Prediction of ECG Cardiac Abnormality Signal using Supervised Prediction Model

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***Abstract*—The detection of a patient's cardiac abnormal activity is crucial when an abnormal symptom occurs. The objective of this initiative is to detect disease using some supervised prediction model. Several data are extracted from the electrocardiogram (ECG) signal and used as input parameters which are amplitude and duration of P peak, amplitude, and duration of QRS wave and amplitude and duration of T peak. The proposed prediction models are K-Nearest Neighbours (KNN), Discriminant Analysis, Principal Component Analysis (PCA) and Decision Tree. The obtained result is then compared to other prediction models to identify the optimal performance based on the accuracy prediction and lowest mean square error (MSE). It shows that KNN prediction model outperforms other models with 94.27% accuracy and 0.24 on the MSE measurement.**

Keywords—cardiac abnormality, amplitude, duration, ECG signal, accuracy, MSE.

I. Introduction

Cardiac abnormal activity, or heart disease, is one of the most common diseases in the world, especially in Malaysia. Heart abnormalities or heart disease occur when blood clots block the heart's blood supply [1]. The presence of blood clots will cause the arteries that connect to the heart to narrow. If a blood clot completely blocks a major artery of the heart, the heart will eventually stop receiving blood. This will cause the heart to lack oxygen, as oxygen is essential to pump blood back to the rest of the body. Due to the lack of oxygen, the heart muscle will quickly weaken, and the blood supply to the whole body will decrease. This will result in a heart attack. An ECG is one of the most effective methods for diagnosing cardiac abnormalities. ECG is an important diagnostic technique for identifying heart abnormalities and heart disease.

It serves as a detector of any electrical activity the heart produces on the body's surface [2]. ECG measurements are obtained by placing several electrodes on the surface of the skin at specific locations on the body. However, there are known pitfalls in ECG [2]. Despite severe heart problems, the ECG may appear normal. In fact, because an ECG is just a picture, a patient with a normal ECG may (rarely) have significant changes that indicate a heart attack 10 minutes after the test. Although the patient may have a history of cardiac symptoms, they may not be present at the time the test is performed.

Therefore, the test may appear normal in patients with severe heart problems because it cannot detect narrowing in the arteries unless it is performed during physical stress or a heart attack. Similarly, although the ECG is the definitive test for patients with arrhythmias, if the patient does not have an arrhythmia at the time of the test, it may appear normal despite the presence of a serious condition [3-4].

Therefore, by extracting certain features from the ECG signal, such as the amplitude and duration of the P peak, QRS wave, and T peak, these data will be used as input parameter for the prediction model to obtain accurate diagnose of cardiac abnormality activity [5].

II. Literature Review

A. Electrocardiogram (ECG)

Typically, an ECG is used to assess and record the electrical activity and function of the heart muscle. Interpretation of ECG tracings requires a large amount of training, even though the test is simple [6]. The heart is equipped with a two-stage electric pump, and the electrical activity of the heart can be measured by placing electrodes on the surface of the skin [6-7]. In addition to measuring pulse rate and rhythm, an electrocardiogram can provide indirect evidence of blood flow to the heart muscle. There are numerous types of heartbeat, also known as rhythm. Typically, the heart pulses in a sinus rhythm, as depicted in Figure 1, with each electrical impulse generated by the sino-atrial (SA) node causing a ventricular contraction, or heartbeat [8] and known as normal ECG signal.

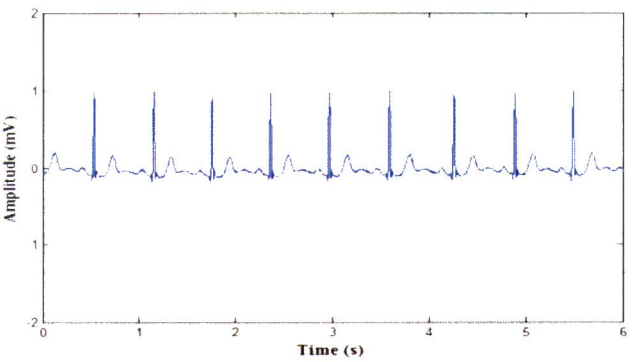

Fig. 1 Normal ECG signal in the heart.

