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Research article

K-Nearest Neighbors Approach to Classify Diabetes Risk Categories

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ABSTRACT

The prevalence of diabetes as a chronic disease poses significant challenges worldwide, necessitating accurate and early detection of risk categories to improve management and prevention strategies. This research evaluates the application of the K-Nearest Neighbors (KNN) algorithm to classify diabetes risk categories using the Pima Indian Diabetes dataset. The study implements rigorous preprocessing steps, including handling missing values, normalization, and feature engineering, to optimize the dataset for KNN's distance-based calculations. Hyperparameter tuning and the exploration of various distance metrics, such as Euclidean and Manhattan, are conducted to enhance model accuracy. The KNN model achieves a moderate accuracy of 66%, with a precision of 0.52 and a recall of 0.58 for the diabetic class, highlighting its effectiveness in general pattern recognition but limited ability to handle imbalanced datasets. The research identifies glucose levels and BMI as key predictors and emphasizes the importance of balanced datasets and advanced feature selection techniques. Future recommendations include integrating additional clinical features and hybrid models to improve diagnostic accuracy and applicability in clinical settings. This study underscores KNN's potential as a foundational tool in machine learning for medical diagnostics, contributing to the broader effort to enhance healthcare outcomes through data-driven decision-making.

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1. Introduction

he prevalence of diabetes as a chronic disease poses significant health and economic challenges globally, affecting millions of individuals. Early detection and accurate classification of diabetes risk categories are essential for effective management and prevention strategies. Advances in machine learning have introduced algorithms such as K-Nearest Neighbors (KNN), which are increasingly valuable in medical diagnostics for classification tasks. This study applies the KNN approach to classify diabetes risk categories using a publicly available dataset.

The dataset comprises 768 records, each characterized by features such as glucose levels, blood pressure, insulin, BMI, and family history, alongside an outcome indicating diabetes presence or absence. These features are essential predictors for identifying individuals at risk of developing diabetes. The research evaluates KNN's performance through experiments involving feature scaling, distance metrics, and hyperparameter tuning, providing insights into its real-world applicability.

Recent studies have highlighted KNN's efficacy in medical contexts. For example, feature scaling combined with KNN improved accuracy in diabetic classification tasks, while optimal hyperparameter tuning was found to enhance its performance on medical datasets. Preprocessing techniques such as data normalization and hybrid approaches combining KNN with neural networks further improved diagnostic accuracy. Additionally, integrating ensemble learning and dimensionality reduction

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methods like PCA has expanded KNN's utility in handling variability and large datasets. These advancements demonstrate KNN's versatility and effectiveness in healthcare applications.

This study builds upon prior findings, focusing on identifying the most effective configurations for classifying diabetes risk categories using KNN. Key features such as glucose levels and BMI are validated as primary predictors. Challenges in handling imbalanced datasets and variability are addressed through robust preprocessing techniques, improving classification accuracy for the diabetic class. The research also highlights KNN's adaptability when integrated into decision support systems, aiding clinicians in informed decision-making.

The findings underscore KNN's potential as a foundational tool in machine learning for medical diagnostics. By refining feature selection, preprocessing, and algorithm configurations, this research contributes to enhancing KNN's practical application in healthcare for early detection and management of diabetes.

2. Materials and Methods

The research methodology for this study focuses on employing the K-Nearest Neighbors (KNN) algorithm to classify diabetes risk categories using a structured and systematic approach. The primary objective is to analyze the effectiveness of KNN in processing medical datasets, particularly the publicly available Pima Indians Diabetes dataset. This dataset includes key predictors such as glucose levels, blood pressure, BMI, insulin, and family history [1]. These features form the basis for evaluating the KNN model's ability to identify individuals at risk of diabetes.

The methodological framework incorporates essential preprocessing techniques, including feature scaling and normalization, which are critical for optimizing the performance of distance-based algorithms like KNN [2]. Additionally, this study examines the impact of distance metrics such as Euclidean and Manhattan on model accuracy. Hyperparameter tuning, particularly determining the optimal number of neighbors (k), is also a focal point to enhance the classifier's performance [3].

