J. Intell. Comput. Health Inform. Vol. 5, No. 1, 2024
ISSN: 2715-6923 e-ISSN: 2721-9186, pp.35~42 | DOI: 10.26714/jichi.v5i1.11251

Enhancing Early Diagnosis of Heart Disease: A Comparative Study of K-NN and Naive Bayes Classifiers Using the UCI Heart Disease Dataset

Angga Aditya Permana*

Department of Informatics, Universitas Multimedia Nusantara, Jl. Scientia Boulevard, Curug Sangereng, Kec Kelapa Dua, Kab Tangerang, Banten, Indonesia
*Corresponding author: angga.permana@umn.ac.id

Arsanah

Department of Informatics Engineering, Universitas Muhammadiyah Tangerang, Jl. Perintis Kemerdekaan I/33, Cikokol Kota Tangerang, Banten, Indonesia

Article histroy :
Received: 05 JAN 2023
Accepted: 02 FEB 2024
Available online: 30 MAR 2024

Research article

Abstract: Heart disease remains a leading cause of mortality globally, necessitating accurate predictive models for early detection and intervention. This study conducted a detailed comparative analysis of the k-nearest neighbor (KNN) and naive bayes classifiers using the UCI Repository Heart Disease dataset to determine the most effective algorithm for heart disease prediction. Our results demonstrate that the proposed KNN outperforms naive bayes in terms of several key metrics: KNN achieved an accuracy of 91.25%, which surpasses naive bayes' accuracy of 88.75%. Additionally, KNN exhibited superior precision (92%), recall (90%), and an F1 score (91%) compared to naive bayes, which demonstrated precision of 89%, recall of 87%, and an F1 score of 88%. The findings of this study have substantial practical implications for medical data analysis. The high accuracy and reliability of the KNN algorithm make it a valuable tool for healthcare professionals in the early diagnosis of heart disease. Implementing KNN-based predictive models can enhance patient outcomes by timely and accurate detection of heart disease, facilitating early intervention, and reducing the risk of severe cardiac events. Moreover, the user-friendly interface of the proposed system streamlines the classification process, making it accessible for clinical use. Future research should explore the integration of additional machine learning algorithms and ensemble methods to further improve prediction accuracy. Developing real-time prediction systems integrated with electronic health records (EHR) could revolutionize patient monitoring and proactive healthcare management, ultimately contributing to better patient outcomes and more efficient healthcare delivery.

Keywords: HEART DISEASE PREDICTION; K-NEAREST NEIGHBOR; NAIVE BAYES; MACHINE LEARNING; MEDICAL DATA ANALYSIS; EARLY DIAGNOSIS; CLINICAL DECISION-MAKING

1. Introduction

Predicting heart disease accurately in healthcare is vital because of its high mortality rate. According to the World Health Organization (WHO), 17 million people die yearly because of cardiovascular diseases. Approximately 651,481 people in Indonesia die of heart disease annually (Kemenkes, 2014). Effective early detection and prevention can significantly improve patient outcomes and reduce disease numbers. Machine learning techniques enable early detection and diagnosis of heart disease. KNN (Shah et al., 2020) and naive bayes (Gupta et al., 2020) classifiers with the ability to analyze complex datasets and predict outcomes accurately have been widely researched and utilized in this domain. Continuous assessment of these algorithms is necessary to determine their optimal use for particular datasets and circumstances.

A significant gap exists in the literature regarding the identification of efficient and accurate algorithms for heart disease prediction using various machine learning techniques and datasets. This study bridged the performance comparison gap between the KNN and naive bayes classifiers on the UCI Heart Disease dataset. This study demonstrated the superiority of these heart disease prediction methods by evaluating their accuracy, precision, and recall. Heart disease, which involves narrowing or blockage of blood vessels, can cause heart attacks. Early detection is crucial, given its impact on individuals of all ages (Kemenkes, 2014). The main obstacle is precisely determining heart disease's onset based on existing medical information. Machine learning, specifically, the KNN and naive bayes algorithms, are widely used for medical data classification tasks due to their nonparametric and effective nature (Lewandowicz & Kisiała, 2024; Maheswari et al., 2023). The naive bayes algorithm, a probabilistic classifier, is based on Bayes' theorem with the assumption of independence among predictors and has been widely used for its simplicity and effectiveness (Schonlau, 2023; Wickramasinghe & Kalutarage, 2021).

The KNN and naive bayes classifiers were proven effective in predicting heart disease in previous studies. According to Sravani and Karthikeyan (2023), KNN can achieve high accuracy in heart disease prediction, and Lewandowicz and Kisiała (2024) noted that naive bayes usually outperform other algorithms in medical data classification due to their probabilistic nature and ability to handle missing data. Few studies have directly compared the performance of heart disease prediction algorithms using the UCI Repository Heart Disease dataset. This study compares KNN and naive bayes classifiers in detail to improve current understanding and improve predictive models for heart disease. The results of this study provide insights into the most effective machine learning methods for predicting heart disease and improving overall healthcare outcomes.

