Variable weight neural networks and their applications on material surface and epilepsy seizure phase classifications

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Abstract

This paper presents a novel neural network having variable weights, which is able to improve its learning and generalization capability, to deal with classification problems. The variable weight neural network (VWNN) allows its weights to be changed in operation according to the characteristic of the network inputs so that it demonstrates the ability to adapt to different characteristics of input data resulting in better performance compared with ordinary neural networks with fixed weights. The effectiveness of the VWNN are tested with the consideration of two real-life applications. The first application is on the classification of materials using the data collected by a robot finger with tactile sensors sliding along the surface of a given material. The second application considers the classification of seizure phases of epilepsy (seizure-free, pre-seizure and seizure phases) using real clinical data. Comparisons are performed with some traditional classification methods including neural network, k-nearest neighbors and naive Bayes classification techniques. It is shown that the VWNN classifier outperforms the traditional methods in terms of classification accuracy and robustness property when input data is contaminated by noise.

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Index Terms

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I. Introduction

CLASSIFICATION is a process that it takes samples from objects and then assigns each one them with a pre-defined group or class label. This is a promising and important field providing a solution to a wide range of applications e.g., just to name a few, classification of different investments, lending opportunities as acceptable or unacceptable risk [1], classification of electrocardiogram (ECG) arrhythmias [2], classification of ECG beat [3], face recognition [4], [5], hand-writing recognition [6]–[10], heart sound classification [11], human body posture classification [12], speaker verification [13], speech recognition [14], [15] and text classification [16], [17].

In general, a classification process usually consists of three main stages. In the first stage, data from objects have to be collected for the design of classifiers. In the second stage, feature extraction is performed to extract characteristics from the collected data to be classified such that redundant information is removed and representative information is extracted resulting in reduction of input dimension and improving classification accuracy. In the third stage, a classifier is designed using the feature data.

In the literature, classification techniques and methods from traditional methods to machine learning methods can be found. Traditional methods, for example, cover linear discriminant analysis [18], logic based method (e.g., decision trees [19]), statistical approach (e.g., Bayesian classification [20]), instance-based methods (e.g., nearest neighbor algorithm [21], [22]) and support vector machines [4], [9], [13], [17].

Linear discriminant analysis (LDA) proposed by R.A. Fisher in 1936 [23] is a feature extraction technique that is used to extract discriminative features from the input data and is therefore very competent at dimensionality reduction [24]. The main objective of this method is to maximize the between-class scatter and minimize the within-class scatter; this would maximize the separability between the input data [25]. The method searches for the vector that provides the best discrimination amongst the classes rather than the vector that provides the best description of the overall dataset [26]. This method has some limitations that, for example, it requires a large amount of samples for the training phase. This would prove difficult for some instances where the large input dataset is not readily available. Another limitation is in the situation where a 2-class problem is presented, the LDA method would be unable to extract adequate features in order to have satisfactory performance. The LDA is also prone to be affected by the presence of outliers, this may have the effect of distorting the desired output vector [24].

Bayesian decision theory [20] is one of most important methods in statistical classification which first offers a model for the further classification procedures. Naive Bayesian classifier is based on the assumption that equal prior probabilities exists for all classes [27] which reduced the analysis complexity and helps in resolving conflicts that occur when two or more classes are not well separable, resulting in improving the classification accuracy. Although Bayesian decision is simple and powerful, the posterior probabilities cannot be determined directly [28]. A recent development of the Bayesian classifier has been the proposal of a hybrid Bayesian classifier [27] and the Bayesian classifier was applied successfully in many cases, for example, weeds identification [20]. k-nearest neighbour technique (kNN) [21] is easy to apply and good in dealing with text based problems such as visual category recognition [22]. However, kNN has its intrinsic limitations, the main disadvantages of the kNN technique are the large memory requirements and the lack of a logical way to choose the best 'k', this would introduce difficulties to a classification application as different data sets require an optimized value of 'k' to improve the performance of this method [29]. Furthermore, the precision accuracy of kNN will be declined when there are too many classes to deal with or when an uneven density of training samples are presented.

Support vector machine (SVM) [30], [31] is a kernel method that is used to map non-linear and inseparable data from an input space into a higher dimensional feature space where the data would then be linearly separable [32] which is done with the aid of the separating hyperplane [33]. The benefit of the kernel method is that the use of kernel functions enables the user to save time and computational power as the mapping is no longer compulsory [34]. The SVM algorithm aims to maximize the margin (the region separating the support vectors on either side of the hyperplane). This would result in an optimal classification accuracy of the hyperplane. Although the SVM sometimes suffers from high complexity and long computational times, it is shown to be very resistant to the problem of over-fitting the data. The SVM has a good generalization ability and also performs well in a high dimensional feature space.

Machine learning methods, for example, cover single layer perceptron [35], artificial neural networks [7], [28], [36], neural-fuzzy networks [2], [3], [8], [12], [15] and self organization map [6], [11], [16], [37]. The first neural networks were designed based on mathematics and algorithms in 1940s. The McCulloch-Pitts neuron proposed in 1943, which laid the foundation of modern neural networks [36]. However, there was no effective neural network training algorithm, so the development of neural networks was stagnated for some years. After that, a trainable network with adaptive elements, which are the building blocks, was designed [36]. A single layer perceptron [35] neural network model was first introduced by Rosenblatt in 1962, which cast a huge impact on the artificial intelligence field, and then different types of perceptron-based techniques have emerged in large numbers. A single layer perceptron has a simple structure which can be seen as a component that just weighted the inputs and then computes the sum to the output of the system. After that, the outputs are used to compare with the corresponding targets to verify the accuracy. With the information of difference between outputs and targets, the weights can be adjusted to achieve higher level of accuracy. However, there is a major limitation that restrain the applications, only learn linearly separable problem can be solved by the single layer perceptron. Although it has the major limitation, for example, the single layer perceptron has also been implemented well to a finger print matching [35] and an image detection [38] applications. Traditionally, a feedforward neural network [39] has three layers (input, hidden, and output layers) of nodes connected in a layer-to-layer manner. Neural Networks have various applications due to its favourable approximation performance and convenient modeling process. However, ordinary neural networks suffers from the ‘overfitting’, ‘local optimization’ problems [40].

Neural-fuzzy network (NFN) involves the merging of fuzzy logic with the neural network. Neural networks are typically useful for non-linear mapping of inputs to outputs whilst fuzzy systems are designed based on the fuzzy set theory which processes data and has the ability to perform human-like reasoning when classifying data [31]. The method has been highly successful in applications due to the low-level learning and computational efficiency of neural networks coupled with the high-level human-like reasoning of fuzzy systems [41], [42]. They use the well known backpropagation algorithm for the learning of the membership functions and fuzzy rules from the training data [31]. One limitation of using this algorithm for this task is its inability to concurrently minimize the training and test error of the system. This therefore limits the attainable classification performance at the testing phase. The method involves the combination of multiple neural network classifiers with the aim that the fusion of their output would produce a higher classification accuracy compared to just utilizing a single classifier [43].

Self-organizing map (SOM) is an unsupervised competitive learning technique that was proposed by Kohonen [44] in 1982. In the SOM technique, neural maps transform data from a high-dimensional input space onto a lower dimensional output space [45] in a way that would preserve the architecture. Neighboring neurons in the output space correspond to neighboring data points in the input space [46]. The SOM technique is competent for dimensionality reduction and topology preservation [47]. This technique however utilizes a fixed network architecture which mostly has to be defined by the user before the commencement of training and thus creates a dilemma concerning the size of the pre-defined output layer. If the fixed size is too small, the model is unable to express the input data effectively. If the output size is too large, the model would take a considerably long time to converge and also produce many redundant neuron units in the output layer [48]. The growing self-organizing map (GSOM) was proposed as a solution to this problem. It provides a dynamic structure to the network model instead of the previously fixed structure used in the SOM [46], [49].

Compared with traditional classification techniques, the machine learning approach in general uses a black-box approach. It demonstrates an appealing advantage that the designer does not need to know much about the problem where its characteristic and information of the problem are obtained through learning algorithm. It motivates us to employ neural networks to deal with some classification problem. However, the traditional feed-forward neural networks demonstrate drawback that the weights are fixed after training which limits learning and generalization capability. Especially in handling a large amount of data in a large spacial domain, a sufficiently large size of neural network is required. In this paper, we consider a variable weight neural network (VWNN) to improve the learning and generalization capability of the traditional neural networks. A VWNN consists of two traditional neural networks, namely tuning and tuned neural networks. The tuned neural network is the one which actually classifies the input data. The tuning neural network is to provide the weights to the tuned neural network according to the characteristic of the input data. Theoretically, the VWNN can be viewed as an infinite number of traditional neural networks with fixed weights. In the operation, the VWNN will used the best traditional neural network to hand the input data for classification.

In this paper, we consider two real-life applications which are surface material recognition and epilepsy seizure phases recognition. In the application of surface material recognition, we develop classifiers to recognize the surface material of an unknown object from 18 classes. The surface information such as frictional coefficients, texture, compliance and roughness are collected using a contact sensing fingertip of a robotic hand mounted on a robot arm. In operation, the contact sensing fingertip, which is capable of identifying the normal and frictional force of an object, will slide along the object with short strokes whilst changing (increasing/decreasing) the velocity as is appropriate. Feature vectors extracted from the raw data to reduce its dimensions are used as the input of classifiers. In the application of epilepsy seizure phases recognition, classification of epilepsy signals is considered using real clinical data. We will develop classifiers which is able to classify the 3 seizure phases namely seizure-free, pre-seizure and seizure phases. Both applications demonstrate a huge potential to be applied in domestic and industrial tasks. In bot of the applications, we will employ the VWNN to implement the classifiers. The classification performance will be compared with the some traditional classifiers such as feedforward-neural-network, naive Bayes and kNN classifiers. Their robustness will be tested using noise-contaminated data.

The paper is organized as follows. Section II gives the background of the traditional neural networks, which provide the foundation developing the VWNNs. Section III introduces the VWNN and explains how it works. Section IV gives presents two applications on material and epilepsy signal classification. Section V gives the conclusion.

II. Traditional Neural Networks

A 3-layer feed-forward fully-connected neural network with n_{in} inputs and n_{n_out} outputs is shown in Fig. 1 where $w_{ji}^{(1)}$ denotes the weight between the j-th hidden node and the i-th input node; $w_{ji}^{(2)}$ denotes the weight between the j-th output node and the i-th hidden node, and $b_j^(1)$ and $b_j^(2)$ denote the weights of the biases in the j-th hidden and output nodes, respectively. It has been shown that a 3-layer feed-forward fully-connected neural network is a universal approximator which can approximate a smooth and continuous nonlinear function in a compact domain to an arbitrary accuracy.

A multiple-layer feed-forward fully-connected neural networks with one input layer, n_l hidden layers and one output layer is briefly presented in this section. It takes $\mathbf{x}(t) = \begin{bmatrix} x_1(t) & x_2(t) & \cdots & x_{n_{in}}(t) \end{bmatrix}$ as the t^{th} input and produces $\mathbf{y}(t) = \begin{bmatrix} y_1(t) & y_2(t) & \cdots & y_{n_{out}}(t) \end{bmatrix}$ as the outputs where n_{in} denotes the number of input nodes in the input layer and n_{out} denotes the number of output nodes in the output layer.

The output of the j-th node in the input layer is given as follows:

$$f_i^{(0)}(t) = x_i(t), i = 1, 2, \ldots, n_{in} \tag{1}$$

and the output of the j-th node in the n_l-th hidden layer is given as follows:

$$f_i^{(n_l)}(t) = tf_{n_l}\Big(\sum_{j=1}^{n_{n_h}^{(n_l-1)}} w_{ij}^{(n_l)} f_j^{(n_l-1)}(t) - b_j^{(n_l)}\Big), i = 1, 2, \ldots, n_h^{(n_l)}, \tag{2}$$

where $tf_{n_l}(\cdot)$ denotes the transfer function; $n_h^{(n_l)}$ denotes the number of hidden nodes, $b_i^{(n_l)}$ denotes the bias in the n_l-th hidden layer; and $w_{ij}^{(n_l)}$ denotes the weight between the j-th node in the $n_h^{(n_l-1)}$-th hidden layer and the i-th node in the $n_h^{(n_l)}$-th hidden layer.

