Support Vector Machine Classifier for EEG-based Emotion Recognition

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ABSTRACT: Emotion Recognition (ER) is becoming a highly significant and rapidly growing area of study in recent decades. Emotion Detection (ED) technology has had a significant effect on a variety of fields, particularly research and development. Previously, face gestures and voice intonation were employed to identify emotions; but body expressions and the spoken words may provide factually inaccurate findings. As a consequence, research has chosen to use the electroencephalogram (EEG) method, which has been shown to be a reliable tool for identifying emotions. Some methods collected EEG data using conventional and pre-defined signal pre-processing and associated processes, whereas others utilized smaller channels or people. This paper describes a quantitative feature-based emotion detection method. After the best characteristics have indeed been selected, the dataset is given to a classification algorithm for training and testing purposes. As per the results of the study, the proposed method has an accuracy rate of 91.54 percent for the data samples examined. Furthermore, in terms of accuracy, the suggested approach surpasses existing methods.

KEYWORDS: EEG, Electroencephalogram (EEG), Emotion Recognition, Human-Computer Interactions (HCI), Support Vector Machine (SVM).

1. INTRODUCTION

Emotion recognition (ER) has recently sparked a lot of attention in the fields of computer imaging as well as human-computer interactions (HCI) [1], [2]. Various HCI-related research topics are shown in Figure 1. It's an important element in a variety of useful applications that need emotion monitoring, and it has a big effect on human intelligence, observation, communication, judgment, and cognition. In the area of human-computer interaction, emotion detection research is very useful.

Computers will be able to think and act like humans as artificial intelligence advances, detecting their emotional states and enabling for deeper human-computer connection. Emotion is a complex state of mind or action that may represent human ideas and attitudes and can affect interpersonal communication. In the past, AI systems or deep supervised learning were used to accomplish text-based sentiment analysis.

It is essential to be able to identify people's emotional responses autonomously as modern media and human-computer interface technologies develop. Until the last decade, HCI technologies, on the other hand, ignored them. HCI systems, when combined with electronic content, offer potential applicability in medical technologies, neuroscience, psychiatry, and other fields where feelings are important. A human-like HCI system must be equipped with a collection of human emotional skills in order to engage people in a relatively human-like and effective manner. Academics are devoting increasing emphasis to automatic human emotion recognition as a consequence of the rising demand for HCI.

In the context of smart healthcare, ER could even improve the quality of life for a wide range of users, including seniors, folks with severe illnesses, and patients with neurological illnesses or severe physical impairments, by analyzing their mental expressions and providing prompt and meaningful suggestions or medical care advice. Text, speech, body movements, and facial expressions may all be used to identify feelings, but instead an EEG gives a better result since it accurately captures actual feelings. Since EEG signals have a high potential for describing changes in brain state, EEG signal emotion detection has become a popular research subject. The EEG is a non-invasive method that has a high temporal precision. Insomnia treatment, gaming consoles, cyber-space, and e-learning, besides these areas, have benefited significantly from the rapid development of portable wearing devices, easy, inexpensive wireless headgear that monitor EEG and categorize their signals even without trained specialists.

