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A Novel Machine Learning-Based Analysis of Affects using EEG Data

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Abstract*:* The main topic of study is mapping human cognition into automated analysis since it has exciting applications in practically every aspect of creating artificially intelligent devices. Studying electroencephalogram (EEG) patterns is the greatest approach to comprehending how the brain functions; hence a lot of research has been focused on this topic. It is challenging to create a generic affect classification system that can effectively deliver robust affect labeling to the EEG patterns since EEG recordings are subject-dependent and show variances according to external influences or kinds of recording devices. A unique generic framework for affect-based cognitive analysis is presented in the proposed study as a solution to this problem. The proposed system includes the following steps: EEG pattern, dataset, pre-processing, feature selection, an Enhanced Squirrel search optimized Naive Bayes (ESSOp-NB) step to reduce inter-class and intra-class variance, and finally, the processed pattern is sent to a trained classifier for classification into the proper effect categories. The effectiveness of well-known classifiers is evaluated using EEG data from single and multiple people from two separate datasets: Database for Emotion Analysis using Physiological Signals (DEAP) and SJTU Emotion EEG Dataset (SEED). The findings of the experiment indicate that the ESSOp-NB classifier is the most effective at categorizing data from both single and mixed participants.

Keywords: *ESSOp-NB, EEG, Machine Learning, DEAP, SEED*

1. Introduction

In A technique for recording brain electrical activity is called electroencephalography, (EEG). It measures the voltage alterations brought on by the passage of ionic current through the brain's neurons. Because EEG data provides valuable information about how the brain functions, it is often used in neuroscience research, clinical diagnosis, and brain-computer interface technologies [1]. Brain electrical activity is tracked using the non-invasive neurophysiological technique known as EEG. Electrodes are affixed to the scalp to record the electrical impulses generated by the brain's neurons. By monitoring the combined activity of tens of thousands or millions of neurons, these electrodes can map out the structure and patterns of brain activity [2]. EEG data is normally recorded between 250 and 1000 Hz, and it is often presented as a time series of voltage values on several channels [3]. Event-related potential (ERP) analysis, connection analysis, and power spectrum analysis are just a few of the methods used in EEG data processing. While power spectrum analysis looks at the power distribution across a variety of frequency bands to look for patterns of brain activity, ERP analysis looks at how the brain reacts to particular events or stimuli. Investigating the functional connection between various brain areas based on their coordinated activity is the aim of connectivity analysis [4]. Numerous uses for EEG data exist in the realms of medicine and neuroscience. Examples of applications for EEG include studies of brain activity during meditation, attention, and emotional processing, as well as monitoring and diagnosis of epilepsy and other neurological disorders, cognitive function testing, and even the control of external devices via brain-computer interfaces [5]. The electrical activity recorded by an electrode at a particular location on the scalp is commonly represented in EEG data as a time series of voltage values. The recorded brain waves' amplitude and frequency, which are often represented in the data as a time series, may be examined to get insight into many elements of brain function [6]. Numerous neurological conditions, such as epilepsy, sleep issues, and brain damage, may be detected with EEG. Unusual brain wave activity patterns may be used to identify certain disorders. In cognitive psychology and neuroscience, EEG is often used to examine brain activity during a range of cognitive activities, including attention, memory, perception, and decision-making. It may provide light on the underlying brain mechanisms involved in these activities [7]. Brain-computer interfaces (BCIs) which let people control external devices using their brain activity, may be created using EEG data. For instance, paralyzed individuals may utilize EEG signals to control robotic limbs or interact with a computer interface [8]. EEG may

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be used in neurofeedback training, a method intended to alter brain activity to enhance cognitive or emotional performance. People get immediate input on their brain activity and developmental techniques to control it [9]. Time-frequency analysis, ERPs, spectrum analysis, and machine learning (ML) algorithms are just a few of the methods utilized to analyze EEG data. These techniques aid in the extraction of relevant data from raw EEG signals, such as the recognition of certain brain wave patterns, the detection of anomalies, or the recognition of cognitive processes [10]. In this article, we propose ESSOp-NB to register EEG records from the same affect modality together, allowing the classifier to more easily assign them to the appropriate emotional category.

