Automatic Diagnosis System for Heart Disorder using ESG Peak Recognition with Ranked Features Selection

Mohammad Subhi Al-Batah

***Abstract*—** Electrocardiography is used in cardiology to record heart's electrical signals over time. An accurate ECG beat classification using high efficient system is a challenging problem. Thus, this paper proposes an automatic system to analyze ECG signals focusing on real peaks recognition. The real peaks: P, Q, R, S, and T contain useful information about the nature of disease affecting the heart. The proposed system includes four main modules: denoising module, features extraction module, features selection module, and classifier module. In the denoising module, ECG signals are filtered, digitized and finally the real peaks are identified. In the feature extraction module, five waveform features; amplitude, duration, pre-gradient, post-gradient and polarity-degree are extracted. In the feature selection module, eight attribute evaluators are applied; Correlation-based Feature Selection, Classifier Attribute Evaluator, Correlation Attribute Evaluator, Gain Ratio, Info Gain, OneR, ReliefF, and Symmetrical Uncertainty. As the classifier module, eleven classifiers are investigated; they are: Decision Table, JRip, OneR, PART, Chi-square Automatic Interaction Detector (CHAID), Exhaustive CHAID, Classification and Regression Tree (CRT), Quick-Unbiased-Efficient Statistical Tree (QUEST), Linear Discriminant Analysis (LDA), Radial Basis Function (RBF), and Multilayer Perceptron (MLP). Classifiers are compared with each other using 1600 ECG signals and the performance is evaluated using stratified ten-fold cross-validation. The results prove that the proposed method can achieve high classification accuracy and has a promising potential application in the automatic diagnosis of heart diseases.

***Keywords*—** Feature Selection, Heart disease, Electrocardiogram beat classification, Morphological features, PQRST Peak recognition, ECG signal classification.

I. Introduction

HEAT are the major killer that causes mortality all over the country [1]. Early and accurate detection is important in detecting heart diseases and choosing appropriate treatment for a patient [2]. An electrocardiogram (ECG) is a bio-electrical signal which is used to record the heart's electrical activity with respect to time [3]. ECG can be used to determine various heart diseases or damages to the heart along with the pace at which the heart beats as well as the effects of drugs or devices used to control the heart [4]. Generally, normal healthy ECG signals have P, Q, R, S and T waves with standard measurement values and these could be different in terms of features or morphological attributes for abnormal ECG signals [5]. Several techniques for identifying peaks, extracting features, selecting appropriate features, and classifying of ECG signals have been proposed. These include template matching, wavelet transform, fuzzy logic, and neural network [6]-[8].

Izzah et al. [9] analyzed the ECG signals using feed forward neural network trained by SCG learning algorithm. Some major important features were extracted from ECG signals. Results obtained showed that neural network pattern recognition was able to classify and recognize the real peaks with an overall accuracy of 81.6%.

Alhady et al. [10] employed Multiple Multilayered Perceptron (MMLP) and Multiple Radial Basis Function (MRBF) networks for the identification of peaks from ECG signals. The feature selection for individual MLP networks, P, R and S peaks recognition networks were found to utilize less features compared to RBF while Q and T peaks recognition networks were the same for both networks. The overall accuracy of MMLP was recorded 86.8% at 25 epochs while that of MRBF was 86.53% at epoch 7.

Weems et al. [11] classified the ECG signals using multilayer feed-forward network with back-propagation learning algorithm. Data obtained from the PhysioBank ATM was used to analyze the structure of the ANN. The results showed that only one misclassification occurred resulting in an accuracy of 96%.

Li et al. [12] used genetic algorithm back propagation neural network (GA-BPNN) for classifying ECG signals with feature extraction using wavelet packet decomposition (WPD). WPD combined with the statistical method is utilized to extract the effective features of ECG signals. GA is employed to decrease the dimensions of feature sets and to optimize the weights and biases of the back propagation neural network (BPNN). The optimized BPNN classifier is applied to classify the types of ECG signals. The GA-BPNN method with the MIT/BIH arrhythmia database achieved a dimension reduction of nearly 50% and produced good classification results with an accuracy of 97.78%.