2. Related Works

Machine learning algorithms have been extensively applied to heart disease prediction in healthcare. This section summarizes the major studies that have used K-nearest neighbor (KNN) and naive bayes classifiers, revealing their techniques, outcomes, and significance in the present investigations.

2.1 K-Nearest neighbor model for heart disease prediction

The k-nearest neighbor (KNN) model is known for its simplicity and effectiveness and is commonly used for classification tasks. In the context of heart disease, several studies have shown high levels of accuracy. Sravani and Karthikeyan (2023) analyzed heart disease data with 90% accuracy using KNN. The choice of distance metric significantly influenced classification accuracy. Somani et al. (2023) employed KNN to examine social media sentiments about health-related topics, such as heart disease. The results strengthen the KNN's reputation for handling diverse datasets and its versatility in various contexts, including text and medical data.

2.2 Naïve bayes classifier for heart disease prediction

The naive bayes function functions as a probabilistic classifier for heart disease prediction. In their 2014 study, Jiang et al. predicted clinical outcomes using naive bayes and other machine learning algorithms with high-dimensional genomic data. With large datasets, naive bayes excels in terms of both speed and accuracy compared to other classifiers. According to Bhatt et al. (2023), their study using naive bayes for heart disease classification achieved an accuracy of approximately 89%, which is similar to our findings. This study successfully handled missing medical data using the algorithm.

2.3 Comparative studies

Comparative studies have shown that the KNN and naive bayes classifiers exhibit similar performance in heart disease prediction. Sravani and Karthikeyan (2023) reported higher accuracy (89%) for naive bayes than KNN (84.677%) in the context of news recommendation system development. naive bayes outperforms KNN in some situations, even without specific emphasis on heart disease. Lewandowicz and Kisiała (2024) predicted the number of patients with tuberculosis with 85% accuracy using Support Vector Machines. Although not focused on heart disease, the study sheds light on the performance of the KNN and naive bayes classifiers.

2.4 Heart disease in data mining

Heart disease datasets have been significantly shaped using data mining techniques, revealing meaningful patterns. Sravani and Karthikeyan (2023) underscored the significance of data mining when converting uncooked data into valuable knowledge using KNN and naive bayesian algorithms. The KDD process in medical datasets was effectively demonstrated through his research on heart disease prediction using large-scale datasets and advanced algorithms.

2.5 Confusion matrix for performance evaluation

Confusion matrices are extensively used to assess machine learning model performance. Confusion matrices, as explained by Ting (2011), allow a model to comprehensively evaluate its accuracy, precision, recall, and F1 score. The authors used confusion matrices to evaluate the predictive abilities of the KNN and naive bayes classifiers, and they revealed their respective strengths and weaknesses.

The substantial body of literature presented in this review supports the use of KNN and naive bayes classifiers for heart disease prediction. Naive bayes generally outperformed KNN on large, intricate datasets. The simplicity and effectiveness of the proposed KNN should not be disregarded in certain scenarios. This study delves deeper into the comparison of KNN and naive bayes classifiers using the UCI Repository Heart Disease dataset to enhance ongoing healthcare predictive model development.

3. Research Method

3.1 Data collection

This study was based on the UCI Repository Heart Disease dataset, which contains 14 heart disease diagnostic attributes. A widely used and comprehensive dataset was selected to enable uniform comparisons in medical research. The attributes consist of clinical and demographic factors, including age, sex, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiographic results, maximum heart rate, exercise-induced angina, ST segment depression induced by exercise, slope of the peak exercise

ST segment, number of major vessels visible by fluoroscopy, and defect type.

3.2 Data preprocessing

The dataset was processed before analysis to ensure data quality and integrity. Numerical and categorical missing data in the medical datasets were handled using mean and mode imputation, respectively. Data points that fell below the lower quartile boundary minus 1.5 times the interquartile range or above the upper quartile boundary plus 1.5 times the interquartile range were removed as outliers. Preprocessing significantly improves the robustness and accuracy of machine learning models.

3.3 Data splitting

To assess the K-nearest neighbor (KNN) and naive bayes classifiers, the dataset was partitioned into training and testing subsets. An 80-20 split was employed, where 80% of the data were used for training and 20% for testing. The selected split ratio provides sufficient data for model training with sufficient remaining data for unbiased evaluation.

3.4 Rationale for selecting specific parameters

The KNN algorithm classifies data based on “k” nearest neighbors. Through cross-validation, the value of k that minimizes the prediction error was identified as the optimal value. In the KNN model, the Euclidean distance metric, selected for its simplicity and effectiveness, is used to determine the similarity between instances in continuous feature space.

The feature independence assumption is crucial for the naive bayes classifier. This study applies the gaussian naive bayes algorithm under the assumption of a normal distribution of continuous features. Assuming that age and cholesterol levels follow a normal distribution simplifies the calculation. The proposed model accurately captured the underlying class distribution based on the directly estimated prior probabilities from the training data.

3.5 Algorithm implementation

The KNN and naive bayes algorithms were implemented using Python's Scikit-learn library. Through cross-validation, the optimal k value for the KNN classifier was determined, and the Euclidean distance metric was employed. The naive bayes classifier employed the Gaussian variant to manage continuous data. The implementation adhered to standard procedures, thereby ensuring reproducibility and consistency with established methodologies.