2. Related works

Research [11], they use an ML technique to first classify participants as having a BED or not, with an overall accuracy of 81.25 percent, and then to isolate the low theta sub-band between 4.5 and 6 hertz as the most salient differentiating characteristic. Those that suffer from a BED tend to have much greater levels of theta activity. The use of ML methods trained on EEG data has great promise as a means of speeding up the process of diagnosing disorders and providing new perspectives to the field of medicine. Research [12], they introduce a novel dynamic filtering approach for identifying and preprocessing the most informative sub-bands related to a specific neurological disorder. More hidden layers are needed for this Recurrent Neural Network with a Gated-Recurrent Unit architecture than in traditional architectures, but the increased ability to learn fitting and extract features from very complicated EEG data recordings allows for more consistent diagnoses. Three hybrid models were suggested for use in the MI-based BCI to categorize the EEG input. Both convolutional neural networks (CNNs) and Long-Short Term Memory (LSTMs) are used in the suggested hybrid models. They used a CNN model with just two blocks that were immune to the vanishing gradient descent. To compensate for the small size of the datasets, they used a transfer learning approach and data augmentation techniques [13]. Instead of needing eight hours to categorize the condition accurately, our method simply takes a 10-minute clip of electroencephalographic recording data. Parkinson's disease and dementia are only two of the many illnesses that might develop as a result of sleep behavior disorder. This highlights the need for their method's ability to rapidly and accurately categorize the disease [14]. They test their method using 499 one-minute EEG recordings from n=28 people deposited in a public repository of neurological and psychiatric data. Due to the lack of currently accessible diagnostic tests or biomarkers, their method opens the path for a rapid and accurate diagnosis of paranoid schizophrenia. The analysis of the electroencephalographic spectrum up to 100 Hz also revealed intriguing information on the most predictive sub-bands [15]. To lessen the effects of the condition and maybe recover motor function, understanding how to effectively implement rehabilitation training for stroke patients is of utmost importance. In light of this context, this study intends to apply deep learning technology to create an EEG-based model for stroke recovery. When a larger margin of error is needed, the support vector machine (SVM) extension known as a large margin support vector machine (LM_SVM) might be used. Better generalization performance may be achieved by optimizing the edge distribution [16]. Research [17], they offer a unique multi-modal ML-based technique to automatically classify brain states using EEG-generated characteristics. The goal of collecting EEGs from people with neurological conditions is to differentiate them from EEGs collected from healthy controls. Research [18], they discuss a strategy for identifying early signs of internet addiction (IA). The strongest predictive frequency sub-bands for distinguishing between healthy individuals and those with early-stage IA have been discovered. We show that IA is associated with neurostructural alterations, which adds to the list of conditions that should be taken seriously. Research [19], they present a multi-layer Convolution neural network (CNN) approach to combining CNNs with distinct features and architectures to enhance the accuracy with which they classify EEG motor imagery (MI). They have conducted many tests using public datasets to gauge the efficacy of the suggested CNN fusion technique. Since there is currently no definitive model for defining and forecasting antisocial conduct, this revolutionary approach establishes a new standard. The established strategy has significant theoretical and practical value due to the high degree of danger to people and society [20].

3. Experimental Method

Data from both the DEAP and SEED EEG datasets was used in the studies. To keep things simple, we only used ratings from the DEAP dataset's 'valance' emotional modality, and we split those ratings into two categories: high valence (HL) for ratings between 4.5 and 9, and low valence (LV) for ratings below 4.5. Experiments were streamlined by using preprocessed EEG data from the DEAP and SEED databases. All of the tests were run on a single CPU in a MATLAB environment. Typical processing stages are shown in Figure 1 for reference.

