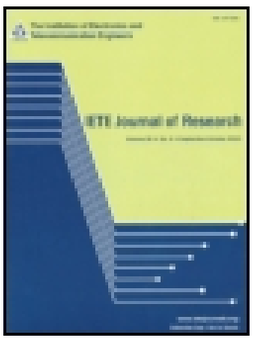

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Classification of Complete Myocardial Infarction Using Rule-Based Rough Set Method and Rough Set Explorer System

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ABSTRACT

In this study, a computerized diagnosis system is developed using Rough set classifier from multi-lead ECG signal for detection as well as the classification of five different types of myocardial infarction (MI) disease. The pathological features of ECG such as Inverted T-wave, ST segment deviation, or pathological Q wave, which are seen during MI, are extracted. An Information table and the knowledgebase are expanded from these pathological features after getting feedback from the cardiologist as well as consulting different medical books. The Information table contains 36 features and 341objects which include normal and five types of MI such as Anterior (AN), Inferior (IN), Antero lateral (ANLA), Inferior lateral (INLA), and Antero septal (ANSE) are used for assessment. The proposed system determines the degree of attributes dependency and their significance to find a smaller set of attributes, called reduct, alike the original set to predict the appropriate decision rules for MI classification. The robustness is justified by the "five-fold cross" validation technique using RSES tools. Finally, the proposed classifier illustrates its outperformance over the existing approaches in terms of sensitivity (99.75%), and accuracy (99.8%) for MI detection and 99.8% accuracy for MI classification.

KEYWORDS

Accuracy; ECG; Knowledge bases; MI; Reduct; RSES; Rough set; Sensitivity; Specificity; Train and test

1. INTRODUCTION

Myocardial Infarction (MI), a harmful cardiovascular disease (CVD), is one of the most dangerous causes of death all over the world. Every year, nearly 8 million deaths occur globally due to the above disease [1]. MI, usually known as heart attack is responsible for creating a global life-threatening circumstance. It is a fact that more than 610, 000 people in the USA only get distressed by MI with annual direct estimated costs of over $316 billion [2]. Different surveys by statistical analysis point out that MI is becoming a major problem in health even in India. MI occurs because of permanent injury to the heart muscle due to a rapid obstruction in coronary arteries by the insufficiency of blood supply that can lead to acute infarction and sudden death [3]. It expands in an epidemic manner and will continuously destroy the heart muscles if not treated timely. So early and accurate detection and classification of MI can improve the diagnoses of the disease and can effectively reduce the mortality rate in the world.

Cardiologists and medical practitioners can diagnosis MI based on the changes in the ECG such as inverted T wave, deviation of ST segment or pathological Q wave. They can also localize the part of the heart muscle which has been infracted area. But due to the very small amplitude (mV) and small duration (sec) in the ECG signal, manual detection and classification of the changes in the signal is not only time consuming and tedious task but also erroneous. Therefore, a computer-aided diagnosis system is needed for detection and classification of MI that may greatly aid the clinician in their accurate diagnostic decision quickly. Hence many researchers have suggested various diagnostic techniques for detection and classification of MI. Among them, we would like to point out some recently reported techniques.

In 2012, Sun et al. [4] reported Latent Topic Multiple Instance Learning (LTMIL) for myocardial infarction detection. Banerjee et al. (2014) [5] had reported spectral differences based cross wavelet transform (XWT) technique and used threshold-based classifier with clinical features of ECG such as ST elevation, T inversion and Q wave for MI classification. Sharma et al. (2015) [6] used multiscale energy and eigenspace (MEES) as diagnostic feature and SVM classifier with RBF kernel for detection and classification of MI. In a more recent paper [7] Seenivasagam and Chitra (2016), Particle Swarm

Optimized Neural Network (PSONN) technique is used for MI prediction. In the same year, Hamidi et.al. [8] applied Naive Bayes classifier and ECG features such as elevated/depressed ST segment and inverted T wave to detect MI events. The same group applied Genetic algorithm and SVM to the same problem in ref. [9] and achieved better accuracy. In ref. [10] (2016), using DWT, ECG beats are decomposed and extracted 12 nonlinear parameters. Furthermore, they proposed MI classification system using KNN. In ref. [11], (2017) DWT and K-Nearest Neighbour (KNN) classifier is also used for detection of normal, CAD and MI. Pawlak [12] applied rough set theory in Bayes' theorem to generate a rule for identifying the present and absent of disease. In ref. [13], DWT and roughest theory are used for arrhymia classification. Mitra *et al.* [14–15] (2006–2008) reported a disease inference engine using rule-based rough-set theory from the different time plane feature of ECG and used three classes of data such as normal, Ischaemia and MI for classification.