The output of the neural network is given as follows:

$$y_i(t) = tf_{n_l+1}\Big(\sum_{j=1}^{n_{n_h}^{(n_l)}} w_{ij}^{(n_l+1)} f_j^{(n_l)}(t) - b_j^{(n_l+1)}\Big), i = 1, 2, \ldots, n_{out} \tag{3}$$

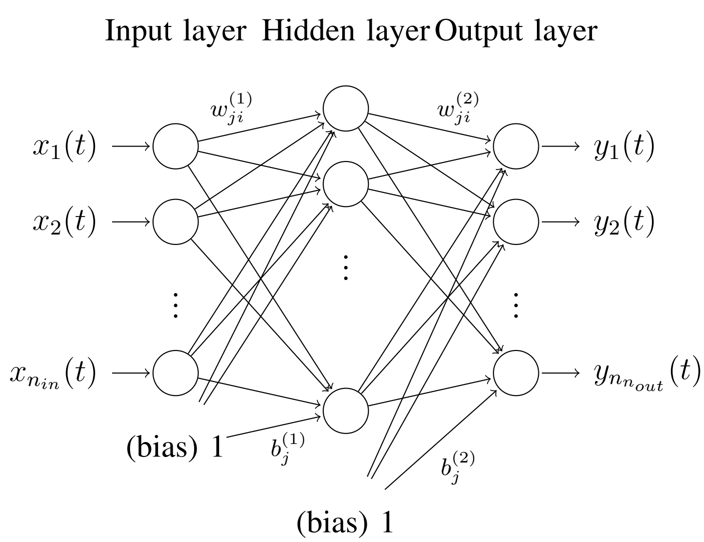

Fig. 1. A three-layer feed-forward fully-connected neural network.

III. Variable-Weight Neural Networks

A feed-forward fully-connected neural network is a network with static weights which processes all input using the same connection weights between layers. Although it has been shown that it is a universal approximator, it requires a sufficiently large number of hidden nodes to offer an acceptable performance. Considering the case that when the number of input data is large, the number of hidden nodes will be large to maintain the learning and generalization capability. However, a large number of hidden layer is not favourable to both hardware and software implementations due to the increase of computational demand. Using a small number of hidden nodes will definitely offer advantages rather than advantages in terms of implementation costs. However, it will degrade the learning and generalization capability of the neural network resulting in a poor performance.

A VWNN is a neural network with dynamic weights which is good in handling a large dataset. Assuming that the large dataset is divided into a number of small sub-datasets, a small neural network (with small number of hidden nodes) will work well. The VWNN works based on this concept that different connection weights are employed by the neural network according to the network input. Consequently, the VWNN seems to consists of infinite number of neural networks and each individual input is processed by an individual neural network.

A three-layer VWNN is shown in Fig. 2. The tuning neural networks (NN_1 and NN_2) will provide connection weights $w_{ji}^{(1)}$ and $w_{ji}^{(2)}$ and bias weights $b_j^{(1)}$ and $b_j^{(2)}$ to a three-layer feed-forward fully connected neural network according to the input $\mathbf{x}'(t)$ which consists of some selected features from $\mathbf{x}(t)$. The neural network will process the input $\mathbf{x}(t)$ according to the provided connection weights. This concept can be generalized to a VWNN with any number of hidden layers.

A block diagram of a general VWNN is shown in Fig. 3 which consists of 2 traditional neural networks, namely turning and turned neural networks. The input $\mathbf{x}(t)$ will be selected by a pre-determined constant selection matrix $\mathbf{S} \in R^{n'_{n_{in}} \times n_{n_{in}}}$ such that $\mathbf{x}'_{n_{in}}(t) = \mathbf{S}\mathbf{x}_{n_{in}}(t)$ where $n'_{n_{in}} \leq n_{n_{in}}$. For example, considering $\mathbf{x}'_{n_{in}}(t) = \begin{bmatrix} x'_1(t) \\ x'_2(t) \end{bmatrix}$, $\mathbf{x}_{n_{in}}(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \end{bmatrix}$ and $\mathbf{S} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, we have $\mathbf{x}'_{n_{in}}(t) = \mathbf{S}\mathbf{x}_{n_{in}}(t) = \begin{bmatrix} x_1(t) \\ x_3(t) \end{bmatrix}$ which selects $x_1(t)$ and $x_2(t)$ as the input of the turning neural network. The tuning neural network will produce output weight vector $\mathbf{W}(t)$ consisting of all connection weights of the tuned neural network. The tuned neural network will then use $\mathbf{W}(t)$ to process the input $\mathbf{x}(t)$. As a result, it seems like that an individual input $\mathbf{x}(t)$ is processed by an

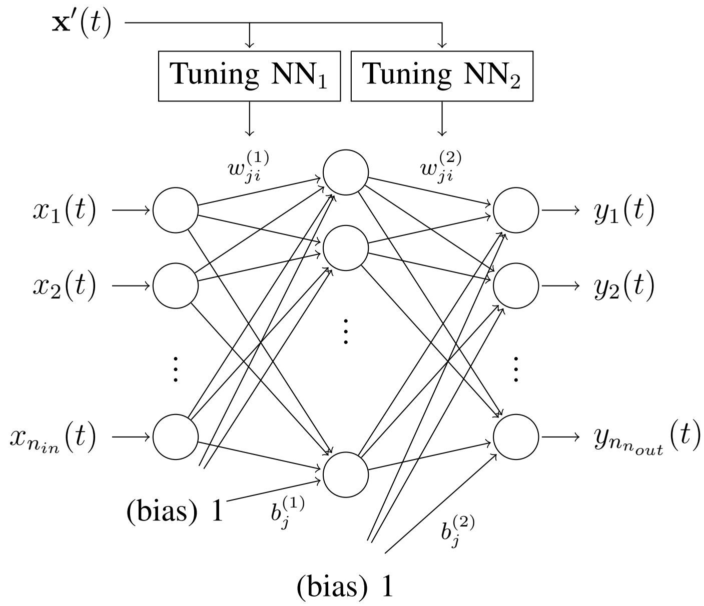

Fig. 2. A three-layer variable-weight neural network.

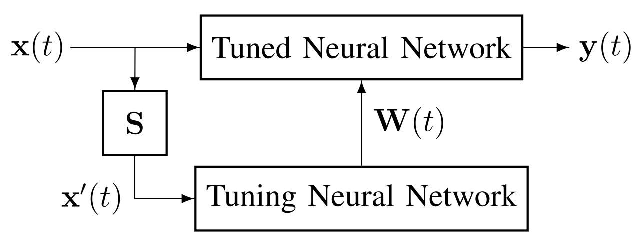

Fig. 3. A block diagram of variable-weight neural network.

individual neural network to produce an output $\mathbf{y}(t)$.

IV. Applications

In this section, we employ the proposed VWNN to implement the classifier to handle two applications. The first application is the classification of materials using the data collected by a robotic finger. The second application is the classification of epilepsy using real clinical data.

A. Material Classification

Classification problem in material surface recognition of an unknown object demonstrates a wide range of potential domestic and industrial applications, just to name a few, robot-assisted surgery [54]–[57], blind grasping application [58], [59], pose classification [60], prosthetic limbs [61], quality assurance [62], shape extraction and industrial inspection [63], [64], and brain-machine-brain interface [65].

The VWNN is employed to implement a classifier to classify 18 materials listed in Table I using data collected from a robotic testing platform shown in Fig 4, which includes a robot arm Mitsubishi RV-6SL, a 6-axis force/torque sensor ATI Nano17 (resolution = 0.003 N, sampling rate = 100 Hz) and a hemispherical plastic fingertip. During experiments, the fingertip rigidly attached to the robot arm was kept perpendicular to the material surface all the time. It was then commanded to slide on a selected object surface, keeping the normal force around 2 N. To obtain the dynamic relationship of friction and velocity, within one stroke, the sliding velocity was increased from zero to 15 mm/s with a constant acceleration rate of 3mm/s2. Each time the fingertip slides along a material surface, 100 numerical values (raw data of fractional force) reflecting the material characteristics are collected. The same experiment was repeated for 60 times for each of 18 materials. In total, 60 sets of data (each set contains 100 numerical values) for each material were collected. Further detailed description of the experiment setup and data collection can be found in [66].

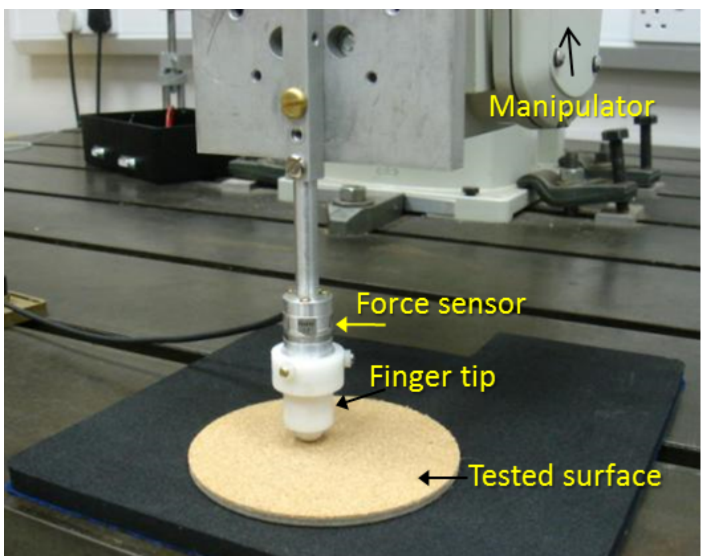

Fig. 4. The test platform.

1) Feature Extraction: In these experiments, the raw data of 100 points (denoted as p_1 to p_{100}) will first be reduced to feature vectors of 3, 4 and 5. The raw data of 100 numerical values of each pattern is first divided into 4 portions such that $\mathbf{p}_1 = [p_1 \quad p_2 \quad \ldots \quad p_{25}]$, $\mathbf{p}_2 = [p_{26} \quad p_{27} \quad \ldots \quad p_{50}]$,

Class label	Material
1	Un-laminated wood
2	Fine polished aluminium
3	Unpolished aluminium
4	Polished brass
5	Ceramic plate
6	Cloth liner
7	Glass
8	Artificial leather
9	Mouse pad (liner surface)
10	A4 paper
11	Laminated book cover
12	Plastic PC mouse
13	Plastic CD cover
14	Polymer composite (smooth surface)
15	Kitchen sponge
16	Stainless steel knife
17	Rubber tape
18	Un-laminated paper package

TABLE I
18 MATERIALS USED IN THE EXPERIMENT.

$\mathbf{p}_3 = [p_{51} \quad p_{52} \quad \dots \quad p_{75}]$ and $\mathbf{p}_4 = [p_{76} \quad p_{77} \quad \dots \quad p_{100}]$. Define

$$f_1(\mathbf{z}) = \frac{1}{S}\sum_{i=1}^{S} z_i, \tag{4}$$

$$f_2(\mathbf{p}) = \sum_{i=1}^{4} |f_1(\mathbf{p}_{i+1}) - f_1(\mathbf{p}_i)|, \tag{5}$$

$$f_3(\mathbf{z}) = \frac{1}{S-1}\sum_{i=1}^{S}(z_i - f_1(\mathbf{z}))^2, \tag{6}$$

where $\mathbf{z} = [z_1 \quad z_2 \quad \dots \quad z_S]$ and S is a integer representing the number of elements in $\mathbf{z}$.