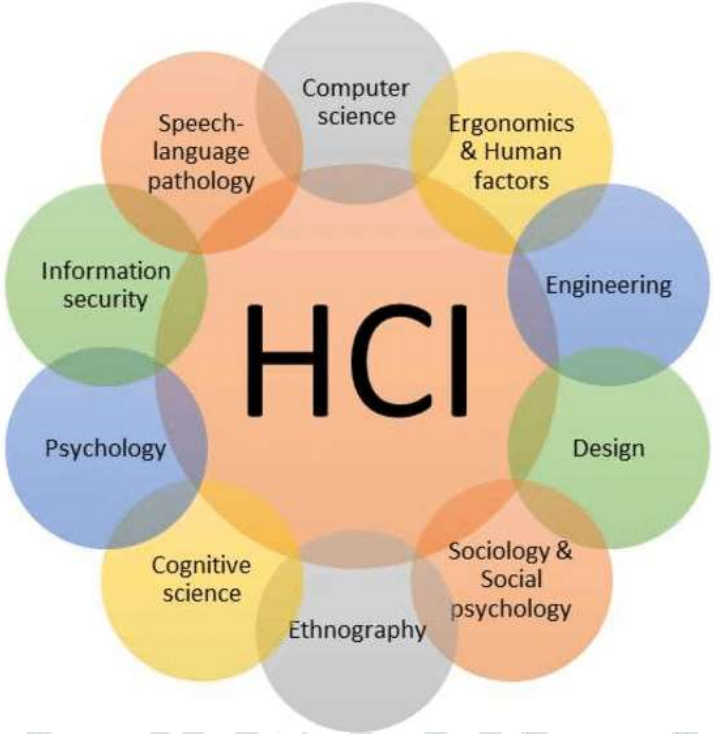

Figure 1: The Human-Computer Interactions and associated study areas are shown. [3]**.**

1.1. Emotions in the Brain:

As seen in Figure 2 the brain has a very complex structure. It regulates and controls everything in the body, from hand movements to pulse rate. The brain has an impact on how people regulate and assess their emotions. Even scientists aren't always clear how the brain plays a role in a variety of feelings, but they've figured out where fear, hate, pleasure, and love come from.

- Surprise is a feeling that may make us happy or sad based on how it is delivered. Surprisingly, the bilateral inferior frontal gyrus as well as the bilateral hippocampus is activated. Because the hippocampus is so closely linked to intellect, the emotion of surprise is inextricably linked to finding something you didn't anticipate or recall.
- Sadness is associated with a rapid increase in activity in the middle occipital lobe, left thalamus and insula, amygdala, and hippocampus. It's no surprise that the hippocampus is so closely connected to memory that recalling certain memories may make you unhappy. Antidepressant effects may be measured by better symptoms since depression can last a long period. Sadness has received much more research than any other emotion.
- The precuneus, right insula, right amygdala, and left frontal cortex, and a slew of other regions of the brain, are activated by pleasure. In this process, relationships between consciousness (the insula and frontal cortex) and the amygdala (the center of emotion) are involved.
- Anger is a powerful emotion that far too many people, both children and adults, want to control. The right hippocampus, amygdala, prefrontal cortex on the both sides, and insular cortex are all activated during anger.
- Fear anxiety activates the bilateral amygdala, hypothalamus, and regions of the left frontal cortex. This involves a lot of thinking (frontal cortex), a cognitive process (amygdala), and a sense of impending doom.
- Disgust is a peculiar emotion that is often associated with procrastination. This feeling is linked to the activity and connections of the left amygdala, left inferior frontal cortex, and insular cortex.

