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A New Approach for Enhancing Human Emotion Recognition from Electroencephalogram Signals Based on Discrete Wavelet Packet Transform

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Abstract. This paper presents a promising approach to enhance emotion recognition from electroencephalogram (EEG) signals by tackling the issue of outliers in the Discrete Wavelet Packet Transform (DWPT) decomposition tree. The proposed method, called Nearest-Neighbor Grubbs DWPT (NN-Grubbs-DWPT), combines nearest neighbor replacement and Grubbs' test to accurately identify and remove outliers in the DWPT decomposition tree, leading to improved quality of the extracted features and overall classification performance. The effectiveness of the NN-Grubbs-DWPT method was evaluated on two sub-datasets of the DEAP database, where the extracted features were classified using the LSSVM classifier, resulting in the classification of nine different human emotions. Our experimental results show that NN-Grubbs-DWPT outperforms the original DWPT method regarding multiple evaluation criteria, including precision, AUC, and F-score. Additionally, the NN-Grubbs-DWPT method achieved superior maximum and mean valence and arousal accuracies compared to the original DWPT algorithm. These promising results underscore the importance of addressing outliers in EEG signal processing and suggest that the NN-Grubbs-DWPT method can significantly enhance emotion recognition accuracy in practical applications of emotion recognition systems.

Keywords: Emotion Recognition; Electroencephalogram Signals; Discrete Wavelet Packet Transform; LSSVM; DEAP Database; Human-Computer Interface

1. Introduction

Human emotions play a critical role in people's daily lives, and the expanding part of Human-Computer Interface (HCI) applications has led to the need for programmed emotion recognition systems (Kim, Kim, Oh, & Kim, 2013). Electroencephalogram (EEG)-based human emotion recognition is possible by placing electrodes at specific locations on the scalp of the brain to measure the signals within a range of frequencies (Kim et al., 2013; Jirayucharoensak, Pan-Ngum, & Israsena, 2014; Yuvaraj, Baranwal, Prince, Murugappan, & Mohammed, 2023). The rhythmic movements in the human brain can be broken down into various frequency bands, such as delta, theta, alpha, beta, and gamma, which correlate with a variety of human emotions, including joy, sadness, rage, and calm (Zainab & Majid, 2021; Gannouni, Aledaily, Belwafi, & Aboalsamh, 2021). However, modeling emotions through EEG is difficult due to the complexity of the signals.

The EEG-based emotion recognition process involves pre-processing to reduce noise, feature extraction to identify relevant EEG information, and classification to categorize the extracted features. The Discrete Wavelet Packet Transform (DWPT) algorithm has been introduced in the literature as a method for feature extraction (Wali, Murugappan, & Ahmmad, 2013). However, despite different investigations attempting to demonstrate emotions through EEG signals, the results remain an open examination study due to the low classification accuracy of current methods for extracting and classifying features that deal with chaotic and non-stationary EEG signals (Jatupaiboon, Pan-Ngum, & Israsena, 2013; Zhuang et al., 2017). EEG signals naturally change over time, producing time-varying signals that make it challenging to extract characteristics (Xiangtan, 2010; Wali et al., 2013; Ackermann et al., 2016).

Various methods for feature extraction have been suggested in the field of EEG data analysis, with the DWPT algorithm noted as particularly suitable due to its ability to localize frequency bands efficiently (Gill & Singh, 2022; Padhmashree & Bhattacharyya, 2022). However, the DWPT algorithm has drawbacks. Each level of down-sampling in the DWPT algorithm decreases the decomposition length by half, resulting in extremely short sequences in the final grade that disperse some frequency bands, such as alpha, throughout the decomposition tree (Fan & Zuo, 2006; Zhu, Zhao, & He, 2010; Wirawan, Wardoyo, & Lelono, 2022). Furthermore, the presence of outliers persists in DWPT, negatively impacting the quality of the extracted features (Wang et al., 2011; Sun & Zhou, 2014; Houshmand, Kazemi, & Salmanzadeh, 2022).

