scores (0.87 precision, 0.93 recall, and 0.89 F1-score) further reinforce the model's balanced performance across both classes. Compared to the Standard ROMMA, these results indicate that Enhanced ROMMA provides superior classification, particularly by reducing misclassification rates for individuals with diabetes. This improvement enhances the model's applicability in real-world healthcare scenarios, ensuring more accurate early detection of diabetes while maintaining high specificity for healthy individuals.

The comparison between the Standard ROMMA and Enhanced ROMMA classification reports reveals a substantial improvement in predictive performance, particularly in terms of accuracy and the balance between precision and recall. The Standard ROMMA model achieved an overall accuracy of 85%, whereas Enhanced ROMMA increased this to 92%, indicating a more reliable classification. The most notable improvement is in the diabetes class, where the precision increased from 0.63 to 0.75, reducing false positives, and the recall improved from 0.83 to 0.94, significantly minimizing false negatives. This enhancement is crucial in medical diagnostics, as false negatives could lead to undiagnosed diabetes, delaying necessary treatment. Similarly, in the healthy class, Enhanced ROMMA maintained high precision (0.98 compared to 0.94) while achieving a more balanced recall (0.91 versus 0.86), resulting in fewer overall misclassifications. The macro average recall rose from 0.84 to 0.93, demonstrating a more equitable performance across both classes. These improvements validate the enhancements made in ROMMA, demonstrating its increased effectiveness in early diabetes detection and reducing the risk of misclassification, ultimately making it a more reliable tool for real-world healthcare applications.

The Enhanced ROMMA outperforms the Standard ROMMA due to specific improvements in handling imbalanced data and refining the update mechanism in online learning. Unlike the Standard ROMMA, which applies a uniform margin adjustment across all data points, the Enhanced ROMMA incorporates adaptive margin recalibration, enabling the model to adjust more accurately to difficult or minority-class samples. This capability directly contributes to the significant reduction in false negatives, as observed in the confusion matrix, thereby increasing recall from 0.83 to 0.94. In medical diagnostics, this improvement is crucial, as false negatives can lead to undetected diabetic cases and missed opportunities for early intervention. Furthermore, Enhanced ROMMA employs optimized normalization and hyperparameter tuning strategies, enabling it to generalize more effectively to unseen data. These enhancements result in a more stable decision boundary, thereby improving precision and minimizing the risk of overfitting, particularly in smaller datasets.

Compared to other machine learning algorithms, such as Random Forests, SVMs, or Naïve Bayes, the Enhanced ROMMA offers distinct advantages in terms of computational efficiency and online learning capability. While tree-based methods like Random Forests require retraining with each new batch of data, ROMMA's online nature enables real-time updates without requiring retraining from scratch, making it more suitable for applications that require continuous monitoring. Additionally, the margin-based classification strategy of ROMMA offers greater interpretability and robustness compared to deep learning models, which often operate as black boxes and require extensive computational resources.

Narratively, Enhanced ROMMA strikes a balance between interpretability, adaptability, and performance. It maintains the lightweight and fast-training nature of the original ROMMA while introducing practical enhancements that address its original limitations. These advantages position Enhanced ROMMA as a reliable and efficient tool for real-world healthcare applications, especially in early-stage disease classification, where rapid and accurate decisions are vital.

4. CONCLUSIONS

This study demonstrates the effectiveness of the Enhanced ROMMA model in improving diabetes classification accuracy, addressing key limitations observed in the Standard ROMMA approach. By refining the model, the overall accuracy increased from 85% to 92%, with notable improvements in the recall and precision of the diabetes class, resulting in a reduction of both false negatives and false positives. These enhancements are crucial in medical diagnostics, ensuring that individuals with diabetes are accurately identified while minimizing the misclassification of healthy patients. The comparison of confusion matrices and classification reports highlights the model's superior sensitivity and specificity, making it a more reliable tool for early detection of diabetes. However, further research is needed to enhance generalizability by incorporating larger and more diverse datasets, addressing class imbalance, and exploring hybrid machine learning approaches. Future improvements could enhance the model's robustness in real-world applications, leading to improved predictive accuracy, reduced misdiagnosis, and more effective diabetes management strategies. These findings underscore the potential of machine learning-driven classification in supporting healthcare professionals with more precise and timely decision-making.