As illustrated in Figure 2(b) there are many aberrant electrical rhythms. Some of them are harmless, while others can pose a threat. In addition, there are electrical rhythms that do not produce a heartbeat and are the cause of sudden death. Figure 2 show the Atrial Fibrillation ECG signal, the signal of heartbeat that's cause of sudden death [9-10].

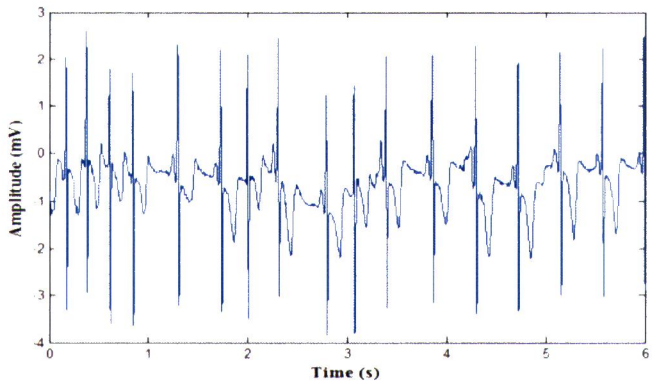

Fig. 2 AF ECG signal in the heart.

B. Ficidual Point Detection

A fiducial point refers to a specific point that corresponds to either the peak or a specific place within the three primary waves observed in an electrocardiogram (ECG) complex. This point serves as a valuable reference point for analysis and interpretation purposes. In an optimal complex, a minimum of nine fiducial points can be discerned. Nevertheless, the human eye lacks the ability to discern the limits of each wave, therefore rendering it impossible to provide a definitive description pertaining to the commencement or conclusion of the primary waves. In their study, Ahmed et. al. introduced a methodology for identifying the specific positions of the three primary waves in the electrocardiogram (ECG) signal [11-12]. This approach involves the computation of signal amplitude, width, and slope. In their study, Khamis also introduced the concept of monitoring the local maximum and minimum radius of curvature [13]. The integration of these two methodologies has the potential to enhance the sensitivity and precision of electrocardiogram (ECG) waveform detection. Numerous manufacturers of electrocardiogram (ECG) recording equipment incorporate a blend of these techniques in their devices. Figure 3 shows the parameters that can be extracted from ECG complex.

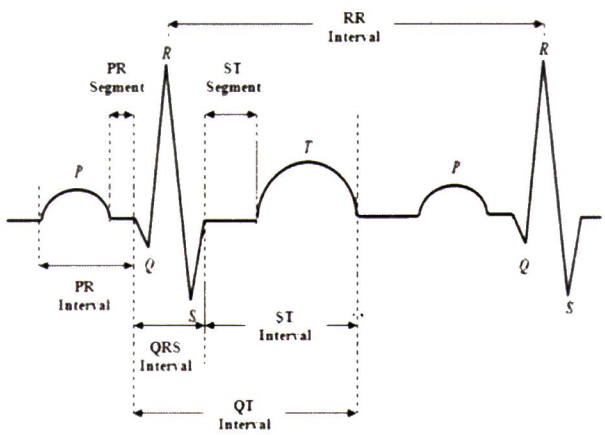

Fig. 3 The fiducial points taken from a complex ECG signal

C. Prediction Model

K-Nearest Neighbours (KNN)

The K-Nearest Neighbours (KNN) algorithm is a commonly employed and straightforward machine learning technique, mostly utilised in the domains of classification and regression. The algorithm in question can be classified as an instance-based, non-parametric method. The KNN algorithm utilises the similarity between a new data point and the existing data points within a dataset to generate predictions [14].