Based on the functions in (4) to (6), we define the feature vectors of 3 to 5 points as follows:

Feature vector with 3 points:

$$\mathbf{x} = \left[\begin{array}{ccc} \sum_{i=1}^{4} f_1(\mathbf{p}_i) & 50 f_2(\mathbf{p}_i) & 50\sum_{i=1}^{4} f_3(\mathbf{p}_i) \end{array}\right]. \tag{7}$$

Feature vector with 4 points:

$$\mathbf{x} = \left[\begin{array}{cccc} \sum_{i=1}^{4} f_1(\mathbf{p}_i) & 50 f_2(\mathbf{p}_i) & 50 \sum_{i=1}^{4} f_3(\mathbf{p}_i) & 20 \sum_{i=1}^{4} \sqrt{f_3(\mathbf{p}_i)} \end{array} \right]. \tag{8}$$

Feature vector with 5 points:

$$\mathbf{x} = \left[\begin{array}{ccccc} \sum_{i=1}^{4} f_1(\mathbf{p}_i) & 50|f_1(\mathbf{p}_2) - f_1(\mathbf{p}_1)| & 50|f_1(\mathbf{p}_3) - f_1(\mathbf{p}_2)| & 50|f_1(\mathbf{p}_4) - f_1(\mathbf{p}_3)| & 50 \sum_{i=1}^{4} f_3(\mathbf{p}_i) \end{array} \right]. \tag{9}$$

It can be seen from (4) to (6) that $f_1(\mathbf{z})$ is the mean of $\mathbf{z}$, $f_2(\mathbf{z})$ is the sum of the difference of the mean of the consecutive portions of raw data, $f_3(\mathbf{z})$ is the variance of $\mathbf{z}$.

2) VWNN-Based Classifier: The proposed VWNN is employed to implement a classifier to recognize the 18 materials using the feature vectors of 3, 4, and 5 points. Fig. 5 shows the structure of classifier consisting of a VWNN with n_{in} inputs (the number of feature points) and one output.

In this experiment, the dataset is divided into training dataset consisting of 40 sets of data for each material and test dataset consisting of 20 sets of data for each material. Supervised learning was employed to train the VWNN classifier according to the class labels shown in Table I.

We have tried different combinations of transfer functions, number of hidden nodes and hidden layers in this study. In the following, only this combination can achieve the best recognition accuracy. The overall network is 6 hidden layers structure, the number of hidden nodes are 3, 4, 6, 4, 3, 4, respectively. The first two layers's transfer function use 'tansig' function and other layers are 'linear' function, and the 3^{rd} and 4^{th} layers are VWNN layer, which tuned by two ordinary networks using 'tansig' transfer function. The linear transfer function is used in the output layer of all classifiers, and number of output nodes is 1. The VWNN classifier was implemented on Matlab and Levenberg-Marquardt back-propagation was used to train the classifiers by minimizing the mean square error.

For comparison purposes, traditional NN, KNN and naive Bayes classifiers were employed as classifiers for this application. To test the robustness of the classifiers, the test dataset extracted from raw data contaminated by Gaussian white noise with variance of 0.005 and 0.01 was considered. Each classifier was tested 10 times using the noisy test dataset.

3) Classification Results: The training and testing recognition results of the VWNN, traditional NN, KNN and naive Bayes classifiers are summarized in Table II. In this table, the worst and average

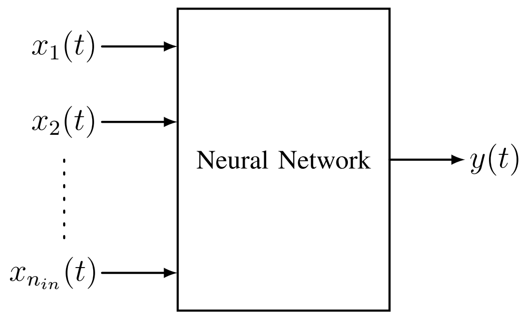

Fig. 5. NN-based classifier for materials.

recognition accuracy for both training and test datasets are shown. The worst recognition accuracy is the worst individual accuracy in the 18 materials while the average recognition accuracy is average the individual accuracy of 18 materials.

Referring to this table, it can be seen that all classifiers perform well achieving 100% of recognition accuracy for training dataset. For test dataset, the naive Bayes classifiers with 3, 4 and 5 feature points offers the best average recognition performance of 99.4444%, 100% and 100%, respectively. The proposed VWNN classifiers with 3, 4 and 5 comes second offering the average recognition performance of 98.6111%, 98.6661% and 99.1667%. All the rest classifiers offer an average recognition performance less than 97%. Among all classifiers, the KNN classifier with 5 feature points offer the worst average performance of 89.7222% and its worst individual recognition accuracy is 70%.

The testing recognition results for the test dataset subject to Gaussian white noise with variance of 0.005 and 0.01 are summarized in Table III and Table IV, respectively, which provide the statistical information including the worst recognition accuracy (the average of the average recognition accuracy of the 18 materials of the 10 times of tests), average recognition accuracy (the worst average recognition accuracy of the 18 materials among the 10 times of tests) and best recognition accuracy (the best average recognition accuracy of the 18 materials among the 10 times of tests), standard deviation of the 10 times of tests and the average of the worst individual recognition accuracy among 18 materials.

It can be seen from the tables that the recognition performance of all classifiers degrade when the noise level increases. Considering the noise level of 0.005, the VWNN with 5 feature points, and naive Bayes with 4 and 5 feature points offer the best average recognition accuracy over 98%. When the noise level increases to 0.01, naive Bayes classifiers degrade their performance significantly compared with the VWNN classifier with 5 feature points. The VWNN classifier with 5 feature points is able

		Recognition Accuracy (%)			
		Training		Testing	
#feature points	Classifier	Worst	Average	Worst	Average
3	1	100	100	90	98.6111
3	2	100	100	80	96.9444
3	3	100	100	80	95.8333
3	4	100	100	90	99.4444
4	1	100	100	90	98.6661
4	2	100	100	85	96.3889
4	3	100	100	70	93.6111
4	4	100	100	100	100
5	1	100	100	95	99.1667
5	2	100	100	85	96.1111
5	3	100	100	70	89.7222
5	4	100	100	100	100

TABLE II
SUMMARY OF RECOGNITION PERFORMANCE UNDER NOISE-FREE DATASET. CLASSIFIER 1: VWNN CLASSIFIER, CLASSIFIER 2: TRADITIONAL NEURAL NETWORK CLASSIFIER, CLASSIFIER 3: K-NEAREST NEIGHBOR CLASSIFIER, 4: NAIVE BAYES CLASSIFIER.

to maintain its recognition performance offering the best of the best average recognition accuracy of 94.7222% while the KNN classifier with 3 feature points comes second offering 93.6111%.

Based on the above discussion, the VWNN classifier with 5 feature points offers the best recognition performance with noise-free raw data. Under the noisy raw data, it is able to outperform the rest classifiers in terms of worst, average and best recognition accuracy suggesting that it has a comparatively superior capability tolerating noise.

B. Epilepsy Classification

Epilepsy is a common neurologic disorder that is a chronic disease of brain causing sudden paradoxical discharge of cortical neurons. Abnormal, excessive or synchronous neuronal activity in the brain [67], [68] will cause spontaneous and unforeseeable occurrence of seizures [69] with transient signs and/or symptoms. The during of absence seizure is typically lasting from a few seconds up to around a minute, causing momentary lapses of consciousness of the sufferers [70]. However, it may recur frequently over 100 times a day [71].

These sudden and abrupt seizures will cause significant impact on the living quality of sufferers [72], [73] and their carers. More importantly, it may cause life-threatening accident when the sufferer is unconsciousness. Therefore, understanding of pre-seizure (the transition of brain activity toward an

		Recognition Accuracy (%)				
#feature points	Classifier	Worst	Average	Best	Std	Worst individual (Average)
3	1	91.3889	94.2222	97.2222	2.0916	50.0000
3	2	86.3889	92.3611	96.3889	3.1882	55.0000
3	3	88.6111	93.8889	98.3333	3.3120	84.0000
3	4	92.5000	93.5278	94.1667	0.5826	0.5000
4	1	88.6111	91.2222	93.0556	1.4722	0.0000
4	2	77.5000	82.3333	86.9444	3.1543	1.5000
4	3	81.6667	86.6667	91.1111	3.3264	27.0000
4	4	95.5556	97.5000	98.6111	0.9631	72.0000
5	1	93.6111	96.3889	98.3333	1.5817	68.0000
5	2	86.3889	92.9444	97.2222	3.5728	60.0000
5	3	83.3333	88.6389	92.7778	3.0588	39.5000
5	4	93.3333	93.9167	94.4444	0.4086	0.5000

TABLE III
SUMMARY OF RECOGNITION PERFORMANCE FOR THE DATASET SUBJECT TO NOISE LEVEL OF 0.005. CLASSIFIER 1: VWNN CLASSIFIER, CLASSIFIER 2: TRADITIONAL NEURAL NETWORK CLASSIFIER, CLASSIFIER 3: K-NEAREST NEIGHBOR CLASSIFIER, 4: NAIVE BAYES CLASSIFIER.

		Recognition Accuracy (%)				
#feature points	Classifier	Worst	Average	Best	Std	Worst individual (Average)
3	1	58.6111	63.9167	68.0556	3.1284	0.0000
3	2	61.1111	68.6944	74.1667	4.1574	0.0000
3	3	77.7778	86.2500	93.6111	5.2281	50.5000
3	4	74.7222	77.9722	81.1111	2.2443	0.0000
4	1	61.9444	64.7500	67.2222	1.8301	0.0000
4	2	58.6111	66.6389	72.2222	4.6941	0.0000
4	3	55.8333	62.2778	66.9444	3.7609	0.0000
4	4	67.7778	71.6111	74.7222	2.1802	0.0000
5	1	84.1667	89.5000	94.7222	3.6503	34.5000
5	2	63.8889	72.9444	80.0000	5.4622	0.0000
5	3	72.5000	82.6111	89.7222	5.8274	38.5000
5	4	79.7222	81.0185	82.5000	1.5608	0.0000

TABLE IV
SUMMARY OF RECOGNITION PERFORMANCE FOR THE DATASET SUBJECT TO NOISE LEVEL OF 0.01. CLASSIFIER 1: VWNN CLASSIFIER, CLASSIFIER 2: TRADITIONAL NEURAL NETWORK CLASSIFIER, CLASSIFIER 3: K-NEAREST NEIGHBOR CLASSIFIER, 4: NAIVE BAYES CLASSIFIER.

absence seizure) is a very demanding task [74], [75]. Early detection of pre-seizure is vital to the sufferers and their carers, providing them an early warning signals taking precautions.

Absence seizures are a form of generalized seizures accompanied by spike-and-wave complexes in the electroencephalograph (EEG) [76], [77]. In general, epileptic EEG classification process can be broken down into 2 sub-processes, namely feature extraction and classification. A wide range of feature extraction methods ranging from traditional linear methods (e.g., Fourier transforms and spectral analysis [78]) to nonlinear methods (e.g., Lyapunov exponents [79], correlation dimension [80] and similarity [81], [82] can be found in the literature. The extracted features will be used for the design of classifiers and classification in the real operation. A wide range of methodologies for epileptic EEG classification can be found in the literature such as artificial neural networks and neuro-fuzzy systems [83]–[85].

In this application, various classifiers (VWNN, traditional NN, KNN and navie Bayes classifiers) are employed to recognize the 3 seizure phases namely seizure-free, pre-seizure and seizure phases. To perform training and testing of classifiers, EEG recordings were collected in Peking University People's Hospital from 10 patients (6 males and 4 females) with absence epilepsy, aged from 8 to 21 years old. The study protocol has been approved by the ethics committee of Peking University People's Hospital and the patients have signed informed consent that their clinical data might be used and published for research purposes. The EEG data (sampled at a frequency of 256 Hz using a 16-bit analogue-to-digital converter and filtered within a frequency band from 0.5 to 35 Hz) were recorded by the Neurofile NT digital video EEG system from a standard international 10-20 electrode placement (Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz and Pz).

