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Comparative Analysis of Machine Learning Techniques for the Classification of Knee Abnormality

1st Ankit Vijayvargiya
Department of Electrical Engineering
Malviya National Institute of Technology
Jaipur, India
ankitvijayvargiya29@gmail.com

2nd Rajesh Kumar
Department of Electrical Engineering
Malviya National Institute of Technology
Jaipur, India
rkumar.ee@mnit.ac.in

3rd Nilanjan Dey
Department of Information Technology
Techno India College of Technology
Kolkata, India
neelanjan.dey@gmail.com

4th João Manuel R. S. Tavares
Instituto de Ciência e Inovação em Engenharia Mecânica e Engenharia Industrial
Departamento de Engenharia Mecânica
Faculdade de Engenharia, Universidade do Porto
Porto, Portugal
tavares@fe.up.pt

***Abstract*—Knee abnormality is a major problem in elderly people these days. It can be diagnosed by using Magnetic Resonance Imaging (MRI) or X-Ray imaging techniques. X-Ray is only used for primary evaluation, while MRI is an efficient way to diagnose knee abnormality, but it is very expensive. In this work, Surface EMG (sEMG) signals acquired from healthy and knee abnormal individuals during three different lower limb movements: Gait, Standing and Sitting, were used for classification. Hence, first Discrete Wavelet Transform (DWT) was used for denoising the input signals; then, eleven different time-domain features were extracted by using a 256 msec windowing with 25% of overlapping. After that, the features were normalized between 0 (zero) to 1 (one) and then selected by using the backward elimination method based on the p-value test. Five different machine learning classifiers: k-nearest neighbor, support vector machine, decision tree, random forest and extra tree, were studied for the classification step. Our result shows that the Extra Tree Classifier with ten cross-validations gave the highest accuracy (91%) in detecting knee abnormality from the sEMG signals under analysis.**

***Index Terms*—Knee Abnormality, Surface Electromyography (sEMG), Discrete Wavelet Transform (DWT), Machine Learning Classifiers.**

I. Introduction

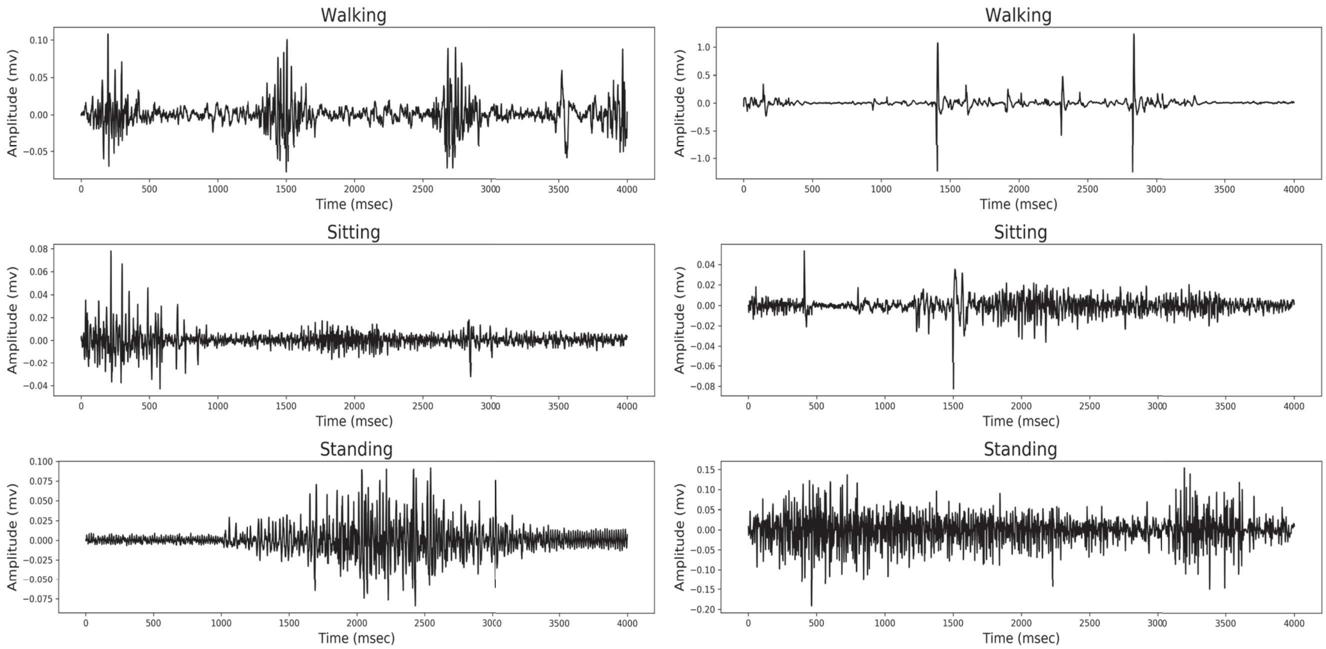
Nowadays, knee pain is a most common healthcare issue in the elderly. The major reasons behind the knee pain are related to injury, aging, repeated stress on the joint or due to an underlying condition such as arthritis. According to a study, more than one in ten adults in the USA suffer from knee osteoarthritis (Knee OA), which is a form of knee abnormality [1].

