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ICTAL EPILEPSY AND NORMAL EEG FEATURE EXTRACTION BASED ON PCA, KNN AND SVM CLASSIFICATION

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ABSTRACT

Driven by a deep interest to find some spesific epilepsy EEG signal features as compared with normal ones. An array of electrodes, normaly the FP1, FP2, F7, F3, F2, F4, F8, C3, CZ, C4, T3, T4, T5, T6, P3, P4, PZ, O1, and OZ. The recorder signals were than processed and the standard sets of statistical quantities of means, variances, skewnesses, kurtosises, entropies, minima and maxima. Principal Component Analysis (PCA) were applied to these quantities to acquire two major one representing each quantity which separate best between epilepsy ictal and normal persons resorting to the SVM and KNN classification algorithms. The results show that the PCA elevates accuracy significantly and KNN achieves the mission better than SVM**.**

Keywords : *Ictal, Normal, PCA, KNN, SVM*

1. INTRODUCTION

Epilepsy is a neurological disorder in human brain which can affect persons of all ages. Report by the World Health Organization (WHO), worldwide over 50 million people sufferfrom epilepsy [1–3], while over the course of a life time, 100 million people will experience an epileptic episode and Globally about 59 millions epileptic patients [5], the majority are from the developingcountries[4].EEGsignals are used to monitor and evaluate brain neurological activities as well as disturbances normally in epilepsy persons. Early detections are carried out to normal people who are potential to epilepsy signals. Therefore, a variety of EEG signal processings have been developed to early detect epileptic phenomena. This research is intended to find the right signal processing scheme with high sensitivity to epilepsy signals, so that medication can be done with minimum risk of brain damage. Feature extraction plays important role in recognizing the signal specific patterns, especially in finding the expected ictal signals apart from the normal ones.

A number of time-domain methods have been proposed to detect and classify the attack types.Classificationof seizure and seizurefreeEEG signals using localbinary patterns [7],Epileptic seizure detection using different transformation techniques[6].Detection of temporallobe epilepsy using support vector machines[7][12][14], wavelet[11][13][15][16].New feature extraction approach for epileptic EEG signal detection using time-frequency distributions[10], using artificial neural networks [9].

2. MATERIAL AND METHOD

In this study the processed EEGs were acquired in Semarang Karyadi Hospital from 51 ictal epilepsy patients, where 1 specifically intracranial, 25 are males and 26 are females ages 3 (youngest) to 55 (oldest). They all were under long term video and EEG monitoring in the Epilepsy Neurosurgery Division of Karyadi Hospital, Semarang, under the supervision of Prof. Dr. dr. Zaenal Muttaqin, Ph.D.,Sp.BS(K), and 50 normal patients as well.Figure 2 show original EEG signal for normal (a) and ictal epilepsy (b).Before data recordings, the Epilepsy Patients must refrain from medication, and the data recordings proceeded for a number of days. The 19 electrodes were placed on

the head skin of the patients according to the International 10-20 Electrode Position System and the data sampling frequency is 256 Hz.Specifically the Intracranial was carried out under epilepsy neurosurgery and the measuring chip was placed in the brain.

2.1 Principle Component Analysis (PCA)

PCA can be used to reduce the dimension of the data without sacrificing significantly the intended characteristics of the data.

