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-RESEARCH ARTICLE-

Determination of the 25th Frame with the Eeg Signals Stored in the Videos

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Abstract

Nowadays, the videos that appear in every part of our lives are a set of images resulting from the sequential addition of a series of image files. One second of the video is the result of the merging of 24 picture frames. The visual subliminal perceives 24 frames per second. It is difficult to see hidden pictures in the frames of videos which is called the 25^{th} frame effect. In this study, electroencephalogram (EEG) signals are analyzed and it is aimed to determine whether or not the 25^{th} frame effect is perceived by the brain. For this purpose, 6 different videos were shown to 50 participants. The participants watched videos which are contain a raw and 25^{th} frame effect. And EEG signals were recorded by Emotive Epoc+. Statistical feature extraction algorithms were applied to EEG signals. K-nearest neighbor (KNN) classifier and Naive Bayes(NB) classifier, were used for classificstion. Training was performed by applying the k-fold cross validation. The KNN classifier's performance are as follows; overall accuracy of 96.60%, recall of 98.00%, F1 score of 96.50%, precision of 95.29%. The NB classifier's performance are as follows; overall accuracy of 92.00%, recall of 92.00%, F1 score of 92.20%, precision of 92.00%.

Keywords:
Electroencephalography Signals, Brain Computer Interface, 25^{th} frame, Subliminal Messages.

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Introduction

A video is called a series of images resulting from the sequential addition of a series of images. The number of images displayed in 1 second of a video is called frame per second (fps) (Davis et al., 2015 ; Özcan et al., 2015). A one-second video has been composed by 24 frames. However, if the video has the 25^{th} frame, the viewer could create it at the level of consciousness and works in

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his subconscious. In the literature, this situation, which is called the 25th frame effect, is usually used by advertising companies to influence the viewer through subliminal message delivery (Vokey, 2013; Karremans et al., 2006; Küçükbezirci, 2013).

The Radio and Television Supreme Council (RTÜK), which provides control of television broadcasts in Turkey, stipulates that subliminal advertisements of this type should not be allowed. Consciousness is the moment of awareness in people. At the level of consciousness, perception is open and emotions are felt. The subconscious is another structure consisting of movements, thoughts and behaviors in the state of consciousness. Movements in the state of consciousness directly affect the subconscious (Florea, 2016).

The aim of this study is to determine if the brain perceives the hidden pictures in the videos that are thought to affect people's subconscious. The signals were recorded using the Emotiv EPOC + device, which is mounted on a wireless hood and is connected to the computer via Wi-fi. Two of the 16 channels of the Emotiv EPOC + device are used as reference points. The Emotiv EPOC + device is non-invasively attached to the scalp, allowing electrode information from the brain.

Electroencephalogram (EEG) recordings can be used for observing the changes of human emotions in brain signals (Altan et al., 2016). EEG signals are widely used in emotion estimation applications In the mid-90s, people began to teach emotion estimation to machines. Hans Berger was the first to associate EEG signals with sleep. The first EEG-based classification was made in 1937 by Loomis and his assistants (Williams et al., 1974).

There are many studies in the literature about the effect of EEG signals on emotions. In the studies, emotion analysis and classification process were used for different types of stimuli using EEG signals and facial expressions (Murugappan et all., 2008 ; Soroush et al., 2018; Daşdemir et al., 2017 ; Atasoy et al., 2014). Emotions are reflected in body language, facial expressions, voice tones. For this purpose, the participants evaluated the audio-visual stimuli. Accordingly, EEG findings were classified according to their positive and negative conditions. (Soleymani et al., 2016 ; Liu et al., 2010 ; Özerdem & Polat, 2016). Emotions are expressed by music, tone, voice, facial expressions, gestures. Music videos are also used for observing the emotional effects. Participants have rated each video in terms of the levels of arousal, valence, like/dislike, dominance, and familiarity by The bodily reactions of the user have been translated into EEG signals (Koelstra et al., 2012). In another study, the participants were listened to unpleasant sounds and EEG recordings were recorded. As a result, it was observed that spontaneous mimic movements increased during the application of unpleasant sounds (Grunwald et al., 2014). In some studies, it has been examined how brain performance is affected by music, picture and meditation by analsing EEG from the patients wtih psychological trauma or chemotherapy treatment (Bhattacharya & Lee 2016 ; Tan et al., 2014; Fidan & Özkan 2018). In a study, classification was performed by EEG signals for the diagnosis of epileptic diseases (Acharya et al., 2011).