The gap of this paper is identifying to the human emotions clearly, so this study aims to present NN-GRUBBS-DWPT to improve the performance of DWPT, increase the accuracy of emotion classification by addressing the negative effects of outliers in EEG data on its decomposition and enhancing the quality of the extracted features; which is represented the novelty of it. The experimental results demonstrate the effectiveness of the proposed method and contribute to the field of EEG-based emotion recognition by offering a technique that addresses the limitations of the existing methods and improves the accuracy of emotion classification.

Here, this paper set two objectives to be achieved; first one, to improve the existing the human emotion recognition techniques and the second one to combine nearest neighbor replacement and Grubbs' test to accurately identify and remove outliers in the DWPT decomposition tree, leading to improved quality of the extracted features and overall classification performance.

The paper is organized as follows: Section 2 provides a literature review, Section 3 introduces the methodology, Section 4 describes the experimental results, and finally, Section 5 and Section 6 provide the discussion and conclusion, respectively.

2. Literature review

6. 2.1. Discrete Wavelet Packet Transform

Wavelets are mathematical functions that organize data into different frequency components and then study each component with a particular scale (Wali et al., 2014). Wavelets were developed independently in mathematics, quantum physics, electrical engineering, and scenic geology. The process of wavelet analysis utilizes wavelets, which are mathematical functions used to represent data (Wali et al., 2014; Hamad, Houssein, Hassanien, & Fahmy, 2016). A crucial component of this analysis is using a wavelet prototype function known as the mother wavelet (Hamad et al., 2016; Chen, Duan, & Peng, 2022). The mother wavelet function represents the filters. The orthogonal wavelets can calculate the coefficients, ensuring that the translated and scaled wavelets are independent (Hamad et al., 2016; Zubair & Yoon, 2018). These kinds of wavelets produce waveforms analogous to those found in the EEG signal (Wali et al., 2014; Chen et al., 2022).

One of the hybrid benefits of DWPT is that it can produce approximation and detail coefficients in addition to providing an effective localization of the frequency band (Wali et al., 2014; Ackermann et al., 2016). The low-pass filter h(m) and the high-pass filter g(m) filter the enter signal to obtain the approximation and detail coefficients, respectively. When a final approximation is only represented by one coefficient, the algorithm is stopped, and the approximation coefficients are used as inputs for consecutive filtering. These coefficients represent the wavelet decomposition. The precise derivation from the CA0, CA1, and CAK approximation coefficients can be obtained by subtracting the N types of suggestions for input signal S and lengthening it to $N^*= N + 2(M-2) + C$ because C is fixed and exactly equals to 0 or 1 which is intended for even or odd N, respectively (Wali et al., 2014). This utilization of wavelet filter coefficients enables the transformation of the input signal into an expanded version that can accommodate a range of input samples. The factor for this expansion must be applied to each input at every level. The result is a new signal, represented as:

$$S = [S_0, S_1, S_2, \dots, S_{N^*-1}] \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

Next, the wavelet decomposition of the signal S results in approximation coefficients that can be derived through the convolution of the input samples with low-pass filtration system coefficients that contain M coefficients. This process generates (N^*−M)/2 approximation coefficients, as demonstrated by the following equations:

$$\begin{gathered} CA_0 = S_0 * h_0 + S_1 * h_1 + \cdots + S_{M-1} * h_{M-1} \\ CA_1 = S_2 * h_0 + S_3 * h_1 + \cdots + S_{M+1} * h_{M-1}, \\ CA_{\left(\frac{N^*-M}{2}\right)} = S_{(N^*-M)} * h_0 + S_{(N^*+M)} * h_1 + \cdots + S_{(N^*-1)} * h_{M-1} \dots\dots\dots\dots\dots (2) \end{gathered}$$

The production of the first-level fine detail coefficients (CD0, CD1, and CDK) is achieved by performing a convolution of the input signal samples with the high-pass coefficients, as follows:

$$\begin{gathered} CD_0 = S_0 * g_0 + S_1 * g_1 + \cdots + S_{M-1} * g_{M-1}, \dots \\ CD_1 = S_2 * g_0 + S_3 * g_1 + \cdots + S_{M+1} * g_{M-1}, \dots \\ CD_{\left(\frac{N^*-M}{2}\right)} = S_{(N^*-M)} * g_0 + S_{(N^*+M)} * g_1 + \cdots + S_{(N^*-1)} * g_{M-1}, \dots\dots\dots\dots\dots (3) \end{gathered}$$

