Classification of Heart Disease Based on Clinical Data Using the K-Nearest Neighbor Method

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ABSTRACT

Heart disease continues to be a major cause of mortality worldwide, highlighting the importance of developing reliable methods for early diagnosis. This study focuses on classifying heart disease using clinical patient data through the K-Nearest Neighbour (KNN) algorithm. The dataset, sourced from Kaggle, contains several clinical features, including age, gender, blood pressure, cholesterol level, maximum heart rate, and other relevant medical indicators, and is divided into five classes. The methodology involves data preprocessing, missing value treatment, categorical data encoding, feature scaling using Standard Scaler, and splitting the dataset into training and testing subsets with an 80:20 ratio. The classification is carried out using KNN with a parameter value of K = 7. Model performance is assessed using a confusion matrix and evaluation metrics such as precision, recall, F1-score, and accuracy. The experimental results show an accuracy of 57%, where the model performs well on the dominant class but shows limited performance on minority classes. The macro-average F1-score of 0.25 indicates weak generalization capability, mainly caused by class imbalance and similarities in clinical features among classes. These results suggest that KNN, in its current implementation, is not sufficiently robust for multi-class heart disease classification. Future improvements should consider incorporating data balancing techniques, optimizing hyperparameters, and comparing multiple machine learning models to obtain more reliable and generalizable outcomes.

I. Introduction

Heart disease refers to disorders affecting the cardiovascular system that may result in severe complications or even mortality if not properly managed [1]. In clinical practice, diagnosis is typically conducted through medical examinations and relies heavily on physicians' experience; however, this approach can be time-consuming and may lead to potential inaccuracies [2]. With the rapid development of information technology, particularly in machine learning, clinical data can now be utilized to support a more structured and data-driven diagnostic process [3]. Previous studies indicate that heart disease is more prevalent among middle-aged and older populations, especially individuals over the age of 40 [4]. Furthermore, the incidence of heart disease has been reported to be higher in males compared to females [5]. These findings emphasize the importance of leveraging clinical attributes to enhance early detection and classification of heart disease.

Various studies have implemented the K-Nearest Neighbour (KNN) algorithm for heart disease classification due to its simplicity and effectiveness in identifying patterns based on data similarity. Nevertheless, many of these studies still lack comprehensive analytical evaluation and do not clearly define research gaps or provide comparisons with alternative methods [6], [7].

Therefore, a more systematic approach is required, not only in applying the KNN method but also in strengthening the analytical aspects of the study. Based on this rationale, this research aims to classify heart disease using patients' clinical data by employing the K-Nearest Neighbor algorithm and utilizing a dataset obtained from Kaggle. In addition, this study seeks to provide a more structured analysis to improve the reliability and interpretation of the results.

Table 1. Clinical data of heart disease patients

No	1	2	3	4	5
Age	63	67	67	37	41
Sex	Male	Male	Male	Male	Female
Chest Pain (cp)	Typical Angina	Asymptomatic	Asymptomatic	Non-anginal	Atypical Angina
Trestbps	145	160	120	130	130
Chol	233	286	229	250	204
FBS	TRUE	FALSE	FALSE	FALSE	FALSE
RestECG	LV Hypertrophy	LV Hypertrophy	LV Hypertrophy	Normal	LV Hypertrophy
Thalach	150	108	129	187	172
Exang	FALSE	TRUE	TRUE	FALSE	FALSE
Oldpeak	2.3	1.5	2.6	3.5	1.4
Slope	Downsloping	Flat	Flat	Downsloping	Upsloping
CA	0	3	2	0	0
Thal	Fixed Defect	Normal	Reversible Defect	Normal	Normal
Num	0	2	1	0	0

Table 1. Presents a subset of patients' clinical data, including attributes such as age, gender, blood pressure, cholesterol levels, and other parameters relevant to heart disease diagnosis. However, it should be emphasized that the table only reflects a limited portion of the dataset and does not capture its overall statistical distribution. Consequently, any interpretation derived from this table should be regarded as preliminary and descriptive rather than inferential.

To gain a more accurate understanding of the relationships among variables, more comprehensive statistical analyses are required, such as correlation analysis or feature importance assessment. These methods are important to ensure that the relationships between clinical attributes (e.g., cholesterol, *thalach*, and *CA*) and heart disease conditions are supported by quantitative evidence rather than limited observations [6], [7].

