



# CLASSIFICATION OF EEG SIGNALS BY USING DEEPLARNING TECHNIQUES

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**Abstract:** This study has been undertaken to classify EEG signals as normal and epileptic by using deep learning techniques. In this work, 100 normal and 100 pathological single channel EEG signals were downloaded from the EEG database of University of Bonn, Germany. From these signals, alpha, beta, gamma, delta and theta waves were extracted by means of filtering. Energy and variance of these waves were calculated and these values were used to train both ANN and SVM classifiers. Performance of different classifiers is measured for different parameters for each wave. ANN provides high classification for Theta signal of 99% for energy as a training parameter and SVM provides high classification for both alpha and beta signals of 98.5% for variance parameter.

**Keywords – ANN, Data classification, EEG signal analysis, Epilepsy, Feature Extraction, SVM**

## I. INTRODUCTION

Brain is a very important part of central nervous system and it performs the co-ordination of different functions of the body. Epilepsy is a disorder, which is caused due to highly frequent electrochemical impulses from the neurons. Neurologists diagnose this disorder by using electroencephalogram (EEG). Through this test we can illustrate the changes in brain activity that might be useful in diagnosing brain disorders. In medical field, there are many techniques for diagnosing and monitoring this disorder. Epilepsy is the fourth most common neurological disease after migraines, stroke, and Alzheimer's disease. According to World Health Organization [1], around 50 million people are suffering from Epilepsy making it most common neurological disease globally. An electroencephalogram is a test that detects electrical activity in the brain using small, metal electrodes attached to the scalp. Human brain is a focal point and takes part important functions related to nervous system. Brain cells communicate via electrical impulses and are active all the time. This activity shows up as wavy lines on an EEG recording cerebrum. The record of EEG is closely related to the record of epilepsy.

## II. DATA AND SOURCES OF DATA

The data used in this study are open-source EEG recordings and are publicly available from University of Bonn, Germany. The database includes EEG recordings both normal and pathological subjects, with each set containing 100 single-channel EEG signals. These data are used to analyze and distinguish between normal and epileptic subjects. This study selected data from surface EEG recordings and EEG records of pre-surgical epileptic patients during epileptic seizure activity.[10]

## III. CLASSIFICATION STEPS

EEG signals from the database are considered. Each signal is filtered with five different filters to extract alpha, beta, gamma, delta and theta waves. After filtering, energy and variance of each extracted wave is calculated. This calculation is repeated for both normal as well as pathological subjects. Two models, SVM and ANN are trained for each feature with each wave separately. 70% of the sample values of both normal and pathological subjects for each feature were considered for training each model. Remaining 30% of sample values were used for testing the models.

## IV SVM (Support Vector Matrix)

A support vector machine (SVM) is a deep learning algorithm that performs supervised learning for classification of data groups. This algorithm is based on the statistical learning theory. Supervised learning systems provide both input and desired output data, which are labeled for classification. SVMs are formulated by training and using those inputs that are near to the decision surface as they provide the most important information about the classification. Gaussian radial basis function, known as kernel is used for training the dataset.

**V ANN (ARTIFICIAL NEURAL NETWORKS)**

An Artificial Neural Network consists of neurons which in turn are responsible for creating layers. The output from each layer is passed on to the next layer. There are different non-linear activation functions to each layer, which help in the learning and to produce output of each layer. Non-linear models and patterns are developed during training. ANNs have evolved as a powerful tool for classification, pattern recognition, prediction as well as pattern completion. Artificial neural network stores and processes data through the connections that exist between its nodes generated by a learning process that distinguishes patterns in the training data.[13]

**VI CONFUSION MATRIX**

The confusion matrix displays the total number of observations in each cell. The rows of the confusion matrix correspond to the true class, and the columns correspond to the predicted class. Diagonal and off-diagonal cells correspond to correctly and incorrectly classified observations, respectively as indicated.