Therefore, the approximation coefficients are obtained through the use of the following equations:

$$\begin{gathered} CA_K = h_0 S_{2*K} + h_1 S_{2*K+1} + \cdots + h_{M-1} S_{2*K+M-1} = \textstyle\sum_{i=0}^{M-1} h_i * S_{i+2*K,} \dots\dots \\ CD_K = g_0 S_{2*K} + g_1 S_{2*K+1} + \cdots + g_{M-1} S_{2*K+M-1} = \textstyle\sum_{i=0}^{M-1} g_i * S_{i+2*K} \dots\dots\dots (4) \end{gathered}$$

Therefore, the relationship between the low-pass and high-pass filter coefficients and the input samples in producing approximation and detail coefficients at any level "b" is depicted in the following equations:

$$CA_{b,K} = \sum_{i=0}^{M-1} h_i * CA_{b-1,i+2*K}, \cdots$$
$$CD_{b,K} = \sum_{i=0}^{M-1} g_i * CD_{b-1,i+2*K} \cdots\cdots\cdots\cdots \quad (5)$$

Therefore, research in EEG has indicated that the DWPT algorithm is an effective solution, as it can accurately distinguish the decomposed signals (Wali et al., 2014; Ackermann et al., 2016). Due to its superiority and efficiency, DWPT is commonly used to extract the four frequency bands by separating high and low-frequency elements. It has strongly connected with high cognitive processes, including human emotions (Lee & Hsieh, 2014). The pseudocode for the DWPT algorithm is shown in Figure 1.

Start
Load EEG signals into the system.
Read in signal S.
Calculate (N*−M)/2 approximation and detail coefficients.
Obtain approximation coefficients using equation 2.
Compute detail coefficients using equation 3.
Derive both approximation and detail coefficients.
Determine approximation coefficients using equation 4.
Calculate detail coefficients using equation 4.
Decompose signal S into its components.
Extract target packets (θ, α, β, and γ bands) based on their assigned packet number.
Calculate the entropy of the target packets (θ, α, β, and γ bands).
Store the entropy values in a feature vector array.
End

Fig. 1: The algorithm of the original DWPT in the form of a pseudocode

DWPT has been used to extract features in several EEG-based recognition studies. Many studies have utilized this algorithm to decompose EEG signals into sub-signals (delta, theta, alpha, beta, and gamma), which can be used as compelling features. For example, in the study by Wali et al. (2014), the authors used wireless EEG signals to classify four levels of driver distraction (neutral, low, medium, and high) by utilizing various wavelets and classifiers. They derived spectral features for three distinct frequency bands by combining DWPT and FFT: alpha, theta, and beta by using spectral features extracted by sym8 wavelet as an input to a subtractive fuzzy inference system as a classifier, classification accuracy of 79.21% was achieved. Wali et al. (2014) calculated the DWPT algorithm's decomposition tree for the 0–64 Hz signal range. This study believes that the reason for the low accuracy rate (79.21%) of this algorithm is due to its reliance on DWPT only.

On the other hand, Aminian, Ameli, Aminian and Schettino (2010) have created a neural network-based classifier of electroencephalography (EEG) signals to identify one of three task categories: extending the arm forward, grasping an object, and pointing to an object. They used a preprocessor for wavelet packet transform analysis that allowed them to extract some appropriate features, which were complementary, compact, and optimized for maximum separability across diverse classes through principal component analysis (PCA) and data normalization modules. They claimed that the preprocessing technique and proposed neural network architecture efficiently dealt with high dimensionality of critical features, outliers, and overtraining, which have been reported as serious problems in EEG classification. They classified the three tasks that humans plan to perform with 100% accuracy. This study finds that the accuracy rate (100%) of this algorithm is unreliable due to its reliance on a very limited number of tasks, which are only 3.

The quality of the extracted features affects the performance of the classification, which is usually degraded due to the outliers that strongly diverge from the distribution of EEG samples (Wang et al., 2011; Sun & Zhou, 2014). Thus, infected samples in EEG data should be pruned to attain a trustworthy classification result (Wang et al., 2011; Luján et al., 2021). As a result, there are assertions that the outliers are still there even though the research suggests that employing DWPT for feature extraction is efficient and that utilizing approximation coefficients as features lowers the risk of noise-induced outliers (Aminian et al., 2010; Wang et al., 2011; Sun & Zhou, 2014). Additionally, it was seen that the breakdown tree of the DWPT method contains outliers in the data signal. A DWPT-based feature extraction approach must be described because the decomposition tree's outliers exist.