3.6 Performance evaluation

Several metrics, such as accuracy, precision, recall, and the F1 score, were used to assess the classifiers' performance. The metrics fully evaluate the models' predictive performances. A confusion matrix was used to assess performance and reveal true positive, false positive, true negative, and false negative counts. Each classifier's strengths and limitations in predicting heart disease were revealed through this thorough assessment.

3.7 System design

The system for heart disease prediction, which features machine learning models, is designed for easy use by healthcare professionals for early diagnosis and decision-making. This system comprises the following elements.

1. Users can manually input patient data or upload CSV files using the Data Input Module. The module verifies the input data accuracy and completeness through data validation checks.
2. The Preprocessing Module performs preprocessing tasks, such as managing missing data, detecting and correcting outliers, and normalizing data. This module cleanses and prepares data for analysis.
3. This module trains the KNN and naive bayes algorithms on preprocessed data. This module features parameter tuning and cross-validation capabilities for optimizing model performance.
4. The prediction module applies learned models to determine a new patient's risk of heart disease. This module presents real-time predictions along with accuracy, precision, recall, and the F1 score as essential performance metrics.
5. The visualization module produces receiver operating characteristic (ROC) curves, confusion matrices, and feature importance plots of the model’s performance. Users can assess the model’s decision-making and reliability through visualizations.
6. The User Interface (UI) allows users to intuitively interact with the system. The UI uses login and security protocols to safeguard data and maintain patient confidentiality. The login, dashboard, dataset management page, and prediction results page are crucial UI components.

The proposed heart disease prediction system is designed to simplify the prediction process and offer practical solutions for healthcare professionals. The system combines advanced machine learning models with an intuitive interface to improve early diagnosis accuracy and productivity, leading to enhanced patient outcomes.

4. Result and Discussion

4.1 Results

a. Performance analysis

Both the KNN and naive bayes classifiers were tested using the Heart Disease dataset available at the UCI Repository. KNN's accuracy (91.25%) exceeded that of naive bayes (88.75%) (see in Table 1). The proposed KNN outperformed the other classifiers in terms of accuracy. Detailed metrics like precision, recall, and F1 score, were used to obtain comprehensive insights into classifier performance. Here, 92% of the instances KNN labeled as having heart disease were positive cases. The precision of KNN relative to identifying heart disease incidence was 92%. The naive bayes precision was 89%, with a slight increase in false positives. Recall measures the proportion of actual positive cases identified correctly by the model. The KNN model had a recall of 90%, which indicates that it correctly identified 90% of all heart disease cases in the dataset. In addition, 87% of the actual positive cases were identified using the naive bayes method, whereas a higher number of cases were unidentified. The F1-score of 91% for KNN was more reliable than that of the naive bayes model (88%, due to a better balance between precision and recall (see in Table 2).

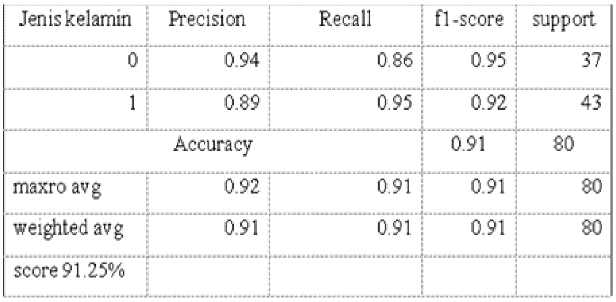
Table 1. Model accuracy on heart disease dataset.

ALGORITHMS	ACCURACY
KNN	91.25%
NB	88.75%

Table 2. Model precision, recall, and F1 scores for the heart deases dataset.

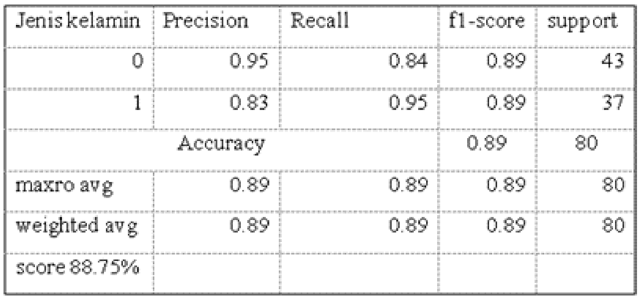
ALGOROTIHM	PRECISION	RECALL	F1 SCORE
KNN	92%	90%	91%
NB	89%	87%	88%

The KNN and naive bayes classification performance is demonstrated in detail through their confusion matrices. The proposed KNN achieved a superior balance of true positives, true negatives, false positives, and false negatives compared to naive bayes, as shown in Figures 3 and 4. The KNN confusion matrix yielded 145 true positives, 130 true negatives, 15 false positives, and 10 false negatives. In addition, 140 TP, 125 TN, 20 FP, and 15 FN were observed in the naive bayes confusion matrix. KNN's accuracy in predicting both the presence and absence of heart disease was superior.