In this paper, a Rough set based diagnosis system has been proposed for detection as well as complete classification of five different types of MI such as AN, IN,ANLA, INLA, and ANSE by the characteristic features of ECG signal from multidimensional data set. This is done to achieve the classification of MI as a whole. The multidimensional dataset contains many attributes that are unnecessary for rule generation and classification. If these unnecessary attributes are not eliminated, the time complexity not only increases but also the quality of the detected rules may be extensively depleted. The Rough set classification system can decrease redundancy among input attributes through finding their relations. It can also categorize Multiclass MI diseases from overlapping parameters, maintains high accuracy and minimizes the complexity of the algorithm for MI classification. Such a procedure is reliable and unambiguous. Therefore, a method for the detection as well as complete classification of MI using Rough set classifier is done in this work.

The rest of this paper is arranged as follows. Section 2 describes the variation of ECG pattern in the case of Myocardial Infarction (MI). Dataset used in this experiment described in section 3. In Section 4 describes the methodology of the proposed system which includes the development of knowledge base, development of classification System using Rough Set. Section 5 describes the Experiment result which includes MI detection, MI localization and five-fold cross validation and in Section 6 discussed the conclusion of the proposed work.

2. VARIATION OF ECG PATTERN IN CASE OF MYOCARDIAL INFARCTION

A 12-lead Electrocardiogram (ECG) is the most effective low-cost diagnostic tool of the heart that can produce a waveform with exact shapes and duration which occur at a certain rate and regularity. It is a reasonably sensitive but hardly perfect indicator of MI.

It gives the electrical activity of the heart and used to measure left ventricular function of the heart. MI usually happens in the left ventricle, although the location may differ depending on the coronary artery exaggerated. The clinically significant features in ECG signal such as inverted T wave, ST segment deviation or pathological Q wave are symptomatic of MI. Five types of MI (AN, IN, ANLA, INLA, and ANSE) are used in this work. The characteristic ECG changes in leads V2 to V4 have shown the causes of an Anterior MI and leads II, III, and aVF show the signature of Inferior MI. The Anterolateral MI are examined from characteristic changes in leads I, aVL V5 and V6. The Inferior lateral MI connecting the inferior and lateral surfaces of the heart and producing pathological changes in leads II, III, aVF, V_5, and V_6. The infarction of an Anteroseptal MI causes the characteristic ECG changes in leads V1 to V3. The normal ECG signal with clinically significant points is shown in Figure 1(a) for reference. During MI, any one of the pathological change such as inverted T-wave (see Figure 1(b)–(c)), elevated ST-segment [see Figure 1(b)] or pathologic Q waves (see Figure 1(c)) may be present in 12 leads ECG.

3. DATASET USED

In this paper, we have used PTB Diagnostic ECG Databases as a data source from Physiobank open access database. It has 549 records with 290 subjects which include 148 MI subjects, 52 normal subjects and the rest are 7 different classes. Each subject contains one to five records. Out of 148 MI subjects, 113 MI along with 52 normal patients are used in this experiment for assessment. We have downloaded a total of 52 normal subjects with 80 records and 113 MI patients with 312 records. The 261 MI records are selected to have five different types MI such as AN, ANLA, ANSE, IN and INLA shown in Table 1.

4. METHODOLOGY

The proposed MI diagnosis system is carried out separately for detection and classification of MI from 12