6. 2.2. Outliers

In Enderlein (1987), Hawkins states, " An observation is considered an outlier if it differs significantly from other observations and leaves room for doubt about its source." A number that stands out from the surrounding correlation noise over particular correlation data on the detection peak is an outlier. Therefore, it is necessary to use the outlier identification theory (Urvoy & Autrusseau, 2014; Gannouni et al., 2021; Wirawan et al., 2022). According to Hampel (1971), many different outlier identification techniques exist in the literature. These all rely on data markers such as sample depth, deviation, distance, density, etc. Or carry out statistical experiments and predict the statistical characteristics of the incoming data. For instance, the Hampel filter was created to eliminate outliers in surface facial EMG (Bhowmik, Jelfs, Arjunan, & Kumar, 2017). However, one of its main shortcomings is that the algorithm parameters must be manually chosen (Walsh, 1959).

In contrast, moving average and median filters were used to smooth the data signals to reduce the impact of outliers (Janifer Jabin Jui et al., 2023). However, these filters may not be suitable for outlier detection when working with chaotic signals, as the smoothing process may result in removing important signal points. Several outlier tests can be used to detect outliers in data, including the Walsh test, which works well for large datasets but can reject outliers in finite samples (Candelon & Metiu, 2013). The Dean-Dixon test can only be used with small datasets, and distance-based techniques such as the Euclidean distance (Dixon, 1950; Nan, Balasubramani, Ramanathan, & Mishra, 2022). In actuality, these and other methods for finding outliers have a unique mix of benefits and drawbacks. Additionally, according to Urvoy and Autrusseau (2014), it is necessary to initially specify the parameters and criteria for the bulk of existing outlier identification techniques.

On the other hand, Grubbs and Stefansky created the outlier test in 1969 and 1972; it examines the normal distribution to find outliers in the data. It is always verified against the value with the most significant absolute departure from the mean. Consequently, the test only repeats after updating the critical value if an outlier was detected and removed, reflecting the update of the representation of the data's distribution value. As a result, only one outlier is seen per iteration. Effective outlier identification is crucial for preserving essential data points.

Additionally, the Grubbs test is a simple test that identifies the most significant absolute difference between the value xi and the sample mean. The standard deviation of the sample is used to divide the result, and if the test statistic g is greater than the critical value, it can be considered an outlier. Therefore, the Grubbs test appears more appropriate and effective for detecting outliers when working with chaotic dynamic data, such as EEG waves (Rached & Perkusich, 2013). Additionally, it is durable, trustworthy, and computationally affordable (Rached & Perkusich, 2013; Urvoy & Autrusseau , 2014; Houshmand et al., 2022).

3. Methodology

6. 3.1.EEG Dataset

Several EEG public databases have been developed to research how people's emotional states change depending on the setting or condition. As a result, the A Database for Emotion Analysis using Physiological Signals (DEAP) EEG database, created by the Queen Mary University of London, is used in this work. Visit http://www.eecs.qmul.ac.uk/mmv/datasets/deap/index.html to access this dataset (Liu, Y., & Sourina, 2014). Because the pre-processed DEAP dataset was utilized in this investigation, pre-processing was unnecessary. In this dataset, 32 patients watched 40 1-minute-long music video snippets while their EEG signals were collected. The participants scored each movie based on its arousal, valence, like/dislike, dominance, and familiarity levels. This landscape permits a greater variety of feelings, introducing freedom in how emotions are predefined on the dimensional space. The three main steps of this study were as follows: (i) acquiring the pre-processed EEG signals dataset (DEAP), (ii) analyzing the details of the dataset and generating a data matrix, and (iii) examining the labels of the resulting EEG dataset and creating appropriate labels based on the valence-arousal dimensional model of emotions.