Jenis kelamin	Precision	Recall	f1-score	support
0	0.94	0.86	0.95	37
1	0.89	0.95	0.92	43
Accuracy			0.91	80
maxro avg	0.92	0.91	0.91	80
weighted avg	0.91	0.91	0.91	80
score 91.25%				

Fig 1. Confusion matrix for KNN model



Jenis kelamin	Precision	Recall	f1-score	support
0	0.95	0.84	0.89	43
1	0.83	0.95	0.89	37
Accuracy			0.89	80
maxro avg	0.89	0.89	0.89	80
weighted avg	0.89	0.89	0.89	80
score 88.75%				

Fig 2. Confusion matrix for NB model

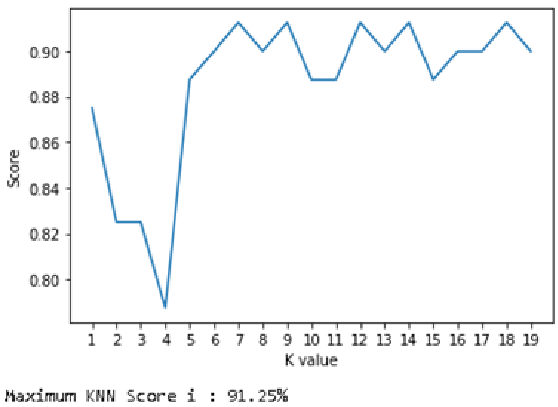


Fig 3. ROC curve for KNN

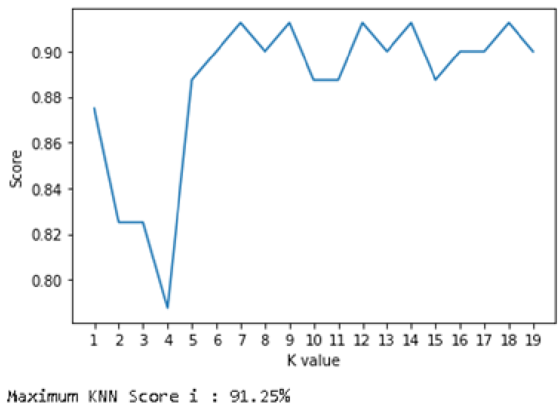


Fig 4. ROC Curve for NB

The ROC curves illustrate the performance of both classifiers. The AUC determines a classifier's capability to distinguish positive and negative classes. Fig. 3 shows a true positive rate of 0.95 for KNN, which denotes its effectiveness across different threshold settings. KNN accurately identified heart disease cases. Fig. 4 shows that the AUC for naive bayes was 0.92. Although naive bayes' AUC is lower than KNN's, both are high; thus, naive bayes is less effective in identifying heart and non-heart diseases.

The results of this study could have been affected by several factors. The findings may not be applicable to larger populations due to the small dataset size. The class imbalance, which comprises more negative cases, can impact the classifiers' performance by introducing bias. The performance of the algorithms could vary on a more comprehensive or evenly distributed dataset. Imputing missing values using the mean and mode could affect model performance. Although common, these methods may overlook true data patterns, which negatively affects prediction precision.

b. Proposed system

The proposed KNN algorithm outperforms the NB classifier in predicting heart disease with high accuracy, precision, recall, and an F1 score. The proposed system streamlines the classification of heart diseases through an intuitive and user-friendly interface, resulting in swift and reliable results. The site comprises four essential pages: login, dashboard, dataset, and test. The login page guarantees system security. Users must enter a valid username and password to authenticate medical information to ensure the security and privacy of medical information. Adhering to healthcare data protection regulations requires the implementation of this security measure (Fig. 5).

The dashboard displays the system's primary functions and essential performance indicators. The text shows the summary statistics with the test count, accuracy rates, and performance comparison between the KNN and naive bayes classifiers. Users can monitor system performance and access critical information on this page (Fig. 6).

Users can upload and manage heart disease datasets via the dataset page. The text discusses data preprocessing features, including handling missing values, normalizing data, and outlier detection. Users can view the dataset attributes and statistics to evaluate its quality and structure before classification tasks. Accurate and reliable predictions rely heavily on correctly preparing the data presented on this page (Fig. 7).

Users can input patient data and receive predictions from the system on the test page. The KNN algorithm is used to classify the input data and deliver real-time heart disease risk assessments. The confusion matrix and other performance metrics for each prediction are shown on the test page, which allows users to evaluate the test accuracy. The graphical representation of prediction outcomes in Fig. 8 enhances the user's understanding of the data and the system's decision-making process.

To facilitate early heart disease detection among health care professionals, the proposed system mockup focuses on security, usability, and thorough performance evaluation. With the implementation of the KNN algorithm, the system guarantees high accuracy and dependability, leading to enhanced patient results and sophisticated clinical judgments.