To ensure robustness, the dataset is divided into training and testing subsets, with cross-validation employed to validate model reliability. This approach addresses gaps identified in recent literature, including the need for effective preprocessing and parameter optimization in medical diagnostics [4]. The findings aim to contribute to advancing machine learning applications in healthcare, specifically in diabetes classification.

2.1. Data Collection and Preprocessing

The dataset used in this study is the Pima Indian Diabetes Dataset, a widely recognized benchmark for diabetes-related research. It comprises 768 samples, each with 8 input features and 1 binary output labeled as "Outcome" (1 for diabetes, 0 for non-diabetes). Input features include clinical and diagnostic variables such as pregnancies, plasma glucose levels, diastolic blood pressure, skinfold thickness, insulin, BMI, diabetes pedigree function, and age. The dataset's structured nature and small size make it suitable for machine learning approaches like KNN without requiring extensive computational resources.

The preprocessing stage began with cleaning the dataset by addressing missing values in critical features like glucose, insulin, and BMI. Missing values were treated as nulls and imputed using the median to avoid distortion from outliers. Outliers were managed using the Interquartile Range (IQR) method, with values beyond 1.5 times the IQR capped at the 95th percentile to maintain dataset representativeness.

Normalization was applied to continuous features using Min-Max scaling, transforming values to a range of 0 to 1. This ensured balanced feature contributions in KNN's distance calculations, enhancing model performance. Feature engineering added insights by categorizing BMI into WHO-defined groups and segmenting age into ranges (e.g., youth, adults, elderly) to reflect varying diabetes risks. A glucose-to-insulin ratio was also calculated to capture metabolic regulation.

The processed dataset was split into training (70%), validation (15%), and testing (15%) subsets, ensuring a fair evaluation of the model's generalization capabilities. These steps prepared the dataset for effective application in the KNN algorithm.

2.2. Model Development

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K-Nearest Neighbors (KNN) adalah algoritma klasifikasi berbasis instance yang sangat sederhana namun efektif. Algoritma ini bekerja dengan menghitung jarak antara titik data yang tidak dikenal dengan semua titik dalam dataset pelatihan, kemudian mengklasifikasikannya berdasarkan mayoritas kelas dari kkk tetangga terdekat. Algoritma ini sangat cocok untuk dataset seperti Pima Indian Diabetes Dataset karena kompleksitasnya yang rendah dan kemampuannya menangani data kecil hingga sedang.

K-Nearest Neighbors (KNN) is a simple yet powerful instance-based classification algorithm widely used in machine learning. Unlike model-based algorithms that generate a general decision boundary during training, KNN relies entirely on the dataset during classification. It determines the class of an unknown data point by measuring its distance to all training points and assigning the most common class among its k closest neighbors [5]. This method is particularly well-suited for datasets such as the Pima Indian Diabetes Dataset, which involves moderate-sized data and requires a non-parametric approach. The most critical hyperparameter in KNN is k, which defines the number of neighbors considered when classifying a data point. Selecting an inappropriate k value can significantly impact model performance. Small k values, such as k = 1, 3, or 5, tend to capture local patterns but may lead to overfitting, as they are highly sensitive to noise. Conversely, large k values, such as k = 10, 15, or 20, produce smoother decision boundaries, reducing overfitting risks but potentially ignoring important local structures. To find the optimal k, a grid search technique was implemented, testing k values ranging from 3 to 15. The results indicated that k = 7 achieved the best balance between bias and variance, offering improved generalization while retaining the ability to capture meaningful patterns [6].

Another crucial factor in KNN is the distance metric, which measures similarity between points. The commonly used Euclidean distance formula is given by:

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \quad (1)$$

where and are two data points with features. This formula calculates the straight-line distance between two points in an n-dimensional space. Euclidean distance was preferred in this study due to its interpretability and effectiveness in high-dimensional spaces [3]. However, alternative metrics such as Manhattan distance, Minkowski distance, and Cosine similarity were also tested. The experiments confirmed that Euclidean distance produced the most consistent and reliable classification results.