With the development of emotion recognition studies, the neuromarketing sector has been emerged. With the transfer of the data obtained in neurological research to the marketing discipline, the field of neuro-marketing has emerged. Studies are integrated into this field. The effect of advertising, brand selection and product design on the brain was investigated. By analyzing at the EEG signals of consumers, it was investigated how they gave the purchase decision and which marketing tools were affected. Neuromarketing has focused on how advertising and marketing stimulates nerve centers in the brain (Wang et al., 2018 ; Yücel & Coşkun 2018). As a matter of fact, EEG signals while watching the advertisements were recorded and emotional reactions were examined (Elden, 2009). As a result of analysis on EEG, studies were conducted to detect the likes of the brands that they have seen in television commercials (Custdio, 2011).

Material and Methods

The study was carried out in three stages as data acquisition, feature extraction and classification respectively. Figure 1 shows the working flow chart.

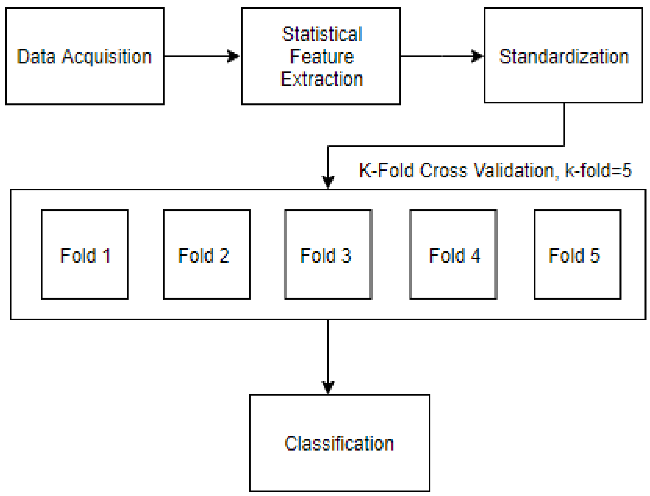

Figure 1. Flow diagram of the study.

Data Acquisition

In this study, six different videos including animal, plant and nature themes were prepared. These videos are divided into frames. Pictures are added to be randomly positioned between the frames. Frames are reassembled to form a new video with hidden pictures. As a result of the videos composed, the participants were shown two types of videos: original video and video with hidden pictures. Figure 2 shows the frames of the video. Figure 3 shows the case of adding hidden pictures to frames.

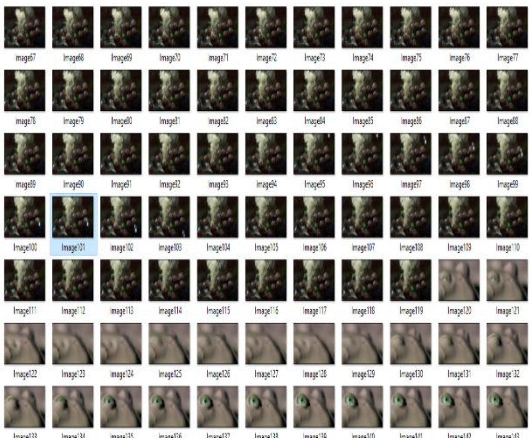
Figure 2. Frames of the video

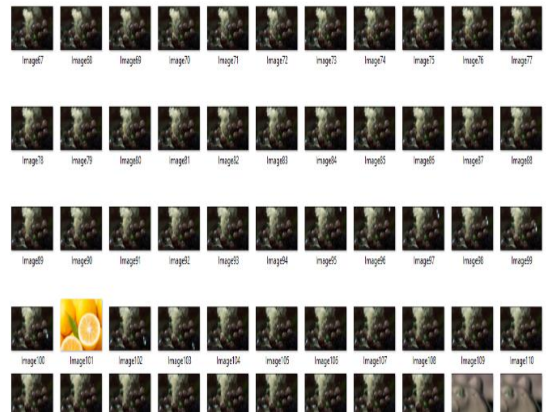
Figure 3. Adding hidden pictures to frames

Emotiv EPOC+ is a 16-channel EEG data device which has a sampling frequency of 128 Hz. Constructed videos for the participants has 15 seconds duration. A total number of 600 EEG recordings were collected on 50 participants following the viewing of 6 different videos with both raw and 25th frame effects. The EEG signals were recorded in a silent and light isolated room. The participants were selected from the students which are 19-26 years old and university staffs on the basis of the ethics report and the necessary permissions on the basis of volunteerism. The sensors of Emotiv EPOC+ do not receive high-quality signals from long-haired participants. Therefore, male participants were used. The mean age of the participants was 23.20 and the standard deviation was 2.338672. Figure 4 shows the EEG signals with 25th frame effect video. Figure 5shows the EEG signals with raw video in random channel.