EEG classification using ANN and SVM produces the classification result as a confusion matrix. The accuracy of a classifier is validated by calculating Mathew’s Correlation Coefficient (MCC). The results are obtained for five different waves with two different features. The formula to calculate accuracy is indicated in equation 1.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{-1}$$

It is observed that larger the value of MCC better will be the performance of the classifier.

**VII RESULTS AND DISCUSSION**

Figure 1 shows the confusion matrix for classification by using ANN classifier for theta wave with energy as a feature.

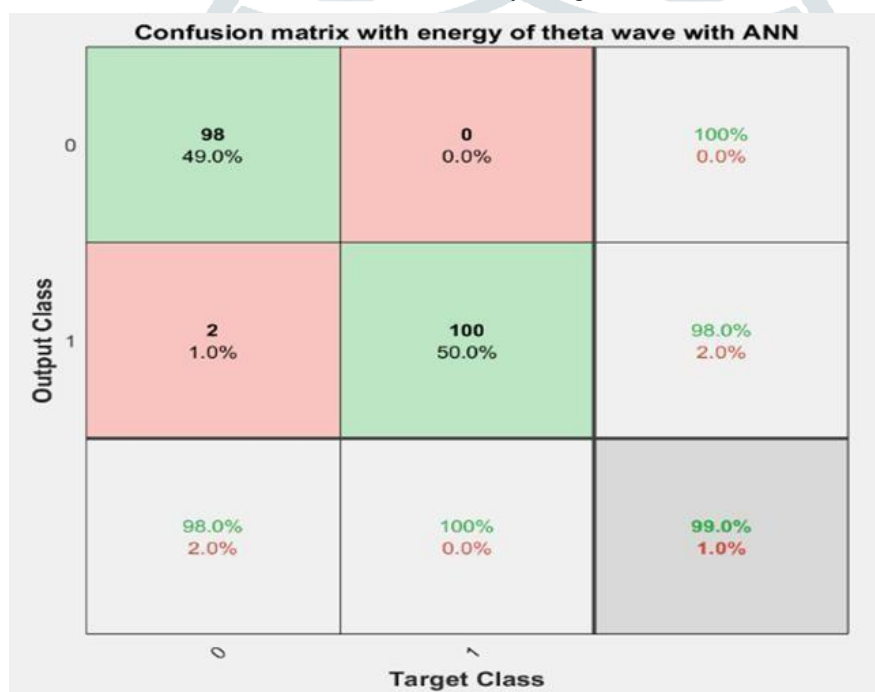


Figure 1 Confusion matrix with energy of theta wave of ANN

Figure 2 shows the confusion matrix for classification by using SVM classifier for theta wave with energy as a feature.