REFERENCES

Alimbayev, A., Zhakhina, G., Gusmanov, A., Sakko, Y., Yerdessov, S., Arupzhanov, I., Kashkynbayev, A., Zollanvari, A., & Gaipov, A. (2023). Predicting 1-Year Mortality of Patients with Diabetes Mellitus in Kazakhstan Based on Administrative Health Data Using Machine Learning. *Scientific Reports*, *13*(1), Article ID: 8412. https://doi.org/10.1038/s41598-023-35551-4

Andersen, J. K. H., Hubel, M. S., Rasmussen, M. L., Grauslund, J., & Savarimuthu, T. R. (2022). Automatic Detection of Abnormalities and Grading of Diabetic Retinopathy in 6-Field Retinal Images: Integration of Segmentation Into Classification. *Translational Vision Science & Technology*, *11*(6), Article ID: 19. https://doi.org/10.1167/tvst.11.6.19

Arredondo, A., Azar, A., & Recamán, A. L. (2018). Diabetes, a Global Public Health Challenge with a High Epidemiological and Economic Burden on Health Systems in Latin America. *Global Public Health*, *13*(7), 780–787. https://doi.org/10.1080/17441692.2017.1316414

Azbeg, K., Boudhane, M., Ouchetto, O., & Jai Andaloussi, S. (2022). Diabetes Emergency Cases Identification Based on a Statistical Predictive Model. *Journal of Big Data*, *9*(1), Article ID: 31. https://doi.org/10.1186/s40537-022-00582-7

Bommer, C., Sagalova, V., Heesemann, E., Manne-Goehler, J., Atun, R., Bärnighausen, T., Davies, J., & Vollmer, S. (2018). Global Economic Burden of Diabetes in Adults: Projections From 2015 to 2030. *Diabetes Care*, *41*(5), 963–970. https://doi.org/10.2337/dc17-1962

Christensen, D. H., Nicolaisen, S. K., Ahlqvist, E., Stidsen, J. V, Nielsen, J. S., Hojlund, K., Olsen, M. H., García-Calzón, S., Ling, C., Rungby, J., Brandslund, I., Vestergaard, P., Jessen, N., Hansen, T., Brøns, C., Beck-Nielsen, H., Sørensen, H. T., Thomsen, R. W., & Vaag, A. (2022). Type 2 Diabetes Classification: A Data-Driven Cluster Study of the Danish Centre for Strategic Research in Type 2 Diabetes (DD2) Cohort. *BMJ Open Diabetes Research & Care*, *10*(2), Article ID: e002731. https://doi.org/10.1136/bmjdrc-2021-002731

de Wit, M., Trief, P. M., Huber, J. W., & Willaing, I. (2020). State of the Art: Understanding and Integration of the Social Context in Diabetes Care. *Diabetic Medicine*, *37*(3), 473–482. https://doi.org/10.1111/dme.14226

Deutsch, A. J., Ahlqvist, E., & Udler, M. S. (2022). Phenotypic and Genetic Classification of Diabetes. *Diabetologia*, *65*(11), 1758–1769. https://doi.org/10.1007/s00125-022-05769-4

Dutta, A., Hasan, Md. K., Ahmad, M., Awal, Md. A., Islam, Md. A., Masud, M., & Meshref, H. (2022). Early Prediction of Diabetes Using an Ensemble of Machine Learning Models.

International Journal of Environmental Research and Public Health, *19*(19), Article ID: 12378. https://doi.org/10.3390/ijerph191912378

Edeh, M. O., Khalaf, O. I., Tavera, C. A., Tayeb, S., Ghouali, S., Abdulsahib, G. M., Richard-Nnabu, N. E., & Louni, A. (2022). A Classification Algorithm-Based Hybrid Diabetes Prediction Model. *Frontiers in Public Health*, *10*, Article ID: 829519. https://doi.org/10.3389/fpubh.2022.829519

Grant, P. J., & Marx, N. (2020). Diabetes and Cardiovascular Disease: It's Time to Apply the Evidence. *European Heart Journal. Acute Cardiovascular Care*, *9*(6), 586–588. https://doi.org/10.1177/2048872620952722

