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COMPARISON OF K-NEAREST NEIGHBOR ALGORITHM AND SUPPORT VECTOR MACHINE IN CLASSIFICATION ARRHYTHMIA IN ECG SIGNALS

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Abstract
Heart disease is one of the biggest causes of death in Indonesia, one of which is arrhythmia, which is a heart rhythm disturbance or a pattern of rapid changes in normal heart rate. Early detection of arrhythmias is very important in reducing the risk of death. In this study, a machine learning approach was used to classify arrhythmias through ECG signal analysis using the K-Nearest Neighbor (K-NN) and Support Vector Machine (SVM) algorithms. The research results show that the K-NN algorithm managed to achieve an accuracy of 82.61%, while the SVM algorithm achieved an accuracy of 79.35%. This shows that the K-NN algorithm has better performance than SVM in the classification of arrhythmia diseases from ECG signals. With higher accuracy, K-NN can identify arrhythmias more precisely, which is very important in the context of early detection. Accurate early detection allows for quicker and more appropriate medical intervention, thereby reducing the risk of serious complications and death. Implementing a K-NN-based early arrhythmia detection system can be an effective solution to be implemented on a wider scale, such as in hospitals or clinics. With this technology, medical personnel can more quickly and accurately diagnose arrhythmias, so that treatment can be carried out earlier. This is very important considering the high death rate due to heart disease in Indonesia. Overall, this study makes an important contribution to the development of an effective early detection system for arrhythmias. By using the K-NN algorithm which has proven to be more accurate, it is hoped that this system can help reduce the death rate due to heart disease in Indonesia. Additionally, further research is needed to continue improving the accuracy and effectiveness of these systems, as well as to explore the potential use of other machine learning algorithms in the medical field.

Keywords : ***Arrhythmia, Comparison, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Machine Learning, Classification, Electrocardiogram (ECG)***

1. INTRODUCTION

Maintaining a healthy heart is very important because this organ plays a vital role in survival and damage to it can be fatal [1]. As the center of blood flow, a problematic heart will paralyze the performance of all the body's organs [2]. Heart problems are a frightening threat, claiming the lives of millions of people around the world. Riskesdas 2018 revealed that 2.7 million Indonesians struggle with heart disease, with 12.9% being the cause of death in the country. Heart disease tops the list of killers in the world, claiming 16% of lives or the equivalent of 8.9 million deaths in 2019 [3]. More Than Just a Heartbeat, Arrhythmia Signals a Heart Rhythm Disorder that Requires Attention [4]. Arrhythmia is a form of heart rhythm disorder that requires immediate attention. Prevention can be done with early detection and correct diagnosis via EKG, which is the key to effective treatment [5]. ECG precisely records the rhythmic electrical activity of the heart over a period using electrodes/leads, which capture electrical changes caused by depolarization and repolarization of the heart muscle and heartbeat. This section covers standard conventional ECG signal recording, the noise associated during acquisition ECG, morphology (structural & physiological), and identification of heart-related diseases from ECG[6]. ECG is like a window that allows us to see the rhythm of the heart. This window displays a typical signal consisting of several waves, P Wave: Represents depolarization, or electrical activation, in the right and left atria. This is like the initial signal that the heart is preparing to pump blood, QRS Wave: A complex consisting of Q, R, and S waves. This wave appears when an electrical impulse travels through the ventricles, the chambers of the heart that are responsible for pumping blood throughout the body, T Wave: Represents repolarization, or relaxation, of the ventricles after pumping blood. This is like a signal that the heart has completed its pumping cycle. [7] Automatic P wave detection results make it possible to obtain more information from the ECG record[8]. Then, recorded electrocardiography data can be displayed in real-time [9].

Even though it is sophisticated, early heart detection via ECG can be better. Increasing accuracy is needed, especially in signal extraction and classification. [10]. Easy and fast data classification using the reliable KNN method [11]. KNN is an intelligent algorithm that determines new data categories based on training data [12]. This classification method is more accurate when used on data with fewer parameters [13]. and the SVM method as a comparison method [14]. The Support Vector Machine (SVM) algorithm was chosen because it has a very good level of robustness and performance. In general, many researchers consider that SVM techniques can improve the accuracy of the models they use [15]. The SVM algorithm is a supervised learning algorithm that finds the optimal hyperplane or separator function to separate classes [16]. Use SVM for classification of arrhythmias using ECG signals [17] is able to produce better accuracy values [18].

