The Effects of Different Wavelet Degrees on Epileptic Seizure Detection from EEG Signals

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***Abstract*— In this study, EEG records taken from healthy people with eyes open and eyes closed, EEG records taken from epileptic patients at the time of seizure and out of seizure were classified using Naive Bayes, K-Nearest Neighbor and Artificial Neural Networks methods. Feature vectors are obtained by using Daubechies wavelet transforms with different degrees and their effect on the classification success is examined. When the results are evaluated, it is determined that Artificial Neural Networks algorithm is the most successful method using db3 and db5 wavelet coefficients as feature vector. Based on the results obtained in this study, it is thought that the recommended methods will help the experts to decide on the epileptic seizure.**

Keywords*— *EEG signals, Wavelet Transform, Naive Bayes, K-Nearest Neighborhood, Artificial Neural Networks, Epilepsy.

I. Introduction

The bioelectrical signals resulting from the neural activity of the brain are called Electroencephalogram (EEG). The EEG has a very complex shape of change and is difficult to interpret. EEG potentials measured from the surface are composed of the sum of the potentials from a large number of points at the bottom and a very large region of the cerebral cortex.

Experiments have shown that the frequency of EEG changes with one's mental activity. This indicates a synchronization state, such as the normal and idle frequency of the brain. When the person wakes up or starts thinking, the alpha rhythm disappears and then an asynchronous rhythm occurs in the beta band. The amplitude of the EEG's perceived over the head is concentrated between 0.5 and 30 Hz with clinical and physiological interest ranging from 1 to 100 µV at the top and 0.5-100 Hz at the frequency band [1].

Epilepsy is one of the most common neurological disorders seen among humans. It is defined as the loss of consciousness caused by abnormal electrical activity in the brain or recurrent seizures with body contractions. Seizures come at random and patients are often unaware of it. Therefore, there is a risk of physical injury. Surveys show that 4-5% of the total world population suffers from epilepsy [2].

EEG contains much important information about the different physiological states of the brain. It is a non-invasive test method that can be applied to people in all ages. During EEG, the patient is not exposed to electricity, so there is no pain and no side effects. It is a very effective tool to understand the complex dynamic behavior of the brain. EEG is the most important laboratory method used especially for the diagnosis of epilepsy. EEG records require long-term registration to detect epileptic seizures and are examined visually by experts. This is a very time consuming process. For this reason, computer assisted automatic decision systems have been developed to support the decision of experts in clinical diagnostics. Therefore, EEG signals are analyzed in different ways to make an objective evaluation. Thus, both the decision making period and the increasingly reliable results are produced.

Techniques based on Fourier transformation and parametric methods have been applied since the beginning of the automatic analysis of epileptic EEG markers [4]. However, because EEG signals are non-stationary signals, these methods are not suitable for spectral analysis of these signals. Time-frequency (t-f) based methods have been shown to be better than traditional frequency analysis methods [5]. Wavelet transform is suitable for analysis of non-stationary signals and has very important advantages over frequency analysis. It is successful in detecting transient states that may occur during epileptic seizures. The features are obtained and divided into sub-bands in the time-frequency domain with wavelet transform of EEG records [6].

In this study, the success of classification methods with Naive Bayes, K-Nearest Neighbor, and Artificial Neural Networks were determined using wavelet transform method with different degrees for epileptic seizure detection in EEG signals.

II. Materials and Methods

A. Wavelet Transform

Wavelet transform is a spectral estimation technique in which wavelets of any general function can be expressed as an infinite array. The basic idea underlying wavelet analysis consists of expressing a signal as a linear combination of a certain set of functions (wavelet transform, WT) obtained by shifting and expanding a single function called the main wavelet. The decomposition of the signal causes a series of coefficients called wavelet coefficients. Hence, the signal can be reconstructed as a linear combination of the wavelet

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functions weighted by the wavelet coefficients. Sufficient number of coefficients must be calculated to recover the signal correctly. The most important feature of wavelets is time-frequency localization. This means that most of the ripple energy is limited by a limited time interval. The advantage of time-frequency localization is to produce window sizes that are narrow for low frequencies, wide for high frequencies, changing the time-frequency aspect ratio of the wavelet analysis. This provides optimum time-frequency resolution for most physical signals, especially transient states [7].

