IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 1, Issue 3, June-July, 2013
ISSN: 2320 - 8791
www.ijreat.org

QRS BASED ARRHYTHMIA CLASSIFICATION USING K-NN ARCHITECTURE

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***Abstract*—In this paper an architecture is proposed for ECG arrhythmia classification based on QRS detection. The ECG-QRS detection is performed using mathematical morphological operations. Basic operations such as dilation and erosion are used to reduce computational complexity. The detected peaks are then applied as input for calculating mean value using K-NN architecture. Manhattan distance formula is used to calculate the mean value. The training sets for each arrhythmia is stored in an LUT. This LUT formed based on K-NN mean calculation is used as disease classifier architecture. Four types of arrhythmias are identified. They are Premature ventricular contraction, Right bundle branch block, Tachycardia and Bradycardia. Adaptive clock gating method is used to reduce the power dissipation of the classifier architecture by 8.2%. The architecture had a power dissipation of 43.71mW which was reduced to 40.11mW after adding clock gating technique. The MIT-BIH arrhythmia database is used to evaluate the results. The QRS detection and peak to peak distance is calculated using Matlab 10.0 software and the K-NN classification architecture is simulated in VHDL using Modelsim 5.6e version. Implementation is done in Altera CYCLONE II DE2 board.**

***Keywords*—Adaptive clock gating, classifier, Electrocardiogram (ECG), K-Nearest Neighbor (K-NN), LUT, mathematical morphology, MIT-BIH database, QRS detection.**

I. INTRODUCTION

Cardiovascular diseases still remain the biggest cause of deaths worldwide. The causes of cardiovascular diseases are diverse among which atherosclerosis and hypertension are the most common. Besides, with ageing there are a number of physiological and morphological changes that alter the cardiovascular functions and causes subsequently increased risk of cardiovascular diseases, even in healthy asymptomatic individuals. Although cardiovascular diseases usually affect older adults, the antecedents of cardiovascular diseases begin in an early phase of life, which makes primary prevention efforts absolutely necessary from childhood. Hence it is required to find an accurate and fast arrhythmia detection technique at the earliest.

For this purpose the ElectroCardioGram (ECG) technique is introduced which makes use of the bio-potentials generated from the electrical activity of the muscles of the heart. It is one of the most important physiological parameters, which is extensively being used for knowing the state of the cardiac patients. Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range is of 1–10 mV. The ECG signal is characterized by five peaks and valleys labeled by the letters P, Q, R, S, and T.

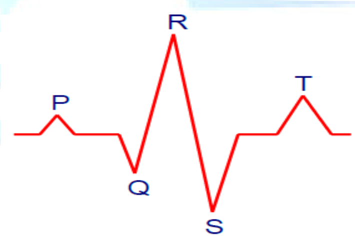

Figure 1. ECG signal

The QRS complex is the spiked shape part of the ECG trace which corresponds to the depolarization of ventricles. Duration, morphology and amplitude of the QRS complex in an ECG signal provide significant contributions to physicians for diagnosing various arrhythmias [6]. For meaningful and accurate detection, steps have to be taken so as to filter out all the noise sources plaguing the ECG signal. Hence, a reliable QRS detection method with low hardware cost, very good sensitivity, and excellent noise susceptibility is of urgent need. For this purpose in this paper an algorithm based on mathematical morphological operations is used [1].

Mathematical morphology is a set-theoretic method of image analysis providing a quantitative description of geometrical structures. It provides an effective way to analyze signals using nonlinear signal processing operators, which incorporates shape information and hence extractes image components that are useful for representation and description. In this paper fundamental morphological operators are used [1]. This helps in reducing the computational complexity. The signal is then averaged followed by multiframe accumulation and finally thresholded for

QRS peak extraction. The extracted peaks are used for arrhythmia classification.

K-Nearest Neighbor (K-NN) classifier is a supervised machine learning method used to accurately assign a class label to a query of un-known class [4]. This is based on K-NN mean value calculation. In this paper a classifier architecture based on K-NN algorithm is used for ECG arrhythmia classification. An architecture for calculating mean value is proposed based on Manhattan distance formula [5]. An LUT based on these mean values is formed for a training set of ECG signals. The input signals are then classified based on these mean values. Both the training and input ECG signals are taken from the MIT-BIH database.