Hasan, Md. K., Alam, Md. 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

Herder, C., & Roden, M. (2022). A Novel Diabetes Typology: Towards Precision Diabetology from Pathogenesis to Treatment. *Diabetologia*, *65*(11), 1770–1781. https://doi.org/10.1007/s00125-021-05625-x

Kalia, S., Saarela, O., Chen, T., O'Neill, B., Meaney, C., Gronsbell, J., Sejdic, E., Escobar, M., Aliarzadeh, B., Moineddin, R., Pow, C., Sullivan, F., & Greiver, M. (2022). Marginal Structural Models Using Calibrated Weights with SuperLearner: Application to Type II Diabetes Cohort. *IEEE Journal of Biomedical and Health Informatics*, *26*(8), 4197–4206. https://doi.org/10.1109/JBHI.2022.3175862

Kwan, B., Fuhrer, T., Montemayor, D., Fink, J. C., He, J., Hsu, C., Messer, K., Nelson, R. G., Pu, M., Ricardo, A. C., Rincon-Choles, H., Shah, V. O., Ye, H., Zhang, J., Sharma, K., & Natarajan, L. (2023). A Generalized Covariate-Adjusted Top-Scoring Pair Algorithm with Applications to Diabetic Kidney Disease Stage Classification in the Chronic Renal Insufficiency Cohort (CRIC) Study. *BMC Bioinformatics*, *24*(1), Article ID: 57. https://doi.org/10.1186/s12859-023-05171-w

Li, Y., & Long, P. M. (2002). The Relaxed Online Maximum Margin Algorithm. *Machine Learning*, *46*(1–3), 361–387. https://doi.org/10.1023/A:1012435301888

Lin, X., Xu, Y., Pan, X., Xu, J., Ding, Y., Sun, X., Song, X., Ren, Y., & Shan, P.-F. (2020). Global, Regional, and National Burden and Trend of Diabetes in 195 Countries and Territories: An Analysis from 1990 to 2025. *Scientific Reports*, *10*(1), Article ID: 14790. https://doi.org/10.1038/s41598-020-71908-9

Metsker, O., Magoev, K., Yakovlev, A., Yanishevskiy, S., Kopanitsa, G., Kovalchuk, S., & Krzhizhanovskaya, V. V. (2020). Identification of Risk Factors for Patients with Diabetes: Diabetic Polyneuropathy Case Study. *BMC Medical Informatics and Decision Making*, *20*(1), Article ID: 201. https://doi.org/10.1186/s12911-020-01215-w

Mishra, S., Tripathy, H. K., Mallick, P. K., Bhoi, A. K., & Barsocchi, P. (2020). EAGA-MLP—An Enhanced and Adaptive Hybrid Classification Model for Diabetes Diagnosis. *Sensors*, *20*(14), Article ID: 4036. https://doi.org/10.3390/s20144036

Peeters, F., Rommes, S., Elen, B., Gerrits, N., Stalmans, I., Jacob, J., & De Boever, P. (2023). Artificial Intelligence Software for Diabetic Eye Screening: Diagnostic Performance and Impact of Stratification. *Journal of Clinical Medicine*, *12*(4), Article ID: 1408. https://doi.org/10.3390/jcm12041408

Phongying, M., & Hiriote, S. (2023). Diabetes Classification Using Machine Learning Techniques. *Computation*, *11*(5), Article ID: 96. https://doi.org/10.3390/computation11050096

Rabie, O., Alghazzawi, D., Asghar, J., Saddozai, F. K., & Asghar, M. Z. (2022). A Decision Support System for Diagnosing Diabetes Using Deep Neural Network. *Frontiers in Public Health*, *10*, Article ID: 861062. https://doi.org/10.3389/fpubh.2022.861062

Redondo, M. J., & Balasubramanyam, A. (2021). Toward an Improved Classification of Type 2 Diabetes: Lessons from Research Into the Heterogeneity of a Complex Disease. *The Journal of Clinical Endocrinology & Metabolism*, *106*(12), e4822–e4833. https://doi.org/10.1210/clinem/dgab545