Thus, Table 1 functions as an initial representation of the dataset characteristics, while more in-depth analysis is conducted on the complete dataset using the K-Nearest Neighbor method to obtain more accurate and reliable classification results.

II. The Proposed Method/Algorithm

This study applies a machine learning–based approach to classify heart disease using patients' clinical data. The dataset utilized in this research is sourced from Kaggle (*Heart Disease Dataset*), which includes various clinical features such as age, gender, blood pressure, cholesterol levels, maximum heart rate, and other relevant medical attributes [6].

An exploratory analysis is first performed to examine the dataset characteristics, including the total number of samples and class distribution, as well as to detect potential class imbalance that may influence model performance.

During the preprocessing phase, missing values are identified and handled appropriately [7], [8]. Followed by the conversion of categorical variables into numerical form using encoding techniques. The data are then scaled using the *StandardScaler* method to ensure uniformity across features, as

KNN relies on distance calculations and is sensitive to variations in feature magnitude. After preprocessing, the dataset is split into training and testing subsets with a ratio of 80% and 20%, respectively. The training data are used to construct the model, while the testing data are used to assess its generalization ability [9].

To obtain more reliable evaluation results, methods such as k-fold cross-validation can be applied to reduce dependency on a single data split.The classification is carried out using the *K-Nearest Neighbor* (KNN) algorithm, where the class of a data instance is determined based on the majority class among its nearest neighbors in the feature space. In this study, the value of K is set to 7 as an initial parameter to balance between overfitting and underfitting. However, this selection is not yet optimized and should ideally be determined through hyperparameter tuning techniques, such as grid search or cross-validation. The distance between data points is calculated using Euclidean distance due to its simplicity, although other distance measures, such as Manhattan distance, may also be explored to improve model robustness [10].

The model is evaluated using the testing dataset with performance metrics including accuracy and confusion matrix. For a more comprehensive assessment, additional metrics such as precision, recall, and F1-score are also considered. Moreover, to enhance the validity of the results, it is important to compare the performance of KNN with other classification methods, such as Support Vector Machine (SVM) and Random Forest, in order to obtain a more objective evaluation of the proposed approach.

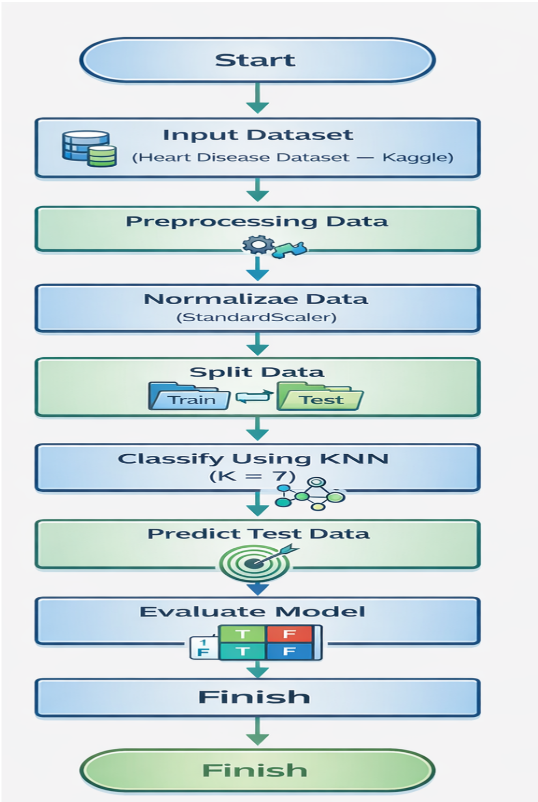

Figure 1. Research Flowchart

Figure 1. The illustration of the overall classification workflow, starting from dataset acquisition, followed by preprocessing, normalization, data splitting, classification using KNN (K = 7), and model evaluation. While the flowchart represents a standard machine learning pipeline, it remains relatively basic. Therefore, incorporating additional steps such as data distribution analysis, hyperparameter tuning, cross-validation, and model comparison would enhance the methodological rigor and scientific contribution of this study.