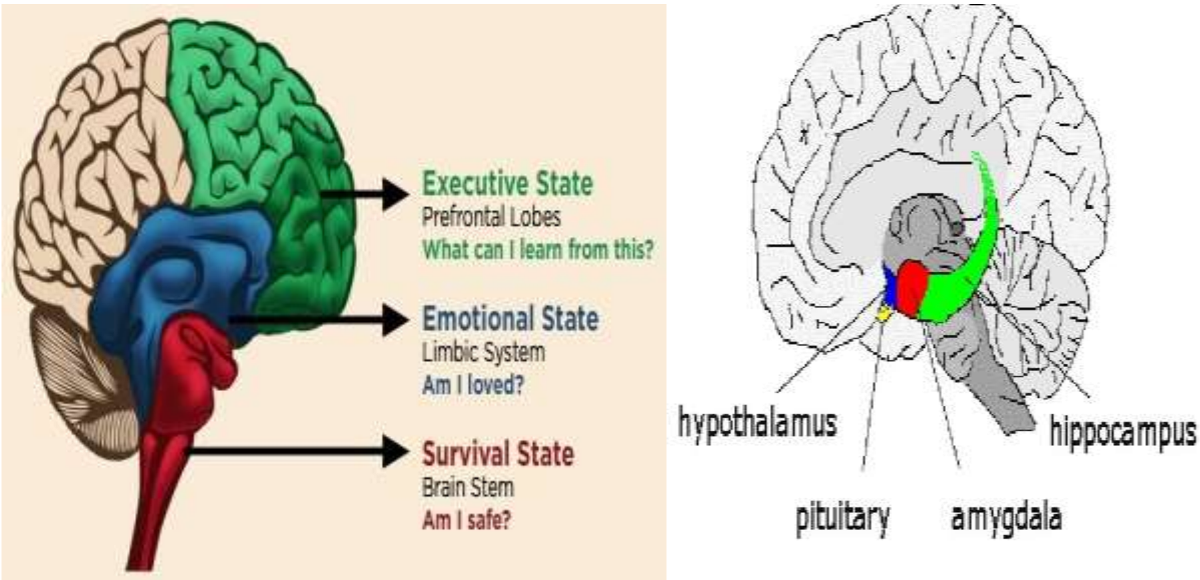

Figure 2: Labels the regions of the brain responsible for emotions are shown in this diagram.

1.2. Electroencephalogram (EEG):

An EEG is a technique for assessing the electrochemical properties of the central nervous by measuring and recording the brain's electrical impulses, as shown in Figure 3. Electrical impulses are used by areas of the head, particularly neurons, to interact with one another. Beta waves have a frequency of 15 to 30 Hz and appear in the frontal and parietal regions of the brain whenever there is a plenty of emotional function or thinking going on. Beta activity is related to motor action, and it usually decreases with fast movements. A re-entrant beta wave is represented by a wide-awake aware person. Gamma rhythms indicate the connecting of several groups of neurons in order to carry out certain muscle movements. The frequency spectrum of gamma waves is 30Hz–100Hz. Electrodes are unique sensors that are attached to your skull and are linked to a computer. It analyzes the characteristics of brain waveforms produced by electrical impulses in the nervous network and displays them as lines of waves on a display or even on parchment. The electrodes are implanted into the scalp and sent data to a computer, which monitors the findings. It creates a standard or known pattern for healthy brain activity, but the structure may be altered or unintelligible for abnormal brain activity.

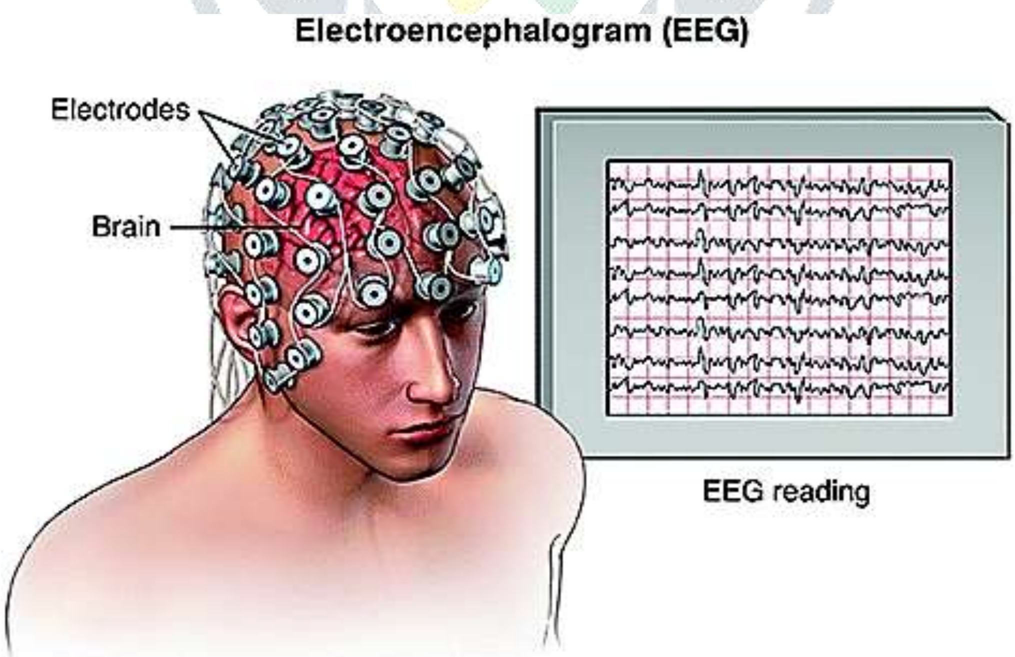

Figure 3: The typical electroencephalogram technique is shown. The electrodes are inserted into the brain and readings are obtained [4]**.**