Three sets of EEG signals from different seizure phases namely seizure-free, pre-seizure and seizure phases were collected where 112 2-second 19-channel EEG epochs from 10 patients were extracted for each dataset. The timing of onset and offset in spike-wave discharges (SWDs) was identified by an epilepsy neurologist, and these SWDs were defined as large-amplitude rhythmic 3-4 Hz discharges with typical spike-wave morphology lasting $>$ 1 second. The seizure-free, pre-seizure and seizure data are determined based on the criteria of 1) the interval between the seizure-free data and the beginning point of seizures is greater than 15 seconds, 2) the interval is between 0 to 2 seconds prior to seizure onset, and 3) the interval is the first 2 seconds of the absence seizure, respectively. Fig. 6 shows the examples of 19-channel EEG recordings in seizure-free, pre-seizure and seizure phases. The generalized SWDs with a repetition rate of 3 Hz are typically associated with clinical absence seizures. Further details regarding the data collection can be found in [86]–[88].

1) Feature Extraction: Feature extraction is an essential step to find and then extract the hidden characteristics and information of EEG signals, and one other important purpose of feature extraction is to reduce the redundancy of the original signals. In order to improve the classification performance, it

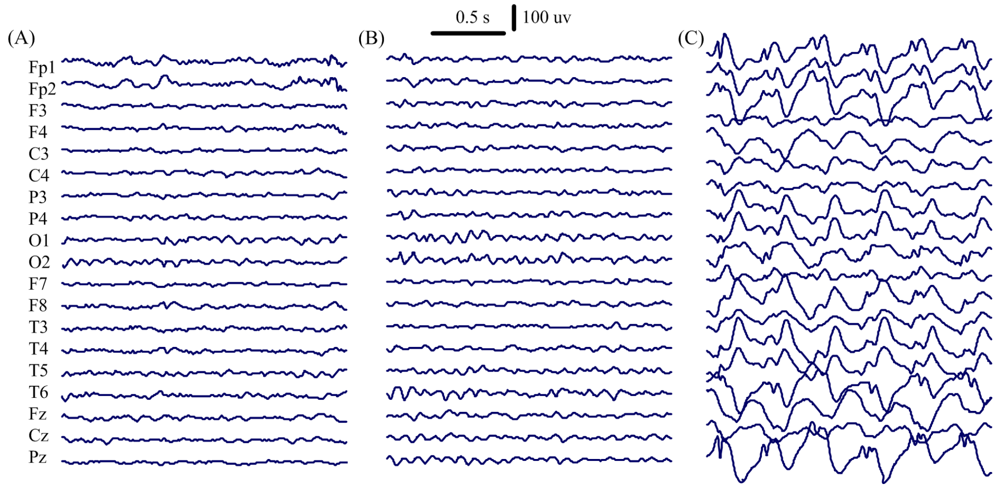

Fig. 6. Examples of raw EEG recordings for (A) seizure-free, (B) pre-seizure and (C) seizure phases.

is necessary to elect appropriate feature extraction methods and then combine them together to achieve better recognition accuracy.

In the EEG case, we have 19 columns of signals as shown in Fig. 6, which are collected from 19 EEG sensors, and each column of the EEG signals has 100 sample points. We need first to extract the useful information from the 19 $\times$ 100 points and then reduce its dimensions to form a feature vector, which will be taken as the input of the classifiers.

Some published results provide the evidence supporting the view of fronto-central network in absence epilepsy which suggested that not all 19 channels are of the same importance. The characteristics of early cortical activities was analyzed and the spatio-temporal dynamics of interactions within and between local cortical neural networks was explaored in [89]. It reveals a reproducible sequence demonstrating increased long-range desynchronisation, local synchronisation and long-range synchronization found a multifocal fronto-central network in absence epilepsy. In the study in [90], the authors compared the functional networks in EEG background between absence epilepsy and healthy control individuals to identify which set of electrodes provide the maximum differentiation. Both studies reported a similar result that electrodes F3, Fz, F4, C3 and Cz are the most representative ones for the differentiation between control and absence patients while the rest carries useful information and patterns that can help to discriminate among different absence seizure phases.

In this study, we selected the most useful channels by considering different channel combinations. It was found that the 1st, 2nd, 3rd, 4th, 5th, 6th, 11th, 12th, 13th, 14th channels out of the 19 channels contain the most significant information for classification, which compile with the results in [89],

[90] that channel F3, Fz, F4, C3 and Cz contain the most important information. From each of the chosen channels, a feature vector consisting of time-domain and frequency-domain components is formed. Features in time domain, which do not have any transformation, is straightforward and easy to comprehend [91]. The standard deviation, second order norm, third order norm, fourth order norm, the absolutely sum, the maximum value, the minimum value of each channel are computed to form part of the the feature vector. The frequency or spectral domain analysis is mostly used to study and analyze the EEG signals in frequency domain. The mean frequency, maximum frequency, minimum frequency, standard deviation of frequency, the windowing filtered mean frequency and windowing filtered maximum frequency of each chosen channel will form the rest part of the feature vector. It is noted that the size of the overall feature vector formed by combining all channel feature vectors is huge. Principle component analysis (PCA) is employed to lower the dimension the dimension of the overall feature vector. Since each channels has its own characteristics, we choose different principle components according to different channels.

At last, we gain 45 points to form the feature vector, which will be further used in the recognition or classification stage. In the following, all NNs and classifiers takes these 45 points as input to perform classification.

2) VWNN Classifier: A tree-structured classifier implemented by the proposed VWNN is employed to classify 3 classes of Epilepsy signals (seizure-free, pre-seizure and seizure phases) using the feature vector achieved in the previous section. Fig. 7 shows the tree-structured VWNN classifier consisting of 2 45-input-single-output VWNNs and a class determiner. The 1^{st} VWNN is used to determine if the testing sample belongs to class 3 (seizure phase), if not, we use the 2^{nd} VWNN to determine if the testing sample belongs to class 1 (seizure-free phase) or class 2 (pre-seizure phase). The classifier will determine the final class according to the rules as shown in Table.V.

In this application, we have tried different combinations of transfer functions, number of hidden nodes and hidden layers in this study. The following combination can achieve the best recognition accuracy. For the 1^{st} VWNN network as shown in Fig. 7, the tuned NN has 45 inputs, 4 hidden layers with 25, 4, 8 and 5 hidden nodes and one output node. The transfer functions corresponding to the 4 hidden layers are hyperbolic tangent sigmoid, hyperbolic tangent sigmoid, logarithm sigmoid function and logarithm sigmoid function, respectively. Linear function and logarithm sigmoid function are used in the input and output layers, respectively. The tuning NN has 45 inputs, 2 hidden layers with 25 and 4 hidden nodes and 32 output nodes. The first 3 layers, i.e., the input and the 2 hidden layers, are common to the tuned NN. The output layers uses hyperbolic tangent sigmoid function as transfer function. The outputs of the tuning NN provide the variable weights to the connections between the 3$^{\text{rd}}$ and 4$^{\text{th}}$ hidden layers of the tuned NN.

The tuned NN of the 2$^{\text{nd}}$ VWNN is shown in Fig. 7 has 45 inputs, 4 hidden layers of 35, 5, 8 and 5 hidden nodes and one output node. The transfer functions corresponding to the 4 hidden layers are hyperbolic tangent sigmoid, hyperbolic tangent sigmoid, logarithm sigmoid function and logarithm sigmoid function, respectively. Linear function and logarithm sigmoid function are used in the input and output layers, respectively. The tuning NN has 45 inputs, 2 hidden layers with 35 and 5 hidden nodes and 40 output nodes. The first 3 layers, i.e., the input and the 2 hidden layers, are common to the tuned NN. The output layers uses hyperbolic tangent sigmoid function as transfer function. The outputs of the tuning NN provide the variable weights to the connections between the 3$^{\text{rd}}$ and 4$^{\text{th}}$ hidden layers of the tuned NN.

For comparison purposes, traditional NN, KNN and naive Bayes classifiers were employed as classifiers for this application. To test the robustness of the classifiers, the test dataset extracted from the raw data contaminated by Gaussian white noise with variance of 0.05 to 1 was considered. The NN classifier has the same structure as the VWNN classifier as shown in Fig. 7 but the VWNNs are replaced by the traditional NNs. The transfer function used in the 3$^{\text{rd}}$ layer of the traditional NN which has the same number of hidden nodes as that of the VWNN. Each classifier was tested 10 times using the test dataset subject to noise of different levels.

3) Classification Results: The classification performance of all classifiers with the original data and data contaminated by noise level from 0.05 to 1. The classification performance corresponding to different noise levels are summarized in Table VI to Table XI.

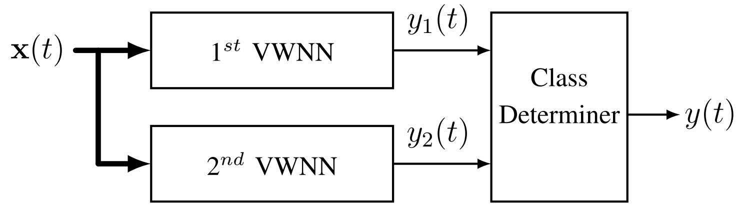

Fig. 7. Tree-structure VWNN classifier for epilepsy.

In Table VI, the worst and average recognition accuracy for both training and test datasets are shown.

$y_1(t)$	$y_2(t)$	$y(t)$
3	1	3
3	2	3
not 3	1	1
not 3	2	2

TABLE V
OUTPUT CLASSES OF CLASS DETERMINER.

	Recognition Accuracy (%)			
	Training		Testing	
Classifier	Worst	Average	Worst	Average
1	100	100	80.0000	91.1111
2	100	100	73.3333	86.6667
3	100	100	23.3333	56.6667
4	41.4286	77.1429	33.3333	77.7778

TABLE VI
SUMMARY OF RECOGNITION PERFORMANCE FOR EEG SIGNALS WITH ORIGINAL DATASET. CLASSIFIER 1: VWNN CLASSIFIER, CLASSIFIER 2: TRADITIONAL NEURAL NETWORK CLASSIFIER, CLASSIFIER 3: K-NEAREST NEIGHBOR CLASSIFIER, 4: NAIVE BAYES CLASSIFIER.

	Recognition Accuracy (%)				
Classifier	Worst	Average	Best	Std	Worst individual(Average)
1	85.5556	89.2222	94.4444	2.9801	75.0000
2	77.7778	85.0000	90.0000	4.0140	75.3333
3	51.1111	56.3333	61.1111	3.2735	20.3333
4	77.7778	78.3333	80.0000	0.7857	35.0000

TABLE VII
SUMMARY OF TESTING SAMPLES RECOGNITION PERFORMANCE FOR EEG SIGNAL UNDER DATASET SUBJECT TO NOISE LEVEL OF 0.05. CLASSIFIER 1: VWNN CLASSIFIER, CLASSIFIER 2: TRADITIONAL NEURAL NETWORK CLASSIFIER, CLASSIFIER 3: K-NEAREST NEIGHBOR CLASSIFIER, 4: NAIVE BAYES CLASSIFIER.

	Recognition Accuracy (%)				
Classifier	Worst	Average	Best	Std	Worst individual(Average)
1	80.0000	86.4444	92.2222	4.1869	67.0000
2	78.8889	85.7778	90.0000	3.6501	70.6667
3	52.2222	56.5556	61.1111	2.9232	20.3333
4	76.6667	78.8889	82.2222	1.8251	37.6667

TABLE VIII
SUMMARY OF TESTING SAMPLES RECOGNITION PERFORMANCE FOR EEG SIGNAL UNDER DATASET SUBJECT TO NOISE LEVEL OF 0.1. CLASSIFIER 1: VWNN CLASSIFIER, CLASSIFIER 2: TRADITIONAL NEURAL NETWORK CLASSIFIER, CLASSIFIER 3: K-NEAREST NEIGHBOR CLASSIFIER, 4: NAIVE BAYES CLASSIFIER.