Bhardwaj et al. [13] applied Support Vector Machine (SVM) technique to ECG dataset for arrhythmia classification in five categories. Nine waveform features: RR interval, P

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height, R height, heart rate, QT interval, ST interval, QRS width, corrected QT interval and PR interval were fed into the LIBSVM classifier, and an accuracy of 95.21% was obtained.

Jatmiko et al. [14] used wavelet transform to extract features from ECG signals. The fuzzy neuro learning vector quantization (FLVQ) is conducted to classify ECG signals into five classes with an accuracy of 95.50%.

Dutta et al. [15] used a cross-correlation approach, in which the cross-spectral density information in the frequency domain was utilized to extract features, and the least squares support vector machine (LS-SVM) classified the features of ECG beats into three categories with an accuracy in the range of 95.51% to 96.12%.

Ebahimzadeh et al. [16] used Higher-order statistics (HOSs) of ECG signals combined with three time interval features. The hybrid bee algorithm–radial basis function (RBF-BA) technique was applied to classify the five types of ECG signals with an accuracy of 95.79%.

Sarkaleh and Shahbahrami [17] applied the Discrete Wavelet Transform for feature extraction in ECG signals. The extracted features along with timing interval features are used to train the neural network. About 10 recording of the MIT/BIH arrhythmia database have been used for training and testing the neural network based classifiers. The model result shows that the classification accuracy is 96.54%.

Karpagachelvi et al. [18] compared the Relevance Vector Machine (RVM) with Extreme Learning Machine (ELM) approach in the automatic classification of ECG beats. The experiments were conducted on the ECG data from the MIT/BIH arrhythmia database to classify five kinds of abnormal waveforms and normal beats. The obtained results confirm the superiority of the RVM approach when compared to traditional classifiers.

Jatmiko et al. [19] employed Back-Propagation Neural Network and Fuzzy Neuro Learning Vector Quantization (FLVQ) as classifiers in ECG classification. The experiments were carried out on MIT/BIH arrhythmia database. The classes that are considered are left bundle branch block beat, normal beat, right bundle branch block beat, and premature ventricular contraction. The experiment provides an average accuracy 99.20% using Back-Propagation and 95.50% for FLVQ.

Nazmy et al. [20] applied adaptive neuro-fuzzy inference system (ANFIS) model for the classification of ECG signals. The feature extraction was done with the help of Independent Component Analysis (ICA) and Power spectrum together with the RR interval. The results indicate a high level of efficient of tools used with an accuracy level of more than 97%.

In this paper, numerous techniques are used as a decision support system for the interpretation of ESG signals of patients with heart disease. The data collected from the patients are images of their cells. During image pre-processing, images will be filtered, digitized and Peaks of ECG signal will be recognized. Then, the features are extracted from the P, Q, R, S and T peaks. The features selected are amplitude, duration, pre-gradient, post-gradient and peak polarity. After that, eight feature selection methods are proposed; Correlation-based Feature Selection, Classifier Attribute Evaluator, Correlation Attribute Evaluator, Gain Ratio Attribute Evaluator, Info Gain Attribute Evaluator, OneR Attribute Evaluator, ReliefF Attribute Evaluator, Symmetrical Uncertainty Attribute Evaluator. Finally the selected features are inputted to 11 classifiers to classify ECG signals into five types.

II. METHODOLOGY

First of all, there are 1600 samples of ECG waveform obtained from healthy and unhealthy patients. An ECG signal has been divided into five segments PQRST peaks. U waveform somehow exists in some ECG signals, but it can be ignored as it is not significant in cardiac diagnosis [21]. A typical ECG tracing of a normal heartbeat (or cardiac cycle) consists of a P wave, a QRS complex and a T wave as shown in Fig 1. The baseline voltage of the electrocardiogram is known as the isoelectric line. Typically the isoelectric line is measured as the portion of the tracing following the T wave and preceding the next P wave.