1.1 Formulation of the problem

Based on the background description above, the problem formulation is obtained, namely

1. How to classify arrhythmia on ECG signals by applying the K-Nearest Neighbor (KNN) algorithm and SVM, to identify people who have the potential to suffer from heart disease.
2. Of the two Machine Learning algorithms discussed in this discussion, namely: Dismantling the advantages and disadvantages of KNN and SVM. Which algorithm is the best to use?

1.2 Objectives and benefits

1.2.1 Objective

The expected objectives in this discussion are:

1. To determine the performance of the K-Nearest Neighbors (KNN) and SVM algorithms in classifying arrhythmias in humans
2. Contributing to the development of methods for early detection of heart disease through ECG signal analysis.

1.2.2 Benefit

The main benefits expected from this discussion are as follows:

a. Through in-depth data analysis, this research aims to produce a more accurate and reliable disease classification system. This system is expected to help other medical personnel diagnose diseases more precisely and quickly, thereby improving the quality of health services.

b. The findings and methods in this research can be a source of information and inspiration for other researchers who want to develop disease prediction methods using the KNN and SVM algorithms. The results of this research can help accelerate progress in the field of disease diagnosis and treatment.

1.2.3 Scope of problem

The following describes the limitations of the problem in this research so that the research continues according to plan, namely:

1. This research will use electrocardiography (ECG) recording data as input for the classification process. Limitations also include data sources, sample size, and characteristics of the data used as evidence in the research.
2. This research only focuses on two main classification methods, namely the KNN algorithm and the SVM algorithm. This study did not consider other classification methods.
3. In this study, student lifestyle factors such as smoking habits, staying up late, and students' eating patterns were not included. which is not good which can predispose someone to heart disease at a young age.

1.2.4 Recency

1. According to GHULAM MUHAMMAD AMJAD, SAAD NAVEED, LUBNA NADEEM, TARIQ MAHMOOD (2023) in research entitled "Improving the Accuracy of Prognosis for Ischemic Neighbor Algorithms: A Powerful Approach". Six ML-based algorithms, including K Nearest Neighbors (KNN), Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), Gaussian Naïve Bayes (GNB), and Decision Trees (DT), were trained on heart data ischemic. The effectiveness of the proposed methodology is carefully evaluated and compared with state-of-the-art techniques, using a set of performance criteria. Empirical findings show that the KNN classifier provides optimal results with 91.8% accuracy, 91.4% recall, 91.9% F1 score, 92.5% precision, and 90.27% AUC[19].
2. According to Binish Fatimaha, Pushpendra Singhb, Amit Singhalc, Dipro Pramanicka, Pranav Sa, Ram Bilas Pachori (2020) in research entitled "Efficient detection of myocardial infarction from single lead ECG signal" using single channel electrocardiogram (ECG) signals to develop two algorithms automatic MI detection, machine learning classifiers such as k-nearest neighbor (KNN), support vector machine (SVM), bagged tree ensemble and subspace ensemble KNN, are used to build the detection model. The best results are obtained for the primary algorithm with the KNN classifier, where The accuracy obtained was 99.96%, sensitivity was 99.96% and selectivity was 99.95%. The modified algorithm, on the other hand, is more computationally efficient because it skips the beat extraction step and only uses FDM once for noise removal and FIBF extraction. The accuracy reached 99.65%, with sensitivity of 99.61% and selectivity of 99.73% [20].
3. According to Balakrishnan Duraisamya, Rakesh Sunkua, Krithik Selvaraja (2024) in research entitled "Prediction of heart disease using support vector machines" SVM can identify patterns and relationships between these factors and the presence or absence of heart disease. SVM's ability to handle high-dimensional feature spaces and its capacity to capture non-linear relationships using kernel functions makes it suitable for complex heart disease prediction tasks. SVM-based models can provide accurate risk assessments and aid early detection, enabling healthcare professionals to implement preventive measures and personalized treatment plans for patients at risk of heart disease. Significant performance improvements have been achieved, reaching an accuracy rate of 89% in heart disease prediction[21].
4. According to Aishwarya Mondal, Banhishikha Mondal, Amaresh Chakraborty, Agnita Kar, Ayanty Biswas, Annwesha Banerjee Majumder (2023) in research entitled "Heart Disease Prediction Using Support Vector Machine and Artificial Neural Network" The aim of this work is to build a machine learning-based model for early and adequate prediction of heart disease. The proposed model has utilized support vector machines and artificial intelligence with an accuracy of 81.6% and 86.6%, respectively. The findings show that the model predicts the risk of heart disease with excellent accuracy, sensitivity, and specificity, thereby offering healthcare professionals a useful tool for determining people who may be at greater risk of heart disease [22].