1.3. A Few Alternatives:

Traditional emotion recognition methods rely heavily on external features such as face movements, body movements, and voice utterances. It is not necessary to wear equipment in order to obtain such impulses, which would have the advantage of being easy to obtain and cheap. Many researchers utilized the facial expressions of the individuals in the video to identify mood. The Naive Bayes method was utilized by many writers to identify joyful, surprise, anger, contempt, fear, sadness, and neutral emotions, among others. The accuracy rate of emotion detection between different people's facial gestures is 64.3 percent, while assessing the same person yields a 90.4 percent accuracy rate, implying that facial characteristics may be changed to effectively recognize emotions. The author combined auditory features with spoken words to identify emotion based on voice impulses.

A SVM network architecture is used to partition the six different feeling of anger, contempt, fear, neutrality, sadness, and surprise, with recognition precision of up to 93%. The results of this research confirmed the effectiveness of speech cues for emotion identification. Those indications, however, are very delicate, and they are easily affected by the investigator's psychological factors. The method has been unable to produce an appropriate evaluation when the participant's own real emotions and external actions are in conflict. Pure external function, on the other hand, is a subclass of emotive efficiency that is incapable of conveying the complex emotions of humans. Physiological changes are controlled by an individual's neurological system that might more accurately reflect a person's emotional state. As a consequence, utilizing human biological characteristics for emotion detection is now a hot topic in emotion computing research across the globe.

2. LITERATURE REVIEW

We'll go over some of the previous studies on common people's emotions in this section. Voice, body expressions, and physiological data have all been used to develop emotion classification systems. Despite their ease of detection, their ability to convey powerful emotions is limited. Since its creation, the EEG signal has been used in a significant number of studies, and psychological studies have used brain signals in a range of study topics during the last few decades. Weinreich et al. utilized an uncommon situation to identify changes in the frontal cortex's alpha frequency range [5].

The data is then used to create a classifier that can detect four different moods with a performance rate of 67.7%. Hidalgo-Munoz et al. studied the EEG signals of 26 females while they viewed emotional videos [6]. In this study, the valence-arousal paradigm was utilized to investigate emotions. In the processing step, they used Spectral Turbulence (ST), which was inspired by EEG research. The findings show that the left temporal lobe is very engaged during emotion elicitation. The authors examine the accuracy of different window sizes. The appropriate window sizes for arousal and valence are 3 to 10 & 3 to 12 seconds, correspondingly. Another author extracted spectral properties from 10 EEG channels, comprising wavelet coefficient energy and entropy. The greatest recognition rate using K Nearest Neighbor (KNN) was 84 percent for arousal and 86 percent for valence. The magnitude mean, average, standard deviation, variance, deviation, and confidence interval are among the temporal domain components examined by Kalaivani et al. [7].

Purpose was to identify the image regardless of its tone. In 16 channels, EEG data from 20 women and 8 men participants was recorded. Nasehi et al. utilized the Gabor function and the wavelet technique to extract harmonic, chronological, and spatial information from three EEG channels [8]. Using an artificial neural network (ANN) classifier, six kinds of emotions were identified with 64.78 percent accuracy. Reversion for the stimuli, a traditional 10 to 20 EEG internal equipment structure, as well as a self-assessment manikin's questionnaire to ensure the accuracy of the data gathered are all part of the study. The EEG signal resource in this investigation is the Database for Emotion Analysis using Physiological-signals (DEAP). The two models used to characterize emotion states are Ekman's six universal sentiments and Russell's circumplex model. Ekman's approach divides human emotion into six categories: anger, contempt, fear, happiness, sadness, and surprise. Russell's circumplex model uses a 2D plane to represent emotions. The arousal level is displayed on the y axis, while the valence is assessed on the x plane. Some ideas have been used in research based on their methodology. On the research, emotional states are depicted in a two-dimensional surface with four quadrants. The second module, feature extraction, defines the project's target types. It's essential to remember that data segregation is a necessary step because EEG signal recording may take a long time. Ishino et al. utilized Power Spectrum Densities (PSDs), wavelet parameters of EEG data to calculate mean and variance [9].