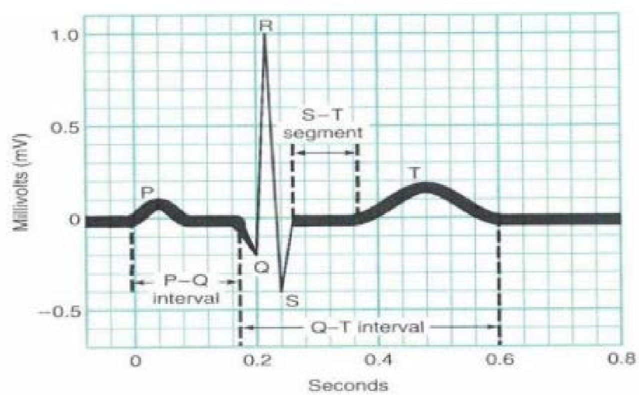

Fig 1. ECG graph

The ECG graph components as shown in Fig. 1 consists of:

- P wave: During normal atrial depolarization, the main electrical vector is directed from the SA node towards the AV node, and spreads from the right atrium to the left atrium. This turns into the P wave on the ECG.
- QRS complex: The QRS complex is a recording of a single heartbeat on the ECG that corresponds to the depolarization of the right and left ventricles.
- PR interval: The PR interval is measured from the beginning of the P wave to the beginning of the QRS complex. It usually is 120 to 200ms long.
- ST segment: The ST segment connects the QRS complex and the T wave. It has duration of 0.08 to 0.12 sec (80 to 120ms).
- T wave: The T wave represents the repolarization (or recovery) of the ventricles. The interval from the beginning of the QRS complex to the apex of the T wave is referred to as the absolute refractory period. The last half of the T wave is referred to as the relative refractory period (or vulnerable period).

- QT Interval: The QT interval is measured from the beginning of the QRS complex to the end of the T wave. Normal values for the QT interval are between 0.30 and 0.44 seconds.

Automatic classification of electrocardiogram (ECG) signals is vital for clinical diagnosis of heart disease. In this paper, the proposed technique used in ECG pattern recognition comprises: ECG signal pre-processing, features extraction, features selection, and signal classification.

A. Data pre-processing

Pre-processing of the signal is required to remove unwanted noise and identify the real peaks. The real peaks are identified by rejecting all noisy peaks [22]. To remove the noisy peaks, analysis of the threshold with a two-stage process was performed. In the first stage, a threshold value of 0.021 was selected where 32.77% of the noisy peaks have been successfully eliminated. A threshold value of 0.45 used in the second stage eliminated 89.16% of noisy peaks. Combinations of these stages produced an elimination of 92.17% of the noisy peaks. These thresholds were selected as an optimum condition in which none of the real peaks were eliminated. Thus, the real peaks are identified at the end of pre-processing stage.

B. Features extraction

The next stage is extracting important data features and characteristics of these waveforms. An automated extraction system using C++ is performed in order to get accurate values and precise computation. Features selected were amplitudes, durations, gradients and polarity [23].

For the purposes of the study, the following notation and definitions for the peaks are adopted. The peaks are symbolized by P_1, P_2… P_i where P_i is the name of peak i. The peak extreme of peak P_i has coordinates (P_{xi}, P_{yi}), where P_{xi} is the x coordinates (time) and P_{yi} is the y coordinates (amplitude).