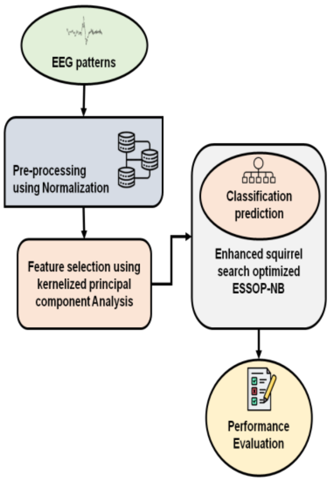

Fig. 1. General processing steps

Experimental Data

Both the DEAP and the SEED datasets are used in this investigation. The data in both sets is multimodal. The purpose of combining the two datasets was to test the suggested method's efficacy on data from different people and different datasets. This was essential in establishing the wide applicability of the suggested approach. Emotional modalities may be analyzed using DEAP, a multimodal dataset Thirty-two respondents' electroencephalograms and other physiological responses to one-minute music videos are included in the collection. This was accomplished with the help of forty separate videos. All participants were given a set of standard rating criteria including arousal, valence, like/dislike, dominance, and familiarity—with which to evaluate these movies. Using a sampling rate of 512 Hz and a total of 32 active AgCl electrodes, all recordings were made. In the SEED Database like SEED, fifteen individuals were captured while viewing movie snippets for this multimodal dataset. Fifteen separate film clips were chosen to represent the negative, positive, and neutral emotions. Each individual participated in a total of fifteen trials over three separate runs of each experiment. EEGs were recorded using 62 electrodes spaced out by the worldwide 10-20 standard.

3.1.1. Classifying Individual Subject EEG Data

Each dataset was evaluated based on one subject's preprocessed EEG signal data. The one subject pre-processed DEAP data has previously undergone down sampling to 128 Hz, as well as elimination of electrooculogram (EOG) data, filtering, and segmentation. There are three dimensions to the data set: the first represents the total number of video clips seen by each subject, the second denotes the total number of channels, and the third represents the total number of data points.

After that, ESSOp-NB was performed independently on each set of data based on their labels. This process makes sure that all of the EEG signals that belong to the same category of emotions are recorded as precisely as feasible. After that, we separated the data from each emotion type into separate training and testing sets. In this case, we used an 80:20 split between the training and testing sets of data. The classifier was given the data and its labels to decide. The goal here is to find a good fit between the given model and a classifier. Four separate classifiers are trained using the training data, and their results are compared using test data.

Table 1 summarizes all of the findings for the DEAP data type. The SEED data set went through a very similar procedure. We used the previously processed EEG recordings of a single individual in a series of replications. Data collected by SEED for a single participant measured 15 video clips by 62 channels by 37 thousand data points. There are three types of categories represented by the labels in seed data: negative, positive, and neutral. We only looked at data with either a positive or negative label to ensure consistency throughout our trials. After applying ESSOp-NB to the data that had been split in half by the presence of two labels, 80% of the processed data was utilized to train the classifiers. On test data, the accuracy with which various classifiers made their predictions was measured.

3.1.2. Classifying Multiple Subjects

This phase required merging many participants' preprocessed data into a single array for each dataset. We pool the EEG data from 10 individuals to create the DEAP dataset. An array containing the labels was also created. For this subcategory, the same procedures were used: first, dimensionality reduction was performed, then ESSOp-NB was applied, and last, the data was sent to classifiers and their results were recorded. Table 2 summarizes the experiments' outcomes for this class. Once again, the ESSOp-NB classifier proves to be more reliable when applied to data in this setting.