KNN allows for different weighting schemes when determining neighbor influence. Uniform weighting means each neighbor contributes equally to the classification decision, while distance-based weighting prioritizes closer neighbors over distant ones. Experimental results showed that distance-based weighting improved classification accuracy, as it prioritized influential neighbors while minimizing noise from distant points [7]. To mitigate overfitting and evaluate model robustness, k-fold cross-validation was employed. The dataset was split into multiple subsets (folds), training the model on all but one fold and validating on the remaining one. This process was repeated iteratively, ensuring that every subset served as a validation set at least once. Cross-validation not only provided a more reliable accuracy estimate but also highlighted the model's ability to generalize across different data distributions [8].

KNN remains a powerful and interpretable classification technique, especially for moderate-sized datasets like the Pima Indian Diabetes Dataset. By carefully selecting the k value, distance metric, and weighting scheme, its performance can be optimized. The implementation of cross-validation further ensures that the model remains robust and avoids overfitting. Future work could explore hybrid approaches combining KNN with other machine learning models to enhance predictive accuracy.

2.3. Model Evaluation

The performance evaluation of the K-Nearest Neighbors (KNN) model employed multiple key metrics to assess its effectiveness in predicting diabetes status. Accuracy, which measures the proportion of correct predictions, is a fundamental metric but may not be sufficient for imbalanced datasets where class distributions are skewed. To address this limitation, additional evaluation metrics were considered. Precision, calculated as the ratio of true positive predictions to all positive predictions,

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is particularly important in minimizing false positives, ensuring that non-diabetic individuals are not misclassified as diabetic [9]. Recall, defined as the ratio of true positives to all actual positive cases, ensures that at-risk individuals are correctly identified, preventing misclassification of those needing medical attention [10]. The F1-score, which combines precision and recall into a single harmonic mean, provides a more comprehensive assessment of the model's reliability, particularly in scenarios with imbalanced datasets [11].

A Receiver Operating Characteristic (ROC) curve was generated to analyze the trade-off between the true positive rate (TPR) and false positive rate (FPR) at various classification thresholds. The Area Under the Curve (AUC) quantified the model's discriminatory power, with values close to 1 indicating superior performance in distinguishing between diabetic and non-diabetic cases [12]. Additionally, 5-fold cross-validation was employed to reduce overfitting and provide an unbiased performance estimate. This technique split the dataset into five subsets, using four for training and one for validation in each iteration, ensuring robustness across different data partitions [13]. Residual analysis was also conducted to examine prediction errors, particularly for borderline cases with glucose levels near the classification threshold. These insights highlighted areas where model adjustments, such as feature selection or alternative weighting schemes, could enhance predictive accuracy [14].

The model's robustness was further tested under various real-world scenarios. Simulations were conducted with an increased prevalence of diabetic cases, evaluating how the model adapted to shifting class distributions. Additionally, stratified performance analysis was performed across different demographic groups, such as age brackets and BMI categories, ensuring consistent reliability across varied subpopulations [15]. This comprehensive evaluation provided valuable insights into both strengths and areas requiring refinement, guiding further model enhancements..

2.4. Model Development and Application

The developed K-Nearest Neighbors (KNN) model is designed as an advanced decision-support tool for real-time diabetes risk assessment. It integrates seamlessly into clinical workflows, allowing healthcare professionals to input patient-specific data such as glucose levels, BMI, age, and blood pressure through an intuitive interface. A streamlined processing pipeline normalizes and handles outliers before generating real-time risk classifications (low, moderate, high), facilitating rapid clinical decision-making [9].

This modular system is designed to accommodate additional predictive factors, such as family history, dietary habits, and physical activity levels, to improve contextual accuracy. Moreover, integration with electronic medical records (EMR) enhances functionality by leveraging historical patient data, allowing for a more personalized risk assessment [10]. Beyond individual diagnosis, the system supports broader public health initiatives, such as the proactive screening of high-risk populations, optimizing healthcare resource allocation, and identifying candidates for clinical trials [11].