Unwanted clock switching is one of the main reasons causing power dissipation. This occurs in regions of the architecture which do not require to be active at that instant. This is a major disadvantage that is to be rectified. For this purpose an adaptive clock gating technique is used along with the K-NN architecture in this paper [3]. A clock tree is formed using AND gates for providing clocks to various portions of the architecture. This is controlled using a control circuit which enables the clock signal to required portions of the architecture at the required time. The remainder of this paper is formulated as given. In Section II, an explanation about the ECG-QRS detection technique. Section III presents the K-NN architecture for arrhythmia classification. This is followed by a briefing on the adaptive clock gating technique in Section IV. Results and discussions is done in Section V. Conclusion remarks are drawn in Section VI

II QRS DETECTION

In this paper mathematical morphological operations are used to perform QRS complex detection. A morphological operation is the interaction between a set or function representing the object or shape of interest with another set or function of simpler shape called the structure element. There are various advantages for these operations such as a strong mathematical foundation with the help of equations, simplicity in computation and information extraction from the spatial domain using a structural element rather than a vague frequency analysis. Because of these many advantages this method was selected for QRS detection in this work. Also these operations play a critical role in removing the noise, baseline wandering and suppressing the P/T waves in the ECG signal as shown in Figure1. Among the various morphological operations, dilation and erosion are the operations used in this paper. A basic block diagram of the QRS detection technique is shown in Figure 2.

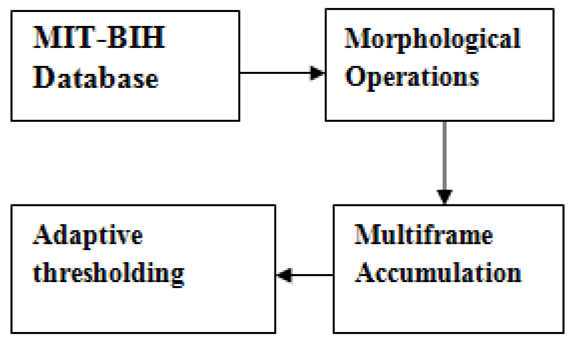

Figure 2. Simple block diagram

A. *MIT-BIH Database*

Here ECG signals are taken from MIT-BIH database [2] for QRS detection and arrhythmia classification. MIT (Massachusetts Institute of Technology) and Beth Israel Hospital (now the Beth Israel Deaconess Medical Center) have together put forward this database. This was formed from 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied at the laboratories of Beth Israel Hospital. The 360 samples per second digitized recordings have 11-bit resolution over a 10 mV range.

B. *Morphological Operations*

In all the previous image processing papers [7][8] a number of morphological operators such as dilation, erosion, opening, closing, top-hat, bottom-hat are used for extracting the QRS peaks from the ECG signal. Multiscale morphological filtering performs these complex morphological operations many times by using the structural elements of different shapes and sizes.

In order to further alleviate the computational complexity, in this algorithm only most fundamental operations such as dilation and erosion are used, as shown in equation (1)and(2), approximately equivalent to the computation complexity of one close operation. Dilation is the process of expanding an image object with respect to the structural element while erosion shrinks the image object with respect to the structural element. Here a horizontal line structural element is used. The input ECG signal taken from the MIT-BIH database is processed as an array of real numbers. The array size is 3600. Hence the straight line structural element also has the same size. The input signal is then both dilated and eroded using the structural element. After this operation an average value of both the operations are taken as show in equation(3). The input signal is then subtracted from the average signal to extract out the QRS information from the signal as given in equation (4).

EROSION : $f \ominus g(n) = \min[(f(n-i)-g(i))]$ (1)

DILATION : $f \oplus g(n) = \max[(f(n+i)+g(i))]$ (2)

Where 'i' indicates the 'i'th element in a length L structural element, and g(n) is a predefined structural element

$$h(n) = [f \oplus g(n) + f \ominus g(n)]/2 \qquad (3)$$

$$v(n) = f(n) - h(n) \qquad (4)$$

This whole process is also called Peak-Valley Extraction.