	Recognition Accuracy (%)				
Classifier	Worst	Average	Best	Std	Worst individual(Average)
1	78.8889	84.4444	90.0000	3.4978	58.6667
2	75.5556	84.1111	88.8889	3.8639	64.6667
3	53.3333	57.2222	62.2222	2.9614	20.6667
4	76.6667	79.0000	82.2222	1.8898	38.6667

TABLE IX
SUMMARY OF TESTING SAMPLES RECOGNITION PERFORMANCE FOR EEG SIGNAL UNDER DATASET SUBJECT TO NOISE LEVEL OF 0.2. CLASSIFIER 1: VWNN CLASSIFIER, CLASSIFIER 2: TRADITIONAL NEURAL NETWORK CLASSIFIER, CLASSIFIER 3: K-NEAREST NEIGHBOR CLASSIFIER, 4: NAIVE BAYES CLASSIFIER.

	Recognition Accuracy (%)				
Classifier	Worst	Average	Best	Std	Worst individual(Average)
1	81.1111	83.5556	85.5556	1.5948	54.6667
2	76.6667	81.2222	86.6667	3.6429	56.0000
3	52.2222	59.0000	64.4444	3.8665	24.6667
4	75.5556	78.2222	80.0000	1.5585	36.3333

TABLE X
SUMMARY OF TESTING SAMPLES RECOGNITION PERFORMANCE FOR EEG SIGNAL UNDER DATASET SUBJECT TO NOISE LEVEL OF 0.5. CLASSIFIER 1: VWNN CLASSIFIER, CLASSIFIER 2: TRADITIONAL NEURAL NETWORK CLASSIFIER, CLASSIFIER 3: K-NEAREST NEIGHBOR CLASSIFIER, 4: NAIVE BAYES CLASSIFIER.

The worst recognition accuracy is the worst individual accuracy in the 3 classes while the average recognition accuracy is the average recognition accuracy of the individual recognition accuracy of all 3 classes. It can be seen that the VWNN offers the best performance over the other 3 traditional classifiers methods evident by average training and testing recognition accuracies of 100% and 91.1111%, respectively.

Table VII to Table XI show the testing data classification performance of all the 4 classifiers with noisy data under noise levels of 0.05, 0.1, 0.2, 0.5,and 1. From these tables, it can be seen that

	Recognition Accuracy (%)				
Classifier	Worst	Average	Best	Std	Worst individual(Average)
1	77.7778	83.4444	85.5556	2.4525	54.6667
2	72.2222	78.3333	82.2222	3.9338	49.0000
3	50.0000	59.6667	66.6667	5.8187	23.3333
4	76.6667	77.7778	80.0000	1.3242	36.3333

TABLE XI
SUMMARY OF TESTING SAMPLES RECOGNITION PERFORMANCE FOR EEG SIGNAL UNDER DATASET SUBJECT TO NOISE LEVEL OF 1. CLASSIFIER 1: VWNN CLASSIFIER, CLASSIFIER 2: TRADITIONAL NEURAL NETWORK CLASSIFIER, CLASSIFIER 3: K-NEAREST NEIGHBOR CLASSIFIER, 4: NAIVE BAYES CLASSIFIER.

the recognition accuracy is in general decreasing when the noise level is increasing. Among the 4 classifiers, the VWNN classifier offers the best recognition performance with the average recognition accuracy in the range of 83.4444% of 89.2222% subject to different noise levels while KNN classifier performs the worst offering the average recognition accuracies in the range of 50% to 53.3333%.

Form the above discussion, it can be concluded that the VWNN classifier outperforms the traditional classifiers offering the best recognition performance and robustness property.

V. Conclusion

In this paper, we presented a novel neural network, the variable weights neural network, which demonstrates a great potential to cope with complicated recognition and classification problems. Different from the traditional NN, the weights of the VWNN change adaptively according to the characteristic of the input data enhancing its learning and generalization capability. We have implemented classifiers using VWNNs for 2 real-life applications, i.e., material recognition using robotic finger and epilepsy classification using clinical data, to verify the effectiveness of VWNN. From the results of these two applications, it has been shown that the VWNN classifier has demonstrated the best recognition performance over the traditional neural networks, KNN method and Naive Bayes method when original input data are considered. Moreover, the VWNN classifier has demonstrated an outstanding robustness property towards noisy input data. In the future, we will keep improving the performance of VWNN and trying to find the best way to determine the structure of VWNN, for example, the number of hidden layers, the transfer function of each layer and the nodes of each layer.

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	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	100.0000
2	100.0000	100.0000
3	100.0000	95.0000
4	100.0000	95.0000
5	100.0000	100.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	100.0000
9	100.0000	100.0000
10	100.0000	100.0000
11	100.0000	95.0000
12	100.0000	100.0000
13	100.0000	100.0000
14	100.0000	100.0000
15	100.0000	100.0000
16	100.0000	90.0000
17	100.0000	100.0000
18	100.0000	100.0000
Average	100.0000	98.6111

TABLE XII
TRAINING AND TESTING ACCURACY FOR MATERIAL RECOGNITION USING VWNN CLASSIFIER WITH 3 FEATURE POINTS.

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	100.0000
2	100.0000	100.0000
3	100.0000	100.0000
4	100.0000	95.0000
5	100.0000	100.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	100.0000
9	100.0000	100.0000
10	100.0000	100.0000
11	100.0000	90.0000
12	100.0000	100.0000
13	100.0000	100.0000
14	100.0000	100.0000
15	100.0000	95.0000
16	100.0000	100.0000
17	100.0000	95.0000
18	100.0000	100.0000
Average	100.0000	98.6111

TABLE XIII
TRAINING AND TESTING ACCURACY FOR MATERIAL RECOGNITION USING VWNN CLASSIFIER WITH 4 FEATURE POINTS.

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	95.0000
2	100.0000	95.0000
3	100.0000	100.0000
4	100.0000	100.0000
5	100.0000	100.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	100.0000
9	100.0000	100.0000
10	100.0000	100.0000
11	100.0000	100.0000
12	100.0000	100.0000
13	100.0000	95.0000
14	100.0000	100.0000
15	100.0000	100.0000
16	100.0000	100.0000
17	100.0000	100.0000
18	100.0000	100.0000
Average	100.0000	99.1667

TABLE XIV
TRAINING AND TESTING ACCURACY FOR MATERIAL RECOGNITION USING VWNN CLASSIFIER WITH 5 FEATURE POINTS.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	100.0000	100.0000	100.0000	0.0000
2	89.0000	80.0000	100.0000	6.1464
3	50.0000	40.0000	65.0000	9.1287
4	100.0000	100.0000	100.0000	0.0000
5	100.0000	100.0000	100.0000	0.0000
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	99.5000	95.0000	100.0000	1.5811
9	100.0000	100.0000	100.0000	0.0000
10	100.0000	100.0000	100.0000	0.0000
11	95.5000	90.0000	100.0000	3.6893
12	74.0000	60.0000	90.0000	9.9443
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	97.5000	95.0000	100.0000	2.6352
16	91.5000	90.0000	95.0000	2.4152
17	99.0000	95.0000	100.0000	2.1082
18	100.0000	100.0000	100.0000	0.0000
Average	94.2222	91.3889	97.2222	2.0916

TABLE XV

TESTING ACCURACY FOR MATERIAL RECOGNITION USING VWNN CLASSIFIER WITH 3 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	25.0000	10.0000	30.0000	7.0711
2	13.5000	5.0000	20.0000	4.7434
3	0.0000	0.0000	0.0000	0.0000
4	59.0000	45.0000	70.0000	8.4327
5	98.5000	95.0000	100.0000	2.4152
6	100.0000	100.0000	100.0000	0.0000
7	97.5000	95.0000	100.0000	2.6352
8	100.0000	100.0000	100.0000	0.0000
9	13.0000	0.0000	20.0000	6.7495
10	100.0000	100.0000	100.0000	0.0000
11	17.0000	5.0000	30.0000	6.7495
12	35.5000	20.0000	55.0000	10.3950
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	1.0000	0.0000	5.0000	2.1082
16	92.5000	90.0000	95.0000	2.6352
17	98.5000	95.0000	100.0000	2.4152
18	99.5000	95.0000	100.0000	1.5811
Average	63.9167	58.6111	68.0556	3.2184

TABLE XVI
TESTING ACCURACY FOR MATERIAL RECOGNITION USING VWNN CLASSIFIER WITH 3 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	96.0000	90.0000	100.0000	4.5947
2	93.5000	85.0000	100.0000	4.1164
3	67.5000	60.0000	80.0000	6.3465
4	99.5000	95.0000	100.0000	1.5811
5	100.0000	100.0000	100.0000	0.0000
6	99.5000	95.0000	100.0000	1.5811
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	97.5000	90.0000	100.0000	3.5355
10	100.0000	100.0000	100.0000	0.0000
11	100.0000	100.0000	100.0000	0.0000
12	93.5000	85.0000	100.0000	4.7434
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	0.0000	0.0000	0.0000	0.0000
16	100.0000	100.0000	100.0000	0.0000
17	95.0000	95.0000	95.0000	0.0000
18	100.0000	100.0000	100.0000	0.0000
Average	91.2222	88.6111	93.0556	1.4722

TABLE XVII
TESTING ACCURACY FOR MATERIAL RECOGNITION USING VWNN CLASSIFIER WITH 4 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	2.0000	0.0000	10.0000	3.4960
2	14.0000	5.0000	25.0000	6.9921
3	0.0000	0.0000	0.0000	0.0000
4	100.0000	100.0000	100.0000	0.0000
5	100.0000	100.0000	100.0000	0.0000
6	99.0000	90.0000	100.0000	3.1623
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	0.5000	0.0000	5.0000	1.5811
10	95.5000	90.0000	100.0000	3.6893
11	56.0000	45.0000	65.0000	6.1464
12	5.5000	0.0000	10.0000	4.3780
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	0.0000	0.0000	0.0000	0.0000
16	100.0000	100.0000	100.0000	0.0000
17	95.0000	95.0000	95.0000	0.0000
18	98.0000	90.0000	100.0000	3.4960
Average	64.7500	61.9444	67.2222	1.8301

TABLE XVIII
TESTING ACCURACY FOR MATERIAL RECOGNITION USING VWNN CLASSIFIER WITH 4 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	89.0000	75.0000	95.0000	6.5828
2	94.5000	85.0000	100.0000	4.3780
3	98.0000	95.0000	100.0000	2.5820
4	100.0000	100.0000	100.0000	0.0000
5	100.0000	100.0000	100.0000	0.0000
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	100.0000	100.0000	100.0000	0.0000
10	95.0000	90.0000	100.0000	2.3570
11	95.5000	90.0000	100.0000	3.6893
12	100.0000	100.0000	100.0000	0.0000
13	95.0000	95.0000	95.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	68.0000	55.0000	80.0000	8.8819
16	100.0000	100.0000	100.0000	0.0000
17	100.0000	100.0000	100.0000	0.0000
18	100.0000	100.0000	100.0000	0.0000
Average	96.3889	93.6111	98.3333	1.5817

TABLE XIX
TESTING ACCURACY FOR MATERIAL RECOGNITION USING VWNN CLASSIFIER WITH 5 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	69.5000	60.0000	85.0000	7.9757
2	65.0000	50.0000	80.0000	11.7851
3	75.5000	55.0000	90.0000	12.7911
4	97.0000	95.0000	100.0000	2.5820
5	100.0000	100.0000	100.0000	0.0000
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	100.0000	100.0000	100.0000	0.0000
10	92.5000	90.0000	100.0000	3.5355
11	85.5000	70.0000	95.0000	7.2457
12	98.5000	90.0000	100.0000	3.3747
13	95.0000	95.0000	95.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	34.5000	15.0000	60.0000	13.8343
16	100.0000	100.0000	100.0000	0.0000
17	100.0000	100.0000	100.0000	0.0000
18	98.0000	95.0000	100.0000	2.5820
Average	89.5000	84.1667	94.7222	3.6503

TABLE XX
TESTING ACCURACY FOR MATERIAL RECOGNITION USING VWNN CLASSIFIER WITH 5 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	95.0000
2	100.0000	90.0000
3	100.0000	100.0000
4	100.0000	100.0000
5	100.0000	100.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	95.0000
9	100.0000	100.0000
10	100.0000	100.0000
11	100.0000	80.0000
12	100.0000	100.0000
13	100.0000	100.0000
14	100.0000	95.0000
15	100.0000	100.0000
16	100.0000	95.0000
17	100.0000	95.0000
18	100.0000	100.0000
Average	100.0000	96.9444

TABLE XXI
TRAINING AND TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NN CLASSIFIER WITH 3 FEATURE POINTS

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	100.0000
2	100.0000	90.0000
3	100.0000	100.0000
4	100.0000	85.0000
5	100.0000	95.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	95.0000
9	100.0000	100.0000
10	100.0000	90.0000
11	100.0000	90.0000
12	100.0000	95.0000
13	100.0000	95.0000
14	100.0000	100.0000
15	100.0000	100.0000
16	100.0000	100.0000
17	100.0000	100.0000
18	100.0000	100.0000
Average	100.0000	96.3889

TABLE XXII
TRAINING AND TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NN CLASSIFIER WITH 4 FEATURE POINTS.