The Knee joint is one of the complex joints in the human body and provides the leg movement, the stability of the human body, and also acts as a shock absorber. Bones, ligaments, tendons, muscles, cartilage, and fluids are the different parts of the knee joint. Tibia, femur and pattela are the three major bones that form the knee joint.

X-Ray, Magnetic Resonance (MR) and Computer Tomography (CT) are different imaging maodalities that commonly use to detect knee abnormalities [2], [3], [4]. X-Ray is used for the initial evaluation of knee pain, but it is of low image resolution. On the other hand, MRI imaging is commonly successfully used to assess knee pain, but is very costly. As per the literature, knee abnormalities can also be diagnosed during daily life activities by means of wearable sensors like EMG, Gyrometer and Accelerometer sensors [5], [6], [7], and visual sensor like image camera [8], [9]. Respect for privacy, pervasiveness and low complexity are some of the advantages of wearable sensors over the visual sensors. In the wearable sensors family, EMG sensors are interesting for human activity recognition applications because they allow the forecast of the movement in advance and also take less time to detect the related signal variations.

Electromyography (EMG) is a technique used to analyze and record the electrical activity generated during muscle contraction by skeletal muscles. Surface EMG (sEMG) and intramuscular EMG (iEMG) are the two ways used to collect EMG signals [10]. sEMG has several advantages over iEMG, therefore, sEMG signals have had a critical role in analyzing lower limb movements, particularly to detect anomalies related to the limbs. Artificial Neural Network based knee abnormalities classification was proposed by Erkamaz et al. [4]. Vijayvargiya et al. analyzed the early detection of knee osteoarthritis by using a support vector machine classifier with different kernels [11]. Ertugrul et al. used the classification of surface EMG signals of the lower and upper limbs based on adaptive local binary patterns [12].

In this work, we present a comparative analysis of the performance of various machine learning classifiers for knee



(a) (b)

Fig. 1: sEMG signals acquired during three different movements: Walking, Standing and Sitting, from a (a) Normal subject and a (b) Abnormal subject.

abnormality detection from sEMG signals. This article is divided into five sections. A brief overview of the used EMG dataset is provided in Section II. The detail of the proposed methodology is given in Section III. Results and discussion are presented in Section IV. Conclusions and possible future research are discussed in Section V.

II. Dataset

In this article, we used a dataset with the surface EMG signals acquired during three different movements: standing, walking and sitting, performed by twenty-two subjects [13]. All of the subjects were more than 18 years old, and eleven of the individuals were healthy and the remaining were suffering from knee abnormalities. The healthy individuals did not have any record of a knee injury while the unhealthy individuals had suffered any knee abnormality already diagnosed by professionals. A DataLog MWX8 and a goniometer were used to collect the data. The surface EMG data were collected around four distinct muscles: rectus femoris (RF), biceps femoris (BF), vastus medialis (VM) and semitendinosus (ST). The goniometer was attached to the external side of the knee joint. All the acquired data were stored on the computer. Fig 1 shows examples of the normal and abnormal subject's sEMG signals acquired during each movement, respectively.