C. Multiframe Accumulation

The absolute value of the peak-valley extracted ECG signal is then combined by multiple-frame accumulation, which is much alike energy transformation. The energy accumulation process is expressed as

$$s(n) = \sum_{i=n-\lfloor\frac{q}{2}\rfloor}^{n+\lfloor\frac{q}{2}\rfloor} |\, v(i) \,| \qquad (5)$$

The value of *q* should correspond to the maximum possible duration of normal QRS complex. This step further enhances the peak-valley extracted ECG signal to make QRS peaks easy to identify as a set of positive peaks. But the QRS peaks are accurately found out using the thresholding module which follows next.

D. Adaptive thresholding

This module operates on the output of the accumulation module and produces a series of events that correspond to the detected QRS complexes. An adaptive threshold is used as the decision function for QRS detection. Adaptive threshold is the process by which threshold levels are computed depending on the input signal such that an adaption to changing signal characteristics is possible. As the input ECG signal varies in amplitude this method is required to correctly identify the peaks. In this paper the required adaptive threshold is taken as a function of the maximum of the transformed ECG waveform s (n). The guideline for selecting the threshold, is given by

$$\mathbf{T} = \left\{ \begin{array}{l} \mathbf{0.5max \quad = max4} \\ \mathbf{0.55max \quad = max3} \\ \mathbf{0.625max = max2} \\ \mathbf{0.714max = max1} \\ \mathbf{0.833max = max0} \end{array} \right\} \qquad \mathbf{(6)}$$

where max is determined from the absolute value of the current signal segment which is within the range of milli volts. With the help of these thresholds a function is formulated so that the peak is accurately identified. This is using the following formula,

$$\mathbf{f(n)} = \left\{ \begin{array}{l} \mathbf{1.6}\ , \quad \mathbf{if\ v(n)} > max0 \\ \mathbf{1.4}\ , \ \mathbf{if\ max0 < v(n) < max1} \\ \mathbf{1.2}\ , \ \mathbf{if\ max1 < v(n) < max2} \\ \mathbf{1}\ , \ \mathbf{if\ max2 < v(n) < max3} \\ \mathbf{0.90}\ , \ \mathbf{if\ max3 < v(n) < max4} \end{array} \right\} \ (7)$$

Here f (n) represents the peak points of a QRS complex. Hence the QRS peaks are identified from the given input.

III K-NN CLASSIFER

The KNN method is an instance based learning method that stores all available data points and classifies new ones based on similarity measure. The idea underlying the KNN method is to assign new unclassified examples to the class to which the majority of its K nearest neighbors belongs. This algorithm proves to be very effective, in terms of reducing the misclassification error[4]. Another advantage of the KNN method over many other supervised learning methods like support vector machine (SVM), decision tree, neural network, etc.,

ISSN: 2320 - 8791
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is that it can easily deal with problems in which the class size is as small as three and higher .

Here the K-NN architecture is used for identification and classification of four different arrhythmias based on the QRS peaks extracted. All four arrhythmias depend upon the QRS and peak to peak time period[6]. Their dependencies are given below

- Bradycardia -->R-R interval>1.5s
- Tachycardia --> R-R interval<0.5s
- Right bundle branch block-->QRS period>=120ms
- Premature Ventricular Contraction -->R-R interval > 0.9*average R-R interval

Using Matlab software the peak to peak time period along with the QRS time period is calculated from the identified QRS peaks. These values are fed into the K-NN classifier architecture which consists of architecture for calculating K-NN mean value and a Training sample LUT.