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	90.0000
2	100.0000	85.0000
3	100.0000	95.0000
4	100.0000	95.0000
5	100.0000	100.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	85.0000
9	100.0000	100.0000
10	100.0000	100.0000
11	100.0000	100.0000
12	100.0000	100.0000
13	100.0000	95.0000
14	100.0000	100.0000
15	100.0000	95.0000
16	100.0000	100.0000
17	100.0000	95.0000
18	100.0000	95.0000
Average	100.0000	96.1111

TABLE XXIII
TRAINING AND TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NN CLASSIFIER WITH 5 FEATURE POINTS.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	100.0000	100.0000	100.0000	0.0000
2	84.0000	65.0000	90.0000	7.7460
3	89.0000	80.0000	95.0000	4.5947
4	97.0000	90.0000	100.0000	3.4960
5	100.0000	100.0000	100.0000	0.0000
6	99.5000	95.0000	100.0000	1.5811
7	100.0000	100.0000	100.0000	0.0000
8	91.5000	85.0000	95.0000	3.3747
9	99.5000	95.0000	100.0000	1.5811
10	95.5000	90.0000	100.0000	3.6893
11	81.0000	70.0000	90.0000	5.6765
12	55.0000	40.0000	70.0000	9.7183
13	100.0000	100.0000	100.0000	0.0000
14	99.5000	95.0000	100.0000	1.5811
15	78.5000	65.0000	100.0000	10.8141
16	95.0000	95.0000	95.0000	0.0000
17	97.5000	90.0000	100.0000	3.5355
18	100.0000	100.0000	100.0000	0.0000
Average	92.3611	86.3889	96.3889	3.1882

TABLE XXIV
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NN CLASSIFIER WITH 3 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	93.0000	85.0000	100.0000	4.8305
2	12.5000	0.0000	25.0000	7.5462
3	12.5000	0.0000	25.0000	7.1686
4	87.5000	75.0000	100.0000	8.5797
5	99.5000	95.0000	100.0000	1.5811
6	94.0000	85.0000	100.0000	5.1640
7	100.0000	100.0000	100.0000	0.0000
8	87.0000	80.0000	90.0000	3.4960
9	36.0000	20.0000	45.0000	8.4327
10	84.0000	65.0000	95.0000	7.7460
11	42.0000	20.0000	60.0000	12.5167
12	0.0000	0.0000	0.0000	0.0000
13	100.0000	100.0000	100.0000	0.0000
14	99.0000	95.0000	100.0000	2.1082
15	0.0000	0.0000	0.0000	0.0000
16	94.5000	90.0000	95.0000	1.5811
17	95.0000	90.0000	100.0000	4.0825
18	100.0000	100.0000	100.0000	0.0000
Average	68.6944	61.1111	74.1667	4.1574

TABLE XXV
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NN CLASSIFIER WITH 3 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	96.0000	90.0000	100.0000	3.1623
2	83.5000	70.0000	95.0000	8.5147
3	75.5000	65.0000	85.0000	5.9861
4	65.5000	60.0000	80.0000	6.4334
5	96.5000	95.0000	100.0000	2.4152
6	98.0000	90.0000	100.0000	3.4960
7	100.0000	100.0000	100.0000	0.0000
8	95.0000	95.0000	95.0000	0.0000
9	100.0000	100.0000	100.0000	0.0000
10	77.5000	65.0000	85.0000	6.3465
11	83.0000	75.0000	90.0000	4.8305
12	18.0000	5.0000	30.0000	7.5277
13	95.0000	95.0000	95.0000	0.0000
14	99.0000	95.0000	100.0000	2.1082
15	1.5000	0.0000	10.0000	3.3747
16	100.0000	100.0000	100.0000	0.0000
17	98.0000	95.0000	100.0000	2.5820
18	100.0000	100.0000	100.0000	0.0000
Average	82.3333	77.5000	86.9444	3.1543

TABLE XXVI
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NN CLASSIFIER WITH 4 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	44.0000	20.0000	55.0000	11.7379
2	63.0000	40.0000	80.0000	10.8525
3	2.5000	0.0000	5.0000	2.6352
4	36.5000	15.0000	45.0000	8.5147
5	96.5000	90.0000	100.0000	3.3747
6	71.0000	55.0000	90.0000	12.8668
7	99.0000	95.0000	100.0000	2.1082
8	99.0000	95.0000	100.0000	2.1082
9	98.5000	95.0000	100.0000	2.4152
10	46.5000	35.0000	60.0000	9.1439
11	50.0000	40.0000	60.0000	6.6667
12	1.0000	0.0000	5.0000	2.1082
13	96.0000	95.0000	100.0000	2.1082
14	99.0000	95.0000	100.0000	2.1082
15	0.0000	0.0000	0.0000	0.0000
16	99.5000	95.0000	100.0000	1.5811
17	98.0000	95.0000	100.0000	2.5820
18	99.5000	95.0000	100.0000	1.5811
Average	66.6389	58.6111	72.2222	4.6941

TABLE XXVII
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NN CLASSIFIER WITH 4 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	86.5000	70.0000	100.0000	8.1820
2	89.5000	80.0000	100.0000	6.8516
3	85.0000	75.0000	90.0000	5.7735
4	97.0000	90.0000	100.0000	3.4960
5	99.0000	95.0000	100.0000	2.1082
6	100.0000	100.0000	100.0000	0.0000
7	96.5000	95.0000	100.0000	2.4152
8	86.0000	80.0000	90.0000	3.1623
9	95.0000	90.0000	100.0000	3.3333
10	100.0000	100.0000	100.0000	0.0000
11	94.5000	80.0000	100.0000	5.5025
12	97.0000	90.0000	100.0000	4.2164
13	96.0000	90.0000	100.0000	4.5947
14	100.0000	100.0000	100.0000	0.0000
15	60.0000	40.0000	75.0000	9.7183
16	99.5000	95.0000	100.0000	1.5811
17	95.0000	95.0000	95.0000	0.0000
18	96.5000	90.0000	100.0000	3.3747
Average	92.9444	86.3889	97.2222	3.5728

TABLE XXVIII

TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NN CLASSIFIER WITH 5 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	62.0000	45.0000	75.0000	11.5950
2	59.5000	45.0000	70.0000	9.5598
3	69.5000	60.0000	75.0000	5.5025
4	61.5000	50.0000	80.0000	10.5541
5	96.5000	90.0000	100.0000	3.3747
6	73.0000	60.0000	85.0000	7.8881
7	92.5000	85.0000	95.0000	3.5355
8	85.5000	70.0000	95.0000	6.8516
9	42.5000	30.0000	55.0000	7.9057
10	100.0000	100.0000	100.0000	0.0000
11	54.5000	35.0000	65.0000	10.1242
12	44.5000	30.0000	55.0000	7.6194
13	97.0000	90.0000	100.0000	3.4960
14	100.0000	100.0000	100.0000	0.0000
15	0.0000	0.0000	0.0000	0.0000
16	94.0000	90.0000	95.0000	2.1082
17	93.5000	90.0000	100.0000	3.3747
18	87.0000	80.0000	95.0000	4.8305
Average	72.9444	63.8889	80.0000	5.4622

TABLE XXIX
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NN CLASSIFIER WITH 5 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	95.0000
2	100.0000	95.0000
3	100.0000	100.0000
4	100.0000	95.0000
5	100.0000	95.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	100.0000
9	100.0000	95.0000
10	100.0000	100.0000
11	100.0000	85.0000
12	100.0000	100.0000
13	100.0000	100.0000
14	100.0000	100.0000
15	100.0000	100.0000
16	100.0000	95.0000
17	100.0000	80.0000
18	100.0000	90.0000
Average	100.0000	95.8333

TABLE XXX
TRAINING AND TESTING ACCURACY FOR MATERIAL RECOGNITION USING kNN CLASSIFIER WITH 3 FEATURE POINTS.

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	100.0000
2	100.0000	90.0000
3	100.0000	100.0000
4	100.0000	70.0000
5	100.0000	95.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	100.0000
9	100.0000	100.0000
10	100.0000	95.0000
11	100.0000	90.0000
12	100.0000	100.0000
13	100.0000	95.0000
14	100.0000	100.0000
15	100.0000	100.0000
16	100.0000	80.0000
17	100.0000	70.0000
18	100.0000	100.0000
Average	100.0000	93.6111

TABLE XXXI
TRAINING AND TESTING ACCURACY FOR MATERIAL RECOGNITION USING kNN CLASSIFIER WITH 4 FEATURE POINTS.

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	100.0000
2	100.0000	90.0000
3	100.0000	100.0000
4	100.0000	95.0000
5	100.0000	100.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	70.0000
9	100.0000	100.0000
10	100.0000	100.0000
11	100.0000	100.0000
12	100.0000	100.0000
13	100.0000	80.0000
14	100.0000	100.0000
15	100.0000	100.0000
16	100.0000	70.0000
17	100.0000	40.0000
18	100.0000	70.0000
Average	100.0000	89.7222

TABLE XXXII
TRAINING AND TESTING ACCURACY FOR MATERIAL RECOGNITION USING kNN CLASSIFIER WITH 5 FEATURE POINTS

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	93.0000	90.0000	100.0000	4.2164
2	88.5000	75.0000	100.0000	8.8349
3	93.0000	85.0000	100.0000	4.8305
4	92.0000	85.0000	100.0000	4.2164
5	95.0000	90.0000	100.0000	3.3333
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	94.5000	90.0000	100.0000	2.8382
10	98.5000	95.0000	100.0000	2.4152
11	84.0000	75.0000	90.0000	5.1640
12	91.0000	80.0000	100.0000	6.1464
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	91.0000	75.0000	100.0000	7.3786
16	92.5000	90.0000	95.0000	2.6352
17	84.5000	75.0000	90.0000	4.9721
18	92.5000	90.0000	95.0000	2.6352
Average	93.8889	88.6111	98.3333	3.3120

TABLE XXXIII
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL kNN CLASSIFIER WITH 3 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	80.0000	65.0000	90.0000	6.6667
2	74.0000	65.0000	85.0000	6.9921
3	62.0000	45.0000	80.0000	11.1056
4	91.5000	85.0000	100.0000	5.2967
5	95.5000	90.0000	100.0000	4.3780
6	98.0000	95.0000	100.0000	2.5820
7	100.0000	100.0000	100.0000	0.0000
8	99.5000	95.0000	100.0000	1.5811
9	83.5000	75.0000	90.0000	5.7975
10	96.0000	80.0000	100.0000	6.5828
11	74.0000	60.0000	85.0000	7.3786
12	74.5000	60.0000	90.0000	11.1679
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	50.5000	40.0000	70.0000	9.5598
16	91.5000	85.0000	95.0000	3.3747
17	90.0000	80.0000	100.0000	5.7735
18	92.0000	80.0000	100.0000	5.8689
Average	86.2500	77.7778	93.6111	5.2281