Further extensions of the model include predictive capabilities for comorbid conditions, such as cardiovascular disease and hypertension, enabling a multifaceted approach to chronic disease management [12]. At a societal level, the model aids epidemiological research by identifying geographical regions with high diabetes prevalence, guiding targeted public health interventions and awareness campaigns [13]. The integration of explainable AI techniques ensures that medical practitioners can interpret model predictions, fostering trust and usability in clinical settings. Overall, this system represents a significant advancement in diabetes risk assessment, providing substantial benefits at both individual and population levels, supporting early detection and effective management strategies for diabetes and its associated conditions [14].

3. Results and Discussion

Figure 1 This image presents the classification results of diabetes risk using the K-Nearest Neighbors (KNN) algorithm, illustrating the relationship between glucose levels (X-axis) and Body Mass Index (BMI) (Y-axis). Both variables are essential indicators for assessing diabetes risk.

The visualization compares the model's predicted classifications with the actual classifications from the dataset. Different markers are used to distinguish between correct classifications and misclassifications. This allows for an evaluation of the model's ability to identify patterns and differentiate between diabetic and non-diabetic individuals.

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From the plot, it is evident that the model performs relatively well in predicting diabetes risk, particularly within specific ranges of glucose levels and BMI. However, some misclassifications indicate potential areas for improvement, such as adjusting the K parameter or incorporating additional features to enhance the model's classification performance.