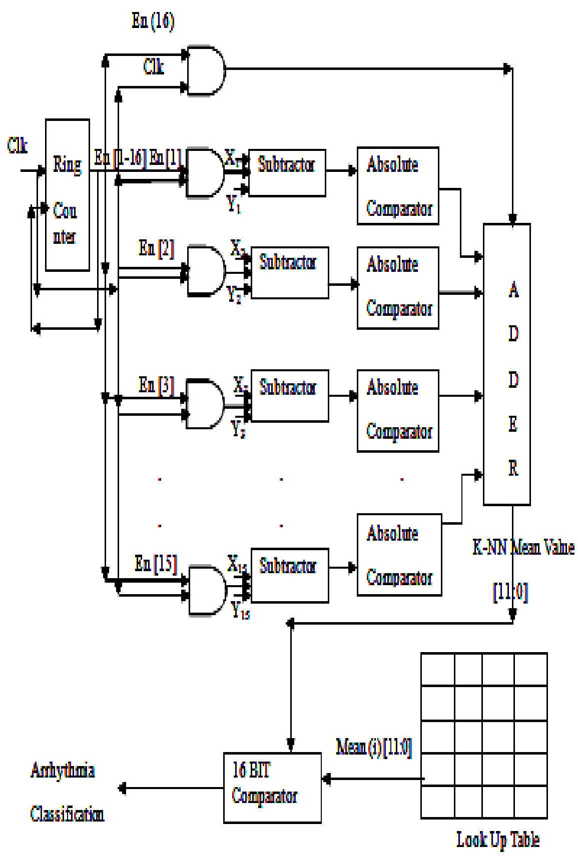

Figure 3. K-NN classifier architecture

A. *Architecture for calculating K-NN mean value*

K-NN mean value is actually a measure of similarity between the unclassified input to the already specified training set. There are many mean value calculations which include Euclidean distance, Manhattan distance etc of which Manhattan distance is the best, due to its simplicity in hardware realization[9].The formula for Manhattan distance is given below[5]

$$\mathbf{D(X,Y)} = \sum_{i=1}^{M}(|\mathbf{Y_i} - \mathbf{X_i}|) \qquad \mathbf{(8)}$$

Where Y_i represents the normal ECG signal and X_i represents the disease affected ECG signal. M is taken as 15. This is because an average of 16 peaks are detected for each ECG signal taken from MIT-BIH database. Hence the total number of peak to peak differences that can be calculated is 15. If any signal has lesser number of peaks then zeroes are added so that it can be given as input to the classifier. The architecture as shown in consists of a subtractor, an absolute value comparator and an adder circuit as shown in Figure 3. X value consists of the peak to peak distances and QRS time periods of the normal ECG signal obtained using Matlab and Y value consists of that of the diseased ECG signals. Hence by using this architecture we calculate the K-NN mean value of each diseased signal taken from the MIT-BIH database. The mean value is taken as a 12 bit binary value.

B. *Training Sample LUT*

The KNN algorithm consists of two phases: Training phase and Classification phase. 20 signals from the database are used as training set for the classification. Each class has 5 ECG signals as training samples. The mean value is calculated for each of these training samples using the above architecture. These 12 bit mean values are stored in a Look Up Table.

A set of 17 signals from the database are taken as input for classification. These signals after QRS detection undergoes time period calculation. These values are fed as input to the K-NN mean value calculation architecture. This 12 bit mean value is then compared with the mean values of the training samples of the four different diseases in the LUT. For this a 16 bit comparator is used. The input signal is then classified into the class with similar mean value. Thus the arrhythmia identification is made possible.

IV ADAPTIVE CLOCK GATING

Power dissipation is one of the major concerns in the field of VLSI circuits. Large power dissipation is unacceptable for any optimum design. Hence power reduction is treated at all design levels of the VLSI chips, from architecture level through block and logic levels, down to gate-level, circuit and physical implementation. Among the various reasons for power dissipation of a circuit the highest priority is for clock switching [3]. Hence it is required to focus on optimally designing the clock circuitry to avoid unnecessary switching processes. In this paper to reduce power dissipation the clocking circuit is modified using adaptive clock gating technique. According to this technique the portions of a design which are required to be active at a particular instant of operation are only clocked, while the rest of the parts remain idle. For this purpose this technique is integrated along with K-NN classifier architecture. The adaptive clock gating unit consists of AND gates, clock tree and a control circuit as shown in Figure 3.

The output of AND gates are given as clock to various parts of the architecture. The inputs of the AND gate are the global clock signal and an enable signal. Global clock corresponds to the clock signal to be provided to the circuit. According to the working of the AND gate only when the enable signal is ON the clock will be triggered at the output. The enable signal is controlled by the control circuit. Hence the signal will be ON only when that portion of the architecture is required to be active. Thus unwanted clock switching is avoided leading to reduced power dissipation.