Therefore, when there are more emotions to categorize, it becomes more difficult to recognize human emotions. However, managing a lot of emotions is crucial (Jatupaiboon et al., 2013). There are only four emotion states available in the DEAP dataset, which are Low Arousal Low Valence (LALV), High Arousal Low Valence (HALV), and Low Arousal High Valence (LAHV) (HAHV). This resulted from mapping the valence and arousal levels on the 1 to 9 emotion scale to two levels. However, the 1 to 9 emotion scale was mapped to three levels for each valence and arousal, similar to the study (Jirayucharoensak et al.,2014). The valence scale is mapped as "negative" from 1 to 3, "neutral" from 4-6, and "positive" from 7-9. The arousal scale, which ranges from 1 to 3, is translated to "passive," "neutral," and "active," respectively, as seen in Figure 2.

On the other side, various brain regions are generally involved in human emotional behavior, including the limbic system, prefrontal cortex, hypothalamus, and thalamus (Jatupaiboon et al., 2013; Janifer et al., 2023). The activity in these regions is crucial for comprehending emotional states. To ensure essential data is not missed, this study analyzed EEG signals from all electrodes in the DEAP dataset: O2, Fp1, CP2, C4, F4, CP6, AF4, PO4, Fz, F8, FC2, P4, Oz, P3, FC1, T8, F7, C3, PO3, Pz, AF3, O1, P7, F3, CP5, FC6, Fp2. On the other hand, the DEAP's pre-processed EEG dataset includes information from 32 people. Due to the extensive computational time required, particularly in the subject-independent proposed model, this investigation was limited to a sample size of 12 volunteers. The volunteers were evenly divided into two groups: Subjects 7, 8, 10, 16, 19, and 20 are included in Data 1, while subjects 1, 3, 6, 24, 29, and 32 are formed in Data 2. (Data2). For each data group, there were six subjects. The first group was selected based on the literature study in Liu and Sourina (2014), and the latter group was chosen randomly to improve the evaluation robustness of the proposed approach.