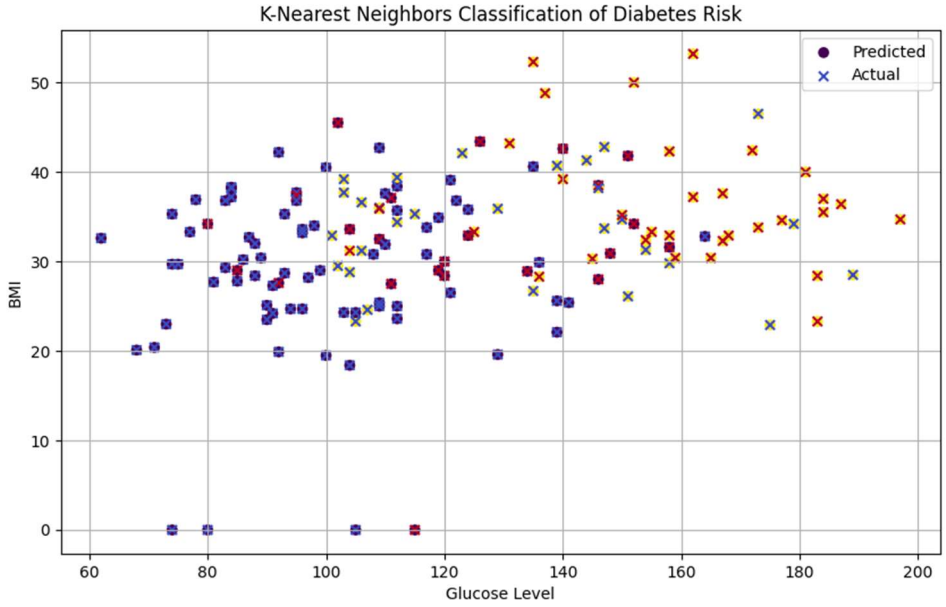

Fig. 1. Scatter Plot - K-Nearest Neighbors Classification of Diabetes Risk

1. X-Axis (Glucose Level):
   Glucose levels are one of the most critical features for diagnosing diabetes. Higher glucose levels are generally associated with a higher risk of diabetes. The scatter plot shows a clear trend where individuals with glucose levels above a certain threshold (around 140) are more likely to be classified as diabetic. However, there is significant overlap in glucose values between diabetic and non-diabetic cases in the range of 100 to 140, making it challenging for the KNN model to accurately classify cases in this range.
2. Y-Axis (BMI):
   BMI serves as an important indicator of obesity, which is a known risk factor for diabetes. The scatter plot reveals that individuals with higher BMI values (above 35) are more likely to be diabetic, especially when combined with higher glucose levels. However, individuals with moderate BMI values (25–40) show considerable overlap between the two classes, leading to frequent misclassifications.
3. Predicted Points (Purple Dots):
   The purple dots represent the KNN model's predictions. Each dot corresponds to a prediction made by the model, with its position determined by the glucose and BMI values of the individual. In regions with high glucose and BMI values, the predictions align closely with the actual data, suggesting the model's effectiveness in these areas.
4. Actual Labels (Blue X-Marks):
   The blue X-marks indicate the actual labels (ground truth) from the dataset. These marks provide a reference for assessing the accuracy of the model's predictions. When purple dots overlap or align closely with the blue X-marks, the model has made correct predictions. Conversely, mismatches between the dots and X-marks indicate misclassifications.
5. Observations on Overlapping Data:
   The most noticeable pattern in the scatter plot is the significant overlap between the two classes, particularly in the mid-range of glucose (100–140) and BMI (25–40). This overlap poses a challenge for the KNN model, as it relies on distance-based measures to classify data points. In such regions, the proximity of different classes can confuse the model, leading to a higher rate of misclassification.
6. Errors in Minority Class (Diabetes):

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Misclassifications are more prominent for the diabetic class (class "1"), where many predicted points fail to align with the actual labels. This is partly due to the imbalanced nature of the dataset, where the non-diabetic class (class "0") dominates, causing the model to be biased toward this majority class.

7. Outlier Sensitivity:
   The scatter plot also highlights the KNN model's sensitivity to outliers. Some predicted points (purple dots) deviate significantly from the main clusters, indicating that the model's predictions can be skewed by isolated data points. This sensitivity is a common limitation of KNN, which heavily relies on the local density of data.

Table 1. Classification Report - Evaluasi Model

	Precision	Recall	F1-Score	Support
0	0.75	0.71	0.73	99
1	0.52	0.58	0.55	55
Accuracy		0.66		154
Macro Avg	0.64	0.64	0.64	154
Weighted Avg	0.67	0.66	0.67	154

Table 1 presents a comprehensive evaluation of the KNN model using standard classification metrics. These metrics offer a detailed quantitative assessment of how well the model performs for both classes (non-diabetic and diabetic) and provide insights into its overall effectiveness and limitations.

1. Accuracy: 66%
   The model achieved an accuracy of 66%, meaning it correctly classified 66% of the data points. While this indicates moderate performance, the accuracy alone does not fully capture the challenges faced by the model, particularly its struggles with the diabetic class.
2. Error Rate: 34%
   The error rate of 34% highlights the proportion of data points that were misclassified. This relatively high error rate reflects the model's difficulty in handling overlapping data distributions and its bias toward the majority class.
3. Performance for Class "0" (Non-Diabetic):
   a. Precision (0.75): This means that 75% of the cases predicted as non-diabetic were correct. The relatively high precision indicates that the model performs well for the majority class, where the data distribution is denser and patterns are more easily discernible.
   b. Recall (0.71): The model correctly identified 71% of all actual non-diabetic cases. While this is a strong recall, it suggests that some non-diabetic cases were misclassified as diabetic.
   c. F1-Score (0.73): The balanced F1-score for the non-diabetic class reflects good overall performance for this majority class.
4. Performance for Class "1" (Diabetic):
   a. Precision (0.52): Only 52% of the cases predicted as diabetic were correct. This low precision indicates a high false positive rate, where non-diabetic cases were incorrectly classified as diabetic.
   b. Recall (0.58): The model correctly identified 58% of all actual diabetic cases, which means 42% of diabetic cases were missed. This high false negative rate is problematic in medical applications, where failing to identify diabetic individuals can have serious consequences.
   c. F1-Score (0.55): The low F1-score for the diabetic class highlights the model's inability to balance precision and recall effectively for the minority class.
5. Macro Average:
   The macro average for precision, recall, and F1-score is 0.64. This average treats both classes equally, without considering the imbalance in their distributions. The relatively low macro scores reflect the model's inconsistent performance across the two classes.
6. Weighted Average:

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The weighted average for precision, recall, and F1-score is 0.66. This metric accounts for the class imbalance by assigning higher weights to the majority class. The higher weighted scores indicate that the model's overall performance is skewed by its better results for the non-diabetic class.