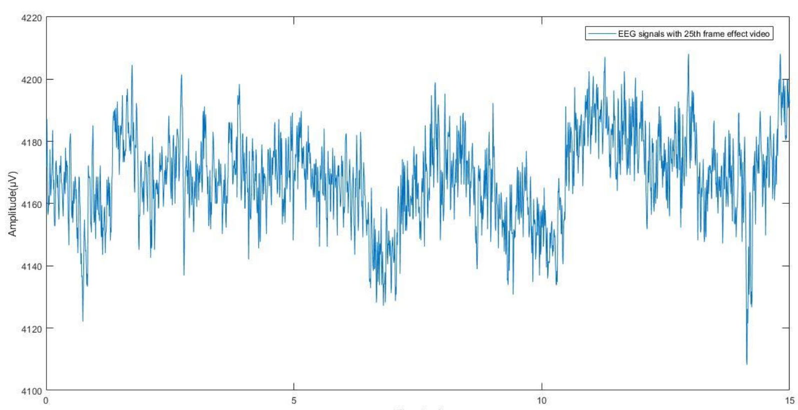

Figure 4. EEG signals with 25th frame effect video of one person

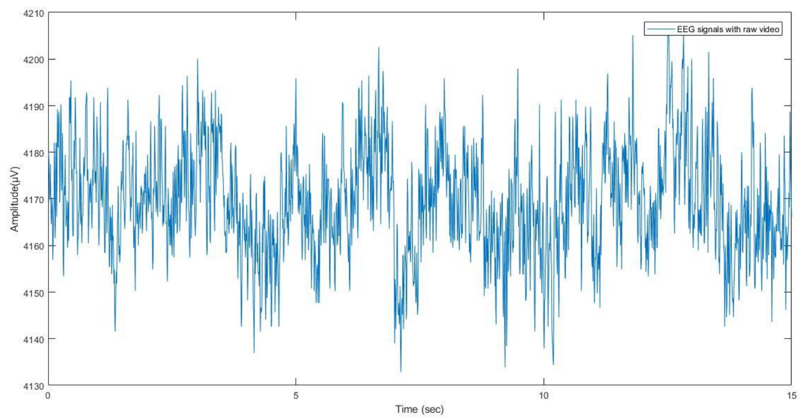

Figure 5. EEG signals with raw video of one person

The brain is divided into sub-regions that handle different roles. The EEG device provides the possibility to receive signals from related areas of the brain in these areas. The occipital lobe, which is the posterior part of the brain, is responsible for visual perception. The frontal lobe, which is the front part of the brain, is responsible for creativity, problem solving, decision-making and planning. The parietal lobe, which is the side part of the brain, is responsible for high perception and language ability. The temporal lobe of the brain is responsible for hearing and memory abilities. Figure 6 shows these sub-regions which have related to different abilities. Since the EEG signals are collected with electrodes placed in the scalp, the region in which each sensor is placed is of great importance for the analysis of signals and positioned by a system called 10-20 system positioning. Figure 7 shows the sensor position of these EEG electrodes.

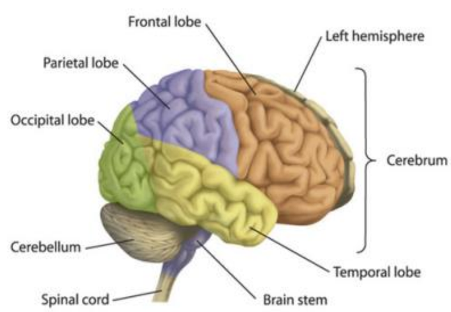

Figure 6. Left and right symmetrical hemispheres of longitudinally divided brain structure (Duarte,2017)