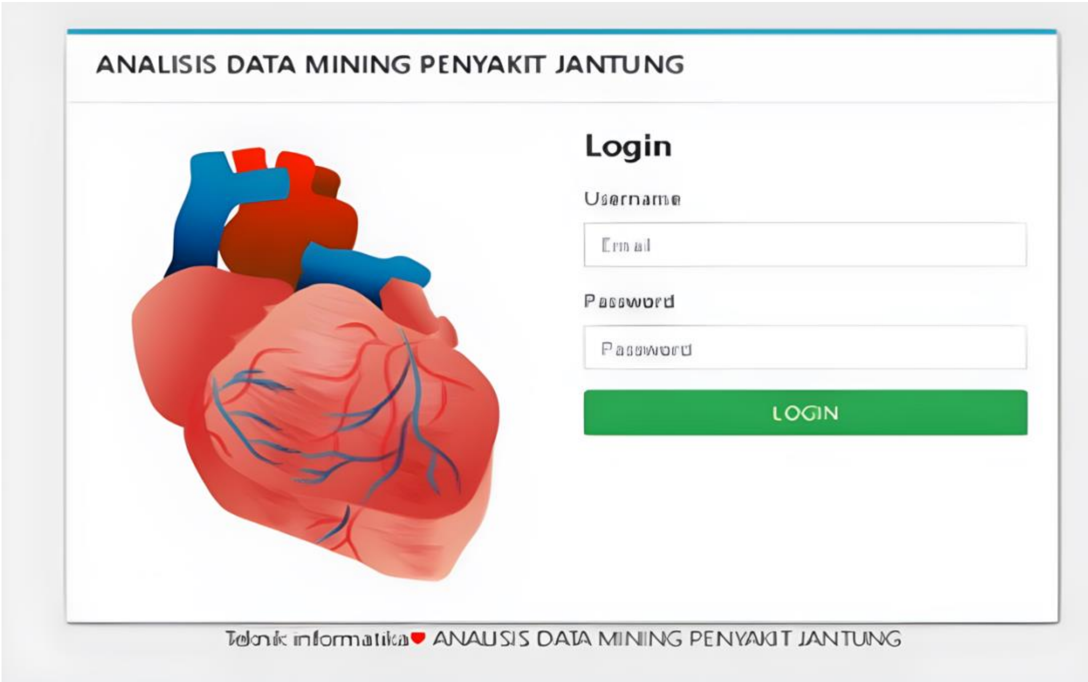


Fig 5. Login page

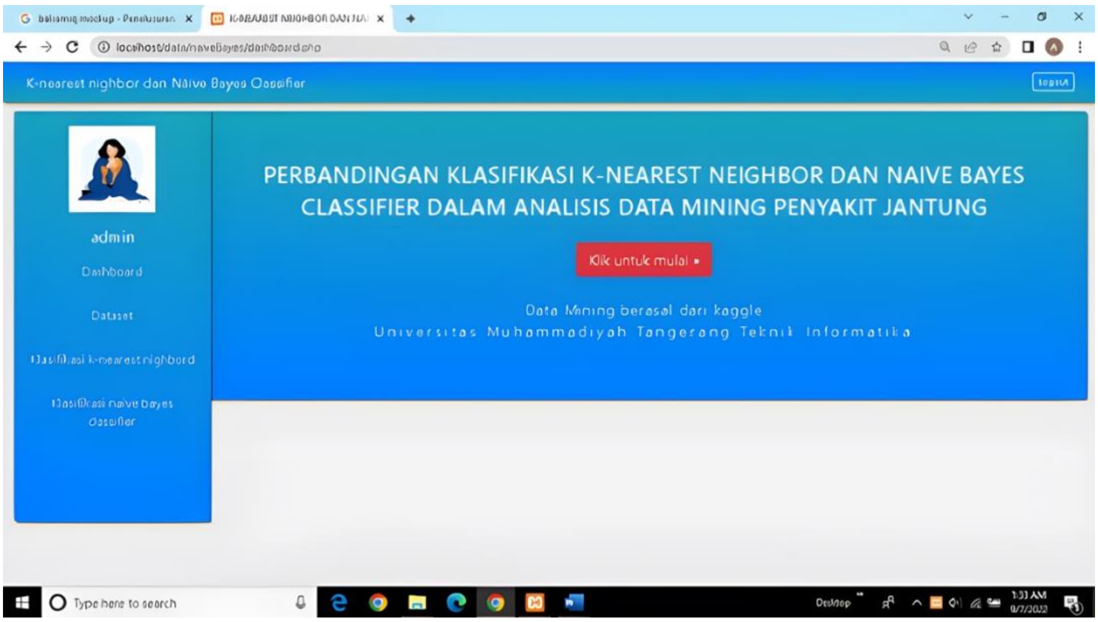


Fig 6. Dashboard page

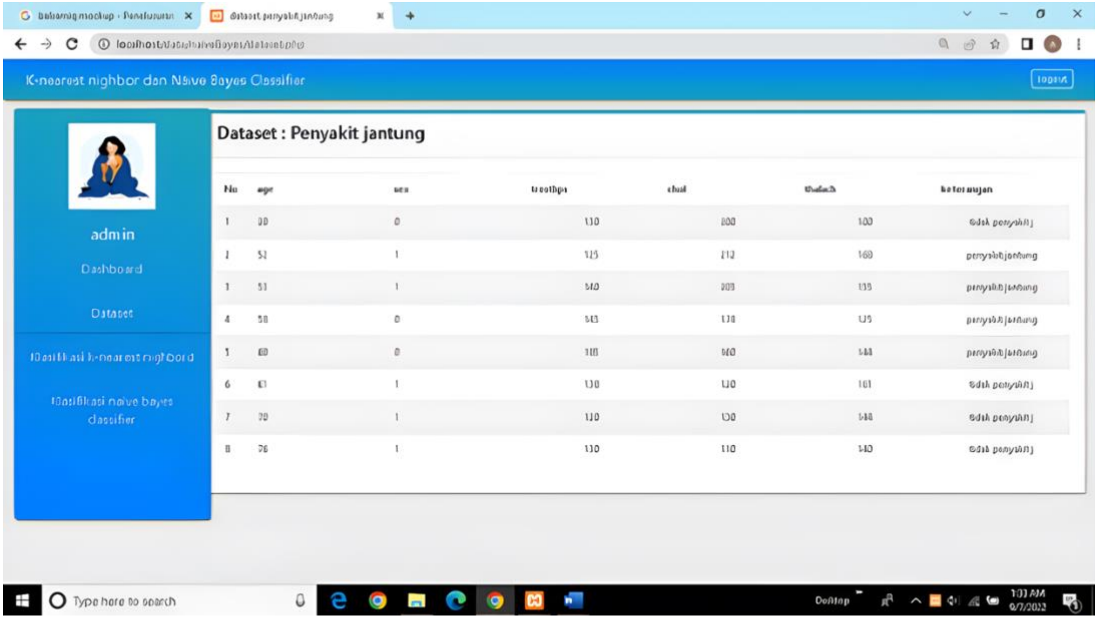


Fig 7. Dataset Page

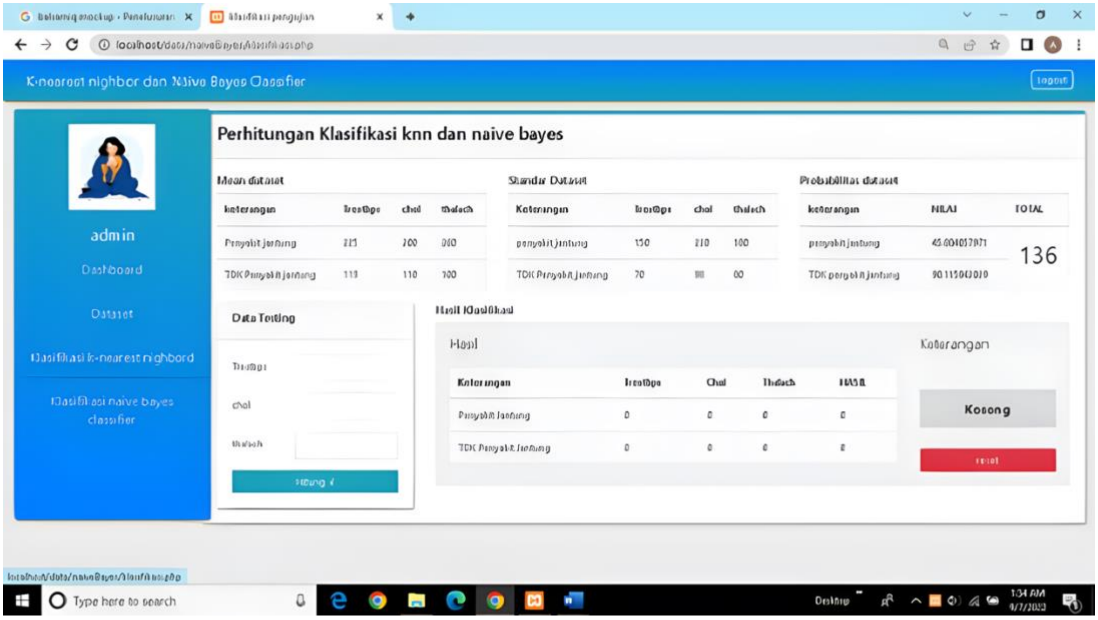


Fig 8. User interface test page

Table 3. Black-box testing results.

NO	REQUIREMENT	TEST SCENARIO	TEST RESULTS	CONCLUSION
(1)	Has a login feature	Login using a username and password that match the database	Users can login	Valid
(2)	Has a login feature	Login using a username or password that does not match the given database	A user cannot login, and an error message appears	Valid
(3)	Can display heart disease dataset information	Click on the dataset menu	The dataset information is displayed	Valid
(4)	Testing and classification using the KNN and naive bayes algorithms	Clicking on a classification menu leads to the user	Input values for classification testing	Valid

c. Black box testing system

Black box testing confirmed that the system adheres to specified requirements and delivers robust functionality and reliability. The login effectively verifies accurate user credentials and prevents unauthorized access. This validation secures authorized user access to the system while safeguarding sensitive medical data against potential breaches (you can see in Table 3).