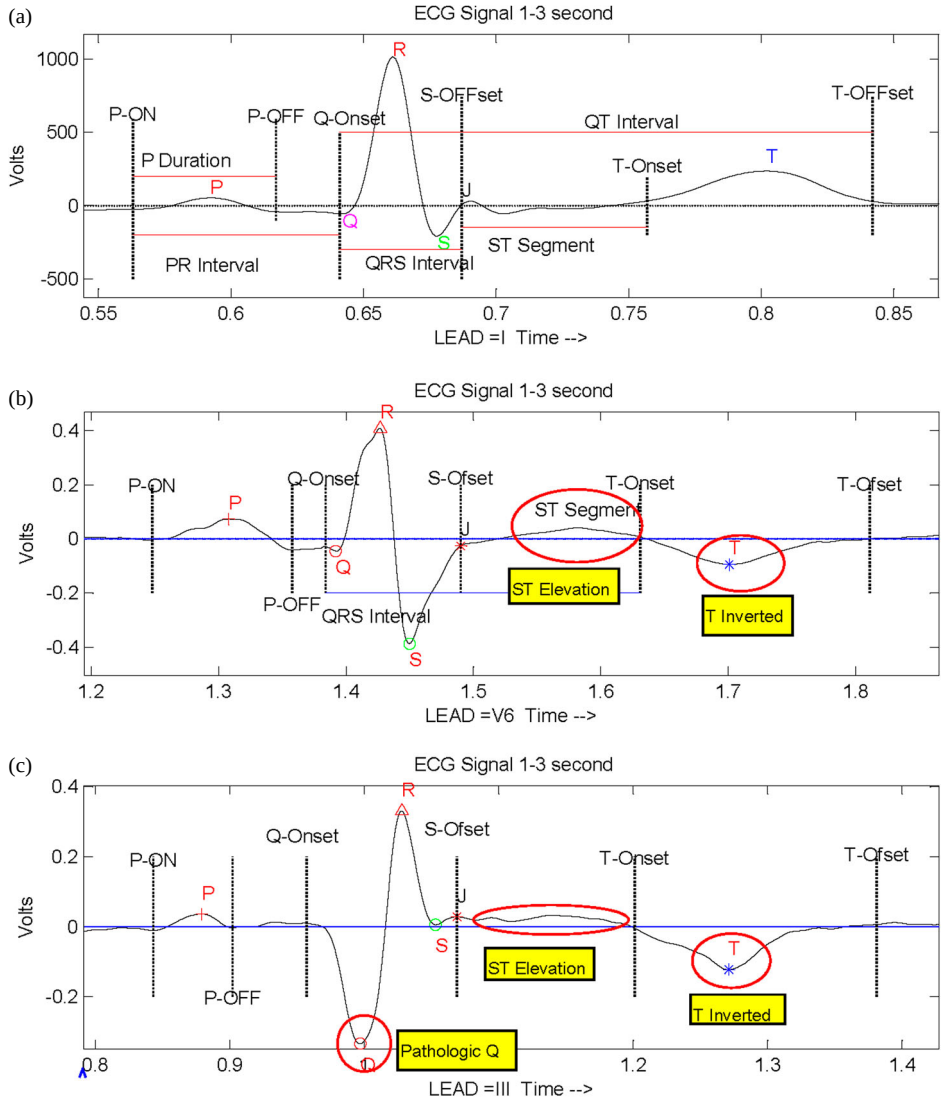

Figure 1: (a) Normal ECG signal with clinically significant points. (b) Fully evolved MI with change in ST elevation and T wave inversion (c) Fully evolved MI with T wave inversion, ST elevation and pathological Q wave

Table 1: Number of selected records for MI classification in the PTB ECG database

Sl No	Multiclass MI	Subject	Records (selected)
1	Anterior (AN)	17	47 (40)
2	Anterolateral (ANLA)	16	43 (40)
3	Anterio septal (ANSE)	27	77 (76)
4	Inferior (IN)	30	89 (55)
5	Inferior laterial (INLA)	23	56 (50)
6	Normal (NOR)	52	80 (80)
	Selected Subject: 165 (113 + 52)	Selected Records: 341(261 + 80)	

lead ECG which includes *pre-processing, feature extraction and classification.* The flow diagram of the proposed classification system is shown in Figure 2.

The pre-processing contains filtering such as power line interference and baseline wandering by FIR and median filter, which is reported in our previous published paper [16].

In the next section, Differential histogram approach depends on an Adaptive window has been used for features extraction from ECG signals which may further be used to identify the cardiac difficulty. The basic idea of feature extraction technique is described in our previous published paper [16–17]. The obtained differential histogram of an ECG signal is shown in Figure 3. The entire clinically significant feature extracted by this technique is shown in Figure 1.

4.1 Development of Knowledgebase

A *knowledgebase* is expanded from the pathological features of ECG signal after getting feedback from the medical practitioners and consultation of different medical books [18–22] shown in Table 2. This infers that all the leads are not essentially required to show the abnormal

patterns for a specific disease rather a specific group of leads shows a particular abnormality for a particular disease and the specific lead combination may be obtained from that.

Hence a knowledge base regarding the characteristic features of the different types of MI has been developed. Mainly, as per the lead position of the specific abnormality, a knowledgebase has been generated which is illustrated in Table 2. From the knowledgebase we know that the pathological features such as inverted T wave, elevated/depressed ST segment or pathological Q wave shown may be present in a specific group of leads for a particular MI during an infarction. For example, for IN type of MI disease, the ST elevated, T inverted and Q pathologic features are found at the lead combinations