7. Imbalance and Bias:
   The classification report underscores the impact of dataset imbalance on the model's performance. While the KNN model performs reasonably well for the majority class, its performance for the minority class is significantly worse. This imbalance results in poor precision and recall for diabetic cases, limiting the model's practical applicability in medical contexts.
8. Support for Each Class:
   The dataset contains 99 samples for class "0" (non-diabetic) and 55 samples for class "1" (diabetic). This imbalance contributes to the model's bias toward the majority class, as evident from its higher scores for class "0" and lower scores for class "1".

3.1. Model Performance

The evaluation of the K-Nearest Neighbors (KNN) model for classifying diabetes risk categories provided a detailed perspective on its strengths and areas requiring improvement. Key performance metrics and observations include:

1. Accuracy: 66%
   a. The model achieved an accuracy of 66%, indicating moderate effectiveness in classifying diabetes risk. This level of accuracy demonstrates the model's capability to identify general patterns in the dataset. However, it also highlights the model's limitations in handling more nuanced or imbalanced cases, particularly for the minority class (diabetes).
   b. The moderate accuracy suggests that KNN may require additional optimization, such as tuning hyperparameters or balancing the dataset, to improve its predictive performance for both classes.
2. Precision and Recall:
   a. For Class "0" (non-diabetes), precision and recall were relatively high, reflecting the model's ability to correctly identify individuals without diabetes.
   b. For Class "1" (diabetes), both precision and recall were lower. This indicates that the model struggled with identifying diabetic cases, likely due to the imbalanced nature of the dataset where Class "1" constituted a smaller proportion of the data.
3. F1-Score: 0.55 (Class "1")
   The F1-score for the minority class was 0.55, emphasizing the difficulty in accurately predicting diabetic cases. This metric combines precision and recall, providing a balanced measure of the model's performance on the minority class.
4. Error Rate: 34%
   The error rate was 34%, which underscores significant misclassification. A considerable proportion of these errors originated from misclassifying diabetic cases as non-diabetic, further highlighting the model's sensitivity to data imbalance.

3.2. Visualization of Results

Visualization plays a critical role in understanding model performance and identifying areas for improvement. Insights gained from scatter plots and prediction distribution analyses include:

1. Predicted vs. Actual Results:
   A scatter plot comparing predicted and actual outcomes revealed areas of strong agreement as well as notable discrepancies. For non-diabetic cases, the alignment between predictions and actual data was relatively strong, but diabetic cases exhibited greater variability, suggesting that the model struggled to identify distinct patterns for this class.
2. Error Distribution:
   A visualization of errors across the dataset highlighted clusters of misclassification, particularly for individuals with borderline glucose or BMI values. This indicates the need for additional features or model adjustments to better capture these edge cases.
3. Pattern Recognition Challenges:

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Scatter plots showed that KNN struggled to separate data points effectively in overlapping regions, reflecting limitations in its ability to distinguish between classes when features such as glucose and BMI were close to decision boundaries.