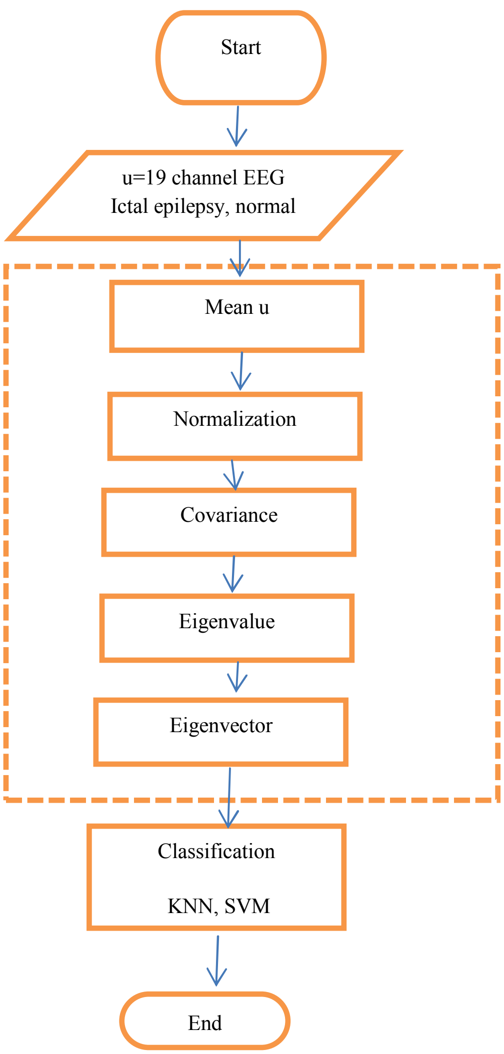


Figure 1. The flowchart of research the overall

PCA steps

The raw data are represented in an nxm matrix. namely $u = [\, u_1, u_{2,} . . ., u_n \,]$

1. Mean vector

$$\bar{u} = \frac{1}{m}\sum_{k=1}^{m} u_{n,k}$$

2. Finding the normalizationdata matrix (norm data).In this step the norm data are found by subtracting the original matrix elements by the respective means

   Norm = $u - \bar{u}$

3. Obtaining the covariance matrix R_u

   The covariance matrix, as slated earlier, is obtained by vector multiplication below;

$$R_u = u^t\, u$$

4. Recording the related Eigenvalues $\propto_1$; of the covariance matrix, so that

$$\propto_1 > \propto_2 > \ldots > \propto_n$$

5. Registering the respective eigenvectors:

$$\beta_1, \beta_2, \ldots, \beta_n$$

2.2 K-Nearest Neighbour (KNN)

KNN is a classification method for a set of data based onleast distances from each data points to the existing representative class points, including those determined through Query instance according to the preceding classification work under nearest majority distance categorization.

2.3 *SVM (Support Vector Machine)*

Let’s assume we can separate the data perfectly[8]. Then we can optimizethe following:

Minimize $\|\omega\|^2$, subject to

$$(\omega +\ x_i\ ) \geq 1, \text{if } y_i = 1$$

$$(\omega +\ x_i\ ) \leq -1, \text{if } y_i = -1$$

The last two constraints can be compacted to

$$y_i\ (\omega +\ x_i\ ) \geq 1$$

3. RESULT

3.1 Pre-Signal Processing

The one second EEG Recording covers the Ictal signal where the Spike Epileptic Form presents. The Medical Doctor decides clinically the one second position of specific interest backed up by video recording of the seizure. At the beginning of this 256 data sample intensive observation is focused on the semiology of the following time span times sample frequency. Mark the position of the electrodes for intracarnial and clinical condition of the patient. For every ictalcondition the seven statistical parameters, namely the means, variances, skewnesses, kurtosises, entropies, minima, and maxima values, for each patient were recorded.

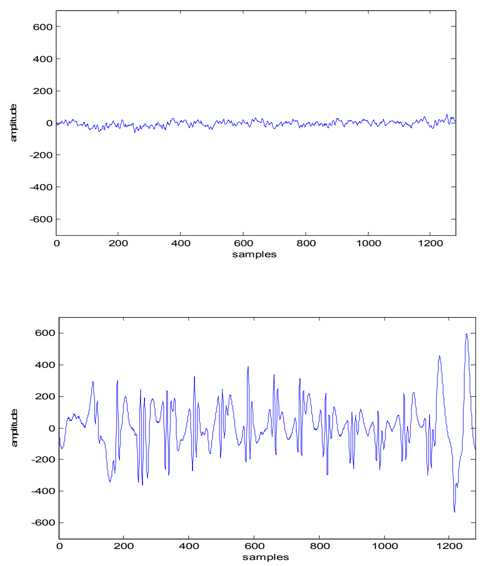


Figure2 Original EEG signal for normal (a) and ictal epilepsy (b)

3. 2. Feature Extraction

The 19 channel electrode signal features were computed from 50 signals with the respective means, variances, skewnesses, kurtosises, entropies, minima, maxima, to get 50x19 matrix of signal features or feature vectors. The raw number 1 to 25 signals of ictal, raw number 26 to 50 signals of normal persons.X_{mean}, $X_{variance}$, $X_{skewness}$, $X_{kurtosis}$, $X_{entropy}$, $X_{\ minimal}$, $X_{maximal}$.