TABLE XXXIV
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL kNN CLASSIFIER WITH 3 FEATURE POINTS UNDER NOISE LEVEL OF 0.01

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	96.0000	90.0000	100.0000	3.9441
2	94.0000	90.0000	95.0000	2.1082
3	99.5000	95.0000	100.0000	1.5811
4	94.0000	85.0000	100.0000	5.6765
5	97.5000	95.0000	100.0000	2.6352
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	67.0000	65.0000	70.0000	2.5820
9	100.0000	100.0000	100.0000	0.0000
10	100.0000	100.0000	100.0000	0.0000
11	97.0000	95.0000	100.0000	2.5820
12	92.5000	80.0000	100.0000	6.3465
13	80.5000	75.0000	85.0000	3.6893
14	100.0000	100.0000	100.0000	0.0000
15	94.0000	85.0000	100.0000	4.5947
16	62.5000	50.0000	80.0000	9.2045
17	27.0000	20.0000	40.0000	6.7495
18	58.5000	45.0000	70.0000	8.1820
Average	86.6667	81.6667	91.1111	3.3264

TABLE XXXV

KTESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL KNN CLASSIFIER WITH 4 FEATURE POINTS UNDER NOISE LEVEL OF 0.005

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	0.0000	0.0000	0.0000	0.0000
2	28.0000	15.0000	35.0000	6.7495
3	0.0000	0.0000	0.0000	0.0000
4	89.5000	80.0000	100.0000	6.8516
5	79.5000	70.0000	90.0000	7.6194
6	94.5000	90.0000	100.0000	2.8382
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	12.0000	0.0000	20.0000	6.3246
10	85.5000	65.0000	95.0000	9.2646
11	83.0000	75.0000	90.0000	5.3748
12	0.0000	0.0000	0.0000	0.0000
13	96.5000	90.0000	100.0000	3.3747
14	98.0000	95.0000	100.0000	2.5820
15	0.0000	0.0000	0.0000	0.0000
16	77.0000	65.0000	85.0000	6.3246
17	91.0000	80.0000	95.0000	4.5947
18	86.5000	80.0000	95.0000	5.7975
Average	62.2778	55.8333	66.9444	3.7609

TABLE XXXVI
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL kNN CLASSIFIER WITH 4 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	96.5000	90.0000	100.0000	3.3747
2	92.5000	90.0000	95.0000	2.6352
3	99.5000	95.0000	100.0000	1.5811
4	93.0000	90.0000	100.0000	3.4960
5	100.0000	100.0000	100.0000	0.0000
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	71.5000	65.0000	75.0000	3.3747
9	100.0000	100.0000	100.0000	0.0000
10	100.0000	100.0000	100.0000	0.0000
11	97.5000	90.0000	100.0000	3.5355
12	94.5000	85.0000	100.0000	4.3780
13	81.5000	75.0000	90.0000	4.7434
14	100.0000	100.0000	100.0000	0.0000
15	90.5000	75.0000	100.0000	8.3166
16	66.0000	50.0000	75.0000	8.0966
17	39.5000	35.0000	50.0000	4.3780
18	73.0000	60.0000	85.0000	7.1492
Average	88.6389	83.3333	92.7778	3.0588

TABLE XXXVII
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL KNN CLASSIFIER WITH 5 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	89.0000	75.0000	95.0000	6.1464
2	87.5000	70.0000	100.0000	9.7895
3	93.0000	80.0000	100.0000	5.3748
4	88.0000	75.0000	95.0000	7.8881
5	97.5000	90.0000	100.0000	3.5355
6	98.5000	90.0000	100.0000	3.3747
7	100.0000	100.0000	100.0000	0.0000
8	74.0000	65.0000	80.0000	4.5947
9	100.0000	100.0000	100.0000	0.0000
10	99.5000	95.0000	100.0000	1.5811
11	94.0000	90.0000	100.0000	3.1623
12	60.5000	45.0000	80.0000	10.3950
13	80.0000	75.0000	85.0000	4.0825
14	99.5000	95.0000	100.0000	1.5811
15	53.5000	35.0000	70.0000	12.0301
16	61.0000	45.0000	75.0000	10.7497
17	38.5000	20.0000	50.0000	10.0139
18	73.0000	60.0000	85.0000	10.5935
Average	82.6111	72.5000	89.7222	5.8274

TABLE XXXVIII
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL kNN CLASSIFIER WITH 5 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	100.0000
2	100.0000	100.0000
3	100.0000	100.0000
4	100.0000	100.0000
5	100.0000	100.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	100.0000
9	100.0000	100.0000
10	100.0000	100.0000
11	100.0000	90.0000
12	100.0000	100.0000
13	100.0000	100.0000
14	100.0000	100.0000
15	100.0000	100.0000
16	100.0000	100.0000
17	100.0000	100.0000
18	100.0000	100.0000
Average	100.0000	99.4444

TABLE XXXIX
NB METHOD FOR MATERIAL RECOGNITION TESTING ACCURACY USING 3 FEATURE POINTS

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	100.0000
2	100.0000	100.0000
3	100.0000	100.0000
4	100.0000	100.0000
5	100.0000	100.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	100.0000
9	100.0000	100.0000
10	100.0000	100.0000
11	100.0000	100.0000
12	100.0000	100.0000
13	100.0000	100.0000
14	100.0000	100.0000
15	100.0000	100.0000
16	100.0000	100.0000
17	100.0000	100.0000
18	100.0000	100.0000
Average	100.0000	100.0000

TABLE XL
NB METHOD FOR MATERIAL RECOGNITION TESTING ACCURACY USING 4 FEATURE POINTS

	Recognition Accuracy (%)	
Material	Training	Testing
1	100.0000	100.0000
2	100.0000	100.0000
3	100.0000	100.0000
4	100.0000	100.0000
5	100.0000	100.0000
6	100.0000	100.0000
7	100.0000	100.0000
8	100.0000	100.0000
9	100.0000	100.0000
10	100.0000	100.0000
11	100.0000	100.0000
12	100.0000	100.0000
13	100.0000	100.0000
14	100.0000	100.0000
15	100.0000	100.0000
16	100.0000	100.0000
17	100.0000	100.0000
18	100.0000	100.0000
Average	100.0000	100.0000

TABLE XLI
NB METHOD FOR MATERIAL RECOGNITION TESTING ACCURACY USING 5 FEATURE POINTS

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	100.0000	100.0000	100.0000	0.0000
2	99.5000	95.0000	100.0000	1.5811
3	86.0000	80.0000	90.0000	3.1623
4	100.0000	100.0000	100.0000	0.0000
5	100.0000	100.0000	100.0000	0.0000
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	98.0000	95.0000	100.0000	2.5820
10	100.0000	100.0000	100.0000	0.0000
11	99.5000	95.0000	100.0000	1.5811
12	100.0000	100.0000	100.0000	0.0000
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	0.5000	0.0000	5.0000	1.5811
16	100.0000	100.0000	100.0000	0.0000
17	100.0000	100.0000	100.0000	0.0000
18	100.0000	100.0000	100.0000	0.0000
Average	93.5278	92.5000	94.1667	0.5826

TABLE XLII
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NAIVE BAYES CLASSIFIER WITH 3 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	63.0000	55.0000	75.0000	7.1492
2	64.0000	50.0000	80.0000	8.7560
3	1.5000	0.0000	5.0000	2.4152
4	100.0000	100.0000	100.0000	0.0000
5	100.0000	100.0000	100.0000	0.0000
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	4.0000	0.0000	10.0000	3.9441
10	100.0000	100.0000	100.0000	0.0000
11	96.0000	90.0000	100.0000	3.9441
12	78.5000	60.0000	90.0000	10.8141
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	0.0000	0.0000	0.0000	0.0000
16	100.0000	100.0000	100.0000	0.0000
17	100.0000	100.0000	100.0000	0.0000
18	96.5000	90.0000	100.0000	3.3747
Average	77.9722	74.7222	81.1111	2.2443

TABLE XLIII
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NAIVE BAYES CLASSIFIER WITH 3 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	100.0000	100.0000	100.0000	0.0000
2	100.0000	100.0000	100.0000	0.0000
3	99.5000	95.0000	100.0000	1.5811
4	100.0000	100.0000	100.0000	0.0000
5	100.0000	100.0000	100.0000	0.0000
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	99.0000	95.0000	100.0000	2.1082
10	100.0000	100.0000	100.0000	0.0000
11	99.5000	95.0000	100.0000	1.5811
12	100.0000	100.0000	100.0000	0.0000
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	72.0000	50.0000	90.0000	12.0646
16	100.0000	100.0000	100.0000	0.0000
17	85.0000	85.0000	85.0000	0.0000
18	100.0000	100.0000	100.0000	0.0000
Average	97.5000	95.5556	98.6111	0.9631

TABLE XLIV
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NAIVE BAYES CLASSIFIER WITH 4 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	26.0000	15.0000	40.0000	7.7460
2	39.5000	20.0000	50.0000	9.8460
3	0.0000	0.0000	0.0000	0.0000
4	100.0000	100.0000	100.0000	0.0000
5	100.0000	100.0000	100.0000	0.0000
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	17.5000	5.0000	30.0000	7.1686
10	100.0000	100.0000	100.0000	0.0000
11	93.5000	85.0000	100.0000	4.1164
12	21.0000	10.0000	30.0000	6.9921
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	0.0000	0.0000	0.0000	0.0000
16	100.0000	100.0000	100.0000	0.0000
17	100.0000	100.0000	100.0000	0.0000
18	91.5000	85.0000	95.0000	3.3747
Average	71.6111	67.7778	74.7222	2.1802

TABLE XLV
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NAIVE BAYES CLASSIFIER WITH 4 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	100.0000	100.0000	100.0000	0.0000
2	100.0000	100.0000	100.0000	0.0000
3	90.0000	80.0000	95.0000	5.7735
4	100.0000	100.0000	100.0000	0.0000
5	100.0000	100.0000	100.0000	0.0000
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	100.0000	100.0000	100.0000	0.0000
10	100.0000	100.0000	100.0000	0.0000
11	100.0000	100.0000	100.0000	0.0000
12	100.0000	100.0000	100.0000	0.0000
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	0.5000	0.0000	5.0000	1.5811
16	100.0000	100.0000	100.0000	0.0000
17	100.0000	100.0000	100.0000	0.0000
18	100.0000	100.0000	100.0000	0.0000
Average	93.9167	93.3333	94.4444	0.4086

TABLE XLVI
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NAIVE BAYES CLASSIFIER WITH 5 FEATURE POINTS UNDER NOISE LEVEL OF 0.005.

	Recognition Accuracy (%)			
Material	Average	Min	Max	Std
1	93.3333	90.0000	95.0000	2.8868
2	73.3333	70.0000	80.0000	5.7735
3	1.6667	0.0000	5.0000	2.8868
4	100.0000	100.0000	100.0000	0.0000
5	100.0000	100.0000	100.0000	0.0000
6	100.0000	100.0000	100.0000	0.0000
7	100.0000	100.0000	100.0000	0.0000
8	100.0000	100.0000	100.0000	0.0000
9	10.0000	5.0000	15.0000	5.0000
10	100.0000	100.0000	100.0000	0.0000
11	100.0000	100.0000	100.0000	0.0000
12	83.3333	80.0000	90.0000	5.7735
13	100.0000	100.0000	100.0000	0.0000
14	100.0000	100.0000	100.0000	0.0000
15	0.0000	0.0000	0.0000	0.0000
16	100.0000	100.0000	100.0000	0.0000
17	100.0000	100.0000	100.0000	0.0000
18	96.6667	90.0000	100.0000	5.7735
Average	81.0185	79.7222	82.5000	1.5608

TABLE XLVII
TESTING ACCURACY FOR MATERIAL RECOGNITION USING TRADITIONAL NAIVE BAYES CLASSIFIER WITH 5 FEATURE POINTS UNDER NOISE LEVEL OF 0.01.