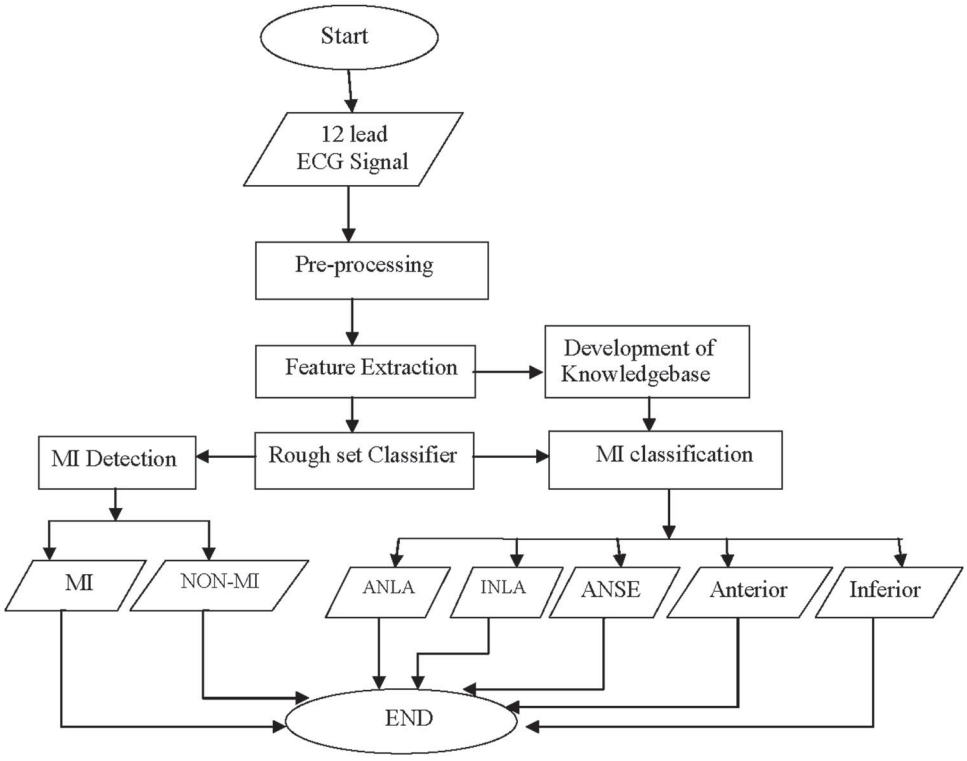

Figure 2: Detection and classification of MI from 12 lead ECG

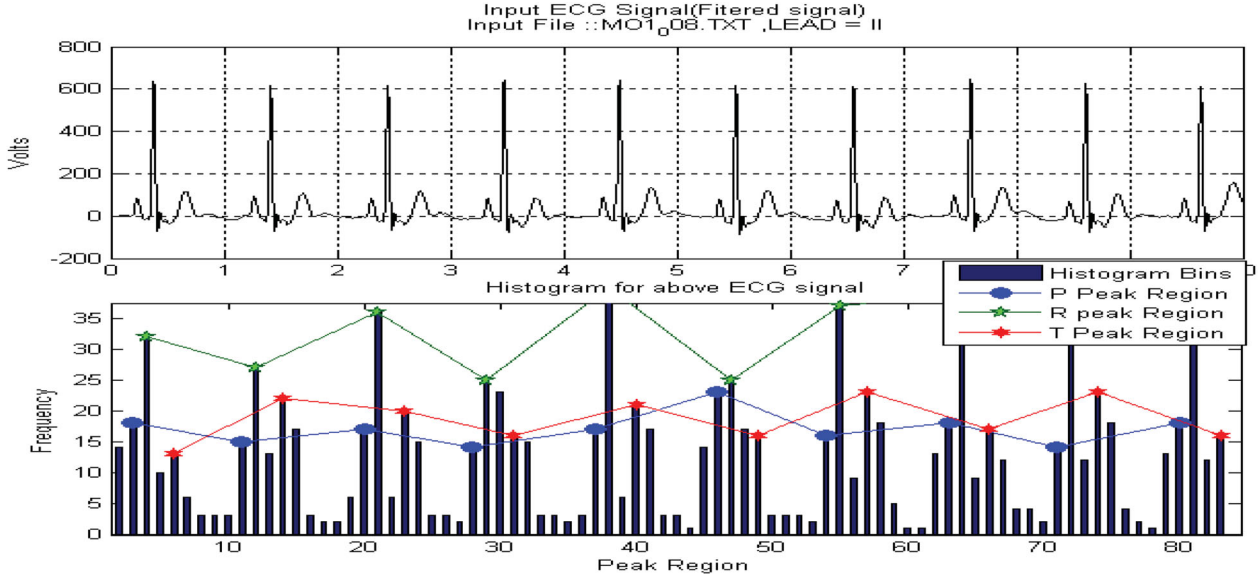

Figure 3: R, P and T peak region of an ECG signal using Histogram

Table 2: Knowledgebase depending on affected MI walls and affected leads

MI wall	ST elevated	ST Depressed	T Inverted	Q Pathologic
Inferior (IN)	II,III,aVF	I,aVL	II,III,aVF	II, III,aVF
Anterior (AN)	V2,V3,V4	II,III,aVF	V2,V3,V4	V1,V2,V3,V4
AnteroSeptal (ANSE)	V1,V2, V3	II,III,aVF,	V1,V2,V3	V1-V3
Anteriolaterial (ANLA)	I,aVL,V3-V6	II,III,aVF,	I,aVL,V3-V6	I,aVL,V3-V6
Inferiolaterial (INLA)	I,V5-V6, II,III,aVF	V1-V4	II,III,VF, V5,V6	II,III,aVF, V5-V6

II,III,aVF whereas ST depressed is found at the reciprocal lead combinations I,aVL. Similarly, for AN type of MI disease, the ST elevated, T inverted and Q pathologic features are found at the lead combinations V2,V3,V4 whereas ST depressed is found at the reciprocal lead combinations II,III,aVF. The explanation is indifferent for the rest of the enlisted MI diseases.