Amplitudes in the ECG signal are measured from the base line to the peaks in mV, which the value is P_{yi}.

$$A(i) = P_{yi} \qquad (1)$$

The duration between the peaks can be calculated as shown in equation (2);

$$\text{Duration} = P_{xi} - P_{xi-1} \qquad (2)$$

Pre-gradient $F_{pre}(i)$ and post-gradient $F_{post}(i)$ are measurements of the slope before and after the peak, which can be calculated as shown in equations (3) and (4) respectively;

$$F_{pre}(i) = \frac{D_{yi} - D_{yi-1}}{D_{xi} - D_{xi-1}} \qquad (3)$$

$$F_{post}(i) = \frac{D_{yi} - D_{yi+1}}{D_{xi} - D_{xi+1}} \qquad (4)$$

where Di is the sample data known as peak investigated, D_{xi} is the x coordinate (time) and D_{yi} is the y coordinate (amplitude).

Polarity Degree of peaks which describes the shape of the peaks can be calculated as shown in equation (5).

$$F_{\deg ree}(i) = abs\left(\arctan\frac{D_{xi} - D_{xi-1}}{D_{y_i} - D_{y_{i-1}}} + \arctan\frac{D_{xi} - D_{xi+1}}{D_{y_i} - D_{y_{i+1}}} \right) \qquad (5)$$

C. Feature selection

In this study, eight attribute evaluators are used for ranking and selecting the features [24]. The evaluation mode in all the evaluators are considered based on the full training data. The CFS subset Evaluator is applied based on the Greedy Stepwise search method, while the other evaluators are applied based on the ranker search method. The original five features are donated as 1 amplitude, 2 duration, 3 pre-gradient, 4 post-gradient and 5 polarity-degree.

- CFS Subset Evaluator: Evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them. Subsets of features that are highly correlated with the class while having low intercorrelation are preferred.
- Classifier Attribute Evaluator: Evaluates the worth of an attribute by using a user-specified classifier.
- Correlation Attribute Evaluator: Evaluates the worth of an attribute by measuring the correlation (Pearson's) between it and the class.
- Gain Ratio Attribute Evaluator**:** Evaluates the worth of an attribute by measuring the gain ratio with respect to the class.
- Info Gain Attribute Evaluator**:** Evaluates the worth of an attribute by measuring the information gain with respect to the class.
- OneR Attribute Evaluator**:** Evaluates the worth of an attribute by using the OneR classifier.
- ReliefF Attribute Evaluator: Evaluates the worth of an attribute by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different class. It can operate on both discrete and continuous class data.
- Symmetrical Uncert Attribute Evaluator: Evaluates the worth of an attribute by measuring the symmetrical uncertainty with respect to the class.

Table1. Selected and Ranked attributes

Attribute Evaluator	Search Method	Ranked attributes
CFS Subset Eval	Greedy Stepwise	Selected attributes: 4 2 duration 3 pre-gradient 4 post-gradient 5 polarity-degree
Classifier Attribute Eval	Ranker	5 polarity-degree 2 duration 3 pre-gradient

		4 post-gradient 1 amplitude
Correlation Attribute Eval	Ranker	0.446 5 polarity-degree 0.374 2 duration 0.374 1 amplitude 0.357 3 pre-gradient 0.297 4 post-gradient
Gain Ratio Attribute Eval	Ranker	0.557 3 pre-gradient 0.537 5 polarity-degree 0.51 2 duration 0.491 4 post-gradient 0.322 1 amplitude
Info Gain Attribute Eval	Ranker	1.6397 3 pre-gradient 1.3621 4 post-gradient 1.1839 5 polarity-degree 1.0157 2 duration 0.9288 1 amplitude
OneR Attribute Eval	Ranker	70.6 3 pre-gradient 66.0667 4 post-gradient 55.3333 5 polarity-degree 52.7333 2 duration 52.3333 1 amplitude
ReliefF Attribute Eval	Ranker	0.2018 5 polarity-degree 0.0884 2 duration 0.0857 1 amplitude 0.0748 3 pre-gradient 0.0594 4 post-gradient
Symmetrical Uncert Attribute Eval	Ranker	0.623 3 pre-gradient 0.535 4 post-gradient 0.523 5 polarity-degree 0.471 2 duration 0.357 1 amplitude

Table 1 shows the results of the selected and ranked attributes using the eight evaluators. From the analysis, we can notice the following results:

- The CFS Subset Evaluator selected 4 useful features: duration, pre-gradient, post-gradient, and polarity-degree. The amplitude is not selected using CFS algorithm.
- The Classifier Attribute Evaluator ranked the importance of the features as polarity-degree, duration, pre-gradient, post-gradient, and amplitude.
- The Gain Ratio Attribute Evaluator arranged the attributes as pre-gradient, polarity-degree, duration, post-gradient, and amplitude.
- Two evaluators; Correlation Attribute Evaluator and ReliefF Attribute Evaluator ordered the five features as polarity-degree, duration, amplitude, pre-gradient, and post-gradient.
- Three evaluators; Info Gain Attribute Evaluator, OneR Attribute Evaluator, and Symmetrical Uncertainty Attribute Evaluator ranked the attributes as pre-gradient, post-gradient, polarity-degree, duration, and amplitude.

In addition, the selected and ranked attributes using the eight evaluators are analyzed and compared. From the analysis, it can be noticed that the amplitude of the peaks is not selected using CFS subset Evaluator, and also ranked as a last feature using five other attribute evaluators. Also, it can be seen that four features are considered important which are: pre-gradient, post-gradient, polarity-degree, and duration. Thus, features selection techniques can be used in the ECG signals and only four important features are considered for the recognition stage.

D. Recognition

In this work, classification accuracy of the ECG signal is compared with eleven different classifiers as follows:

- *Decision Table*: builds and using a simple decision table majority classifier as proposed by Kohavi [25]. Decision Table employs the wrapper method to find a good subset of attributes for inclusion in the table.

1. *JRip*: implements a propositional rule learner, Repeated Incremental Pruning to Produce Error Reduction (RIPPER), which was proposed by William W Kohen as an optimized version of IREP [26].
2. *OneR*: uses the minimum-error attribute for prediction, and discretizing numeric attributes [27].
3. *PART*: generates a PART decision list. Uses separate-and-conquer. Builds a partial C4.5 decision tree in each iteration and makes the "best" leaf into a rule [28].
4. *CHAID*: Chi-squared Automatic Interaction Detection. At each step, CHAID chooses the independent (predictor) variable that has the strongest interaction with the dependent variable. Categories of each predictor are merged if they are not significantly different with respect to the dependent variable [29].
5. *Exhaustive CHAID*: A modification of CHAID that examines all possible splits for each predictor [30].
6. *CRT*: Classification and Regression Trees. CRT splits the data into segments that are as homogeneous as possible with respect to the dependent variable. A terminal node in which all cases have the same value for the dependent variable is a homogeneous, "pure" node [31].
7. *QUEST*: Quick, Unbiased, Efficient Statistical Tree. A method that is fast and avoids other methods' bias in favor of predictors with many categories. QUEST can be specified only if the dependent variable is nominal [32].
8. *LDA*: Linear discriminant analysis (LDA) or discriminant function analysis is a generalization of Fisher's linear discriminant, a method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification [33].
9. *RBF*: The RBF procedure fits a radial basis function neural network, which is a feed-forward, supervised learning network with an input layer, a hidden layer, and an output layer. The RBF uses Euclidean distances between inputs and weights, which can be viewed as centers and usually Gaussian activation functions, which makes neurons more locally sensitive. Thus, RBF neurons have maximum activation when the center/weights are equal to the inputs. Also, RBFs may use back-propagation for learning, or hybrid approaches with unsupervised learning in the hidden layer. The RBFs make it easier to grow new neurons during training [34].
10. *MLP*: The MLP procedure fits a particular kind of neural network called a multilayer perceptron. The multilayer

perceptron uses a feed-forward architecture and can have multiple hidden layers. The MLP uses dot products between inputs and weights and sigmoidal activation functions (or other monotonic functions). The training is usually done through back-propagation for all layers. This type of neural network is used in deep learning with the help of many techniques such as dropout or batch normalization [35]-[42].