Wavelet transform is examined in two different ways, continuous and discrete. Calculation of wavelet coefficients for each scale is difficult and time consuming due to the continuous variation of scaling and transform parameters in continuous wavelet transform. For this reason, discrete wavelet transform is used more frequently. The signal is divided into a number of scales by wavelet transform. This process, called the multiple resolution decomposition (MRD), is shown in Fig. 1 for the x(n) signal. In Fig. 1, the sampled outputs belong to the first high pass filter (g[.]) and the low pass filter (h[·]) form the sub-bands detail D1 and approximation A1. A1 approach band is again broken down and this process continues as shown in Fig.1.

The wavelet transform can be specified by a low-pass filter.

$$H(z)H\left(z^{-1}\right)+H(-z)H\left(-z^{-1}\right)=1 \tag{1}$$

Where H(z) is the z-transform of the h filter. The complementary high-pass filter of this filter can be defined as:

$$G(z)=zH\left(-z^{-1}\right) \tag{2}$$

The filter array (with i index) with increasing lengths is obtained as follows:

$$H_{i+1}(z)=H\left(z^{2^i}\right)H_i(z) \tag{3}$$

$$G_{i+1}(z)=G\left(z^{2^i}\right)H_i(z),\ i=0,1,\cdots I-1 \tag{4}$$

Where the initial condition is $H_0(z)=1$. This is expressed in the time domain as:

$$h_{i+1}(k)=[h]_{\uparrow 2^i}*h_i(k) \tag{5}$$

$$g_{i+1}(k)=[g]_{\uparrow 2^i}*h_i(k) \tag{6}$$

Here, the index $[.]_{\uparrow m}$ indicates that upsampling is performed with the factor m, and k indicates the discrete time sampled evenly.

Normalized wavelet and scale-based functions are defined as $\varphi_{i,l}(k)$ and $\psi_{i,l}(k)$:

$$\varphi_{i,l}(k)=2^{i/2}h_i\left(k-2^i l\right) \tag{7}$$

$$\psi_{i,l}(k)=2^{i/2}g_i\left(k-2^i l\right) \tag{8}$$

Here, $2^{i/2}$ is the inner product normalization. i is the scaling parameter, l is the conversion parameter. The disjoint wavelet transform decomposition is specified as:

$$a_{(i)}(l)=x(k)*\varphi_{i,l}(k) \tag{9}$$

$$d_{(i)}(l)=x(k)*\psi_{i,l}(k) \tag{10}$$

Here, $a_{(i)}(l)$ and $d_{(i)}(l)$ are the approximate and detailed coefficients in the *i* resolution, respectively [8].

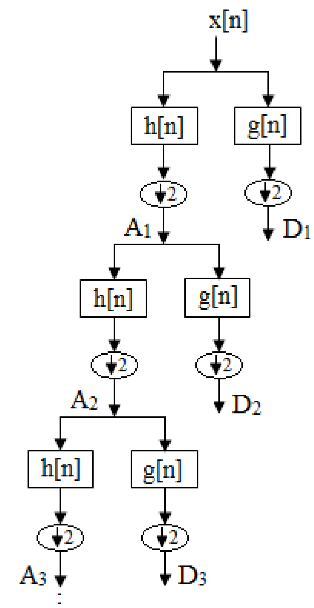

Fig.1. Disjointment to sub-bands when discrete wavelet transform is performed; g[n] high pass filter, h[n] low pass filter

B. *Classification Methods*

1) *Naive Bayes*

The Naive Bayes (NB) method is a supervised learning algorithm based on the baseline Bayes Theorem, assuming independence between dataset. It is an approach that calculates the likelihood of a new data belongs to any of the existing classes using the example data in the present classified case. The attributes in this classifier are considered to be independent of each other. All the samples have the same level of prescription. The value of an attribute does not contain information about another attribute value [9].

If a new x data that is not known to belong to which class, c is a class variable, is desired to be classified, the probability of belonging that class is calculated, for example, for each class using the formula (11). The class with the highest probability among these values is considered to be the class to which it belongs.

$$P(c|x)=[P(x|c)\times P(c)]\ /\ P(x) \tag{11}$$

P(c|x) : Probability of occurrence of event c when x occurs
P(x|c) : Probability of occurrence of event x when c occurs
P(c), P(x): The preliminary probabilities of c and x events

The value of $P(x)$ is the same for each sample data because each x instance has the same rank prefix. In this case, the formula (11) can be simplified to the formula (12).

$$P(c|x)=P(x_1|c)\times P(x_2|c)\times\cdots\times P(x_n|c)\times P(c) \qquad (12)$$

For each class, after applying the formula (12) and calculating the probabilities, the class to which it belongs is found [9].