3.1.3. Mixed data classification from both datasets

We used DEAP and SEED EEG data to do the affect categorization in the proposed study. Six participants' EEG recordings were utilized in these trials, with three from the DEAP dataset and three from the SEED dataset combined. Data alignment while mixing helped smooth out the disparities. We have simplified our analysis by simply considering the two possible response values (positive and negative) from the SEED data, which also facilitates the clean separation of the aforementioned groups and maps according to valence level. In addition, we modified our experimental setup such that we only utilize the top 40 channels and point values per channel from the SEED information set. This resulted in a final mixed data size of 150x40x8064 for this group. The classification was performed after data alignment and mixing, as described in the preceding section. Table 3 provides a summary of the findings for this group. The results indicate that the ESSOp-NB classifier is useful for categorizing this kind of data. The following part provides a comprehensive analysis of the data collected.

3.2. Data processing using normalization

By computing the mean (M) and standard deviation (SD) of each feature throughout a training dataset and dividing it by the dataset size, Z-score normalization, often referred to as zero-mean normalization, normalizes each input feature vector. The average and standard deviation for each attribute are computed. The general formula states that the transformation is necessary.

$$n' = \frac{(n-\mu)}{\sigma} \tag{1}$$

The mentioned property n has a mean and SD of σ and, respectively. Before training can start, the data set's features are all z-score normalized. The mean and SD of each character should be saved after training data has been collected to utilize them as algorithm weights.

3.3. Kernelized Principal Component Analysis (K-PCA)

A nonlinear version of the principal component analysis is kernel principal component analysis, which is frequently utilized in wavelet transform and denoising applications. When the manifold is linearly immersed in the observation space, classical PCA is intended to decrease dimensionality. By linearizing the manifold with the help of the kernel technique, which is one of the two components of KPCA, the latter component, which is PCA, gets the prerequisites it needs. Using feature mapping, KPCA implicitly projects data into a feature space and uses the kernel's calculation of the pairwise specific formula between the data that is mapped in the feature set. Finding a suitable kernel that linearizes the surface in the feature space while taking the geometry of the input space into account is not an easy task. The insufficiency of KPCA in nonlinear dimensionality reduction would result from a poor projection that does not meet these requirements.

3.4. Enhanced Squirrel search optimized Naive Bayes

Enhanced Squirrel search optimized Naive Bayes is a sophisticated search algorithm that leverages the power of ML to improve search accuracy and efficiency. This approach combines the Enhanced Squirrel's sophisticated features with optimization methods used with the Naive Bayes classifier.

The probabilistic technique known as Naive Bayes is often used for classification tasks, but it may also be modified for information retrieval tasks like search. The Enhanced Squirrel search uses an optimized version of Naive Bayes that includes several improvements to boost speed. As part of these improvements, word dependencies are handled, unbalanced data distributions are addressed, and hybrid techniques are used.

The method can capture the relative value of various phrases or qualities throughout the search process by choosing pertinent features and allocating suitable weights. N-grams and word embeddings are two techniques that aid in capturing word dependencies and enhancing model accuracy. Additionally, dealing with uneven data distributions makes ensuring that no class is excessively favored by the algorithm. By merging Naive Bayes with other ML methods, hybrid approaches may also be advantageous for the algorithm. It gives customers more insightful search results by taking into account a variety of variables and relationships to better evaluate the relevancy of content.

Based on Bayesian theory, a naïve Bayes classifier assumes that no two features belonging to the same class are interdependent. Maximum likelihood is used to estimate the probability of an event occurring or not occurring in the NB model. The NB classifier performs classification as described below and needs minimal training data. Consider the data set D to be an in-class training set with attributes and labels. Using Equations (2 & 3), we can determine that the attribute is part of the class for which the posterior probability is the greatest**.**

$$B(V_j|X) > B(V_j|X) \text{ for } 1 \le i \le m, i \ne j \tag{2}$$

$$B(V_j|X) = \frac{B(X|V_j)B(V_j)}{B(X)} \tag{3}$$

By Bayes theorem, Where

$B(V_j)$ is the class prior probabilities.