2. RESEARCH METHODS

2.1 Types of research

This research was carried out by collecting and processing ECG data numerically to obtain measurable results. KNN and SVM algorithms are implemented in this research to extract information from the data.

2.2 Time and Place of Research

The period for carrying out this research is in October 2023 at Prima Indonesia University.

2.3 Work procedures

The stages followed in this research are as follows:

1. Literature Study Studying international and national journals specifically related to electrocardiograms (EKG) using the KNN and SVM methods
2. The proposed framework
   a. Data collection stage
   The data collection stage begins with examining and recording an ECG using an electrocardiogram during a medical examination. Each ECG recording produces a series of waves that represent heart activity. Raw data from ECG recordings is then processed to extract specific features such as RR, PR, QS, QT, and ST intervals along with their standard deviations.
   b. Data Analysis Stages
   At the data analysis stage, data preprocessing is first carried out. The data is normalized to ensure that each feature has the same scale, usually by changing the data range to between 0 and 1 using techniques such as Min-Max Scaling, then evaluating the model using test data to predict labels.
   c. Model Comparison Stage
   At this stage, the evaluation results of the two models (KNN and SVM) are compared based on the calculated evaluation metrics, such as accuracy, precision, recall, and F1-score. The Confusion Matrix of the two models is also compared to see error patterns.
   d. Report Creation Stage
   The report creation stage begins by presenting an introduction containing the research background, research objectives, and the importance of ECG data analysis for diagnosing heart conditions. The methodology used in the research is explained, including the stages of data collection, preprocessing, model training, model evaluation, and model comparison, as well as a description of the dataset and its features. The results and discussion section presents the evaluation results of the two models in the form of tables and graphs. The evaluation results are discussed by analyzing metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The performance of both models is compared and the results obtained are interpreted. The conclusion summarizes the results of the model comparison and explains the implications of the research findings, as well as presenting suggestions for further research or practical application of the developed model. The reference section includes references from the literature used during the research.

2.4 Tools and materials

A. Tool

In order to carry out this research, several tools and materials used were as follows:

1.2.4.1 EKG device

An EKG machine is a special device used to record the electrical activity of the heart. This is a core element in the process of collecting data on an ECG.

1.2.4.2 Mouse/Keyboard and PC Computer

The ECG machine can be connected to a PC computer via a USB port or other connector. This research utilizes a PC to run special ECG software, which makes it easy for users to record,

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analyze and store ECG data. A mouse and keyboard are used to operate the computer and ECG software.

1.2.4.3 Raspberry Pi

The Raspberry Pi can be used as an additional data processing device in an ECG system. It can be used to store ECG data locally, send data to a server or cloud for further analysis, or even to control ECG hardware.

1.2.4.4 Connector and USB Type-C

Connector and USB Type-C can be used to connect various components in the ECG system. For example, USB Type-C can be used to connect an ECG machine to a PC or Raspberry Pi. Other connectors can also be used to connect electrodes to the ECG machine and connect other devices in the system.

1.2.4.5 WiFi connection

A WiFi connection can be used to wirelessly transfer ECG data between the ECG machine and another device, such as a PC, Raspberry Pi, or server/cloud for data storage or analysis. This provides flexibility in using the ECG system without the limitations of cables.

B. Material

Research activities and at the same time collecting this dataset were carried out at Prima Indonesia University. This study used an electrocardiogram (ECG) to assess and document the electrical activity of the participants' hearts. The following is when collecting data, there were 3 students from a prime Indonesian university who were asked to be respondents to this testing experiment. First, the measuring instrument was placed on the respondent's chest for 3 points, then one respondent was measured while sitting, the measurement time was 3 minutes and after finishing measuring when sitting, followed by measuring the respondent's heart rate while walking, then finally the respondent was asked to run.