Despite overly simplified assumptions, Naive Bayes classifiers work well in many real-world conditions, such as excellent text classification and spam filtering. They require small amounts of training to estimate the required parameters. Training and evaluation is very fast [9].

2) K-Nearest Neighbor Algorithm

The K-Nearest Neighbor (KNN) algorithm is a simple and intuitive supervised learning method that is often used by many researchers to classify signals and patterns. This classifier compares a new labeled sample (testing data) with the underlying data (training data). Accordingly, the closest k neighbor of the pattern sample to be recognized is determined. Then, it is determined the class of these k neighbors, and the label value of class is assigned to the pattern sample to be recognized [10].

It is important for this algorithm that the training set is large and the k value is chosen appropriately. The k value defines the number of elements to be considered. If k = 3, the nearest 3 neighbors are considered. Distance calculation methods such as Euclidean, Minkowski, Manhattan and Chebyshev distances can be used.

One of the factors affecting the success of the algorithm in the classification process is that k is chosen correctly. If k is set too large, samples of different classes can be included in the same class. In the other case if the k value is selected very small, on the contrary, the samples which need to be found in the same class can be placed in different classes. Many methods have been developed for selecting the k parameter. However, the most common method is to select the most successful k value by testing with different values. This process causes time loss [11].

In Fig.2, two featured data records are shown that contain examples of two data classes (square, triangle). If k is 3, the nearest three neighbors are determined around the testing (circle) data. Two values are triangular, one value is square. In this case, testing data will be added to the triangle class.

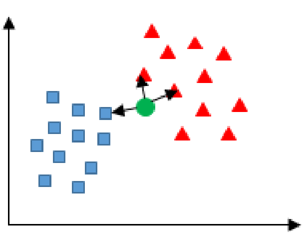

Fig.2. A sample classification of the KNN algorithm (k = 3) [12]

3) Artificial Neural Networks

Artificial neural networks (ANN) are computer systems that perform the learning function, which is the most basic feature of the human brain. They perform the learning process with the help of examples. These nets consist of interconnected artificial nerve cells. Each link has a weight value.

In artificial neural cells, information collected from outside is added by an addition function, then pass through the activation function. It then sends the output to other cells over the network connections. Different addition and activation functions are available. The values of links connecting artificial neural networks are called weight values. Artificial neural networks are basically composed of three layers. These are input layer, hidden layer and output layer.

“Fig.3” shows a three inputs-two outputs three-layer artificial neural network with a hidden layer.

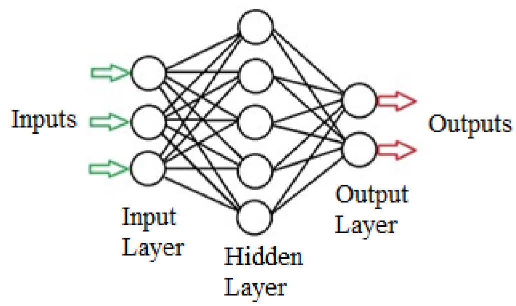

Fig.3. Basic structure of ANN [13]

The extracted features of the problem are intended to be input to the artificial neural network after conversion of a vector to obtain appropriate decision value at the output layer. Here, the correct training of the network increases the network quality.

The most commonly used model of artificial neural networks is multilayer perceptron (MLP) networks. In MLP networks, "Sigmoid function" is generally used as the activation function. Sigmoid is a continuous and derivable function and generates a value between 0 and 1 for each input value [13].

III. Experimental Setup

The flow diagram of this study is given in Fig.4. The feature vectors of EEG data are obtained by using wavelet transform and these feature vectors are statistically processed to reduce their size. After that, classification is done by using three different classification algorithms.