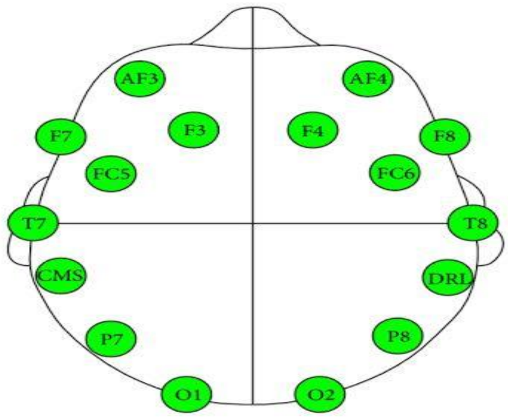

Figure 7. Sensor position of EEG electrodes for Emotiv EPOC + systems (Wang et al., 2014)

Feature Extraction

In the feature extraction stage, 10 different statistical features were calculated from raw signals including difference between maximum and minimum values, mean, median, standard deviation, power, variance, energy, kurtosis, skewness, interquartile range value. The features which are calculated from raw and 25 frame effects videos are shown in Figure 8. Each value in the x-axis represents features. The y axis in the graph is the amplitude values of the feature. Table 1 shows the numbers and frequency values represented by the names of the feature.

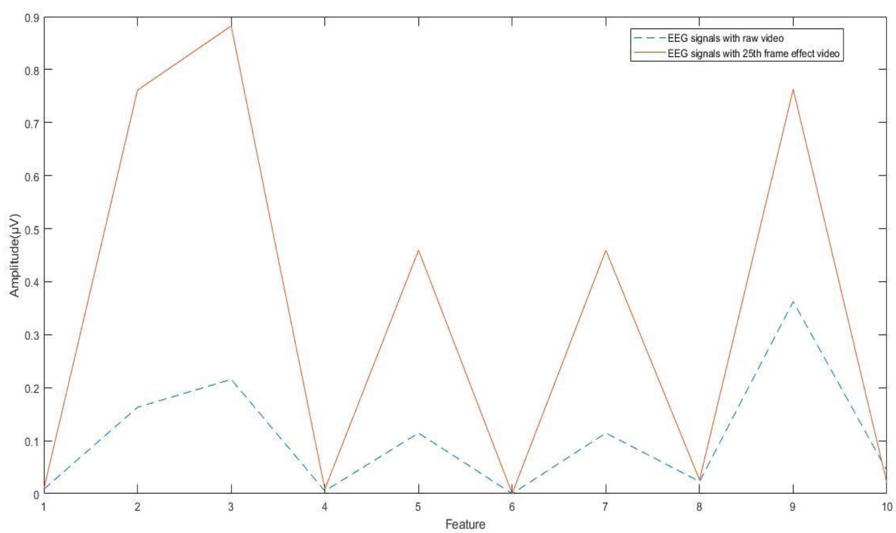

Figure 8. The feature of EEG signals with raw video and 25th frame effect

Table 1. Numbers and amplitude values represented by the names of the features.

Features	Amplitude of EEG signals with raw video	Amplitude of EEG recordings with 25th effect frames
Difference between maximum-minimum	0,008537	0,008608
Mean	0,163005	0,761194
Median	0,215715	0,882353
Standard deviation	0,005072	0,008683
Power	0,114452	0,459141
Variance	0,000113	0,000312
Energy	0,114453	0,459141
Kurtosis	0,022925	0,025955
Skewness	0,362387	0,762613
Interquartile Range	0,043651	0,020248

For KNN and NB classifiers, Median, Skewness and Mean value features were exprienced as the most to be more successful features. Median is taken into account in cases where deviation or endpoints are affected by the distribution of data. Since EEG signals are variable data endpoints have an effect on signals (Türk & Özerdem, 2017). The median feature, which is more resistant to noise and outliers, showed the highest success. At the same time, the median value was found to be consistent. Skewness selects a central point in the signal and checks if the signals to the right and left of this point are the same. If it is the same, it is concluded that the data is symmetrical (Alpaslan et al., 2015). The symmetry is inversely proportional to the skewness. Since the EEG signal are non-symmetrical, this feature gave high success. The average values of EEG signals of videos containing the 25th frame effect were higher than the EEG signals of raw videos. Therefore, the mean value was a distinctive value for the classifier. The formulas of the features are shown in Table 2. Where, x_n= *1, 2, 3 … n* is a time series, *N* is the number of data points, *AM* is the mean of the sample.