2.5 Method

In this research, the comparison of algorithms using the KNN and SVM methods can be illustrated in the form of a flow diagram as seen in the image below:

a. K-Nearest-Neighbor (KNN)

The K-Nearest Neighbors (K-NN) algorithm is included in instance-based learning and is classified as a lazy learning technique. KNN works by classifying new data based on its similarity to the k nearest neighbors in the training data. One of the weaknesses of KNN is its sensitivity to the k value. Cross Validation (CV) offers a solution to overcome this by dividing the data into several sub-folds, where each sub-fold is alternately used as training data and testing data. This allows for more comprehensive and accurate model evaluation.[23] In the KNN algorithm, calculating the distance between data is an important step to determine the nearest neighbors. One of the commonly used formulas for calculating this distance is the Euclidean distance formula, as shown below:

$$d(x,y)= 2\sqrt{\sum_{i=1}^{m}(xi + yi)}$$

b. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a relatively new supervised learning technique for making predictions, both in classification and regression. This algorithm has several advantages over other methods, and its implementation involves two main stages: training using sequential training SVM and testing. SVM's ability to handle high-dimensional datasets is possible with the use of kernel tricks. The accuracy of the SVM model resulting from the switching process is largely determined by the kernel function and the parameters chosen. In linear SVM, the dataseparating data into two classes using a straight line (hyperplane) and considering data that is not perfectly separated (soft margin) in the classification process.[24]

- Support Vector Machine Equation:

$$f(x) = wx + b$$

Source of equations
Or

$$f(x) = yes\ (x,y) + b\sum_{i=1}^{m} a$$

Source of equation:
Information:

w : hyperplane parameters being sought (perpendicular lines between lines (hyperplane and support vector points)
x : Support Vector Machine input data points
ai : the weight value of each data point
$K(x,y)$: functionkernels
b : parameters*hyperplane*what you are looking for (bias value)

- Linear
- The linear kernel is the simplest kernel function in SVM, suitable for linearly separable data and ideal for situations with many features, where mapping to a high-dimensional space does not necessarily improve performance, such as in text classification.

$K(x,y)$=xy Source of equation:
Information:
$K(x,y)$: kernel value of data x and data y
x : data value 1
y : data value 2

3. RESULTS AND DISCUSSION

3.1. Results

3.1.1. Datasets

In this studyusing 780 electrocardiogram data. The data used is value data such as the attribute values rr, rr_stdev, pr, pr_stdev, qs, qs_stdev, qt, qt_stdev, st, st_stdev, and heartrate.

3.1.2. Data Preprocessing

1. Data normalization
   This process is an important step in preprocessing data before applying it to a machine learning model. The main goal of normalization is so that all features have a comparable scale, so that they can be compared and processed effectively by machine learning algorithms. The datasets are at the same scale, which helps in improving model performance and speeding up the training process. In this research, the normalization technique used is min-max scaling, which was chosen because it is easy to understand and implement, and can normalize numerical attribute values into the range 0 to 1.
2. Data Transformation
   For machine learning algorithms to work well, categorical (non-numerical) features must be converted into numerical form. One of the techniques used is One-Hot Encoding. One-Hot Encoding converts each unique category in a categorical feature into a distinct binary column (0 or 1). In this dataset, the classification_result feature is a categorical feature with two classes: Arrhythmia and Normal. One-Hot Encoding can be used to convert these features into numeric format.

Data taken or determined uses real time data sourced from electrodiagrams. With total data of 456 people as respondents. After the data has been obtained from Prima Indonesia University, the next stage of the process is preprocessing the data using LabelEncoder which has been provided from scikit-learn to prepare the data which includes several processes that have been carried out such as dropping unneeded columns, cleaning data, transforming data and integrating data into

KNN and SVM machine learning algorithms. The data preprocessing process is carried out by importing LabelEncoder. Start by changing arrhythmia to 0 and normal to 1.

The research was carried out as a comparison of how the KNN and SVM models work, using data spitting with a ratio of 90:10, 80:20, 70:30, 60:40. Through testing on two models, KNN and SVM, the results of accuracy, precision and satisfactory recall. KNN showed the best performance with an average accuracy of 80.12%, while SVM excelled in average precision (81%) and KNN in average recall (90.4%). Based on comparisons with several data divisions, the KNN algorithm was proven to be superior in predicting arrhythmias in 456 real-time patients.

3.1.3. Data Approach

Testing uses the K-Nearest Neighbors (KNN) algorithm with parameters (k=5). This process involves normalizing the data using the Min-Max scaling method to ensure that all features are on the same scale. For the model training and testing process, the data is divided into two parts, namely 80% for training data and 20% for testing data. to test model performance. The KNN model is trained using the value k=5, where the KNN algorithm works by looking for the five closest neighbors of the data points to be predicted and determining its class based on the majority class of these neighbors. Evaluation of the model is carried out using four metrics, namely accuracy, precision, recall, and F1-score. The results show that the KNN model with k=5 provides an accuracy of 82.61%. With precision of 82%, recall of 91%, and F1-score of 86%, the model shows good performance. Next, testing is carried out.