The KNN algorithm computes the Euclidean distance between a given location and all other points inside the dataset. The Euclidean distance metric is widely recognised as the most prevalent method for measuring distance. However, alternative distance metrics such as Manhattan distance or Minkowski distance are equally viable options for distance calculation. The parameter denotes the quantity of closest neighbours to be taken into consideration. Selecting an adequate value for K is crucial as it has the potential to significantly influence the performance of the algorithm.

A lower value of K may render the model more susceptible to noise, whereas a higher value of K may reduce the model's sensitivity to local patterns. After identifying the K nearest neighbours, the KNN algorithm proceeds by conducting a majority vote for classification tasks or computing an average for regression tasks based on the target values of those neighbours. In the context of classification issues, the new data point is assigned the label that is most observed among its K nearest neighbours. In regression analysis, the target values are assigned the average value.

Discriminant Analysis

The assumption used by Linear Discriminant Analysis (LDA) is that the covariance matrix is equal across all classes. This assumption posits that the variability of the features remains constant across all classes, whereas only the means of the classes exhibit differences. LDA is a linear methodology that generates linear decision boundaries to effectively classify different classes [15].

Quadratic Discriminant Analysis (QDA), in contrast, relaxes the assumption established by LDA. In the context of QDA, it is permissible for each class to own its unique covariance matrix. This implies that it has the capability to represent intricate connections among the characteristics of diverse categories. QDA could capture non-linear decision boundaries, making it more flexible compared to LDA. Nevertheless, the computing intensity of this approach may increase, necessitating a larger amount of data to effectively estimate the extra parameters [16].

The decision of whether to utilise QDA or LDA is contingent upon the distinctive attributes of the dataset and the fundamental assumptions made about the data. In cases when there is evidence suggesting notable disparities in variances between classes and the ineffectiveness of linear decision boundaries, it is advisable to consider employing QDA as an alternative approach. If the assumption of variance holds, LDA exhibits superior computational efficiency and demonstrates satisfactory performance.

LDA and QDA are commonly employed in the context of supervised classification tasks. In such scenarios, the primary objective is to make predictions regarding the class or category of a given data point by leveraging its associated features. The K-Nearest Neighbours (KNN) algorithm is a commonly employed and straightforward machine learning technique, mostly utilised in the domains of classification and regression.

Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a commonly employed method in the fields of statistics, machine learning, and data analysis for the purpose of reducing dimensionality. The major objective of this technique is to decrease the number of dimensions in a dataset while retaining the maximum amount of pertinent information. The process of Principal Component Analysis (PCA) involves the transformation of the initial characteristics into a novel set of features known as principal components. These principal components are obtained through linear combinations of the original features [17].

Principal Component Analysis (PCA) is a statistical technique that aims to standardise the process of mean centering and scaling to unit variance. This standardisation ensures that each feature within a dataset possesses a comparable scale. Subsequently, PCA proceeds to determine the covariance matrix of the standardised data. The covariance matrix provides a description of the relationships between features, indicating whether pairs of features are correlated or independent.

The eigenvectors correspond to the principal components, whereas the eigenvalues indicate the amount of variation that each principal component accounts for. The primary components are defined by the eigenvectors and eigenvalues, which are arranged in descending order. Subsequently, researchers have the option to preserve a specific number of principal components, depending on the desired level of variance preservation. The original data can be projected onto the chosen principal components by the researchers to acquire a representation of the data with reduced dimensions.

Tree Decision

The decision tree classification technique is widely employed in the field of machine learning to categorise data points into distinct classes or categories. The technique in question is a supervised learning method that exhibits strong performance in both binary classification scenarios, involving two distinct classes, as well as multi-class classification scenarios, including more than two classes. The dataset comprises labelled instances, wherein each individual data point is linked to a specific class label. The decision tree algorithm constructs a hierarchical structure like a tree. At each node inside the tree structure, the algorithm determines the optimal characteristic from the given dataset to divide the data into distinct subsets. The objective is to select the characteristic that yields the greatest reduction in uncertainty regarding the classification labels. Different measures, such as Gini impurity, information gain, and entropy, are employed to assess the efficacy of a split [18].