III. Results and Discussion

3.1 Discussion of the Data Preprocessing Stage

The initial analysis identified the presence of missing values in several clinical attributes, including *trestbps, chol, fbs, thalach, exang, oldpeak, slope, ca,* and *thal*, while other attributes were complete. The existence of missing values indicates potential data quality issues that may affect model performance if not properly handled. Therefore, preprocessing was applied to ensure data consistency prior to model training. However, beyond handling missing values, further analysis such as examining class distribution is necessary, as class imbalance can significantly influence classification outcomes.

3.2 Discussion of KNN Method Parameters

The classification process utilized the K-Nearest Neighbor algorithm with K = 7. While this value was selected as a compromise between sensitivity and stability, the choice was not supported by systematic validation such as hyperparameter tuning or cross-validation. Consequently, the selected K value may not represent the optimal configuration. A more rigorous approach is required to evaluate different K values and ensure that the model achieves optimal performance.

3.3 Confusion Matrix Results

The evaluation results of the KNN model are presented using a confusion matrix, which illustrates the distribution of correct and incorrect predictions for each heart disease class. Based on the confusion matrix, it can be observed that the model is able to classify class 0 (patients without heart disease) well, as indicated by a high number of correct predictions for this class. However, misclassifications still occur in the other classes, indicating similarities in clinical characteristics among different heart disease classes. The confusion matrix provides a detailed overview of the model's performance in distinguishing each class and ensures that the evaluation is not solely dependent on the overall accuracy value.

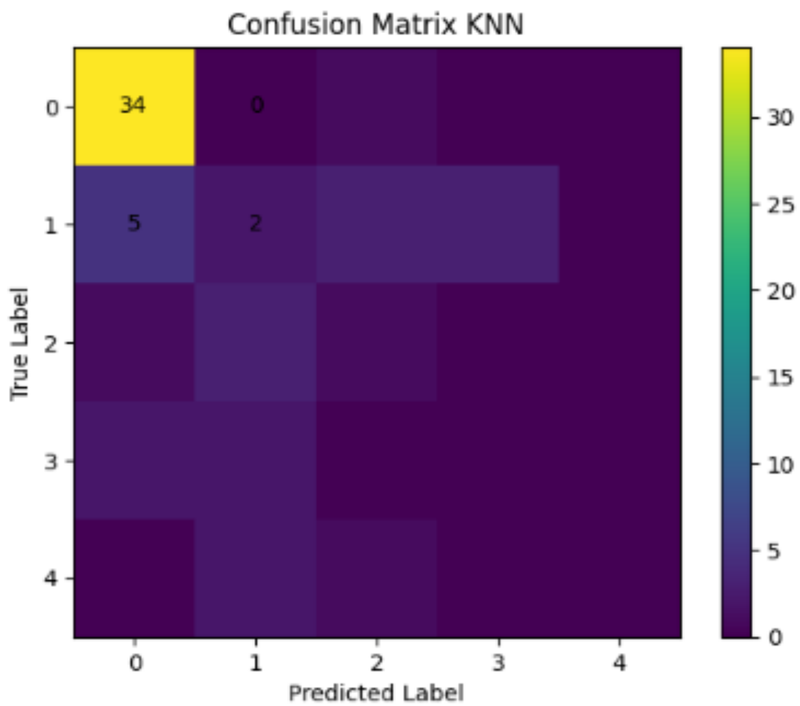

Fig 2. Confusion Matrix

Figure 2. The confusion matrix provides a detailed evaluation of the model's performance across all classes. The results indicate that the model performs relatively well in classifying class 0 (patients without heart disease), as shown by the high number of correct predictions. However, performance

in other classes (classes 1–4) is significantly lower, with substantial misclassification observed across these categories.

A critical observation is that certain classes, particularly higher severity levels, exhibit very low or near-zero predictive performance. This suggests that the model fails to generalize effectively across all classes. The overall accuracy of approximately 57% further confirms that the model performance is relatively low for a multi-class classification problem. In addition, the macro-average F1-score (0.25) indicates poor generalization, especially in handling minority classes.

The misclassification pattern reveals a strong bias toward the majority class (class 0), which is likely caused by class imbalance in the dataset. The model tends to predict samples as the dominant class, resulting in degraded performance for minority classes. This issue is not addressed in the current study, as no resampling techniques such as SMOTE or under sampling were applied.

Furthermore, the analysis remains limited due to the absence of statistical validation methods such as cross-validation or variance analysis. Without these evaluations, it is difficult to assess the stability and reliability of the model performance. Additionally, no comparison with baseline or alternative models (e.g., SVM or Random Forest) is provided, making it unclear whether KNN is an appropriate choice for this problem.