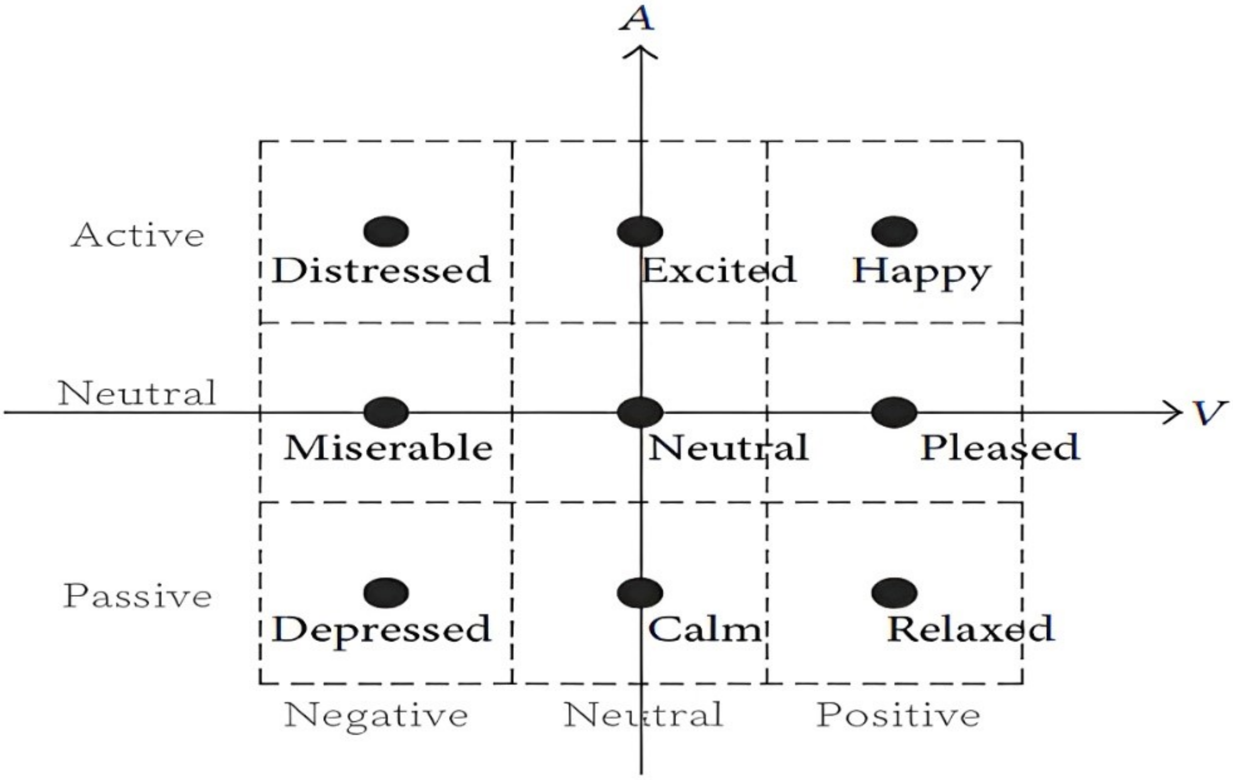

Fig. 2: Classification of emotional states.

6. 3.2. Features Extraction

Once the data collection phase was finished, theta, alpha, beta, and gamma signals were extracted from the EEG signals utilizing the NN-GRUBBS-DWPT algorithm, depicted in Algorithm 1. The Daubechies 4 discrete wavelet (db4) is used to break down the EEG data since it provides the best representation of the signals (Wali et al., 2013; Gill & Singh, 2022). This paper is utilizing DEAP dataset which is consisted of 32 patients watched 40 1-minute-long music video snippets while their EEG signals were collected, so it used the Daubechies 4 wavelet classifier. During the decomposition stage of packet transformation in NN-GRUBBS-DWPT, Grubbs' test was run on each output packet to identify outliers in the packet data (Stefansky, 1972; Sanei & Chambers, 2013; Urvoy & Autrusseau, 2014). At an alpha level of 5% significance, the outliers were found. After being identified, the outlier points were swapped with appropriate ones using the closest neighbor method. With the nearest neighbor approach, the non-outlier signal points most relative to the outlier signal points were substituted for the outlier signal points.

The method of searching for a non-outlier signal point in pak_{sp} involved using a forward search. If this search did not yield the desired result or the signal point location$sp_{Out_{loc}}$ in the data packet, Pak was at the end of the packet data (i.e., $sp_{Out_{loc}} = N$ length(Pak)), the search was then conducted in a backward direction. The final result of this process is the determination of the non-outlier signal point Y for a specific outlier signal point x:

$$Y = \begin{cases} x_{loc+i}, & 0 < loc < N, \ with\ Forward\ search \\ x_{loc-i}, & 0 < loc = N, \ with\ Backward\ search \\ & \text{where,} x_{loc\pm i} \notin sp_{Out} \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

As For example, Figure 3 demonstrates how the NN-GRUBBS-DWPT algorithm substitutes the anomalous signal point located at index 312. If the signal points at 312 and 313 are identified as outliers, the nearest neighboring point to replace the outlier at 312 is the signal point at index 314.