4.2 Development of Classification System using Rough Set

In this research, Rule-based MI classification system is developed for producing the minimal form of rules (*i.e.* rules with a least number of attributes on left-hand side) for detection as well as classification of five types of MI disease. Rough set [23–28] method, applied to calculate the degree of attributes dependency for reduct generation and decision rules prediction, is used in this system. For MI detection, two class classifications with MI and Non-MI is used and for MI classification, five types of MI such as AN, ANLA, ANSE, IN and INLA are used. The pathological features such as inverted T wave, elevated/depressed ST segment or pathological Q wave shown in Table 2 may be present in a specific group of leads for a particular MI during an infarction. Hence all the leads of ECG are needed for complete MI classification. These sets of extracted features of 12-lead ECG are used as an Information table shown in Table 3. In this work, the generated information table (known as multidimensional table) contains 341 objects, 36 (features) conditional attributes, and a decisional attribute. Each attribute has multiple attribute values. So our experimental dataset contains a lot of attributes that are redundant and unnecessary for rule generation and classification of a specific MI. Due to the complexity and high dimensionality of this data set always it is not possible to classify with certainty whether a given object belongs to MI or not.

Rough set classifier allows us to determine a degree of attributes dependency [29] and their significance to find a smaller set of attributes(without redundant), called minimal reduct, with the same as the original set and predicted the universal decision rules for detection and classification of MI.

Let I = (U,A) be an Information table, where U is called the universe which is a non-empty, finite set of objects and A is called the attribute which is a non-empty finite set. To describe more precisely, consider a Information table I = (Z, Y, X), where X (***decision***) and Y (***condition***) be subsets of A and Z be subset of U. Decisional attribute (X) is depends completely on conditional attribute (Y), designated Y ⇒ X, if all the decisional attribute (X) are uniquely determined by the value of conditional attribute Y which is called the ***reduct***. ***Degree of attribute Dependency*** of X on attribute Y, designated $Y \Rightarrow_K X$ is defined by

$$K = \gamma(Y, X) = \frac{|POS_Y(X)|}{|U|} = \frac{\sum_{X \in U/X} |\underline{Y}(Z)|}{|U|} \quad (1)$$

where $POS_Y(X)$ is knows as positive region of the partition U/X with respect to Y. If $K = 1$, X completely depends on Y, if $0 < K < 1$, X partially depends on Y and if $K = 0$, X does not depends on Y. So Degree of dependency $(K = 1)$ means the set is crisp with respect to conditional attributes (Y),which is the minimal reduct, otherwise set is rough. So every object $z \in U$ establishes a series $y_1(z), \ldots \ldots y_n(z), x_1(z), \ldots .., x_n(z)$ where $\{y_1, \ldots ., y_n\} = Y(\text{condition }) \text{and} \{x_1, \ldots ., x_n\} = X(\text{decision})$. When some conditions are fulfilled for a particular decision that conditions (also called reduct) states the decision rules from the Information table. Thus, an information table with result of information reduct can be built the required decision rules for the detection and classification of MI. In this work, RSES 2.2.2 [30–31] tool is used for reduct generation, rules set computation and classification.

5. EXPERIMENTAL RESULTS

In rough set classification system, the performance is evaluated in term of accuracy, sensitivity, and specificity. These parameters are defined as follows [32–33]

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (3)$$

where *TP*, *FP*, *TN* and *FN* represented the number of True positive, false positive, true negative, and False negative respectively.