Table 2. Formulas of features

Names of Features	Formula	Names of Features	Formula
Maximum Minimum Values Difference	$MaxV = max[x_n]$ $MinV = min[x_n]$ $max[x_n]$-$min[x_n]$	Variance (V)	$V = \frac{\sum_{n=1}^{N} x_n - AM^2}{N-1}$
Mean(AM)	$AM = \frac{1}{N}\sum_{n=1}^{N} x_n$	Skewness (S)	$S = \frac{\sum_{n=1}^{N} x_n - AM^3}{(N-1)SD^3}$
Median(MN)	$MN = \left(\frac{N+1}{2}\right)^{th}$	Kurthosis (K)	$K = \frac{\sum_{n=1}^{N} x_n - AM^4}{(N-1)SD^4}$
Standard deviation(SD)	$SD = \sqrt{\frac{\sum_{n=1}^{N} x_n - AM^2}{N-1}}$	Power(P)	$P = \lim_{N\to\infty} \frac{1}{N}\sum_{n=0}^{n=N-1} \lvert x_n^2 \rvert$

Interquartile Range(IQR)	$IQR=Q_3-Q_1$ $Q_1=\left(\frac{N+1}{4}\right)^{th}$ $Q_3=\left(\frac{3(N+1)}{4}\right)^{th}$	Energy(E)	$E=\int_{-\infty}^{\infty}\lvert x_n\rvert^2$

Classification

During the classification stage, the EEG signals from raw and 25th frame effect videos were compared. There are lots of classification methods but in this study two of them are used. First, k classification methods, the nearest neighbor (KNN) classifier and the other is Naive Bayes classifier (NB), a linear classifier. A major disadvantage in calculating distance measurements from the direct training set is that the variables have different measurement scales. Therefore, the fetaure is standardized before classification stage. So all values have become values close to each other. The formula of standardization process is shown in Eq.(1).

$$X_s=\sum_{i=1}^{N}\frac{X_i-X_{min}}{X_{max}-X_{min}} \quad (1)$$

K- Fold Cross Validation

K-fold cv divides the dataset into k folds. The first (training set) is used to determine the model parameters of the classifier, while the other (test set) is used to measure the performance of the trained classifier (Duda et al., 2012).

In a data set with a total number of n samples, the k-part verification method is divided into separate discrete parts, each with n / k. Each time a different set of data sets is left for testing, the remaining k-1 data set is used for training. By changing the test set of the classifier 'k' times training is done. The average of the 'k' errors obtained in this way is estimated by the classifier performance. In addition, diversification of data into training and testing sections is ensured (Altan et al. 2019; İşçimen et al., 2014). In this study, 5- fold cross validation method was used. An equal number of samples are available in each of the five allocated data sets to provide homogenity in distribution.

K- Nearest Neighborhood Classification

K- nearest neighbor (KNN) classifier is a distance based classifier used for the classification process. It compares a particular unidentified test data with training data that are available in an ndimensional space and the calculated distance measure is used for measuring the nearness of data values(Vimala et al., 2019). The basis of the KNN method, which is a popular classification algorithm, is to give new unclassified examples to the class of the majority. The advantage of the KNN is that it can easily overcome the problems which high number of classes using simple mathematical solutions. Its purpose is to classify existing learning data when a new sample is available. When the algorithm arrives, a new instance looks at its closest 'k' neighbor to decide its class, for example (Yıldız et al., 2008). KNN focuses on the closest training examples in the feature space (Bahari & Janghorbani, 2013).

In the KNN algorithm, the value 'k' must be determined first. Once the value 'k' has been determined, the distance from all learning samples must be calculated using ascending sortings.

After sorting, it is found which class value it belongs to. Here, determining the value of 'k' means how many values should be considered closest to us (Yağanoğlu et al., 2014). The nearest k neighbor algorithm takes into account the distance between the test and the training data (Piotrowski & Szypulska, 2017). In the study, 'k' value is taken as 3. In this case, it was decided that the nearest 3 of the data in the learning set was taken and which class belonged. The method uses Euclidean distance in calculating distances. The Euclidean method is the most commonly used distance measure in classification and clustering algorithms. Euclidean method is shown in Eq.(2) .

$$d = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (2)$$

'x' represents the data entry classified, 'y' represents the training set data, 'n' is the number of the data set. Euclidean measure is calculated according to the equasition 'x' to measure the linear distance C= $(x_1, x_2, x_3 \dots x_n)$ and D= $(y_1, y_2, y_3 \dots y_n)$ between two points in space (Kresse & Danko, 2012; Eraldemir et al., 2017).