$X_{maximal}$are ordered in the following matrix format

$$\begin{bmatrix} \mathrm{FP1}_1 & \mathrm{FP2}_1 & \dots & \mathrm{Pz}_1 & \mathrm{O2}_1 \\ \mathrm{FP1}_2 & \mathrm{FP2}_2 & \dots & \mathrm{Pz}_2 & \mathrm{O2}_2 \\ \dots & \dots & \dots & \dots & \dots \\ \dots . & \dots . & \dots & \dots & \dots \\ \mathrm{FP1}_{50} & \mathrm{FP2}_{50} & \dots & \mathrm{Pz}_{50} & \mathrm{O2}_{50} \end{bmatrix}$$

$$\begin{bmatrix} 297 & 222 & \dots & 890 & 725 \\ 380 & 740 & \dots & 243 & 270 \\ \dots & \dots & \dots & \dots & \dots \\ 39 & 29 & \dots & 178 & 162 \\ 47 & 25 & \dots & 156 & 111 \end{bmatrix}$$

Then the Covariance matrix is

$$\begin{bmatrix} 83170 & 89350 & \dots & 94370 & 97780 \\ 89350 & 111810 & \dots & 112810 & 119170 \\ \dots . & \dots & \dots & \dots & \dots \\ 94370 & 112810 & \dots & 133390 & 141010 \\ 97780 & 119170 & \dots . & 141010 & 180710 \end{bmatrix}$$

And the Eigenvector matrix is

$$\begin{bmatrix} 0.1663 & 0.2004 & \dots & 0.2261 & 0.2622 \\ 0.1701 & 0.2923 & \dots & 0.0901 & -0.2714 \\ \dots . & \dots & \dots & \dots & \dots \\ -0.0020 & 0.1268 & \dots & 0.0434 & -0.0773 \\ 0.1150 & 0.5686 & \dots . & -0.0178 & -0.0517 \end{bmatrix}$$

Then eigenvalueare in decreasing order

$$\begin{bmatrix} PC1 \\ PC2 \\ PC3 \\ PC4 \\ PC5 \\ PC6 \\ PC7 \\ PC8 \\ PC9 \\ PC10 \\ PC11 \\ PC12 \\ PC13 \\ PC14 \\ PC15 \\ PC16 \\ PC17 \\ PC18 \\ PC19 \end{bmatrix} = \begin{bmatrix} 2426200 \\ 108800 \\ 43100 \\ 18700 \\ 13200 \\ 10300 \\ 6000 \\ 5200 \\ 3700 \\ 3500 \\ 2100 \\ 1600 \\ 1200 \\ 700 \\ 600 \\ 300 \\ 300 \\ 100 \\ 100 \end{bmatrix}$$

3.3Features Selection

After features extraction process, the best representing ones are chosen for the following step where the classification prosesses are practical to carry out.Figure 3 shows the ictal epilepsy and normal signals and their spesific values of the assosiated means, variances, skewness, kurtosis, entropies, minima and maxima. The eigenvalues PC1 up to PC19 are listed in the decreasing order. In percentage the recorded data are shown in table 1. Figure 4 shows the points spreads representing the effectiveness of the PC's for class discriminations and Figure 5 shows the Dots Plots for each statistical parameters.

X = mean

Y= variance

Z=skewness

R= kurtosis

U=entropy

P=minima

Q= maxima

Table 1 percentage variance PC1 – PC19

	X %	Y %	Z %	R %	U %	P %	Q %
PC1	67	89	49	67	40	94	92
PC2	18	7	19	8	23	3	4
PC3	8	1	6	7	12	1	2
PC4	3	1	5	5	10	1	1
PC5	1	1	4	3	4	0	0
PC6	1	1	3	2	3	0	0
PC7	1	0	3	2	2	0	0
PC8	0	0	2	1	1	0	0
PC9	0	0	2	1	1	0	0
PC10	0	0	2	1	1	0	0
PC11	0	0	1	1	1	0	0
PC12	0	0	1	1	1	0	0
PC13	0	0	1	1	1	0	0
PC14	0	0	1	0	0	0	0
PC15	0	0	1	0	0	0	0
PC16	0	0	0	0	0	0	0
PC17	0	0	0	0	0	0	0
PC18	0	0	0	0	0	0	0
PC19	0	0	0	0	0	0	0