III. Proposed Methodology

This section presents the methodology proposed for knee abnormality detection from surface EMG signals. Fig. 2 illustrates the basic steps involved in the proposed classification of the sEMG signals. First, the discrete wavelet transform (DWT) is used to denoised the raw sEMG signals and then different features are extracted using overlapping windowing techniques. To reduce the feature space dimensionality and improve the classification performance, a backward elimination method for feature selection is used. After that, the selected features are fed to the machine learning classifiers and their performance analyzed.

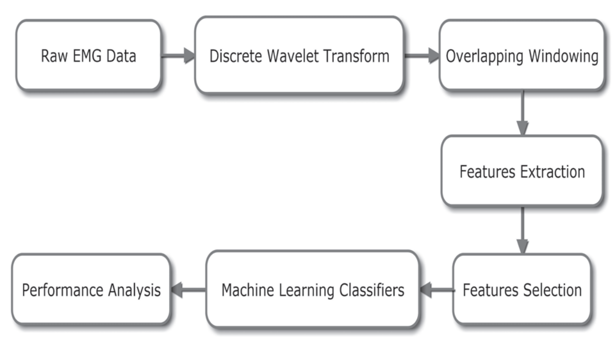


Fig. 2: Flowchart of the proposed methodology for knee abnormality detection from sEMG signals.

A. Discrete Wavelet Transform

During the aquisition of the sEMG signal, several different kinds of noise are introduced in the data. Particularly, the noises are due to external disturbances and psychological disturbances. Owing to the combination of various noise signals or artifacts, the specifities of an EMG signal can be lost. The attributes of the acquired EMG signal depend on the skin temperature, internal structure of the subject, skin formation, blood flow rate, tissue structure, measurement location, etc.

It is not possible to use traditional filtering techniques such as high-pass, low-pass and band-pass to eliminate unwanted noise like impulse within the EMG signal spectrum band. Several noise removal techniques have been proposed for sEMG signals including Independent Component Analysis (ICA), Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) [14], [15], [16], [17], [18]. In this work, DWT is applied to denoise the raw sEMG signals because it has minimum signal distortion and gives information in both frequency and time domains.

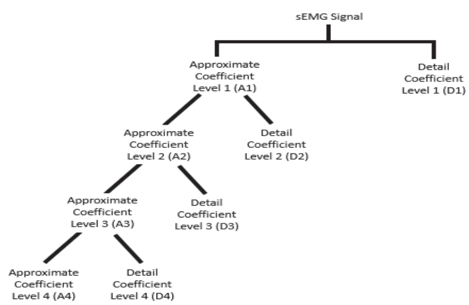


Fig. 3: A wavelet decomposition up to level 4.

A sEMG signal can be decomposed into various levels in a discrete wavelet transformation using various wavelets such as Haar, Daubechies, Marlet and Symlet. The transformation can be implemented as a bank of filters which contain low pass filters (approximate coefficients) and high pass filters (detail coefficients). Further, the signal is passed through the next level of low and high pass filters. The number of coefficients depends on the level of decomposition. Fig. 3 shows a wavelet decomposition up to level 4. A wavelet is generated from a mother wavelet (ψ_t), by scaling (s) and translation (τ) [19]:

$$\psi_{s,\tau} = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right). \quad (1)$$

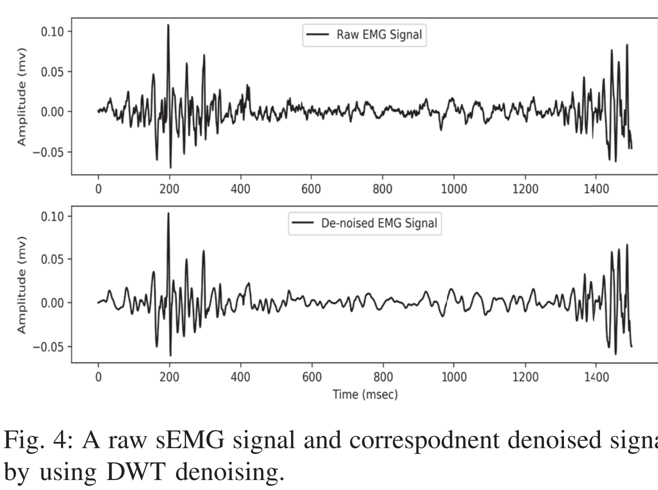


Fig. 4: A raw sEMG signal and correspodnent denoised signal by using DWT denoising.