Naive Bayes Classification

Thomas Bayes, the pioneer of Bayes' theorem named Naive Bayes(NB) which predicts the probability that the samples belong to classes. NB argues that features do not affect each other. Each feature has the same importance in itself (Kutlu & Köse 2014). Bayesian classifiers are statistical classifiers that predict class membership possibilities. Estimations of the probability of the training data are calculated by Bayesian classifiers (Bhattacharyya et al., 2011). The NB classifier requires less training data than the others for classification (Sharma,2017). The NB classifier assumes that the existence of a particular property of a class is not related to the presence of another property. Depending on the exact nature of the probability model, the NB classifier can be trained very efficiently in a supervised learning environment (Wang & Zhang 2016).

The probability of generating the d instance of the cj class represented by n feature is shown in Eq.(3) . The Bayes' theorem is given in Eq.(4) .

$$p(d|c_j) = p(d_1|c_j) * p(d_2|c_j) * \dots * p(d_n|c_j) \quad (3)$$

$$p(c_j|d) = \frac{p(d|c_j)p(c_j)}{p(d)} \quad (4)$$

Results

The aim of this study is to determine if the brain perceives the hidden pictures in the videos that are thought to affect people's subconscious. Signals were recorded using the Emotiv EPOC + device. Within the scope of the study, 50 participants watched 6 different videos include raw and 25th frame effect. The EEG signals are recorded as a result of viewing videos containing the raw and 25th frame effect. Statistical features from each EEg signals were calculated. Classification was performed to compare the EEG signals of videos containing the raw and 25th frame effect using KNN and NB. Training was provided by applying k-fold cross validation method. The learning sample numbers (k) of the KNN classifier were tested as 1,3,5,7,9. The cross validation fold was processed as 5 in both classifiers.

In this study, the performance for each feature in the system were calculated. KNN classifier has achieved overall accuracy rates of; 78.80% for the Maximum Minimum Values Difference, 95.00% for the Mean, 96.00% for the Median, 83.20% for the Standard Deviation, 95.20% for the Power, 78.00% for the Variance, 94.40% for the Energy, 78.40% for the Kurtosis, 97.00% for the Skewness, 86.40% for the Interquartile Range. Table 3 shows the success of the features using the KNN classifier with different k values.

Table 3. The success of features using the KNN classifier

Distance metrics	**k=1**	**k= 3**	**k=5**	**k=7**	**k=9**	**Achievement Averages**
Maximum	77.00%	83.00%	77.00%	79.00%	78.00%	78.80%
Mean	95.00%	95.00%	95.00%	95.00%	95.00%	95.00%
Median	95.00%	97.00%	95.00%	97.00%	96.00%	96.00%
Standard Deviation	78.00%	85.00%	84.00%	86.00%	83.00%	83.20%
Power	96.00%	95.00%	95.00%	95.00%	95.00%	95.20%
Variance	76.00%	78.00%	81.00%	79.00%	76.00%	78.00%
Energy	93.00%	95.00%	94.00%	95.00%	95.00%	94.40%
Kurtosis	80.00%	80.00%	82.00%	78.00%	72.00%	78.40%
Skewness	94.00%	97.00%	98.00%	98.00%	98.00%	97.00%
Interquartile	77.00%	87.00%	89.00%	88.00%	91.00%	86.40%

NB classifier has achieved overall accuracy rates of; 57.00% for the Maximum Minimum Values Difference, 93.00% for the Mean, 95.00% for the Median, 60.00% for the Standard Deviation, 92.00% for the Power, 48.00% for the Variance, 92.00% for the Energy, 57.00% for the Kurtosis, 86.00% for the Skewness, 68.00% Interquartile Range. Table 4 shows the success of the features using the NB classifier.

Table 4. The success of features using the Naive Bayes classifier

Values Difference	%
Mean	93
Median	95
Standard Deviation	60
Power	92
Variance	48
Energy	92
Kurtosis	57
Skewness	86
Interquartile Range	68

Median, Skew and Mean value features are the most successful for both classifiers. There is a deviation in the distribution of EEG data. In addition, the effect of endpoints is large. In such cases, the median value is taken into account. Skewness is the measurement of the non-symmetrical probability distribution of the random variable. Therefore, the non-symmetrical values of the EEG signals gave high values for this feature. The average values of EEG signals of videos containing the 25th frame effect were higher than the EEG signals of raw videos. Therefore, the mean is a distinctive value for the classifier.