$B(X)$ is the prior probability of X.

$B(V_j|X)$ is the posterior probability.

$B(X|V_j)$ is the t posterior probability of X conditioned on V_j

As, $B(X)$ is constant for all classes, only the numerator of $B(V_j|X)$ needs to be maximized. If the class prior probabilities are unknown, then $B(V_1) = B(V_2) = \cdots = B(V_m)$, and $B(X|V_j)$ is maximized. Otherwise, the class prior probabilities can be calculated by $B(V_j) = |V_{j,T}|/|T|$where$|V_{j,T}|$ is the number of a training set of the class V_j in T.

To reduce the computation in an estimation of $(X|V_j)$, the classifier adopts the independent attributes conditionally of each other. Thus show in equation (4 & 5),

$$B(X|V_j) = \prod_{r=1}^{m} B((x_r|V_j) \quad (4)$$

$$= B(x_1|V_j) \times B(x_2|V_j) \dots B(x_m|V_j) \quad (5)$$

The probabilities $B(x_1|V_j), B(x_2|V_j), \dots . B(x_m|V_j)$ is determined from the training set and $'x_r'$ represent the value of an attribute for the data set X.

To estimate the class label of, $X, B(X|V_j)B(V_j)$ is evaluated for each classV_j .

$B(X|V_j)B(V_j) > B(X|V_j + B(V_j)$ for $1 \le i \le m, i \ne j$. (6)

Based on the following condition in equation (6), the classifier determines that the class label of attribute X is V_j.

4. Results and Discussion

Classification of single-subject EEG data into affect classes was the focus of the initial set of research. Classification outcomes for single-subject EEG data from both datasets are summarized in Table 1, figure 2, and figure 3.

Table 1. Accuracy (%) for Data from a Single Subject

Methods	***Dataset***			
	SEED		***DEAP***	
	Accuracy	***F-score***	***Accuracy***	***F-score***
Decision Tree [22]	87.5	88.73	87.5	88.73
K-Nearest Neighbor [21]	50.0	50.27	87.5	88.73
Support Vector Machine Neighbor [21]	92.5	92.99	87.5	88.73
ESSOp-NB [proposed]	92.5	92.99	95.0	92.99

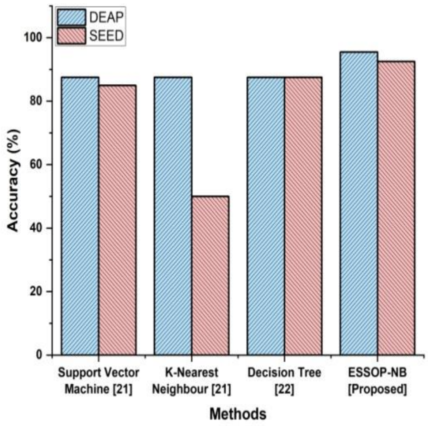

Fig.2. Comparison of Accuracy (Data from a Single Subject)

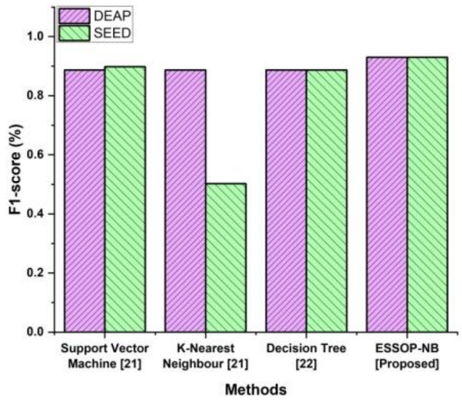

Fig. 3. Comparison of F1-score (Data from a Single Subject)