Table 3: A Portion of the Information table

Object (U) / Condition (C)	ST_segment_I	T_Wave_I	Q_ Pathologic_I	ST_segment_II	T_Wave_II	Q_Pathologic_II	ST_segment_III	T_Wave_III	Q_Pathologic_III	ST segment L aVR	T Wave L Avr	Q Pathologic L Avr	ST_segment_aVL	T_Wave_aVL	Q_Pathologic_aVL	ST_segment_aVF	T_Wave_aVF	Q_Pathologic_aVF	ST_segment_V1	T_Wave_V1	Q_Pathologic_V1	ST_segment_V2	T_Wave_V2	Q_Pathologic_V2	ST_segment_V3	T_Wave_V3	Q_Pathologic_V3	ST_segment_V4	T_Wave_V4	Q_Pathologic_V4	ST_segment_V5	T_Wave_V5	Q_Pathologic_V5	ST_segment_V6	T_Wave_V6	Q_Pathologic_V6	Disease (D) Decision
1	E	I	N	D	U	N	D	U	Y	E	I	N	E	I	N	D	U	N	E	I	N	E	I	N	E	I	Y	E	I	N	E	I	N	D	U	N	ANLA
2	E	I	N	D	U	N	D	U	N	D	U	N	E	I	N	D	U	Y	D	U	Y	D	U	N	D	U	N	D	U	N	E	I	N	E	I	N	ANLA
3	E	I	N	D	U	N	D	U	N	D	U	N	E	I	Y	D	U	N	E	I	N	E	I	Y	E	I	N	E	I	N	E	I	N	D	I	N	ANLA
4	D	U	Y	E	I	N	E	I	Y	D	U	Y	D	U	N	E	I	N	E	I	N	E	I	N	E	I	N	E	I	N	D	I	Y	E	I	N	INLA
5	D	U	N	E	I	N	E	I	Y	D	U	N	D	U	N	D	I	N	E	U	N	E	U	N	E	U	N	E	U	Y	D	U	N	iso	I	N	INLA
6	D	U	N	E	I	N	E	I	Y	D	U	N	D	U	N	E	I	N	D	U	Y	D	U	N	D	U	N	D	U	N	D	I	N	iso	I	N	INLA
7	D	U	N	D	U	N	E	I	N	D	I	Y	D	U	N	D	I	Y	E	U	N	E	U	N	E	U	N	E	U	N	D	U	N	D	U	N	INLA
8	D	U	N	E	I	Y	E	I	Y	E	I	Y	D	U	N	E	I	Y	E	I	N	E	I	N	E	I	Y	E	I	N	D	U	N	E	I	Y	INLA
9	D	U	N	D	U	N	D	U	N	D	U	N	D	U	N	D	I	N	D	U	Y	D	U	N	D	U	N	D	U	N	D	U	N	D	U	N	INLA
10	iso	U	N	D	U	N	D	U	N	iso	U	N	iso	U	N	D	U	N	iso	U	N	E	U	N	E	U	N	E	U	N	E	U	N	E	U	N	normal
11	E	U	N	iso	U	N	iso	U	N	iso	U	N	iso	I	N	iso	U	N	iso	U	N	E	U	N	E	U	N	E	U	N	E	U	N	E	U	N	normal
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16	E	I	N	D	U	N	D	U	N	D	I	Y	E	I	N	D	U	Y	E	U	N	E	I	Y	E	I	Y	E	I	Y	E	I	N	E	U	N	anterior
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19	D	U	Y	D	U	N	D	U	N	E	U	Y	E	I	N	D	U	N	E	U	N	E	I	N	E	I	N	E	I	N	E	I	N	E	U	N	anterior
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23	D	U	N	E	I	Y	E	I	Y	D	I	N	D	U	N	E	I	Y	D	U	N	D	U	N	D	U	N	D	U	N	D	U	Y	E	U	N	inferior
24	D	U	N	E	U	Y	E	I	Y	E	U	N	D	U	N	E	I	Y	D	U	N	D	U	N	D	U	N	D	U	N	D	U	N	E	U	N	inferior
25	D	U	N	E	U	Y	E	I	Y	E	U	Y	D	U	N	E	I	Y	D	U	Y	D	U	N	D	U	N	D	U	N	D	U	Y	E	U	N	inferior
26	D	U	N	E	I	Y	E	I	Y	D	I	N	D	U	N	E	I	Y	E	U	N	D	U	N	D	U	N	D	U	N	D	U	N	E	U	Y	inferior
27	D	U	Y	E	I	Y	E	I	Y	D	I	N	D	U	N	E	I	Y	D	I	N	D	U	N	D	U	N	D	U	N	D	U	N	E	U	N	inferior
28	D	U	N	D	U	N	E	U	N	D	I	N	E	U	N	E	U	N	E	I	N	E	I	N	E	I	N	E	I	N	E	U	N	E	U	N	ANSE
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31	D	U	N	D	U	N	E	I	N	E	I	N	D	U	N	E	U	N	E	I	N	E	I	N	E	I	N	E	U	N	E	I	N	D	I	N	ANSE

Table 4: Performance evaluation for MI detection using Rough set classifier

	No. of training records		No of testing records		Detected datasets					
Classifiers	MI	Non-MI	MI	Non-MI	TP	TN	FP	FN	Sensitivity (%)	Accuracy (%)
Rough set (Data set 1)	211	99	186	69	186	68	0	1	99.46	99.6
Rough set (Data set 2)	240	99	175	69	175	68	0	1	99.43	99.6
Rough set (Data set 3)	264	114	133	54	133	53	0	1	99.25	99.5

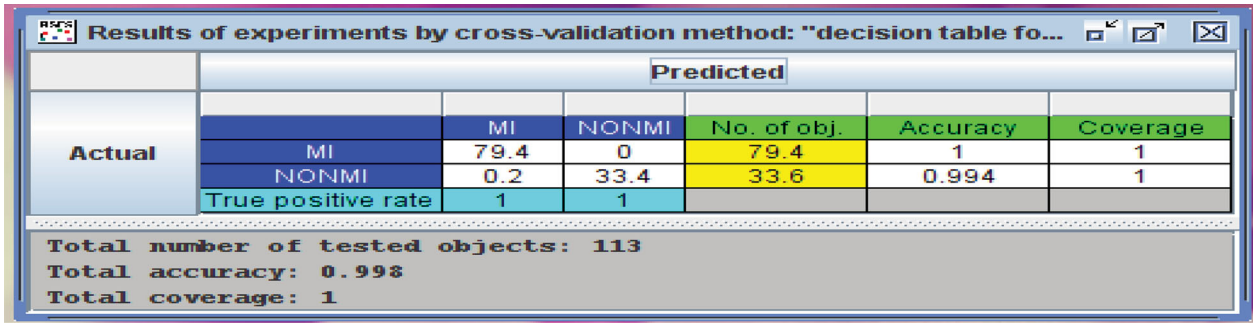

Figure 4: Confusion matrix obtained for MI detection using 5 fold CV with Rough set classifier

The details of two classification results are given in the following subsections.