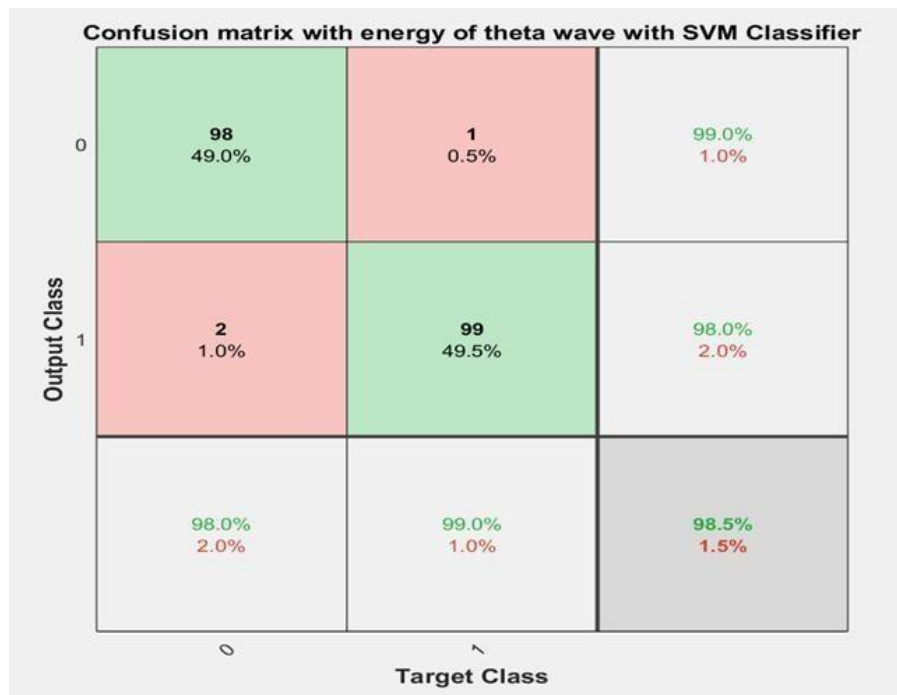


Figure 2 Confusion matrix with energy of theta wave of SVM

Figure 3 shows the confusion matrix for classification by using ANN classifier for alpha wave with energy as a feature.

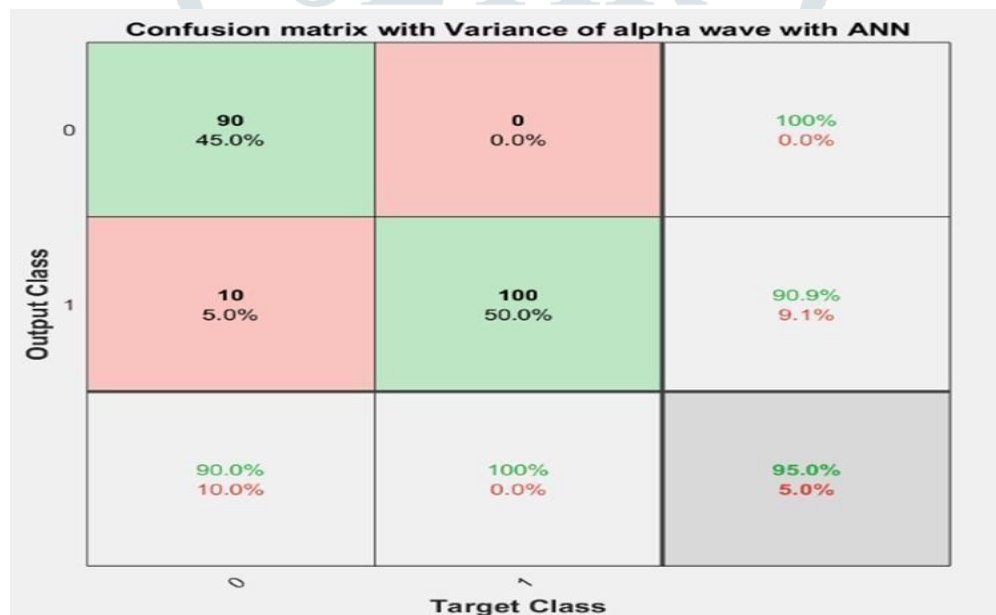


Figure 3 Confusion matrix with energy of alpha wave of ANN

Figure 4 shows the confusion matrix for classification by using SVM classifier for beta wave with variance as a feature.