Overall, while the confusion matrix provides useful insight into prediction distribution, the results indicate that the KNN model, in its current configuration, is not sufficiently robust for multi-class heart disease classification. Future improvements should include handling class imbalance, conducting hyperparameter optimization, performing statistical validation, and comparing multiple models to obtain more reliable and generalizable results.

3.4 Discussion of Model Evaluation Results

To evaluate the performance of the K-Nearest Neighbor (KNN) model, several metrics were used, including precision, recall, F1-score, and accuracy. These metrics provide a comprehensive assessment of classification performance across all classes. The evaluation results are presented in Table 2.

Table 2. Model Evaluation Results

Kelas	Precision	Recall	F1-Score	Support
0	0.81	0.97	0.88	35
1	0.22	0.15	0.18	13
2	0.17	0.20	0.18	5
3	0.00	0.00	0.00	4
4	0.00	0.00	0.00	3
Accuracy			**0.57**	60
Macro Average	0.24	0.27	0.25	60
Weighted Average	0.53	0.62	0.57	60

Table 2. The model demonstrates highly uneven performance across different classes. The model achieves strong performance in class 0 (patients without heart disease), with a precision of 0.81, recall of 0.97, and F1-score of 0.88. This indicates that the model is highly effective in identifying the majority class. However, this performance is strongly influenced by the dominance of class 0 in the dataset (35 instances), which introduces bias toward this class.

In contrast, the performance for class 1 and class 2 is considerably lower, with F1-scores below 0.20. This indicates that the model struggles to correctly classify these classes, likely due to limited sample size and overlapping clinical characteristics. The issue becomes more critical in class 3 and class 4, where the model completely fails, as indicated by precision, recall, and F1-score values of 0.00. This means that all instances in these classes are misclassified, highlighting a severe limitation of the model.

The overall accuracy of 57% suggests that the model has limited effectiveness for multi-class classification. More importantly, the macro-average F1-score of 0.25 indicates poor generalization across all classes, especially for minority classes. While the weighted-average score appears higher (0.57), this is largely influenced by the dominance of the majority class and does not reflect balanced model performance.

These results clearly indicate that the model is significantly affected by class imbalance, as it tends to Favor the majority class while failing to capture patterns in minority classes. Despite this, the current study does not implement any data balancing techniques such as SMOTE or under sampling, which could potentially improve performance. In addition, no statistical validation (e.g., cross-validation) is conducted, making it difficult to assess the robustness of the results.

Furthermore, the study does not provide any comparison with baseline or alternative models, such as Support Vector Machine (SVM) or Random Forest. As a result, it cannot be concluded that KNN is an effective method for this problem without further comparative evaluation.

Overall, the findings indicate that while KNN performs well on the majority class, it fails to generalize across all classes and is not sufficiently reliable for multi-class heart disease classification in its current form. Future work should focus on addressing class imbalance, optimizing model parameters, applying statistical validation, and comparing multiple algorithms to achieve more robust and generalizable results.

IV. Conclusion

Based on the results of this study, the K-Nearest Neighbour (KNN) method was applied to classify heart disease using patients' clinical data through a workflow consisting of preprocessing, normalization, data splitting, and classification. The evaluation results show that the model performs well in classifying the majority class (patients without heart disease), as indicated by relatively high precision, recall, and F1-score values. However, the model demonstrates significantly lower performance on minority classes, with very low or zero scores in several categories. This indicates that the model is unable to generalize effectively across all classes. The overall accuracy of 57% and macro-average F1-score of 0.25 further confirm that the model's performance is limited, particularly in handling imbalanced multi-class data. These findings highlight several limitations of the study, including class imbalance, lack of hyperparameter optimization, absence of statistical validation, and no comparison with alternative models. Therefore, it cannot be concluded that KNN is an effective method for this problem without further investigation.

For future research, several improvements are recommended, including the application of data balancing techniques (e.g., SMOTE or under sampling), systematic hyperparameter optimization, feature selection, and the use of ensemble or alternative classification methods such as Support Vector Machine (SVM) and Random Forest. Additionally, incorporating cross-validation and more comprehensive evaluation metrics is necessary to obtain more reliable and generalizable results.

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