To remove the noise after the signal decomposition, several thresholding techniques such as soft thresholding and hard thresholding have been used. In this study, wavelet denoising was applied to the sEMG signals using the Daubechies 7 wavelet family (db7) till the fourth level of decomposition. Garotte thresholding was applied to detail coefficients D2, D3 and D4, as shown in Fig. 3. Fig. 4 shows the a raw EMG signal and the corespondent denoised signal obtained by wavelet denoising.

B. Segmentation

EMG signals are random in nature. Due to this randomness, the segmentation of a EMG signal is necessary. Windowing technique has been used for the segmentation of EMG signals. There are two different techniques (Fig 5) for EMG data segmentation: overlapping windowing and adjacent windowing [20], [21]. In this work, we used overlapping windowing with 256 msec window length and 25% of overlapping [7].

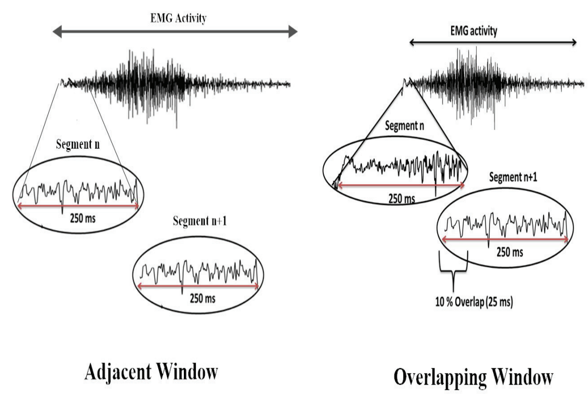


Fig. 5: Windowing techniques used in EMG sinal segmentation.

C. Feature Extraction and Selection

Different types of artifacts and noises are still present after the usual pre-processing of the EMG data. Those noises degrade the performance of the further classification model. Different kinds of features in time domain, frequency domain and time-frequency domain can be extracted from the pre-processed EMG data to improve the performance of the classification model. In this study, eleven time-domain features, which are indicated in Table I, were extracted from each of the four different muscle EMG signals (i.e. 44 features in total) and used in the classification of knee abnormality.

After the features extraction, the selection of the relevant features or removal of the redundant features is a very challenging task. We applied the backward elimination technique for the diagnosis of knee abnormality. In this approach, we begin with all of the model's attributes, followed by their removal based on the p-value test. Those attributes are discarded with p-values greater than 0.05 and the model is refitted

TABLE I: Extracted sEMG features and their mathematical formulation.

	Extracted Feature	Mathematical formulation
1	Mean Absolute Value (MAV)	$\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert$ where x_i is a sample of the EMG signal
2	Root Mean Square (RMS)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert^2}$
3	Zero Crossing (ZC)	$\sum_{i=1}^{N-1} f(x_i)$ where $f(x_i)=\begin{cases}1 & if,(x_i>0\ and\ x_{i+1}<0)\\ & or\ (x_i<0\ and\ x_{i+1}>0)\\ 0 & otherwise\end{cases}$
4	Slope Sign Change (SSC)	$\sum_{i=2}^{N-1} f(x_i)$ where $f(x_i)=\begin{cases}1 & if, if,(x_i>x_{i-1}\ and\ x_i>x_{i+1})\\ & or\ (x_i<x_{i-1}\ and\ x_i<x_{i+1})\\ 0 & otherwise\end{cases}$
5	Variance (VAR)	$\frac{1}{N-1}\sum_{i=1}^{N}x_i^2$
6	Willison Amplitude (WAMP)	$\sum_{i=1}^{N-1} f(\lvert(x_{i+1}-x_i)\rvert)$ where $f(x_i)=\begin{cases}1 & if,(x\geq Threshold)\\ 0 & otherwise\end{cases}$
7	Myopulse Percentage Rate (MYOP)	$\frac{1}{N}\sum_{i=1}^{N} f(x_i)$ where $f(x_i)=\begin{cases}1 & if,(x\geq Threshold)\\ 0 & otherwise\end{cases}$
8	Difference Absolute Standard Deviation Value (DASDV)	$\sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(x_{i+1}-x_i)^2}$
9	Average Amplitude Change (AAC)	$\frac{1}{N}\sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert$
10	Skewness (Skew)	$\frac{E[(x-\mu)^3]}{\sigma^3}$
11	Kurtosis (Kurt)	$\frac{E[(x-\mu)^4]}{\sigma^4}$ where σ is the Standard deviation of the signal dataset, μ = Mean of the dataset and E is the Expected value estimator of the dataset.