3. METHODOLOGY

3.1. Design:

The entire flow of our study is shown in the proposed paradigm in Figure 4. The data for this research was preprocessed after the EEG readings were collected. After then, the key determinants were utilized to select bands with certain frequencies. After that, suitable features were gathered and selected for use in the classifier. Finally, a classification known as SVM was used to classify the selected attributes.

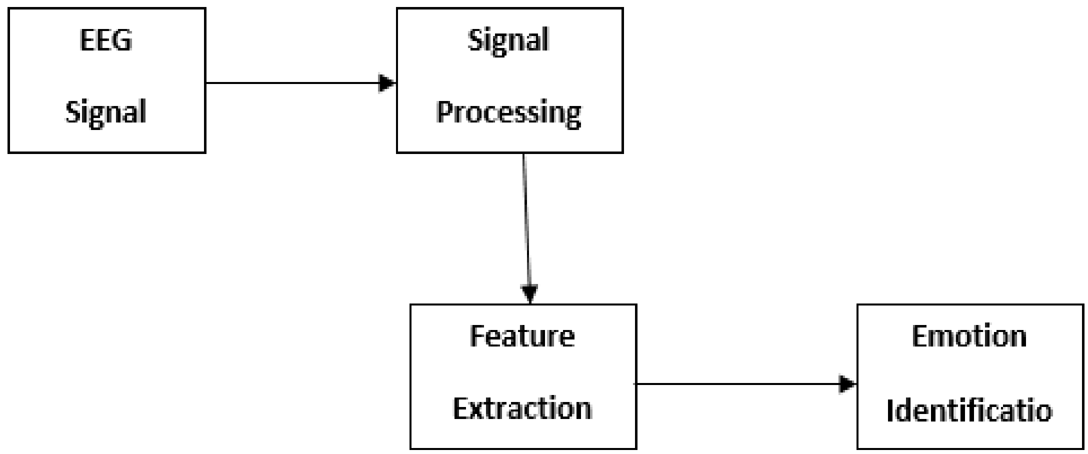

Figure 4: The flowchart depicts the suggested approach.

3.2. Data Gathering:

The DEAP repository was used in this study [10], which is an analysis of information for emotion identification using biological characteristics and is classified using the valence-arousal-dominance feeling paradigm. The DEAP dataset has 32 individuals. Individuals were given one-minute films with music to engage their visual and auditory brains. EEG was used in this study, and further information may be obtained on their website. Each participant was shown 40 movies, and seven different modalities were recorded. The length of the 40 movie pieces was selected to suit within the scope of the project. On a scale of 1 to 9, each respondent was asked to evaluate each short video on valence, arousal, dominance, and liking. As a consequence, the arousal or valence label is substantial if the score is more than 4.5, and low if the value is much lower, i.e., less than 4.5. At a sampling rate of 512 Hz, all of the signals were recorded.

3.3. Data Analysis:

3.3.1. Processing of the Signal:

The source is re-sampled at a 128 Hz sampling rate. With a lower sample frequency, computing feature values takes less time. Because eye motion is the primary source of noise, electrooculography (EOG) is therefore not anymore utilized. A bandpass filter was employed to remove noises that were below 4 Hz or larger than 45 Hz. To reduce electromagnetic amplification, power line, and exterior interfering noise, the average mean reference (AMR) method was employed. For each selected channel, the average is calculated and subtracted from each observation inside the channel. The noise-free EEG data is used to construct a 60-second time frame. The extraction features process would be applied to all parts, with 30% of the segments entering into the classifier's information foundation and 70% moving into the classifying job.