Clock gaters providing clock to different pa of the architecture are grouped to form a clock tr For this the architecture is analyzed to find out pattern of working. The modules which require clo directly form the highest level of the clock tree. T output of these modules act as clock trigger to a set other modules which forms the succeeding lev Thus successive levels are decided based on worki strategy of the architecture. Here the highest le consists of subtractor modules, followed by t absolute value comparators in the next level and finally the adders in the last level. This tree style modeling provides ease in reducing unwanted clock switching. Individual enable signals are provided to each module in each level which are controlled by the control circuit.

The control circuit consists of a ring counter. It is designed such that initial state of the ring counter triggers the clock for all the subtractor modules, whose output triggers the absolute value computing module. Hence till the next state of the ring counter lasts the absolute computing module will be triggered by the subtractor module. Finally the adder module will be triggered in the third state of the ring counter, which computes all the outputs from the absolute computing modules and produces the K-NN mean value for each input signal. Thus from above it is understood that during each state of the counter only one module is active while rest of the modules are idle. Thus power dissipation is reduced.

V RESULTS AND DISCUSSION

A total of 37 ECG signals are taken from the MIT-BIH database. All these signals undergoes QRS detection which is implemented both in Matlab and VHDL. Further the peak to peak time period and QRS time period for each signal is calculated using Matlab software. Using a Matlab-Modelsim linker model these time period values are linked to the K-NN mean value calculation architecture. Hence the K-NN mean value is found for each signal. For the training set ECG signals these values are stored in the LUT. For the input ECG signals their mean values are calculated and compared with the mean values of the four different arrhythmias stored in the LUT. Thus the arrhythmia is correctly identified and classified once the mean values are similar for the training set as well as input signal.