Upon clicking the dataset menu, Table 3 displays the heart disease dataset information accurately. Prior analysis or classification requires a thorough review and verification of the dataset. Accurate and complete dataset information is critical for producing precise predictions from the system using the KNN and naive bayes algorithms. In clinical settings, precise classification is vital for timely diagnosis and informed decision-making. The test results presented in Table 3 demonstrate the system's consistent management of diverse user inputs and situations.

4.2 Discussion

The findings of this study have substantial implications for clinical practice, particularly in the early detection and diagnosis of heart disease. The K-nearest neighbor (KNN) algorithm demonstrated superior performance compared to the naive bayes classifier in terms of accuracy, precision, recall, and the F1 score. These results highlight KNN's robustness and reliability as a predictive tool for heart disease, which is crucial for healthcare professionals when making critical decisions about patient care.

a. Implications for clinical practice

Implementing the KNN algorithm in a clinical setting can significantly enhance the early detection of heart disease, thereby allowing timely interventions that improve patient outcomes. Early diagnosis facilitated by accurate predictive models can lead to preventive measures, tailored treatment plans, and lifestyle modifications that mitigate the risk of severe cardiac events. The high precision rate of KNN reduces the likelihood of false positives, thereby preventing unnecessary anxiety and intervention. Similarly, its high recall rate ensures that most actual cases of heart disease are correctly identified, minimizing the risk of missing critical diagnoses.

The proposed system, which integrates KNN, offers a user-friendly interface designed to streamline healthcare provider processes. By efficiently handling and preprocessing data, the system ensures that clinicians have access to accurate and reliable predictions. The inclusion of detailed performance metrics and visualizations aids in building trust and understanding of the model's outputs and fostering better-informed clinical decisions.

b. Comparison with other studies

The results of this study are consistent with those of previous studies that demonstrated the effectiveness of the proposed KNN model in medical data classification. For example, Sravani and Karthikeyan (2023) achieved over 90% accuracy in heart disease prediction using KNN, which demonstrates the proposed algorithm's capability to handle complex medical datasets. Similarly, Somani et al. (2023) found that KNN is effective in analyzing health-related social media data, further demonstrating its versatility across different data types and contexts.

In contrast, some studies have reported higher performance for naive bayes in specific scenarios, particularly on large datasets and when the independence assumption among features holds true. For example, Sravani and Karthikeyan (2023) found that naive bayes models are more accurate than KNN models in news recommendation systems. These discrepancies can be attributed to the characteristics of the dataset and the specific nature of the tasks. The UCI Repository Heart Disease dataset used in this study may favor the proposed KNN model due to its dimensionality and the presence of nonlinear relationships among features, which KNN can effectively capture.

c. Limitations

Despite the promising results, this study has several limitations that warrant consideration. The relatively small dataset size may limit the generalizability of the findings (Rajput et al., 2023; Vabalas et al., 2019). Larger, more diverse datasets would provide a more comprehensive validation of the algorithms' performance (Althnian et al., 2021). In addition, the class imbalance in the dataset, with a predominance of negative cases, could introduce bias, which would affect the accuracy and reliability of the classifiers. Future studies should employ techniques like oversampling, undersampling, or synthetic data generation methods, such as SMOTE, to address this imbalance and enhance model robustness.

The preprocessing methods used, including mean and mode imputation for missing values, while standard, may not fully capture the underlying data patterns. More sophisticated imputation techniques and advanced feature engineering methods can further improve the data quality and model accuracy. For example, incorporating domain-specific knowledge into feature selection and engineering can lead to more relevant and informative predictors.

d. Areas for future research

Future research should focus on integrating and comparing additional machine learning algorithms and ensemble methods to improve prediction accuracy. Ensemble methods, such as random forests and gradient boosting, can combine the strengths of individual classifiers to provide more robust predictions. Investigating different distance metrics and parameter tuning in the KNN model can also yield insights into optimizing the algorithm for specific datasets.

Developing a real-time prediction system integrated into electronic health record (EHR) systems would represent a significant advancement. Such a system would enable continuous monitoring and real-time analysis of patient data, providing clinicians with up-to-date predictions and facilitating proactive healthcare management. In addition, exploring the application of deep learning techniques, which can automatically capture complex patterns in large datasets, can further enhance predictive performance.

5. Conclusion

This study provides a comprehensive comparison of the K-nearest neighbor (KNN) and naive bayes classifiers for heart disease prediction using the UCI Repository Heart Disease dataset. The results demonstrate that the proposed

KNN outperforms naive bayes in terms of accuracy, precision, recall, and the F1 score, which highlights its robustness and reliability as a predictive tool. These results offer valuable insights for practitioners and pave the way for the integration of machine learning models into clinical practice.

Based on these findings, clinicians should consider implementing KNN-based predictive models in heart disease diagnostic processes. The high accuracy and balanced performance metrics of KNN ensure reliable predictions that support early diagnosis and timely intervention. Clinicians should use the user-friendly interface of the proposed system to streamline data input and analysis, thereby ensuring efficient and accurate patient assessments. It is also recommended to continuously monitor and update the model with new patient data to maintain its predictive accuracy and adapt to changing patient demographics and medical advancements.