Data regarding emotions is mainly retained in the frontal lobes areas of the brain, according to previous studies. Furthermore, researchers focused on Fp1, F3, F7, FC5, FC1, Fp2, Fz, F4, F8, FC6, and FC2 channels, which are connected to the frontal lobe of the brain, in order to minimize computational costs for the proposed method. Due to the difficulties in altering the data to suit our requirements, creating a classifier and characteristics from an array took a long time. As a consequence, the pre-processed data was split into 40 records, each of which represented a distinct DEAP data collecting video clip. Each video contained an array of 8064x352 pixels, with rows indicating data length and columns determining the maximum number of channels for said 32 participants.

3.3.2. Feature Extraction:

The discrete wavelet transform (DWT) was employed to extract characteristics from windowed EEG recordings of the selected channels for its outstanding multi-resolution skills in the assessment of non-stationary signals. The EEG data is windowed to improve the likelihood of rapidly identifying emotional states. The db4 function, also known as the mother wavelet function, is used to separate theta, alpha, beta, gamma, and sounds from EEG data. The entropy and energy of the each frame of each frequency spectrum were then extracted. As illustrated in Figure 5, each film was categorized into one of four emotional quadrants.

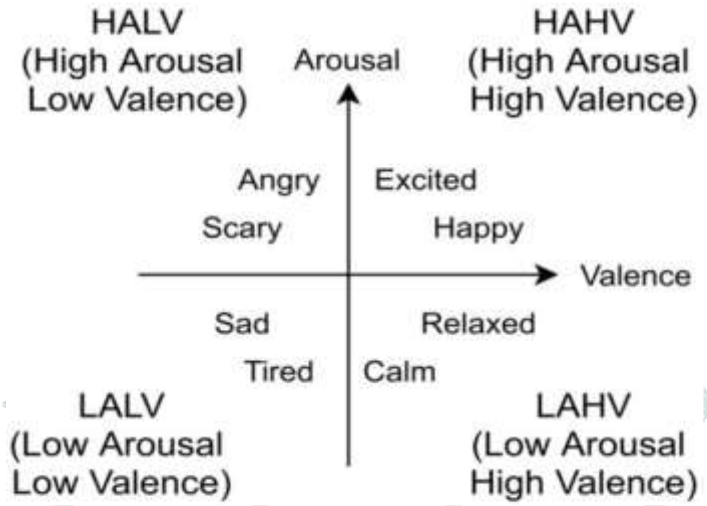

Figure 5: The Arousal-Valence Model's four quadrants are shown.

Four video files comprising only the mean of the acquired bands were generated after selecting the films by sector and combining the groups of nearly every one of the films out of each quadrant. The aforementioned band frequencies were also tweaked so that certain large band harmonics had minimal impact on the classifiers. Just after band harmonics were converted, the source signal's characteristics were restored. We developed the statistical features lower threshold, maximum bound, unpredictability, variance, entropy of wave, and energy bandwidth for our study depending on the location or standard error, the dissemination or spread, and the form of the distribution.

3.3.3. Classification of Emotions:

Many studies on machine learning techniques have been conducted, with SVM being among the most efficient classifiers for classifying emotions. The basic idea behind the SVM is to constantly identify a decisive hyper plane to split knowledge or input into 2 categories. To determine the optimum hyperplane for differentiating two classes, the paths between the nearest data points of both categories, and also the hyperplane, have been maximized. The classification procedure includes predicting a confusion matrix model by splitting the data samples into a training dataset and a test data for testing and training, correspondingly, using the k-fold back propagation technique. This technique randomly divides the dataset in k equal subgroups and then repeats the procedure. Every time, a selection of the k subsamples is used as the testing dataset, while the remaining k-1 subgroups are merged to form a training dataset.