The process of constructing the tree persists in a recursive manner, wherein the data is divided at each node until a predetermined stopping criterion is satisfied. The selection of this criterion may depend on various aspects, such as the depth of the tree, the quantity of data points presents at a node, or other relevant considerations. Once the stopping requirement is met, the node undergoes a transition to become a leaf node, which is subsequently linked to a specific class label. The assignment of this label is frequently determined by the majority class of the data points located at the leaf node.

To assign a classification to a novel and unobserved data point, the process commences by traversing the decision tree from the root node, thereafter, progressing along the path determined by the feature values associated with said data point. Ultimately, the data point traverses the tree structure until it reaches a leaf node, at which time the prediction for the new data point is determined by the class label assigned to that leaf node.

III. Methodology

A. Data Collection

The ECG data for the study were obtained from the Physionet database. The samples include raw signals for cardiomyopathy and other types of arrhythmias. Normal ECG with healthy data was also collected for control purposes. The ECG signals were all captured at a frequency of 1 kHz. All signal processing tasks and classification utilising several statistical prediction models were carried out in this article using MATLAB R2023b. The ECG is subject to interference from power lines, electromyogram (EMG) signals, and motion artefacts. As a result, it is necessary for the raw signal to go through a preprocessing stage for noise removal and baseline correction.

B. Pre Processing Dataset

Six (6) features extracted from the ECG data will serve as input parameter for the statistical prediction model. The characteristics are amplitude and duration of P peak, amplitude and duration of QRS wave, and amplitude and duration of T peak. This implies that the prediction model will have six input nodes that will be integrated into a structure. Selected of all six features is based on the variations in the ECG signal from normal to abnormal. 200 total data points are utilised for each condition with random data is inserted into the prediction model. The prediction model is employed to classify the cardiac condition as normal or abnormal based on the six ECG signal features that are set as input parameters [19-21]. As shown in Figure 4, the classification of the cardiac condition as normal or abnormal is represented by two output nodes. Each output node functions as a heart condition detector.

Based on Figure 4, the input parameters are represented by:

P_a = Amplitude of P peak
QRS_a = Amplitude of QRS wave
T_a = Amplitude of T peak
P_d = Duration of P peak
QRS_d = Duration of QRS wave
T_d = Duration of T peak

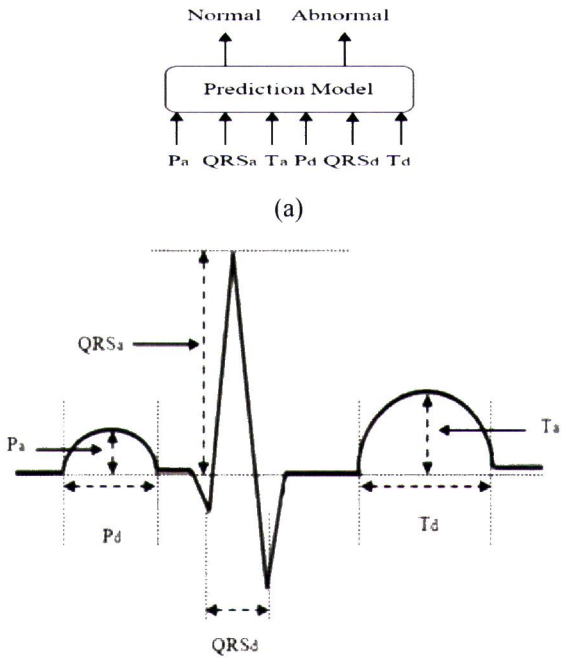

Fig. 4 (a) Cardiac abnormality detection blocks by using supervised prediction model, (b) parameters extracted from ECG complex.