with the remaining attributes. This process is iterated several times until each existing variable has a significant level for the model. After the selection of the feature, all selected features are normalized between 0(zero) and 1 (one) according to:

$$X_{Fnew} = \frac{X_F - X_{Fmin}}{X_{Fmax} - X_{Fmin}}, \tag{2}$$

where X_{Fnew} is the normalized EMG feature, X_F is the actual EMG feature, X_{Fmax} is the maximum value of the actual EMG feature, and X_{Fmin} is the minimum value of the actual EMG feature.

D. Machine Learning Classifiers

In this section, support vector machine, decision tree, k-nearest neighbor, random forest and extra tree machine learning classifiers, which were used in this work in the classification between knee healthy and unhealthy individuals from sEMG signals, are introduced.

Support Vector Machine (SVM) [22] is a supervised machine learning classifier that can be used for both linear and non-linear classification by using different kernels. In a linear SVM classifier is built a hyperplane with maximum margin width.

K-Nearest Neighbour (KNN) [23] is used for both regression and classification problems. A KNN classifier is trained with all the available cases and then categorized new cases by neighboring majority votes. The case is assigned to that class, most similar to its nearest k neighbors, determined by a distance function which can be the Euclidean, Manhattan or Minkowski distance.

Decision Tree (DT) [24] is a supervised learning classifier that can be used for both numerical or categorical data. It uses a kind of tree structure of decision based on entropy:

- 1) Calculate the entropy of each feature:

$$H(X) = -\sum_{t\epsilon Y} \boldsymbol{p}(t) log_2 p(t) \tag{3}$$

  where X is the dataset, Y is the set of classes in s, and $p(t)$ is number of elements in class Y to the number of elements in X.
- 2) Split the dataset into subsets using the attribute with maximum information gain:

$$IG(X, A) = H(X) - H(X|A) \tag{4}$$

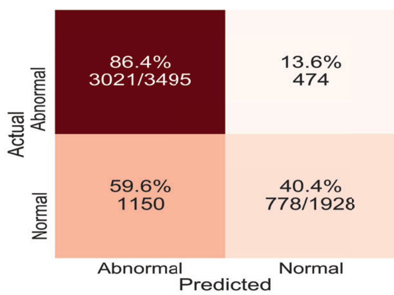
- 3) No further splitting is required if the value of entropy is 0 (zero); otherwise, further splitting is performed as above.

Random Forest (RF) [25] is a similar kind of decision tree algorithm, but it creates several trees rather than a single tree:

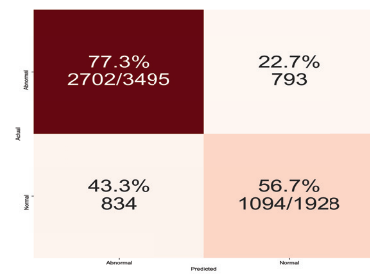
- 1) Select randomly the number of samples in the dataset randomly which is called bootstraps sample.
- 2) Create the decision tree for every bootstrap sample and calculate the prediction results from each decision tree.

TABLE II: Classification performance achivied by each classifier in terms of different performance metrics.