To extend the proposed model, the organization performance of 3 well-known classifiers (Tree classifiers, SVM and KNN) was compared, and a winner was selected. An ESSOp-NB classifier, trained on the training set and then evaluated on the remaining 20% of data, was utilized in the tests. ESSOp-NB used a polynomial kernel function of order two. ESSOp-NB achieves 95% accuracy in classifying subjects from the DEAP data set, and 92.5% accuracy in classifying subjects from the SEED dataset. Classification accuracy of 87.5 percent was attained by applying the suggested methods to a multiclass ESSOp-NB model with a normalization that was trained using predictors supplied in the training data with their associated labels. A three-neighbor KNN classifier is the experimental third classifier. The categorization outcomes for pooled data from numerous patients are shown in Table 2 and figure4. Ten participants' EEG data are pooled together to create the DEAP dataset, which is used to evaluate the effectiveness of different classifiers.

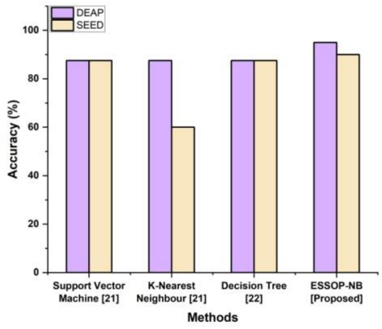

Fig.4. Comparison of Accuracy (Data for Multiple participants)

Table 2. Accuracy (%) on the Valence Attribute for Multiple participants (all participants from the same dataset)

Methods	***Dataset***	
	SEED	***DEAP***
ESSOp-NB [proposed]	84.0	95.0
Decision Tree [22]	87.5	87.5
K-Nearest Neighbor [21]	60.0	87.5
Support Vector Machine [21]	87.5	87.5

The capacity of a model to handle any sort of information, as is the case with real-time EEG processing systems, is referred to as generalization. Experiments were then conducted to see how well-selected classifiers performed when applied to data from EEG subjects that had been combined from two datasets (in this case, DEAP and SEED). We have combined three individuals from the DEAP dataset with three subjects from the SEED dataset, which may be thought of as cross-dataset learning. Then, the suggested approach is implemented, and the resulting data is recorded and shown in Table 3 and Figure 5.

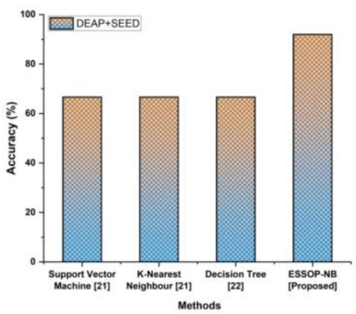

Fig.5. Comparison of Accuracy (Data for Multiple Mixed Subjects

Table 3. Accuracy (%) for Multiple Mixed Subjects (subjects from both the DEAP and SEED datasets combined)

Methods	**SEED+ DEAP**
Support Vector Machine [21]	66.67
Decision Tree [22]	66.67
K-Nearest Neighbor [21]	66.67
ESSOp-NB [proposed]	92.00

Table 3 shows that the suggested method works well in this circumstance as well and that the ESSOp-NB classifier is the most generalizable of the tested methods. ESSOp-NB classifiers have an average accuracy of 93.7%, whereas SVM classifiers have an accuracy of 90.8% across all instances. Emotion categorization in real-time EEG recordings using ESSOP-NB classifiers is now a feasible alternative.

5. Conclusion

This study introduced a unique framework for the dispensation of EEG data in real-time for affect classification, which may be used to automatically tag and retrieve relevant films depending on their emotional content and the user's current mood. The suggested method employs ESSOp-NB to register EEG records from the same affect modality together, allowing the classifier to more easily assign them to the appropriate emotional category. Extensive trials were carried out, and their findings were analyzed, to prove the efficacy of the suggested technique for identifying EEG patterns both within and between datasets. In comparison to SVM's 90.8% accuracy, results showed that Naive Bayes' average accuracy was 93.7%. This proves the ESSOp-NB classifier's superiority and demonstrates the suggested method's flexibility for categorizing practically any sort of data, despite the data's intrinsic variations.

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