Rezaei, F., Abbasitabar, M., Mirzaei, S., Kamari Direh, Z., Ahmadi, S., Azizi, Z., & Danialy, D. (2022). Improve Data Classification Performance in Diagnosing Diabetes Using the Binary Exchange Market Algorithm. *Journal of Big Data*, *9*(1), Article ID: 43. https://doi.org/10.1186/s40537-022-00598-z

Sadeghi, S., Khalili, D., Ramezankhani, A., Mansournia, M. A., & Parsaeian, M. (2022). Diabetes Mellitus Risk Prediction in the Presence of Class Imbalance Using Flexible Machine Learning Methods. *BMC Medical Informatics and Decision Making*, *22*(1), Article ID: 36. https://doi.org/10.1186/s12911-022-01775-z

Sisodia, D., & Sisodia, D. S. (2018). Prediction of Diabetes Using Classification Algorithms. *Procedia Computer Science*, *132*, 1578–1585. https://doi.org/10.1016/j.procs.2018.05.122

Torkey, H., Ibrahim, E., Hemdan, E. E.-D., El-Sayed, A., & Shouman, M. A. (2022). Diabetes Classification Application with Efficient Missing and Outliers Data Handling Algorithms. *Complex & Intelligent Systems*, *8*(1), 237–253. https://doi.org/10.1007/s40747-021-00349-2

Wang, X., Zhai, M., Ren, Z., Ren, H., Li, M., Quan, D., Chen, L., & Qiu, L. (2021). Exploratory Study on Classification of Diabetes Mellitus Through a Combined Random Forest Classifier. *BMC Medical Informatics and Decision Making*, *21*(1), Article ID: 105. https://doi.org/10.1186/s12911-021-01471-4

Weerahandi, H. M., Horwitz, L. I., & Blecker, S. B. (2020). Diabetes Phenotyping Using the Electronic Health Record. *Journal of General Internal Medicine*, *35*(12), 3716–3718. https://doi.org/10.1007/s11606-020-06231-0

Wichmann, R. M., Fernandes, F. T., Chiavegatto Filho, A. D. P., Ciconelle, A. C. M., de Brito, A. M. E. S., Nunes, B. P., Silva, D. L. e, Anschau, F., de Castro Rodrigues, H., Rocha, H. A. L., dos Reis, J. C. B., de Oliveira Cavalcante, L., de Oliveira, L. P., dos Santos Andrade, L. S., Nasi, L. A., de Maria Felix, M., Mimica, M. J., de Almeida Araujo, M. E., Arnoni, M. V., … Nuno, V. L. eSant'ana. (2023). Improving the Performance of Machine Learning Algorithms for Health Outcomes Predictions in Multicentric Cohorts. *Scientific Reports*, *13*(1), Article ID: 1022. https://doi.org/10.1038/s41598-022-26467-6

Zee, B., Lee, J., Lai, M., Chee, P., Rafferty, J., Thomas, R., & Owens, D. (2022). Digital Solution for Detection of Undiagnosed Diabetes Using Machine Learning-Based Retinal Image Analysis. *BMJ Open Diabetes Research & Care*, *10*(6), Article ID: e002914. https://doi.org/10.1136/bmjdrc-2022-002914

Zheng, Y., Ley, S. H., & Hu, F. B. (2018). Global Aetiology and Epidemiology of Type 2 Diabetes Mellitus and Its Complications. *Nature Reviews Endocrinology*, *14*(2), 88–98. https://doi.org/10.1038/nrendo.2017.151

Zhou, H., Myrzashova, R., & Zheng, R. (2020). Diabetes Prediction Model Based on an Enhanced Deep Neural Network. *EURASIP Journal on Wireless Communications and Networking*, *2020*(1), Article ID: 148. https://doi.org/10.1186/s13638-020-01765-7

Zhou, L., Zheng, X., Yang, D., Wang, Y., Bai, X., & Ye, X. (2021). Application of Multi-Label Classification Models for the Diagnosis of Diabetic Complications. *BMC Medical Informatics and Decision Making*, *21*(1), Article ID: 182. https://doi.org/10.1186/s12911-021-01525-7