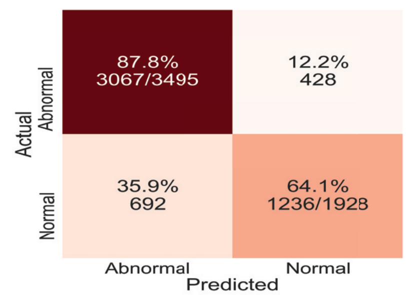
Classifier	Accuracy		Sensitivity		Specificity		F1-Score	
	μ	σ	μ	σ	μ	σ	μ	σ
SVM	0.701	0.019	0.404	0.028	0.864	0.024	0.550	0.027
DT	0.700	0.018	0.567	0.043	0.773	0.022	0.653	0.028
KNN	0.793	0.012	0.641	0.028	0.878	0.017	0.740	0.018
RF	0.888	0.017	0.789	0.037	0.943	0.015	0.859	0.024
ET	0.913	0.013	0.825	0.034	0.962	0.011	0.888	0.02



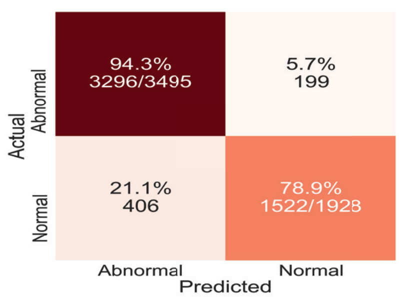
(a) SVM



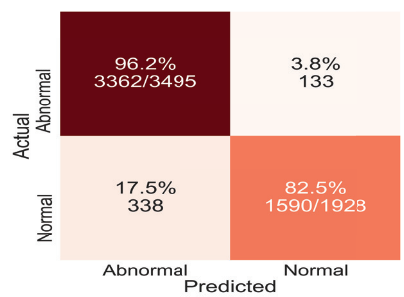
(b) Decision Tree



(c) KNN



(d) Random Forest



(e) Extra Tree

Fig. 6: Confusion matrices built from the results obtained by each classifier under study.

- 3) Voting is performed between the results of decision trees, and the most voted prediction result shows the output of the overall prediction.

Extra Tree (ET) [26] is very similar to the random forest classifier. It considers the entire input dataset instead of the bootstrap dataset.

IV. Results and Discussion

This section presents the performance analysis of the different machine learning classifiers studied. In this application, the problem is a binary classification problem: either subject is knee healthy or unhealthy. A machine learning algorithm for binary classification gives four possible outcomes, which are: True Negative (TN), True Positive (TP), False Negative (FN) and False Positive (FP). The classification performance metrics were computed for each classifier under study from its number of occurrences of each of these four possible results:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{5}$$

$$Precision = \frac{TP}{TP + FP}, \tag{6}$$

$$Sensitivity(Recall) = \frac{TP}{TP + FN}, \tag{7}$$

$$Specificity = \frac{TN}{TN + FP}, \tag{8}$$

$$F1 - Score = \frac{2 * Recall * Precision}{Recall + Precision}. \tag{9}$$

K-fold cross-validation is a re-sampling method that uses a constrained data test to evaluate the classification performance of machine learning models. In this k-fold approach, the input data are randomly divided into k groups of equal size. Then the model is trained using $k-1$ groups of data and validated with the k^{th} group of data. This process is repeated for all the groups of obtained from the input data.

In this work, the classification performance metrics were evaluated for each model under study by using 10 fold cross-validation. The obtained classification performance results for each of the used metrics and studied classifiers are indicated in Table II. The accuracy for the extra tree classifier was of 91.3% while it was equal to 70.1%, 70.0%, 79.3% and 88.8% for the support vector machine, decision tree, k-nearest neighbor and random forest classifiers, respectively. Extra Tree classifier shows a superior classification performance to the other classifiers. Fig. 6 shows the confusion matrices built for each of the studied classifiers in the knee abnormality classification from sEMG signals.

V. Conclusion and Future Work

A comparative analysis of different machine learning classifiers in the classification of knee abnormality from sEMG signals acquired from the lower limb of subjects suffering from knee abnormality and healthy subjects was presented. First, raw EMG signal was denoised using a discrete wavelet transform then eleven signal features were extracted from the pre-processed signal by using an overlapping windowing technique. Then, the relevant signal features were selected by using the backward selection method. Afterwards, five different machine learning models were used and their classification performance was evaluated, where the Extra Tree classifier shown its superiority.

In this study, a public available EMG dataset was used. The dataset only includes data from 22 subjects, therefor, as a future work, we will collect EMG data from more subjects and study more advanced machine learning classifiers as Convolution Neuronal Networks (CNNs), which have obtained very promising results in several classification problems.

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