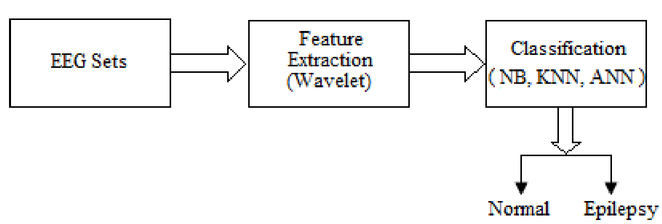

Fig.4. The flow diagram of the study

A. Database

In this study, the EEG dataset from the Bonn University Epileptology Department was used. This dataset, which is open to the public, is recorded by sampling with a 128-channel, 12-bit EEG recording system at a sampling frequency of 173.61 Hz, and these 128 channels are reduced to a single channel by taking the average value of signals. Each set contains 100 single channel EEG segments for 23.6 seconds and each segment contains 4097 discrete samples (A, B, C, D and E). EEG signals were filtered with a band of 0.53 - 40 Hz and all experiments were cleaned from artifacts due to eye and muscle movements. Recording was performed according to the international 10-20 lead system. Set A consists of 5 healthy volunteers with eyes open and recorded from outside the skull. Set B is the surface EEG record taken from 5 volunteer healthy individuals with eyes closed in a wakeful and calm state. C and D sets are records from within the skull, measured in individuals with no epileptic seizure in five epileptic patients. In set E, the same 5 patients were recorded from within the head cavity during the seizure period. Typical EEG signals from these 5 sets are shown in Fig.5.

B. Feature Extraction

Proper wavelet selection and determination of the number of decomposition levels is very important in wavelet transform analysis of the signals. The number of decomposition levels according to dominant frequency components of the signal is determined [8]. As given in Table I, EEG signals are divided into detail and approximation sub-bands. The accuracy (Acc) of classification depends on the type of wavelet selected for the application. In this study, Daubechies wavelet coefficients, which are the most preferred method in EEG signal analysis, are used. The effects on classification success of wavelets with different degrees are examined. These wavelets are db1, db2, db3, db4, db5, db6, db8 and db10. Since the EEG signals do not have useful frequency components above 30 Hz, the number of decomposition level is set at 5.

D3, D4, D5 and A5 wavelet coefficients for each level wavelet function are given as feature vectors. In order to reduce the size of these feature vectors, the following statistical operations are performed on the wavelet coefficients:

1. The maximum of the coefficients in each sub-band
2. The minimum of the coefficients in each sub-band
3. The standard deviation of the coefficients in each sub-band
4. Averages of the coefficients in each sub-band [8].

The feature vectors are calculated from the EEG dataset by using the MATLAB program.

C. Classification

For testing the success of the classification methods, the dataset is divided into two as training set and testing set. Two different methods have been used in this study. In the first method (percentage split (PS)), 66% of the dataset is reserved for training and the rest is used for testing. The second method is cross-validation (CV).

TABLE I. RANGES OF FREQUENCY BANDS IN WAVELET DECOMPOSITION

Approximation and Detail Sub-bands	**Frequency Range (Hz)**
D1	43,4-86,8
D2	21,7-43,4
D3	10,8-21,7
D4	5,4-10,8
D5	2,7-5,4
A5	0-2,7

Since the most preferred value in the literature is 10, the number of cross validation is taken as 10 for all algorithms. The method is run 10 times. At each step, 1/10 of the dataset is used for testing, while the remaining part is used for training. In this study, sets consisting of different combinations of A, B, C, D and E epileptic EEG dataset are classified by using machine learning classification algorithms (NB, KNN and ANN algorithms). In the KNN algorithm, k neighbor values were taken 3, 5, and 7. Euclidean distance was used in the distance calculation process. The MLP-ANN structure has a single hidden layer and sixteen input layer. Since different combinations of data sets are used, the number of output layers varies according to the combination.

In the experiments used in this study, five sets of data (A, B, C, D and E) were used with different sets of combinations. For example, in the AB-CD-E experiment where 5 sets were used for epileptic seizures, the AB and CD classes represent a three-class experiment consisting of two sets and a single class E class. Similarly, the names of all experiments in the study are shown in Table II together with the general representation.

TABLE II. CLASS AND SET NUMBERS OF EXPERIMENTS CONDUCTED IN THE STUDY

Experiment No	Experiment Name	Number of Class	Number of Set
1	ABCD-E	2	5
2	AB-CD-E	3	5
3	A-B-C-D-E	5	5