	Recognition Accuracy (%)	
EEGClass	Training	Testing
1	100.0000	96.6667
2	100.0000	80.0000
3	100.0000	96.6667
Average	100.0000	91.1111

TABLE XLVIII
TRAINING AND TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	95.6667	93.3333	100.0000	2.2498
2	75.0000	70.0000	83.3333	4.2310
3	97.0000	93.3333	100.0000	2.4595
Average	89.2222	85.5556	94.4444	2.9801

TABLE XLIX
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER UNDER NOISE LEVEL OF 0.05.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	96.3333	93.3333	100.0000	2.9187
2	67.0000	56.6667	76.6667	5.5444
3	96.0000	90.0000	100.0000	4.0976
Average	86.4444	80.0000	92.2222	4.1869

TABLE L
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER UNDER NOISE LEVEL OF 0.1.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	98.6667	96.6667	100.0000	1.7213
2	58.6667	50.0000	70.0000	5.7090
3	96.0000	90.0000	100.0000	3.0631
Average	84.4444	78.8889	90.0000	3.4978

TABLE LI
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER UNDER NOISE LEVEL OF 0.2.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	100.0000	100.0000	100.0000	0.0000
2	54.6667	53.3333	56.6667	1.7213
3	96.0000	90.0000	100.0000	3.0631
Average	83.5556	81.1111	85.5556	1.5948

TABLE LII
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER UNDER NOISE LEVEL OF 0.5.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	99.3333	93.3333	100.0000	2.1082
2	54.6667	50.0000	56.6667	2.3307
3	96.3333	90.0000	100.0000	2.9187
Average	83.4444	77.7778	85.5556	2.4525

TABLE LIII
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER UNDER NOISE LEVEL OF 1.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	99.7143	97.1429	100.0000	0.9035
2	98.8571	95.7143	100.0000	1.4754
3	100.0000	100.0000	100.0000	0.0000
Average	99.5238	97.6190	100.0000	0.7930

TABLE LIV
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER UNDER NOISE LEVEL OF 0.05.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	99.7143	98.5714	100.0000	0.6023
2	94.1429	90.0000	98.5714	2.2788
3	100.0000	100.0000	100.0000	0.0000
Average	97.9524	96.1905	99.5238	0.9604

TABLE LV
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER UNDER NOISE LEVEL OF 0.1.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	99.8571	98.5714	100.0000	0.4518
2	83.7143	71.4286	91.4286	7.1966
3	100.0000	100.0000	100.0000	0.0000
Average	94.5238	90.0000	97.1429	2.5495

TABLE LVI
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER UNDER NOISE LEVEL OF 0.2.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	99.5714	98.5714	100.0000	0.6901
2	65.4286	57.1429	78.5714	7.3710
3	100.0000	100.0000	100.0000	0.0000
Average	88.3333	85.2381	92.8571	2.6870

TABLE LVII
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER UNDER NOISE LEVEL OF 0.5.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	98.1429	95.7143	100.0000	1.7881
2	56.5714	50.0000	68.5714	5.9170
3	99.4286	98.5714	100.0000	0.7377
Average	84.7143	81.4286	89.5238	2.8143

TABLE LVIII
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING VWNN CLASSIFIER UNDER NOISE LEVEL OF 1.

	Recognition Accuracy (%)	
EEGClass	Training	Testing
1	100.0000	96.6667
2	100.0000	73.3333
3	100.0000	90.0000
Average	100.0000	86.6667

TABLE LIX
TRAINING AND TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	90.0000	83.3333	96.6667	4.1574
2	75.3333	66.6667	80.0000	4.2164
3	89.6667	83.3333	93.3333	3.6683
Average	85.0000	77.7778	90.0000	4.0140

TABLE LX
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER UNDER NOISE LEVEL OF 0.05.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	95.3333	90.0000	100.0000	3.2203
2	70.6667	60.0000	76.6667	4.9191
3	91.3333	86.6667	93.3333	2.8109
Average	85.7778	78.8889	90.0000	3.6501

TABLE LXI
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER UNDER NOISE LEVEL OF 0.1.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	98.6667	93.3333	100.0000	2.3307
2	64.6667	50.0000	73.3333	6.5168
3	89.0000	83.3333	93.3333	2.7442
Average	84.1111	75.5556	88.8889	3.8639

TABLE LXII
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER UNDER NOISE LEVEL OF 0.2.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	98.6667	96.6667	100.0000	1.7213
2	56.0000	50.0000	66.6667	6.0451
3	89.0000	83.3333	93.3333	3.1623
Average	81.2222	76.6667	86.6667	3.6429

TABLE LXIII
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER UNDER NOISE LEVEL OF 0.5.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	98.6667	96.6667	100.0000	1.7213
2	49.0000	40.0000	53.3333	4.4583
3	87.3333	80.0000	93.3333	5.6218
Average	78.3333	72.2222	82.2222	3.9338

TABLE LXIV
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER UNDER NOISE LEVEL OF 1.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	95.7143	92.8571	98.5714	2.5198
2	94.2857	91.4286	98.5714	2.1296
3	100.0000	100.0000	100.0000	0.0000
Average	96.6667	94.7619	99.0476	1.5498

TABLE LXV
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER UNDER NOISE LEVEL OF 0.05.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	96.1429	92.8571	100.0000	2.1349
2	90.8571	85.7143	95.7143	2.9508
3	99.8571	98.5714	100.0000	0.4518
Average	95.6190	92.3810	98.5714	1.8458

TABLE LXVI
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER UNDER NOISE LEVEL OF 0.1.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	96.0000	94.2857	97.1429	1.3128
2	82.7143	70.0000	92.8571	7.6621
3	100.0000	100.0000	100.0000	0.0000
Average	92.9048	88.0952	96.6667	2.9916

TABLE LXVII
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER UNDER NOISE LEVEL OF 0.2.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	97.5714	95.7143	98.5714	0.9642
2	66.1429	52.8571	82.8571	10.6703
3	99.8571	98.5714	100.0000	0.4518
Average	87.8571	82.3810	93.8095	4.0287

TABLE LXVIII
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER UNDER NOISE LEVEL OF 0.5.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	94.2857	91.4286	97.1429	1.9048
2	55.4286	45.7143	72.8571	7.0244
3	99.1429	97.1429	100.0000	0.9989
Average	82.9524	78.0952	90.0000	3.3093

TABLE LXIX
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING TRADITIONAL NN CLASSIFIER UNDER NOISE LEVEL OF 1.

	Recognition Accuracy (%)	
EEGClass	Training	Testing
1	90.0000	100.0000
2	41.4286	33.3333
3	100.0000	100.0000
Average	77.1429	77.7778

TABLE LXX
TRAINING AND TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	100.0000	100.0000	100.0000	0.0000
2	35.0000	33.3333	40.0000	2.3570
3	100.0000	100.0000	100.0000	0.0000
Average	78.3333	77.7778	80.0000	0.7857

TABLE LXXI
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER UNDER NOISE LEVEL OF 0.05.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	99.0000	96.6667	100.0000	1.6102
2	37.6667	33.3333	46.6667	3.8650
3	100.0000	100.0000	100.0000	0.0000
Average	78.8889	76.6667	82.2222	1.8251

TABLE LXXII
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER UNDER NOISE LEVEL OF 0.1.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	98.3333	96.6667	100.0000	1.7568
2	38.6667	33.3333	46.6667	3.9126
3	100.0000	100.0000	100.0000	0.0000
Average	79.0000	76.6667	82.2222	1.8898

TABLE LXXIII
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER UNDER NOISE LEVEL OF 0.2.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	98.3333	96.6667	100.0000	1.7568
2	36.3333	30.0000	40.0000	2.9187
3	100.0000	100.0000	100.0000	0.0000
Average	78.2222	75.5556	80.0000	1.5585

TABLE LXXIV
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER UNDER NOISE LEVEL OF 0.5.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	97.0000	96.6667	100.0000	1.0541
2	36.3333	33.3333	40.0000	2.9187
3	100.0000	100.0000	100.0000	0.0000
Average	77.7778	76.6667	80.0000	1.3242

TABLE LXXV
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER UNDER NOISE LEVEL OF 1.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	87.7143	85.7143	90.0000	1.2047
2	37.0000	32.8571	38.5714	1.8381
3	100.0000	100.0000	100.0000	0.0000
Average	74.9048	72.8571	76.1905	1.0143

TABLE LXXVI
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER UNDER NOISE LEVEL OF 0.05.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	87.5714	85.7143	88.5714	1.1761
2	37.7143	34.2857	41.4286	1.8070
3	100.0000	100.0000	100.0000	0.0000
Average	75.0952	73.3333	76.6667	0.9944

TABLE LXXVII
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER UNDER NOISE LEVEL OF 0.1.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	88.1429	87.1429	88.5714	0.6901
2	38.5714	37.1429	40.0000	0.9524
3	100.0000	100.0000	100.0000	0.0000
Average	75.5714	74.7619	76.1905	0.5475

TABLE LXXVIII
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER UNDER NOISE LEVEL OF 0.2.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	89.4286	87.1429	91.4286	1.6768
2	38.5714	37.1429	40.0000	1.3469
3	100.0000	100.0000	100.0000	0.0000
Average	76.0000	74.7619	77.1429	1.0079

TABLE LXXIX
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER UNDER NOISE LEVEL OF 0.5.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	89.2857	87.1429	90.0000	1.0102
2	38.0000	37.1429	41.4286	1.3801
3	100.0000	100.0000	100.0000	0.0000
Average	75.7619	74.7619	77.1429	0.7968

TABLE LXXX
TRAINING ACCURACY FOR EPILEPSY CLASSIFICATION USING NAIVE BAYES CLASSIFIER UNDER NOISE LEVEL OF 1.

	Recognition Accuracy (%)	
EEGClass	Training	Testing
1		96.6667
2		23.3333
3		50.0000
Average		56.6667

TABLE LXXXI
TRAINING AND TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING KNN CLASSIFIER.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	96.0000	90.0000	100.0000	3.0631
2	20.3333	16.6667	26.6667	3.3148
3	52.6667	46.6667	56.6667	3.4427
Average	56.3333	51.1111	61.1111	3.2735

TABLE LXXXII
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING KNN CLASSIFIER UNDER NOISE LEVEL OF 0.05.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	98.3333	93.3333	100.0000	2.3570
2	20.3333	16.6667	26.6667	3.6683
3	51.0000	46.6667	56.6667	2.7442
Average	56.5556	52.2222	61.1111	2.9232

TABLE LXXXIII
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING KNN CLASSIFIER UNDER NOISE LEVEL OF 0.1.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	98.0000	93.3333	100.0000	2.3307
2	20.6667	16.6667	30.0000	4.6614
3	53.0000	50.0000	56.6667	1.8922
Average	57.2222	53.3333	62.2222	2.9614

TABLE LXXXIV
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING KNN CLASSIFIER UNDER NOISE LEVEL OF 0.2.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	96.3333	86.6667	100.0000	3.9907
2	24.6667	20.0000	30.0000	3.2203
3	56.0000	50.0000	63.3333	4.3885
Average	59.0000	52.2222	64.4444	3.8665

TABLE LXXXV
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING KNN CLASSIFIER UNDER NOISE LEVEL OF 0.5.

	Recognition Accuracy (%)			
EEGClass	Average	Min	Max	Std
1	97.0000	90.0000	100.0000	3.6683
2	23.3333	13.3333	30.0000	5.4433
3	58.6667	46.6667	70.0000	8.3444
Average	59.6667	50.0000	66.6667	5.8187

TABLE LXXXVI
TESTING ACCURACY FOR EPILEPSY CLASSIFICATION USING KNN CLASSIFIER UNDER NOISE LEVEL OF 1.