The algorithm used is Support Vector Machine (SVM), the same as in KNN, the data is normalized. The data is normalized with Min-Max scaling and allocated into two parts, with 80% as training data and 20% as test data. SVM model trained using a linear kernel. Model evaluation is carried out using the same metrics, namely accuracy, precision, recall and F1-score. The SVM model shows good performance with an accuracy of 79%, precision of 81%, recall of 85%, and F1-score of 83%. Model comparison shows that KNN is superior in terms of performance compared to the SVM model in terms of all evaluation metrics used. KNN's fairly good performance shows that the model is able to classify most of the test data correctly. The high precision and recall also show that the model can identify arrhythmia cases with a relatively small number of errors. However, there are several limitations in using KNN, such as high computing time on large datasets and dependence on feature scale.

From the results of the model using the K-Nearest Neighbors (KNN) algorithm and Support Vector Machine (SVM), the following evaluation metrics can be seen:

K-Nearest Neighbors (KNN)

- Accuracy: 82.61%
- Precision for class 0 (arrhythmia): 0.82, for class 1 (normal): 0.84
- Recall for class 0 (arrhythmia): 0.91, for class 1 (normal): 0.70
- F1-score for class 0 (arrhythmia): 0.86, for class 1 (normal): 0.76

Support Vector Machine (SVM)

- Accuracy: 79.35%
- Precision for class 0 (arrhythmia): 0.81, for class 1 (normal): 0.76
- Recall for class 0 (arrhythmia): 0.85, for class 1 (normal): 0.70
- F1-score for class 0 (arrhythmia): 0.83, for class 1 (normal): 0.73

In the confusion matrix, it can be seen that:

- KNN has 50 correct predictions for the normal class and 26 correct predictions for the arrhythmia class.
- SVM had 47 correct predictions for the normal class and 26 correct predictions for the arrhythmia class.

Absolute error is an evaluation metric that measures the average absolute difference between the predicted value and the actual value of the target. In this context, absolute error measures how far the average model prediction is from the actual value in the dataset.

- For the K-Nearest Neighbors (KNN) model, the absolute error is around 0.1739. This means that the average KNN model prediction has a difference of 0.1739 from the actual value in the dataset.

- Meanwhile, for the Support Vector Machine (SVM) model, the absolute error is around 0.2065. This shows that the average SVM model prediction has a difference of 0.2065 from the actual value in the dataset.

From the explanation above:

- Precision measures how precise the model is in identifying a particular class. For example, for KNN, the precision for the arrhythmia class is 0.82, meaning that of all the data predicted as arrhythmia by the model, 82% of it is actually arrhythmia.
- Recall measures how good the model is at finding all instances of a positive class. For example, for KNN, the recall for the normal class is 0.70, which means the model successfully found 70% of all true normal cases.
- F1-score is the harmonic average of precision and recall. This provides an overall picture of the model's performance in predicting classes.

4. CONCLUSION

4.1. Conclusion

K-Nearest Neighbors (KNN) with parameters k=5 and Support Vector Machine (SVM) were tested to test the model performance. KNN uses the value k=5 to determine the nearest neighbor. shows that the model in data classification testing, KNN is proven to be superior to SVM. KNN with k=5 achieved 82.61% accuracy, 82% precision, 91% recall, and 86% FI-score, while SVM with linear kernel only achieved 79% accuracy, 81% precision, 85% recall, and 83% FI-score. . Data normalization was carried out using the Min-Max scaling method, and a data division of 80% for training and 20% for testing was carried out to train the model optimally and evaluate its performance accurately. KNN's superior performance is demonstrated by this model achieving higher accuracy, precision and recall, showing better performance in identifying and classifying data. A higher FI-score value also indicates a better balance between precision and recall. Although KNN shows good performance, some limitations such as high computing time on large datasets and dependence on feature scale need to be noted.

4.2. Suggestion

Here are some suggestions that can be considered for further research:

1. Testing was carried out with different algorithms with the same dataset.
2. Various approaches are used to handle missing values in order to achieve maximum results.
3. Dataset updates are carried out with information or explanations that are easy to understand.
4. Testing for heart disease is carried out with different tools.
5.

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