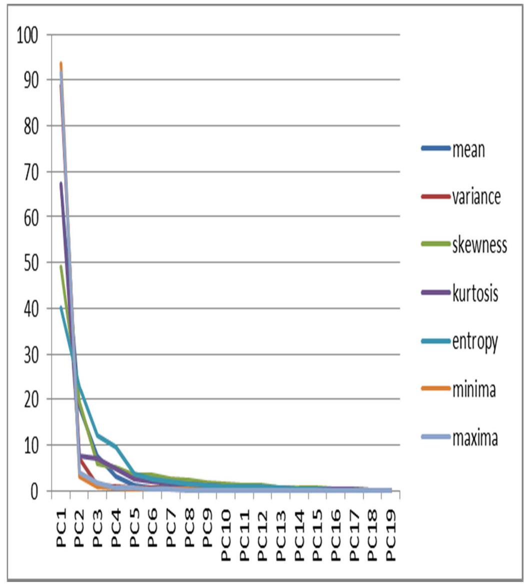
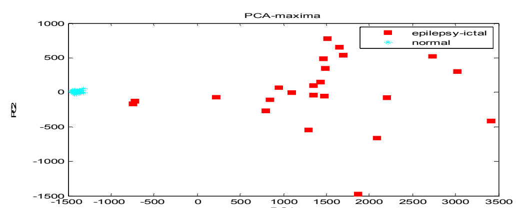
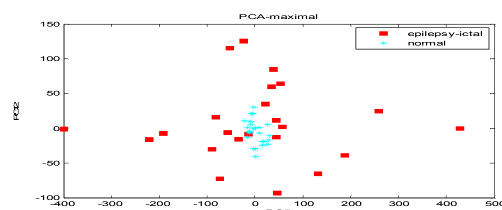
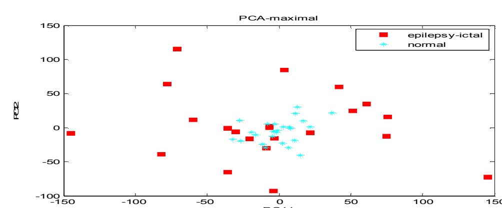
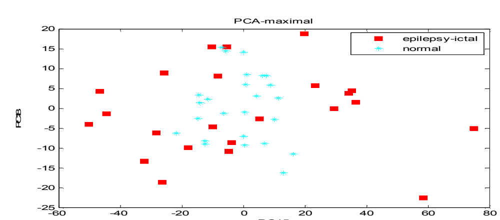


Figure3Percentage graphical comparation of the effectivenes of the statistical parameters in terms of the PC's









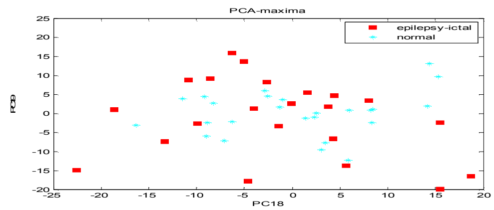
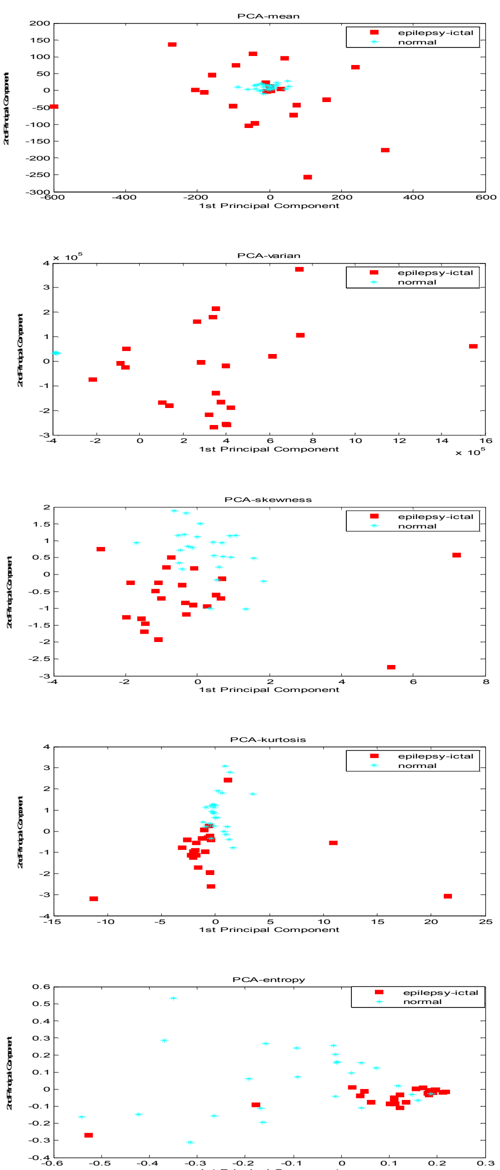