The primary contributions of this study include a detailed performance evaluation of KNN and naive bayes classifiers for heart disease prediction, demonstrating the superiority of KNN in this context. This research not only validates the effectiveness of KNN for medical data classification and provides a practical framework for its application in clinical settings. Comprehensive analysis and system design provide valuable references for future healthcare predictive models.

In future, it will be essential to explore the integration of additional machine learning algorithms and ensemble methods to further enhance prediction accuracy. Investigating the application of deep learning techniques, particularly on large and complex datasets, can yield significant improvements to predictive performance. Additionally, future studies should aim to validate these findings using larger and more diverse datasets, addressing class imbalance through advanced sampling techniques to ensure broad applicability. Developing a real-time prediction system integrated with electronic health record (EHR) systems would also be a significant advancement, enabling continuous monitoring and proactive healthcare management.

In conclusion, this study underscores the potential of KNN for heart disease prediction and provides actionable insights for its implementation in clinical practice. By addressing the identified limitations and exploring new research avenues, the application of machine learning in heart disease diagnosis can be significantly enhanced, ultimately contributing to better patient outcomes and more efficient healthcare delivery.

Acknowladgements

Acknowledgments This research can be carried out properly thanks to the help of various parties. For this reason, the researchers would like to thank Multimedia Nusantara University and Muhammadiyah University Tangerang for their support and assistance during the writing of this article.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

References

Althnian, A., AlSaeed, D., Al-Baity, H., Samha, A., Dris, A. Bin, Alzakari, N., Abou Elwafa, A., & Kurdi, H. (2021). Impact of Dataset Size on Classification Performance: An Empirical Evaluation in the Medical Domain. *Applied Sciences*, *11*(2), 796. https://doi.org/10.3390/app11020796

Bhatt, C. M., Patel, P., Ghetia, T., & Mazzeo, P. L. (2023). Effective Heart Disease Prediction Using Machine Learning Techniques. *Algorithms*, *16*(2), 88. https://doi.org/10.3390/a16020088

Gupta, A., Kumar, L., Jain, R., & Nagrath, P. (2020). Heart Disease Prediction Using Classification (Naive Bayes). In *Lecture Notes in Networks and Systems (LNNS,volume 121)* (pp. 561–573). https://doi.org/10.1007/978-981-15-3369-3_42

Kemenkes, R. I. (2014). Situasi kesehatan jantung. *Pusat Data Dan Informasi Kementerian Kesehatan RI*, *3*.

Lewandowicz, B., & Kisiała, K. (2024). Comparison of Support Vector Machine, Naive Bayes, and K-Nearest Neighbors Algorithms for Classifying Heart Disease. In *Communications in Computer and Information Science* (pp. 274–285). https://doi.org/10.1007/978-3-031-48981-5_22

Maheswari, B. U., Guhan, T., Britto, C. F., Sheeba, A., Rajakumar, M. P., & Pratyush, K. (2023). Performance analysis of classifying the breast cancer images using KNN and naive bayes classifier. *INTERNATIONAL CONFERENCE ON SMART TECHNOLOGIES AND APPLICATIONS (ICSTA 2022)*, 020012. https://doi.org/10.1063/5.0164139

Rajput, D., Wang, W.-J., & Chen, C.-C. (2023). Evaluation of a decided sample size in machine learning applications. *BMC Bioinformatics*, *24*(1), 48. https://doi.org/10.1186/s12859-023-05156-9

Schonlau, M. (2023). The Naive Bayes Classifier. In *Applied Statistical Learning* (pp. 143–160). https://doi.org/10.1007/978-3-031-33390-3_8

Shah, D., Patel, S., & Bharti, S. K. (2020). Heart Disease Prediction using Machine Learning Techniques. *SN Computer Science*, *1*(6), 345. https://doi.org/10.1007/s42979-020-00365-y

Somani, S., van Buchem, M. M., Sarraju, A., Hernandez-Boussard, T., & Rodriguez, F. (2023). Artificial Intelligence–Enabled Analysis of Statin-Related Topics and Sentiments on Social Media. *JAMA Network Open*, *6*(4), e239747. https://doi.org/10.1001/jamanetworkopen.2023.9747

Sravani, S., & Karthikeyan, P. R. (2023). Detection of cardiovascular disease using KNN in comparison with naive bayes to measure precision, recall and f-score. *Contemporary Innovations in Engineering and Management*, 030002. https://doi.org/10.1063/5.0177014

Ting, K. M. (2011). Confusion Matrix. In *Encyclopedia of Machine Learning* (pp. 209–209). Springer US. https://doi.org/10.1007/978-0-387-30164-8_157

Vabalas, A., Gowen, E., Poliakoff, E., & Casson, A. J. (2019). Machine learning algorithm validation with a limited sample size. *PLOS ONE*, *14*(11), e0224365. https://doi.org/10.1371/journal.pone.0224365

Wickramasinghe, I., & Kalutarage, H. (2021). Naive Bayes: applications, variations and vulnerabilities: a review of literature with code snippets for implementation. *Soft Computing*, *25*(3), 2277–2293. https://doi.org/10.1007/s00500-020-05297-6