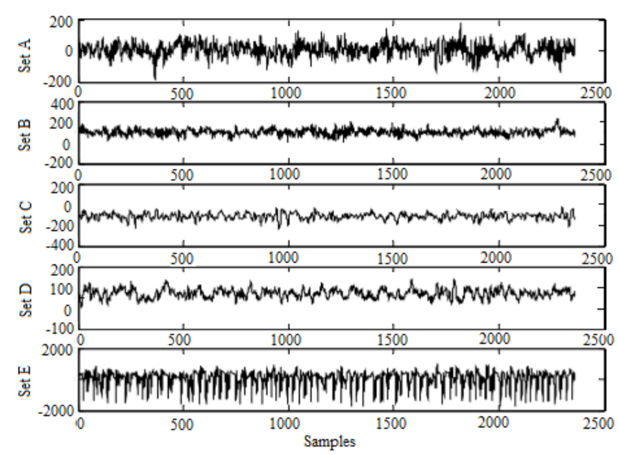

Fig.5. Examples of five different sets of EEG signals

In the ABCD-E experiment, which used 5 dataset, the set A and set B representing healthy individuals and the set C and set D representing the epileptic patients who did not experience seizures together constitute the "Normal" class. Set E, which contains the activities of patients with seizure epilepsy, represents the "Seizure" class alone. Similarly, in the AB-CD-E experiment, set A and set B represent "normal" class representatives of healthy individuals, set C and set D represent seizures of seizure-free epilepsy patients, and set E represents the seizure category alone. In the last experiment, all the sets were considered on their own.

IV. RESULTS

The results of experiment 1 are given in Table III. We have achieved 100% success in the KNN and ANN algorithms in classification by using the feature vectors obtained with the given wavelet types and degrees. When the classification speed is examined, KNN is much faster than ANN. In addition, the accuracy of the NB algorithm has been observed as quite good.

The results of experiment 2 are given in Table IV. It has been observed that ANN algorithm is the most successful method with 99.375% accuracy by using db3 wavelet coefficients in the classification. In addition, very good results have been observed with the KNN algorithm at high speed. Although NB is a fast algorithm, it is not as successful as the other two methods. Both the KNN and NB algorithms gave the best result using the db1 wavelet coefficient.

TABLE III. CLASSIFICATION RESULTS OF EXPERIMENT 1

Classification Method		**Training-Test Dataset**	**Degrees of Wavelet**							
			db1, db4, db6, db8, db10		***db2***		***db3***		***db5***	
			Acc (%)	***Time (s)***	***Acc (%)***	***Time (s)***	***Acc (%)***	***Time (s)***	***Acc (%)***	***Time (s)***
NB		CV	98.7500	0.01	98.67.19	0.01	98.8281	0.01	98.7500	0.01
		PS	99.0805	0.01	99.0805	0.01	99.0805	0.01	98.8506	0.01
KNN	K=3, 5, 7	CV	100	0.01	100	0.01	100	0.01	100	0.01
		PS	100	0.06	100	0.06	100	0.06	100	0.06
ANN		CV	100	2.17	100	2.20	100	2.17	100	2.19
		PS	100	2.16	100	2.20	100	2.17	100	2.19

TABLE IV. CLASSIFICATION RESULTS OF EXPERIMENT 2

Classification Method		**Training-Test Dataset**	**Degrees of Wavelet**							
			db1		***db2***		***db3***		***db4***	
			Acc (%)	***Time (s)***	***Acc (%)***	***Time (s)***	***Acc (%)***	***Time (s)***	***Acc (%)***	***Time (s)***
NB		CV	**88.8281**	**0.02**	78.2031	0.01	79.2188	0.02	79.9219	0.01
		PS	88.7356	0.02	77.9310	0.01	77.7011	0.04	78.1609	0.01
KNN	K=3	CV	97.0313	0.01	95.7031	0.01	96.6406	0.01	95.4688	0.01
		PS	97.4713	0.06	94.4828	0.05	96.5517	0.05	95.6322	0.05
	K=5	CV	97.3438	0.01	96.0938	0.01	96.8750	0.01	95.3125	0.01
		PS	**97.7011**	**0.07**	93.7931	0.05	96.3218	0.05	94.7126	0.05
	K=7	CV	97.1094	0.01	95.5469	0.01	96.9531	0.01	95.3906	0.01
		PS	97.2414	0.06	94.7126	0.05	96.3218	0.06	95.4023	0.05
ANN		CV	98.3594	2.63	94.3750	2.73	**99.3750**	**2.30**	95.2344	2.70
		PS	98.8506	2.50	89.1954	2.72	99.3103	2.30	95.1724	2.70
Classification Method		**Training-Test Dataset**	**Degrees of Wavelet**							
			db5		***db6***		***db8***		***db10***	
			Acc (%)	***Time (s)***	***Acc (%)***	***Time (s)***	***Acc (%)***	***Time (s)***	***Acc (%)***	***Time (s)***
NB		CV	76.9531	0.01	74.3750	0.01	72.4219	0.02	76.5625	0.01
		PS	76.7816	0.01	73.3330	0.01	71.0345	0.02	74.2529	0.01
KNN	K=3	CV	95.9375	0.01	95.4688	0.01	96.0938	0.01	95.6250	0.01
		PS	95.6322	0.06	96.3218	0.06	95.1724	0.05	97.0115	0.06
	K=5	CV	96.4063	0.01	95.4688	0.01	96.3281	0.01	96.0938	0.01
		PS	95.8621	0.06	95.1724	0.06	96.5517	0.05	96.5517	0.05
	K=7	CV	96.0156	0.01	95.7031	0.01	96.0938	0.01	96.5625	0.01
		PS	95.6322	0.07	94.023	0.06	96.0920	0.05	96.5517	0.05
ANN		CV	98.5938	2.50	95.5469	2.97	96.8750	2.69	97.8906	2.78
		PS	91.4943	2.51	91.954	2.75	93.3333	2.68	95.6322	2.70