Figure4 The points spreads representing the effectiveness of the PC's for class discriminations



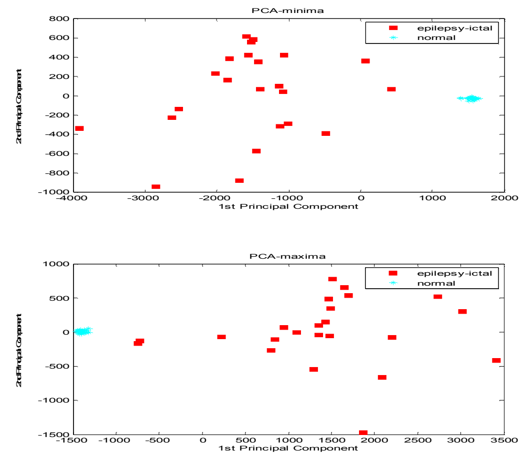


Figure5 The Dots Plots for each statistical parameters.

3.4Classifications based on KNN and SVM

The 100 raw data consist of 50 for training, where 25 are ictal and 25 are normal, and the other 50 are for testing where 25 are ictal and 25 are normal as well.

Figure 6 shows maximum values for KNN k=7, which are 96% and with SVM the highest is 92%. This high accuracy of 96 % is also reached with respect to the minima and maxima where KNN k = 7. On the other hand the accuracies of kurtosis and entropies with KNN as well as SVM drop to bellow 60 %. Likewise for skewness the accuracies with KNN and SVM are above 70 %, likewise for mean, variance the accuracies with KNN and SVM are above 80% while with SVM mean is 60 %.

Figure 7 shows maximum values for KNN k=3,5,7, which are 92% and with SVM the highest is 100%. This high sensitivity of 92 % is also reached with respect to the mean and maxima. On the other hand the sensitivity of kurtosis and entropies with KNN as well as SVM drop to bellow 70 %. Likewise for skewness the sensitivity with KNN and SVM are above 70 %, likewise for mean, variance the sensitivity with KNN and SVM are above 80% while with SVM mean is 100 %.

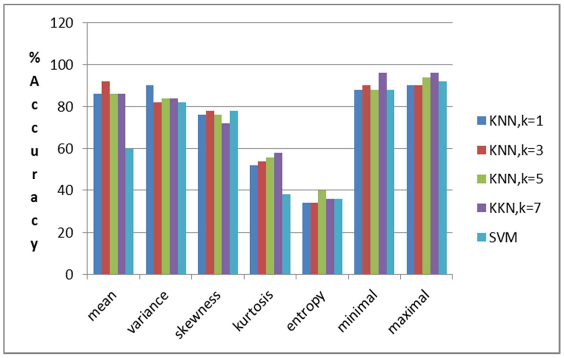


Figure 6.Result of selected feature (1st Principle Component and 2nd Principle Component) accuracy KNN, SVM

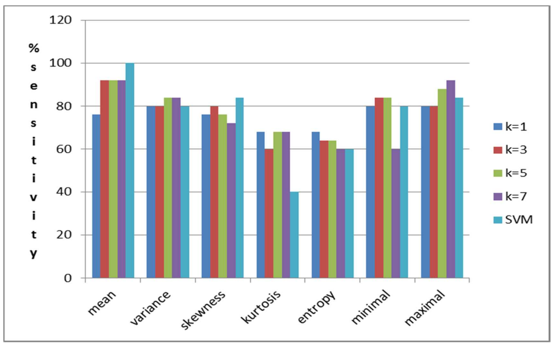


Figure7.Result of selected feature (1st Principle Component and 2nd Principle Component) Sensitivity KNN, SVM

4. CONCLUSION

We concluded our research based on experiment and performance test result feature reduction using PCA assure that selected feature is the most principal feature of signal ,the best representivepresentageparameters are variance, minima, maxima shown in tabel 1,the ictal and normal signal accuracies of KNN are much higher than SVM.

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