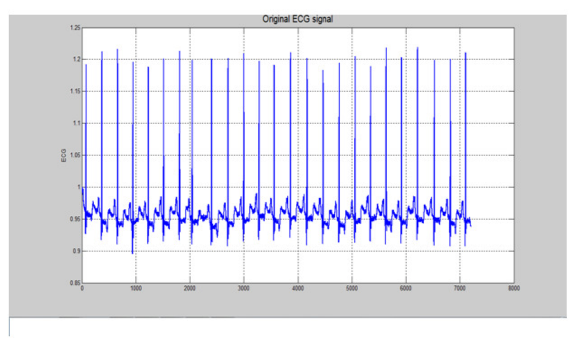

Figure 4. Normal ECG signal

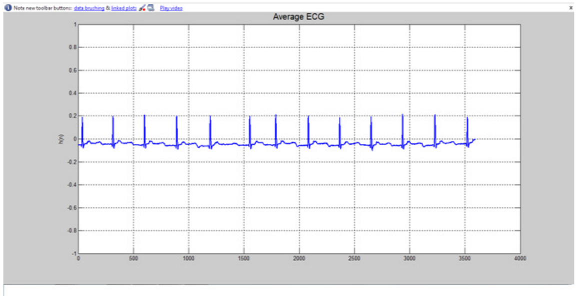

Figure 5. Averaged signal

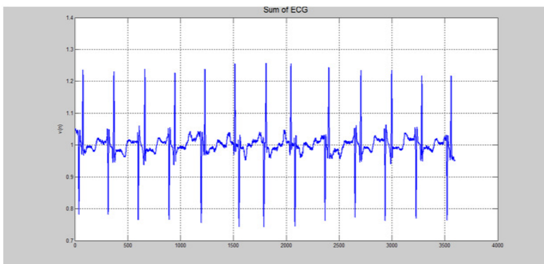

Figure 6. Differenced ECG signal

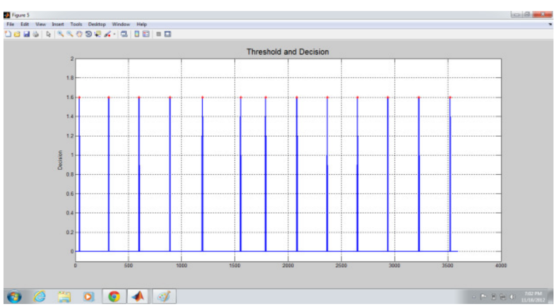

Figure 7. Peak detected signal

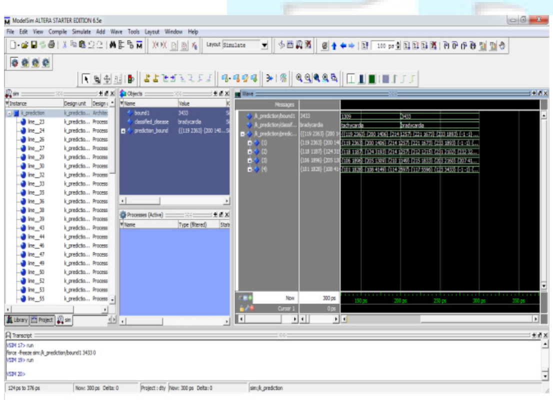

Figure 8. K-NN training set LUT output

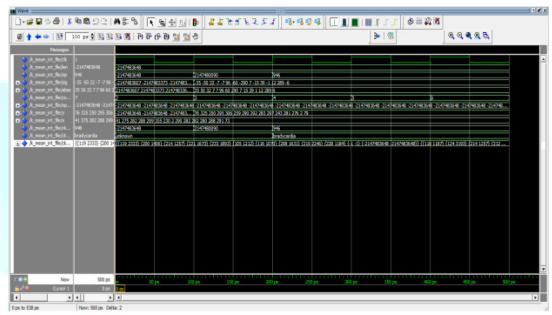

Figure 9. K-NN arrhythmia classification output.

Table 1: Training sets from database

Name of the arrhythmia					
Tachycardia	106	205	210	203	207
Bradycardia	101	108	114	117	123
PVC	119	200	214	221	233
RBBB	118	124	214	212	111

Table 2: Input sets from database

Name of the arrhythmia					
Tachycardia	220	234	215	217	223
Bradycardia	121	201	222	202	113
PVC	105	116	208	219	228
RBBB	231	232			

Figure 4 to 7 shows the output for QRS peak detection using Matlab R2011 version. Table 1 shows the training set samples with their tape number taken from MIT-BIH database. These samples are given to the K-NN architecture to find out the mean value with which the LUT is designed. The LUT output is given in Figure 8. For mean value calculations the X input is taken as the time period values from the QRS detected output of normal ECG tape number 100. Hence all the diseased ECG signals are compared with the normal ECG signal to find out their specific mean values. Table 2 consists of the input ECG signals which are used for arrhythmia classification taken from the same database. The LUT output is implemented and results are observed in Altera CYCLONE II DE2 board.

To fully evaluate the performance of the classification algorithm, several indexes are introduced including false negative (FN) which means failing to detect an arrhythmia, and false positive (FP) which represents a false arrhythmia detection. By using FN and FP, the sensitivity (Se) and positive Prediction (+*P*) can be calculated using the following equations, respectively [1]

$$\textbf{Se (\%)} = \textbf{TP/ (TP+FN)} \qquad \textbf{(9)}$$
$$\textbf{+P (\%)} = \textbf{TP/ (TP+FP)} \qquad \textbf{(10)}$$

where true positive (TP) is the total number of input samples correctly classified by the algorithm.

Table 3: Classification results using K-NN architecture

Arrhythmia	Brady cardia	Tachy cardia	PVC	RBBB
Se(%)	80	80	80	100
+P(%)	100	100	100	100

If the numbers of training and input samples are increased we can increase the percentage of sensitivity even further.

Table 4: Power comparison table

Properties	K-NN without adaptive clocking	K-NN with adaptive clocking
Total Thermal Power Dissipation	43.71 mW	40.11 mW
Core Static Thermal Power Dissipation	18.03 mW	18.02 mW
I/O Thermal Power Dissipation	25.68 mW	22.09 mW

Thus from the table it is clear that the power dissipation is reduced by 8.2% with the help of adaptive clocking. The simulations are done in Modelsim 5.6e version while the power analysis was done in Quartus II 10.0 version.

VI CONCLUSION

An architecture of K-NN algorithm for arrhythmia classification based on QRS detection is designed and verified in this paper. The architecture consists of K-NN mean calculation architecture and training set LUT. This algorithm is used to identify and classify four different types of arrhythmias taken from the MIT-BIH database. QRS detection is based on morphological operations. Adaptive clocking is used in the K-NN architecture which reduces power dissipation by 8.2%. The LUT output is obtained and results are verified using Altera CYCLONE II DE2 board. The number of training set and input set examples can be increased to further enhance the classification rate.

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