4. RESULTS AND DISCUSSION

In order to build the ambiguity decision matrix in our research, several types of features were used to train and evaluate the Classification algorithm. The framework and k-fold validation data were then used to evaluate the capacity. The parameters, kernel, and normalization that were utilized to integrate SVM utilizing 10-fold cross-fold assessment were chosen using the grid-search method. The “libsvm” package has been used to create SVM, which is a popular SVM framework. To obtain a decent outcome, it was not easy to categorize the statistical features. Because the initial tests had unsatisfactory results, numerous variables had to be considered before a choice could be made. In this study, 10-fold cross verification was coupled with a classification algorithm that included an SVM decoder and a technique for determining normalization and kernel parameters. The technique was used to test the effectiveness of the categorization method using a k-fold classifier. The accuracy equation is as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100$$

Where,

TP: the number of true positive

TN: the number of true negative

FP: the number of false positive

FN: the number of false negative.

Table 1: The average categorization accuracy at various kernels k1 through k5 is shown.

Kernel (k)	Accuracy (%)
k1	83
k2	85
k3	92
k4	80
k5	88

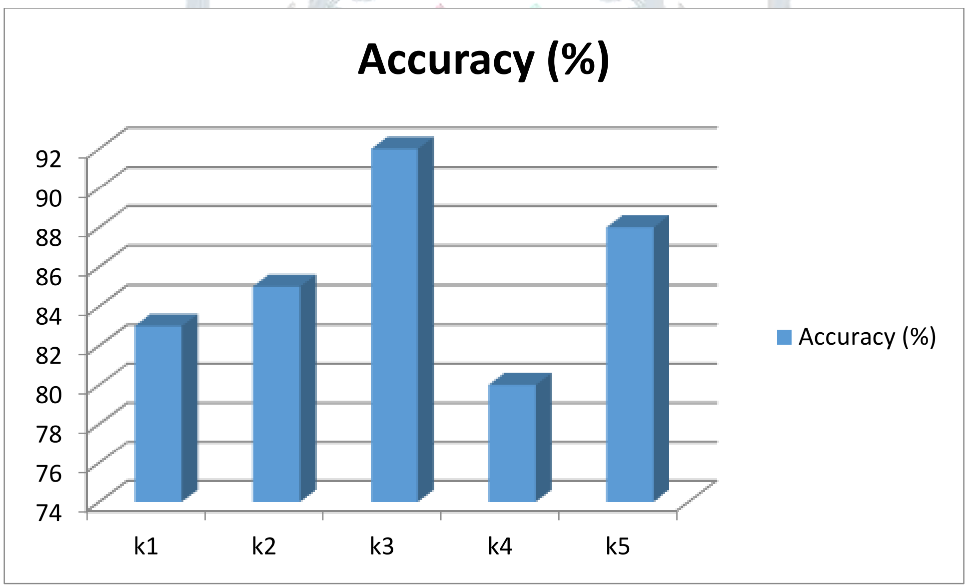

Figure 6: Shows a graphical depiction of accuracy when various kernels are used.

Table 1 shows the variation in recognition rate for various kernels of the Classification model for the dataset in question. K4 classifiers have had the lowest categorization accuracy when contrasted to other kernels. As demonstrated in Figure 6, the kernel k3 has the greatest categorization accuracy of 92 percent.

5. CONCLUSION

The research presents a novel idea for an EEG-based sentiment classification system. Using the DEAP dataset as input data, three variables are computed: comparative waveform energy, comparative waveform entropy, and a novel parameter, a mixture of standard deviations and discrete wavelet transform coefficients. With the aim of enhancing prediction performance, an SVM Classification technique is also developed. As a result, the package that combines all three qualities produces the best accuracy. It suggests that the categorization system may be able to enhance the emotion detection system over time.

Different individuals may be considering various subjects. Other thoughts and cognitive functions may nevertheless have a substantial effect on people's brain activity even when they are encouraged to experience a particular feeling. The use of music or visual data to trigger sentiments in a person's mind is possible. To enhance noise or artefact reduction performance, further techniques may be used. Improved feature extraction and classification techniques may be employed in the future. The work may be improved to incorporate functions such as mental state recognition, operating devices such as an automated music player depending on the user's feelings, and so on. In the future years, the classification technique might have been tweaked to produce a higher accuracy utilizing the customized tailor kernel function. Other computational combinations may be attempted as well.

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