KNN classifier for all features has achieved overall accuracy rates of; 94.50% for the overall accuracy, 97.20 %for the recall, 95.49% for the F1 score, 94.19% for the precision. Table 5 shows the overall achievement for the KNN classifier.

Table 5. Performance achievement of the KNN classifier on all features

Distance Metrics	**k=1**	**k= 3**	**k=5**	**k=7**	**k=9**	**Achievement Averages**
Overall accuracy	92.00%	95.00%	96.00%	98.00%	96.00%	94.50%
Recall	92.00%	98.00%	98.00%	100.00%	98.00%	97.20%
F1 Score	91.87%	95.14%	96.18%	98.09%	96.17%	95.49%
Precision	92.36%	92.54%	94.85%	96.36%	94.84%	94.19%

NB classifier for all features has achieved overall accuracy rates of; 83.00% for the overall accuracy, 83.00% for the recall, 83.40% for the F1 score, 83.05% for the precision. Table 6 shows the overall achievement for the NB classifier.

Table 6. Performance achievement of the Naive Bayes classifier on all features.

Overall accuracy	83.00%
Recall	83.00%
F1 Score	83.40%
Precision	83.05%

The best 5 features have been selected to improve system performance. These features are; Median, Skewness, Mean, Power, Energy Values. KNN and NB classification was applied to these selected features. As a result, the performance of the system increased in both cases. KNN classifier for high successful features has achieved overall accuracy rates of; 96.60% for the overall accuracy, 98.00% for the recall, 96.50% for the F1 score, 95.29% for the precision. Table 7 shows the performance of the KNN classifier on high successful features.

Table 7. Performance achievement of the KNN classifier on high successful features.

Distance Metrics	**k=1**	**k= 3**	**k=5**	**k=7**	**k=9**	**Achievement Averages**
Overall accuracy	97.00%	96.00%	96.00%	97.00%	97.00%	96.60%
Recall	98.00%	98.00%	98.00%	98.00%	98.00%	98.00%
F1 Score	97.04%	96.17%	96.19%	97.04%	96.09%	96.50%
Precision	96.18%	94.84%	94.54%	96.36%	94.55%	95.29%

NB classifier for high successful features has achieved overall accuracy rates of; 92.00% for the overall accuracy, 92.00% for the recall, 92.20% for the F1 score, 92.00% for the precision. Table 8 shows the performance of the NB classifier on high successful features.

Table 8. Performance achievement of the Naive Bayes classifier on high successful features.

Overall accuracy	92.00%
Recall	92.00%
F1 Score	92.20%
Precision	92.00%

Discussion

As a result, EEG signals of videos containing the 25th frame effect were found to differ between the EEG signals of raw videos. Some of the images in the videos we watch can pass at the speed that our eyes cannot detect. In this case, the frames we see without awareness may affect our subconscious. If this event is detected, it is possible to turn the situation in our favor. The 25th frame effect in the videos can be determined by looking at the EEG signals of the participants watching the videos.

For both classifiers, Median, Skewness, Mean, Power, Energy Values features have shown high success. The values were reclassified with the selection of the best features. As a result, the success rate for both classifiers increased. There is a deviation in the distribution of EEG data and that showed why the median feature is successful in EEG data. Skewness is the measurement of the non-symmetrical probability distribution of the random variable. The fact that the EEG signals do not have a symmetrical structure increased the success of the Skewness feature. The concept of variance relates to how far each value of the distribution is from the average of the distribution. Since EEG data did not have a normal distribution, high success was not obtained from the variance feature.

KNN and NB classifiers were used in the study. KNN classifier has been found to improve performance according to NB classifier. The learning example of the KNN classifier was tested with different numbers. The number of best learning examples was determined as 3 and 7. In the cross-validation method, it was observed that the performance of the classifier decreased as the number of folds increased.

Detecting the 25th frame in the videos provides awareness of the circumstances affecting the subconscious. With this study, it is possible to eliminate the conditions that negatively affect the subconscious. İf it is considered the videos which are watched effect the subconcious, it is possible to use this feature in a possitive way.

EEG signals are very sensitive to noise. Therefore, the signals need to be filtered and processed in the first stage. The future work of the study will be developed by trying different filtering processes and classification methods.

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