The Pa parameter is taken from the highest point of the P peak while Pa parameter at the sharpest point of R peak while T peak is taken from the highest point of T peak. The duration of P peak is measured from the starting point of P peak until the end of P peak. For the QRS duration, the starting point is at Q peak to S peak while T duration, it is measured from the starting point of T peak until the end of T peak. The research suggested all the parameters are used as the input parameters to all supervised prediction models in classifying the cardiac abnormality into normal or abnormal signal condition.

IV. Result and Discussion

Certainly, the model is designed to make predictions about cardiac abnormalities, such as identifying cardiac abnormal ECG signal. The evaluation involves a computational experiment, which means that it's conducted using a computer and involves processing data. The data used in this experiment comes from the ECG dataset, which contains a collection of ECG recordings. Six specific parameters from the ECG data are used as input features for the prediction model. These parameters are related to the duration of various components of the ECG signal, including the P peak, QRS wave, and T peak. It's important to note that there seems to be a repetition of these parameters, resulting in a total of 200 data points [19-21].

The study goes on to compare the results produced by different prediction models. These models include KNN, Decision Tree, PCA, LDA (Linear Discriminant Analysis), and QDA. The purpose of this comparison is try to determine which model performs the best in classifying cardiac abnormalities based on the input parameters. The performance of these prediction models is assessed using two specific metrics: accuracy and mean square error (MSE). Accuracy measures how often the model's predictions are correct, while MSE quantifies the average squared difference between the model's predictions and the actual values.

The best-performing model is one that achieves the highest accuracy and the lowest MSE values. In other words, the model with the most accurate predictions and the least error is considered the most effective in classifying cardiac abnormalities. The results of the analysis of these prediction models are presented in a table, denoted as "Table I." This table would provide a detailed breakdown of how each model performed in terms of accuracy and MSE, allowing readers to compare and assess their relative effectiveness.

TABLE I. Performance of several prediciton model.

Prediction Model	*Accuracy, %*	*MSE*
KNN	94.27	0.24
Decision Tree	92.34	0.32
PCA	91.72	0.50
LDA	90.57	0.86
QDA	88.38	0.89

From Table I, the KNN model achieved the highest prediction accuracy among all the models, with an impressive 94.27% accuracy. The KNN model also had the lowest MSE value, which was measured at 0.24. A lower MSE indicates that the predictions made by the model were, on average, closer to the actual values. In this case, an MSE of 0.24 suggests relatively small prediction errors. The decision tree classifier came in second with 92.34% on accuracy and 0.32 value of MSE. The decision tree classifier achieved the second-highest prediction accuracy, which was 92.34%. The decision tree classifier also had a low MSE value, which was measured at 0.92. A lower MSE suggests that the model's predictions were close to the actual values.

PCA gives the third best result with 91.72% on accuracy and 0.90 of MSE. PCA achieved the third-highest prediction accuracy, which was 91.72% accuracy. The MSE value for PCA was 0.90, indicating relatively small prediction errors and good precision in its predictions. Cardiac abnormality classification using LDA capable to with 90.57% on the accuracy, follow with 0.86 on MSE. The LDA is capable of outperforming QDA but not for other prediction models. QDA prediction model show the capability to classify the cardiac abnormality with 88.38% on accuracy and MSE with 0.89, respectively. However, the results are unable to outperform other prediction models on cardiac abnormality classification.

V. Conclusion

The paper investigates the ability of prediction model classify data related to heart abnormalities and then compares the outcomes with those obtained from clinical monitoring methods. This study provides evidence to support the assertion that prediction model possess the capability and reliability to accurately categories heart abnormalities by considering both the amplitude and duration of the P peak, QRS wave and T peak in ECG signals. This paper also discusses all prediction model capable to give high accuracy results and low MSE reading.

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