The results of experiment 3 are given in Table V. ANN algorithm is determined as the most successful method with 94.9425% accuracy by the use of db5 wavelet coefficients in the classification. At the same time, it has been determined that using db3 wavelet coefficients provides 94.2529% accuracy. This is very close to the accuracy achieved by using db5 wavelet coefficients. KNN and NB algorithms have similar results in terms of accuracy and speed. Both algorithms gave the best result using the db1 wavelet coefficient.

When all the tables are evaluated together; The ANN algorithm gave the most successful results for the various combinations of EEG data sets with the use of db3 and db5 wavelet coefficients. In the KNN algorithm, better results were obtained with k = 5 and k = 7 selections. It is observed that KNN and NB algorithms are much faster than the ANN algorithm.

TABLE V. CLASSIFICATION RESULTS OF EXPERIMENT 3

Classification Method		Training -Test Dataset	db1 Acc (%)	db1 Time (s)	db2 Acc (%)	db2 Time (s)	db3 Acc (%)	db3 Time (s)	db4 Acc (%)	db4 Time (s)
NB		CV	**92.2656**	**0.05**	88.1250	0.02	89.7656	0.02	87.2656	0.03
		PS	91.9540	0.05	88.0460	0.02	90.3448	0.02	87.1264	0.03
KNN	K=3	CV	91.5625	0.01	88.9844	0.01	89.3750	0.01	89.8438	0.01
		PS	92.4138	0.06	88.9655	0.05	91.2644	0.06	89.8851	0.05
	K=5	CV	91.7969	0.01	88.9844	0.01	91.6406	0.01	89.7656	0.01
		PS	91.9540	0.08	89.4253	0.05	91.0345	0.06	90.8046	0.05
	K=7	CV	**92.4219**	**0.01**	89.3750	0.01	90.9375	0.01	88.9063	0.01
		PS	92.4138	0.08	89.8851	0.05	91.9540	0.06	91.4943	0.05
ANN		CV	93.6719	3.20	91.4063	3.41	92.5781	3.06	90.4688	3.38
		PS	92.1839	3.49	91.0345	3.38	**94.2529**	**2.84**	91.7241	3.39

Classification Method		Training -Test Dataset	db5 Acc (%)	db5 Time (s)	db6 Acc (%)	db6 Time (s)	db8 Acc (%)	db8 Time (s)	db10 Acc (%)	db10 Time (s)
NB		CV	88.4375	0.01	86.7969	0.01	86.0938	0.02	87.6563	0.01
		PS	87.8161	0.03	87.1264	0.01	85.9770	0.03	87.8161	0.03
KNN	K=3	CV	88.1250	0.01	89.3750	0.01	87.6563	0.01	88.5156	0.01
		PS	88.7356	0.05	88.9655	0.06	88.2759	0.05	90.1149	0.06
	K=5	CV	88.9844	0.01	88.9063	0.01	88.9063	0.01	88.6719	0.01
		PS	89.6552	0.05	88.2759	0.06	90.5747	0.05	90.3448	0.06
	K=7	CV	89.3750	0.01	89.2188	0.01	89.2969	0.01	89.5313	0.01
		PS	89.6552	0.06	87.8161	0.06	90.3448	0.05	90.1149	0.06
ANN		CV	91.8750	3.36	91.5625	3.13	91.4063	3.38	89.8438	3.00
		PS	**94.9425**	**3.30**	90.8046	2.83	92.8736	3.38	91.0345	2.86

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