III. RECOGNITION RESULT AND DISCUSSION

The data set used in this study contains 1600 data collected at Hospitals of Jordan and Malaysia. There are five waveforms that need to be recognized by classifiers, which are the waveforms of P, Q, R, S, and T. Four important features for ECG signals are selected which are pre-gradient, post-gradient, polarity-degree, and duration. The performance of each classifier is evaluated using ten-fold cross-validation [43]-[46]. To evaluate the performance of the classifiers in better way, the percentage accuracy for each waveform and the overall accuracy using the 11 classifiers is calculated as shown in Table 2.

Based on the results obtained, the overall accuracy of the 11 classifiers conducted in this study can be ordered as follows: MLP (99.0%), RBF (95.3%), JRip (93.0%), PART (92.9%), Decision Table (89.6%), CRT (87.8%), LDA (82.3%), OneR (79.2%), CHAID (77.5%), Exhaustive CHAID (77.3%), and QUEST (75.4%) model. We can see clearly from Table 2 that the MLP classifier achieved superior performance over other classifiers while using the same data of ECG signals.

The comparison results show that the lowest overall accuracy among the classifiers conducted are reached by QUEST, Exhaustive CHAID, CHAID, and OneR. The LDA, CRT, and Decision Table produced satisfactory classification results. While, the PART, JRip, and RBF exhibited good classification accuracy. However, the MLP produced excellent classification accuracy compared to other classifiers. The MLP classifier achieved better identification results, and only a few samples were incorrectly classified. Thus, the results show that the proposed MLP is the best classifier for ECG beats.

The results in Table 2 show that the MLP is able to achieve better classification performance than other classifiers. For example, the MLP outperformed the OneR classifier in terms of the percentage of waveform accuracy by more than 28.2% as for P, 31.5% for Q, 0.3% for R, 13.1% for S, and 25.9% for T waveform. In addition, the MLP outperformed the other classifiers with difference of accuracy percentage equal to 3.7%, 6.0%, 6.1%, 9.4%, 11.2%, 16.7%, 19.8%, 21.5%, 21.7%, and 23.6% for RBF, JRip, PART, Decision Table, CRT, LDA, OneR, CHAID, Exhaustive CHAID, and QUEST model, respectively. The outcomes consistently demonstrate the effectiveness of the MLP for classifying ECG signals task.

Fig. 2 presents a comparison for the classification accuracy for each waveform and also the overall classification accuracy using the 11 classifiers. As can be seen in Fig. 2, the five types of ECG signals have different classification results. Accordingly, the RBF classification accuracy of P, Q, R, S, and T were 92.9%, 94.0%, 98.7%, 98.8%, and 92.2%, respectively. While, The MLP produced 98.5%, 99.2%, 100.0%, 98.8%, and 98.6% for classification of P, Q, R, S, and T waveform, respectively. The comparison results of different classifiers prove that the MLP can classify all the waveforms with high classification accuracy.

As stated, The MLP network achieved a higher classification accuracy of 99.0% than the classification accuracy obtained by other classifiers. This result is also important when it is taken into account that the average classification accuracy of the eleven classifiers applied for this problem is 86.3%. Thus, this problem can be seen as a hard medical recognition problem and MLP has reached a considerably better classification results for this problem. Also, the selected features; pre-gradient, post-gradient, polarity-degree, and duration were found to be appropriate for recognition of ECG signals.