5.1 MI Detection

In this research, detection of MI is treated as two-class classification with MI and Non-MI classes by Rough set classifier. A multidimensional dataset is generated with 341 ECG records as rows and 36 features extracted from 12 ECG lead as column with a decision. Clinical feature such as T inversion, elevation or depression of ST segment and pathologic Q are extracted for MI detection by Histogram approach. Three different datasets have been used for evaluation and the numbers of *TP*, *FP*, *TN*, and *FN* values are evaluated. The accuracy and sensitivity are measured in each dataset of the proposed system given in Table 4.

In this work, five-fold cross validation with rough set technique as the classifier is used for choosing testing and training ECG records to confirm the performance of MI detection. In each fold, the accuracy and sensitivity are evaluated and finally the average result is considered as the ultimate performance of the proposed system. They produce an average accuracy of 99.8% and average sensitivity of 99.75% as shown in Table 5. The experimental result for MI detection by cross-validation method is shown in Figure 4.

5.2 Result Discussion

The efficiency of MI detection is reported by comparing the classification performance of the proposed system with the different studies and the results are given in Table 6. It is observed that the proposed system yielded maximum classification *accuracy (99.8%) and sensitivity (99.75%) on multidimensional dataset with 5 fold cross validation by* using the rough set technique as the classifier.

5.3 MI Classification

In this work, Multiclass MI classification has been done by rough set as classifier. Five classes of MI such as ANLA, INLA, AN, IN, and ANSE are used for assessment. During the training stage, 187 ECG records including normal and for the testing stage, total 154 ECG records are considered for assessment. Table 7 shows the performance of classification accuracy for different classes. The estimated average accuracy for multiclass Rough set classifier is 99.4%.

Table 5: Performance of Rough set classifier over each fold for MI detection

Classifier	Feature election	Tested Records	Parameters	Fold1	Fold2	Fold3	Fold4	Fold5	Average
Rough set	All Features	113	Accuracy (%)	100	99.1	100	100	100	99.8
			Sensitivity (%)	100	98.79	100	100	100	99.75

Table 6: Performance comparison of the proposed diagnostic method with existing technique

Author	Year	Lead No	Features	Subjects	Method	Performances (%)
Jayachandran, et. al. [34]	2010	Lead II	Energy and entropy	2282 normal, 718 MI beats	DWT	Acc:96.93
Al-Kindi et al. [35]	2011	12	Q, R,S, J, REF	20 normal, 20 MI records	ST segment analysis	Sen:85 Spec:100
Sun, L [4]	2012	12	ST detection	79 normal, 369 MI records	SVM	Sen:92.60 Spec: 82.40
Banerjee[5]	2014	3 (II,III, aVf)	ST elevation and attenuated QRS complex	Normal: 10546 & MI: 40182 beats	XWT and Threshold Based	Acc: 97.6 Sen:97.3 Spec:98.8
Sharma [6]	2015	12	Wavelet transform Multiscale energy and Eigenspace	148 MI & 52 normal (549 records)	SVM with RBF kernel	Acc: 96 Sen: 93 Spec:99
Hamidi [8]	2016	12	Forward selection	297 MI and 222normal records	genetic algo SimpleCART	Acc:96.53 Sen:95.62 Spec:97.75
Acharya[10]	2016	12	Detection of R-peaks	Normal: 125652 & MI: 485,753 beats	KNN	Acc:98.80 Sen: 99.45 Spec:96.27
Acharya[11]	2017	Lead II	DWT coefficients	7 CAD, 148 MI and 52 normal records	DCT and KNN	Acc: 98.5 Sen: 99.7 Spec:98.5
Kumar, [36]	2017	Lead II	sample entropy (SEnt)	Normal: 10548 & MI: 40182 beats	SEnt in FAWT and LS-SVM	Acc: 99.31
Sharma,[37]	2018	Single lead	RE, FE and SFD	Normal: 10,546 & MI: 40,182 beats	KNN	ACC:99.74 Sen: 99.76 Spec: 99.12
Proposed system	2019	12	ST segment, T & Q wave analysis	261 MI & 80 normal records	Rough set	Acc: 99.8 Sen:99.75

Table 7: Classification results using multiclass Rough set classifier

Multiclass type	Number of training datasets	Number of test datasets	TN	TP	FN	FP	% Classification accuracy
ANLA	19	21	-	21	-	0	100
Normal	41	39	39	-	0	-	100
INLA	32	18	-	17	-	1	94.5
AN	25	15	-	15	-	0	100
IN	35	20	-	20	-	0	100
ANSE	35	41	-	41	-	0	100
	187	154	21	132	0	1	99.4
Total records: 187(train)+ 154(test) = 341							

The 5-fold cross-validation technique is used for choosing testing and training ECG records of multiclass Rough set classifier to validate the performance of MI classification. Table 8 shows that the accuracy of MI classifications is evaluated in each fold and finally the maximum average accuracy of 99.8% is estimated. The experimental result for MI classification by the cross validation technique is shown in Figure 5.