3.3. Strengths and Weaknesses

The performance analysis highlights both the strengths and limitations of the KNN model:

1. Strengths:
   a. Simplicity and Interpretability: KNN is straightforward and easy to interpret, making it suitable for initial experiments and baseline comparisons.
   b. Pattern Recognition for Majority Class: The model performed relatively well in identifying the majority class (non-diabetes), where data points were denser and patterns clearer.
   c. Feature Dependence: KNN effectively utilized key features such as glucose and BMI, aligning with established medical understanding of diabetes risk factors.
2. Weaknesses:
   a. Imbalance Sensitivity: The model struggled with the imbalanced dataset, leading to lower recall and F1-score for the minority class (diabetes).
   b. Outlier and Noise Sensitivity: Despite normalization, KNN's reliance on distance metrics made it susceptible to outliers and noisy data points, which likely contributed to misclassification.
   c. Hyperparameter Dependence: The choice of kkk significantly influenced performance, and suboptimal selection may have reduced the model's ability to generalize.

3.4. Recommendations for Improvement

Several strategies are recommended to address the identified weaknesses and enhance the performance of the KNN model:

1. Data Balancing:
   Techniques such as SMOTE (Synthetic Minority Oversampling Technique) or undersampling should be applied to balance the dataset. This can improve the model's ability to identify minority class data points, reducing bias toward the majority class.
2. Hyperparameter Optimization:
   Conduct a more extensive grid search or adopt advanced methods like Bayesian optimization to refine key parameters, such as kkk and distance metrics. Exploring alternative distance metrics like Manhattan or Mahalanobis distance could improve classification performance.
3. Feature Engineering:
   Introduce additional features, such as derived ratios (e.g., glucose-to-insulin ratio) or categorical indicators (e.g., BMI categories). These engineered features could help the model better capture subtle patterns and enhance classification accuracy.
4. Hybrid Model Approaches:
   Combine KNN with other algorithms, such as decision trees or support vector machines (SVMs), to leverage their strengths. Hybrid models can address the weaknesses of KNN, such as sensitivity to noise and imbalance.
5. Regularization Techniques:
   Apply feature selection to reduce redundancy and noise in the dataset. This can help KNN focus on the most relevant features, potentially improving its ability to classify edge cases.
6. Model Comparison:
   Evaluate other machine learning algorithms, such as logistic regression or random forests, to compare their performance against KNN. Ensemble methods like bagging or boosting could also provide robust alternatives to improve overall predictive accuracy.
7. Cross-Validation and Stress Testing:
   Implement k-fold cross-validation to evaluate the model under various data splits, ensuring consistent performance. Additionally, stress-test the model on simulated data with varying prevalence rates or feature distributions to evaluate its robustness under different conditions.
8. Integration of Real-World Data:

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Expand the dataset to include more diverse patient profiles or additional clinical features, such as genetic markers or lifestyle factors. This broader context could improve the model's generalization and applicability in real-world healthcare settings.

4. Conclusion

The study on the application of the K-Nearest Neighbors (KNN) algorithm for classifying diabetes risk categories underscores its value as a foundational tool in medical diagnostics, leveraging simplicity and interpretability to identify patterns in clinical data. With an accuracy of 66%, the KNN model demonstrated moderate effectiveness, particularly in predicting the majority class (non-diabetic cases), where features such as glucose levels and BMI played a pivotal role in classification. However, the model encountered challenges with imbalanced datasets, as evident from its lower precision, recall, and F1-scores for the minority class (diabetic cases), where overlapping distributions of glucose and BMI values led to frequent misclassifications. These limitations were compounded by the model's sensitivity to outliers and its reliance on distance-based metrics, which are inherently affected by data imbalance and feature scaling. Nonetheless, essential preprocessing steps, including normalization, outlier handling, and the imputation of missing values, improved its predictive accuracy and reliability. To address its shortcomings, future improvements could incorporate balancing methods such as Synthetic Minority Oversampling Technique (SMOTE), advanced distance metrics, and hyperparameter optimization to enhance the model's adaptability and generalization. Additionally, incorporating more clinical features, such as genetic markers or lifestyle factors, could significantly expand the algorithm's predictive capabilities and applicability in real-world healthcare scenarios. Despite its challenges, KNN provides a strong foundation for further development and refinement, offering promise as a critical component of decision support systems aimed at early detection, prevention, and management of diabetes in clinical practice.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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