Table 2. Result of ECG classification using eleven classifiers

Type	Decision Table	JRip	OneR	PART	CHAID	Exhaustive CHAID	CRT	QUEST	LDA	RBF	MLP
P	84.0	85.0	70.3	89.7	52.7	52.7	86.0	79.0	76.0	92.9	98.5
Q	74.0	86.7	67.7	82.0	63.0	84.0	70.0	60.7	78.7	94.0	99.2
R	99.7	99.7	99.7	100.0	98.7	98.7	100.0	100.0	100.0	98.7	100.0
S	93.7	96.3	85.7	97.3	87.0	65.3	92.3	63.7	83.3	98.8	98.8
T	96.7	97.3	72.7	95.7	86.0	86.0	90.7	73.7	73.3	92.2	98.6
Overall	89.6	93.0	79.2	92.9	77.5	77.3	87.8	75.4	82.3	95.3	99.0

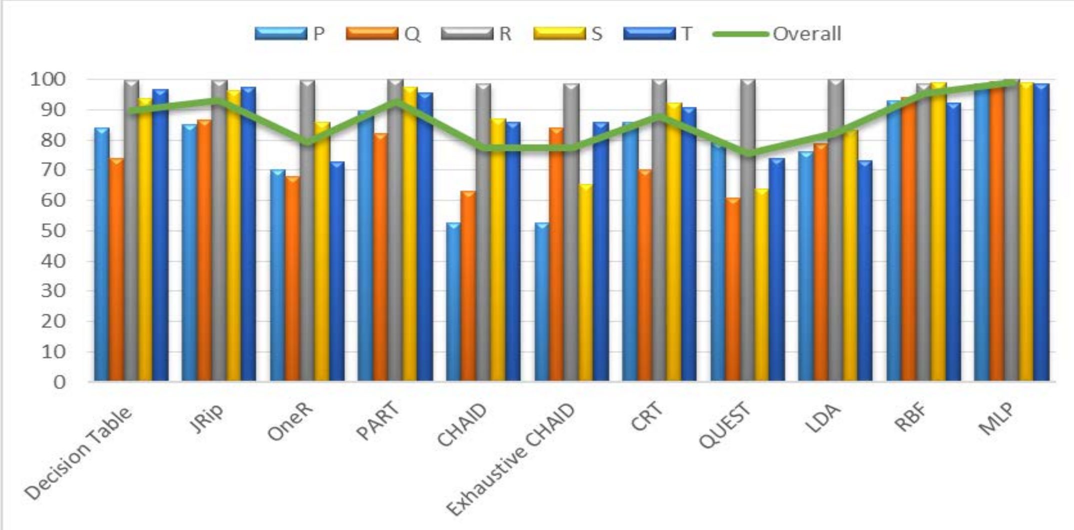

Fig. 2 ECG classification results

I. CONCLUSION

Precise recognition of ECG peaks will provide useful information for doctors to diagnose any heart disorder or abnormalities as well as for cardiac arrhythmias classification. This research was conducted to develop a computerized system to identify peaks of ECG signals, eliminating noisy peaks, extracting features, selecting suitable features, and diagnosing heart conditions based on these ECG signals. A total of 1600 samples containing 5 types of ECG signals were collected using the ECG acquisition experimental platform. During pre-processing stage, noise was eliminated and the identification of real peaks in the ECG was performed. In feature extraction stage, the method was applied to extract five ECG waveform features; amplitude, duration, pre-gradient, post-gradient and peak polarities. Eight attribute evaluators are considered for selecting and ranking the features. Four important features are chosen which are: pre-gradient, post-gradient, polarity-degree, and duration. In the classification stage, eleven classifiers are conducted for classifying the ECG signals. The result show that the highest ECG signal classification is obtained via MLP with an accuracy of 99.0%, as compared to RBF (95.3%), JRip (93.0%), PART (92.9%), Decision Table (89.6%), CRT (87.8%), LDA (82.3%), OneR (79.2%), CHAID (77.5%), Exhaustive CHAID (77.3%), and QUEST (75.4%) model. Moreover, the waveforms classification using the MLP ranked first compared to other classifiers has a recorded accuracy of P (98.5%), Q (99.2%), R (100.0%), S (98.8%), and T (98.6%). Although the proposed method using the ECG data achieved excellent identification results, the current study can be extended using more samples for a complete diagnosis of a heart disorder. Also, we intend to investigate the work further with regard to additional features extraction, other features selection methods, and more intelligent classification techniques in the diagnosis of heart disease.

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