The proposed multiclass Rough set classifier based on the clinical feature of 12 lead ECG is compared with the other reported classifiers and results are shown in Table 9.

It is observed that results obtained from the proposed system are maximum than the other reported techniques. Hence proposed classifier is useful to localize multiclass MI from multidimensional dataset using 12 lead ECG.

Table 8: Performance of Rough set classifier over each fold for MI classification

Classifier	Feature election	Tested Records	Parameters	Fold1	Fold2	Fold3	Fold4	Fold5	Average Accuracy
Multiclass Rough set classifier	All Features	103	Accuracy (%)	99	100	100	100	100	99.8

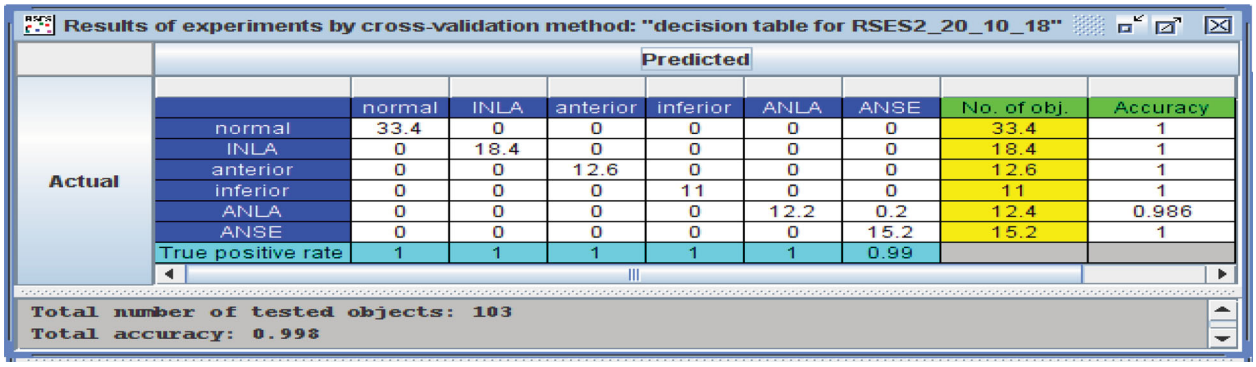

Figure 5: Confusion matrix obtained for MI classification using 5 fold CV with Rough set classifier

Table 9: Proposed system compared with Existing technique for MI classification

Author	Year	Number of leads	Classification method	Number of class	Accuracy
Arif.M [38]	2010	12 leads	BPNN	7	93.7
Arif et al [39]	2012	12leads	KNN	11	98.8
Safdarian [40]	2014	2 Leads	PNN	4	76.67
Sharma [6]	2015	12 leads	SVM	6	99.58
Acharya [10]	2016	12 leads	KNN	11	98.74
Proposed	2018	12 leads	Rough set	6	99.8

6. CONCLUSION

This paper proposed a disease diagnosis System using Rough set classifier from the features of ECG signal for complete MI detection as well as classification. The proposed method not only finds the suitable rules to explore better knowledge but also the important factors affecting the decision making of MI by using Rough set Explorer system (RSES) software. The performance parameters such as accuracy and sensitivity show that the Rough set classifier is not only capable to detect MI and Non-MI class but can also classify 5 different types of MI. Most importantly, the proposed system can able to identify the interrelated types of MI with overlapping leads, such as Inferior and Inferior lateral (overlapping leads II,III,aVF) or Anterior and Anterior lateral (overlapping leads V3,V4). The robustness of this system is justified with "Five-fold" cross-validation technique using RSES. Finally, the comparative study of the system with the existing methods illustrates that, it outperforms in terms of sensitivity (99.75%), and accuracy (99.8%) for MI detection and for MI classification, the accuracy is found to be 99.8%.

Hence, the proposed method owing to its cleanliness, quickness and high classification accuracy may be very useful in accurate and reliable diagnosis of MI disease. It may be helpful in making decisions in the early stage referring to the treatment of MI patients to save life and can also reduce the work load of cardiac specialists drastically.

To find the infarcted region of the heart during MI and classification of different MI, based on their infracted locations should be investigated in the future work. Applying deep learning technique we aimed to enhance the performance and consistency of our proposed work and detection of Coronary artery disease (CAD) and CHF in addition to the MI without using feature extraction or feature selection technique also be included in future work.

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