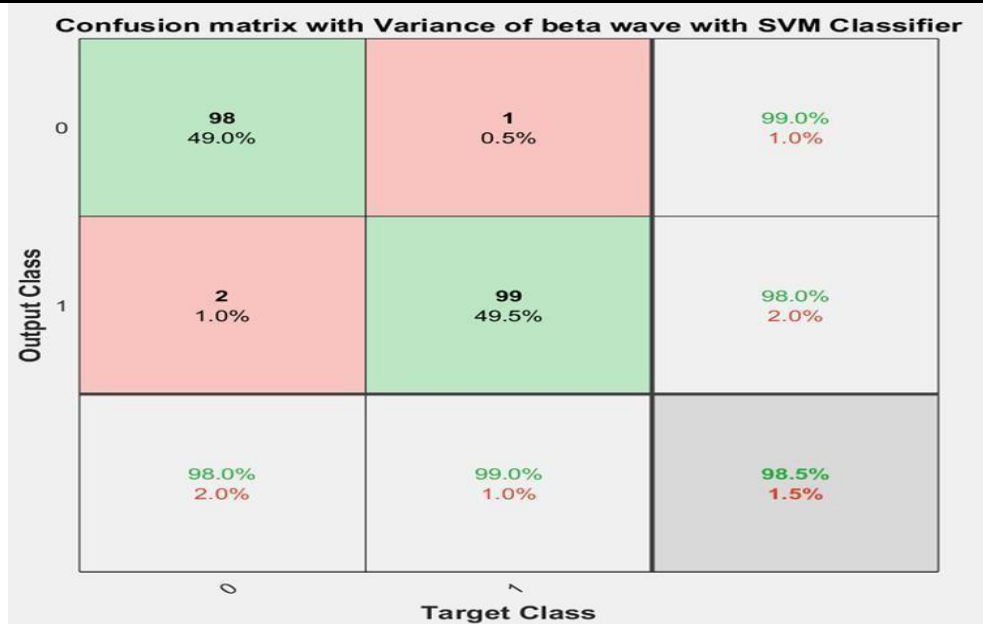


Figure 4 Confusion matrix with energy of beta wave of SVM

Table 1 summarizes the results of classification of different classifiers for different features for different signals.

Table 1 Classification performance of ANN and SVM modeling

SIGNALS	ANN		SVM	
	ENERGY	VARIANCE	ENERGY	VARIANCE
ALPHA	92.0%	95.0%	95.0%	98.5%
BETA	92.5%	90.5%	95.0%	98.5%
GAMMA	93.0%	79.0%	95.0%	79.0%
THETA	99.0%	78.0%	98.5%	79.5%
DELTA	92.0%	80.5%	95.0%	85.0%

From the table 1, it may be inferred that SVM has better classification accuracy when compared with ANN for same data input. ANN classifier provides better accuracy for all the waves except alpha wave for energy. Whereas SVM classifier provides higher accuracy for variance with alpha and beta waves. However, with other three waves energy performs the best. It is also very clear that with ANN classifier, highest accuracy of classification is obtained with theta wave for energy. For SVM classifier, highest accuracy of classification is obtained for both alpha and beta wave for variance and with theta wave, energy provides highest classification accuracy. Table 2 provides validation performance of both classifiers for both features for each input signal. Higher the MCC value of the signal for the feature better is the classification performance.

Table 2 Validation by using MCC of ANN and SVM modelling

SIGNALS	ANN		SVM	
	ENERGY	VARIANCE	ENERGY	VARIANCE
ALPHA	0.85	0.90	0.90	0.97
BETA	0.85	0.82	0.90	0.97
GAMMA	0.86	0.63	0.90	0.58
THETA	0.98	0.61	0.97	0.59
DELTA	0.85	0.66	0.90	0.70

From the table 2, it may be concluded that classification performance of SVM classifier is relatively superior when compared with ANN classifier. With respect to features, variance performs better with alpha and beta waves and energy performs better for remaining waves.

This work is of particular relevance in the area of electroencephalography and deep learning, presenting an approach that allows classifying an exam of a patient through two different techniques. This work could become a starting point for the construction of medical equipment and systems that support neurologists and doctors' work in the diagnosis of epilepsy. It can even be used as alternative or system that acts in those spaces where there is lack of specialists in the field.

## VIII CONCLUSION

To improve classification accuracy of the EEG signals various methods are suggested. This study presents the use of ANN and SVM classifiers for EEG signal classification. The extracted features like energy and variance are used for training and classification of EEG signals and performance of these classifiers for different features and for different signals is also studied.

## VI ACKNOWLEDGMENT

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