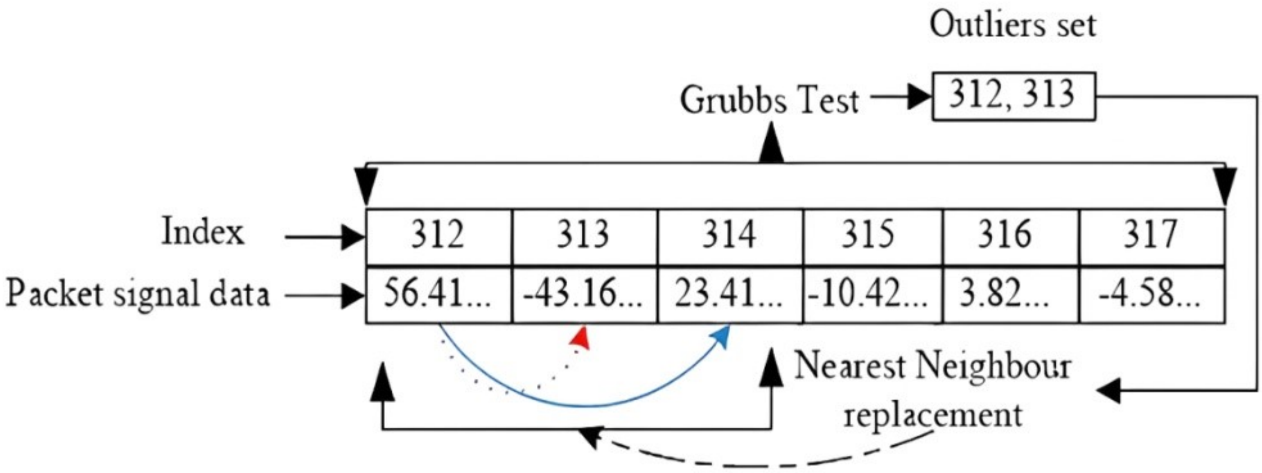

Fig. 3: Replacement of the NN-GRUBBS-DWPT-based outlier signal point at index 312.

In this study, entropy played a crucial role as a feature for EEG signal analysis. Entropy measures a signal's degree of randomness or unpredictability and is often used as a statistical description of the variability within the EEG signal (Murugappan et al., 2014). This concept is helpful in characterizing EEG signals and classifying emotions (Suykens & Vandewalle, 1999; Lee & Hsieh, 2014). The entropy of an EEG signal provides information about energy distribution across different frequencies and can be used to differentiate between normal and abnormal signals. Additionally, entropy can be used to assess the overall complexity and randomness of EEG signals and to identify changes in EEG signals that might indicate certain emotional states. The use of entropy as a characteristic for EEG signal analysis in this study highlights the importance of considering the randomness and unpredictability of EEG signals when characterizing emotions (Al-Qammaz, Ahmad & Yusof, 2018; Alqawasmi & Alsmadi, 2023).

The NN-GRUBBS-DWPT algorithm is a systematic approach to analyzing EEG data and identifying outliers. In the first step, the EEG data collected from a participant is organized into a matrix format that includes trials and channels. In step two, the signal (S) is analyzed, and the approximation and detail coefficients are derived using the MATLAB functions "wpdec" and "wpcoef." In step three, Grubb's test is applied for outlier detection, where Grubbs' statistic values are calculated, and if they exceed the critical region, the point is marked as an outlier. Step four involves replacing the outlier points with the nearest non-outlier point through a most relative neighbor replacement method. Finally, in step five, a new decomposition tree is generated, and the entropy value for each packet is calculated using the MATLAB function "wentropy". It is stored as a feature vector in the feature space array.

Therefore, this study employs the DEAP pre-processed dataset, encompassing EEG signals with a frequency range of 4-45Hz. The resulting decomposition tree, ranging from packets 0-62, is displayed in Figure 4, showcasing that the intended frequency bands are dispersed into different packets. Information regarding the intended frequency bands is provided in Table 1.

Table 1. Information on Extracted Frequency Bands.

Frequency Band	**Packet Number**	**Signal Range (Hz)**
Theta (θ)	15	4–6.5
Alpha (α)	34, 17, & 37	7.8–12.97
Beta (β)	4, 11, & 51	14.25–30.9
Gamma (γ)	52, 26, & 6	30.9–45

Therefore, to compute the target feature when a specific target frequency Y is dispersed among a varying number of packets p in the DWPT, where each packet p is a component of Y (i.e., $p \in Y$), the frequency bands of interest (theta, alpha, beta, and gamma) were extracted by employing the following equation:

$$\mathrm{F(y)} = \sum_{i=1}^{n} f\big(p(i)\big),\ n \geq 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(7)}$$

Whereby, In this formula, the feature type of a particular packet p(i), which is part of the target frequency y, is represented by f(p(i)). The target frequency being analysed is represented by y, and n represents the highest number of packets considered part of y. Therefore, in the process of feature extraction, the Shannon entropy is employed. To determine the entropy value of packet p, the following formula is used:

$$\mathrm{e(p)} = -\sum_{1}^{\mathrm{n}} \mathrm{x}^2 - \log(\mathrm{x}^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(8)}$$

Where x represents a possible outcome of p, and p is a discrete random variable representing its specific frequency. As a result, the following formula is used to calculate the entropy characteristic of the target frequency y when y is distributed across many packets:

$$\mathrm{e(y)} = \sum_{i=1}^{n} - \sum_{1}^{\mathrm{n}} \mathrm{x}^2 - \log(\mathrm{x}^2)\ _{(i)},\ n \geq 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(9)}$$

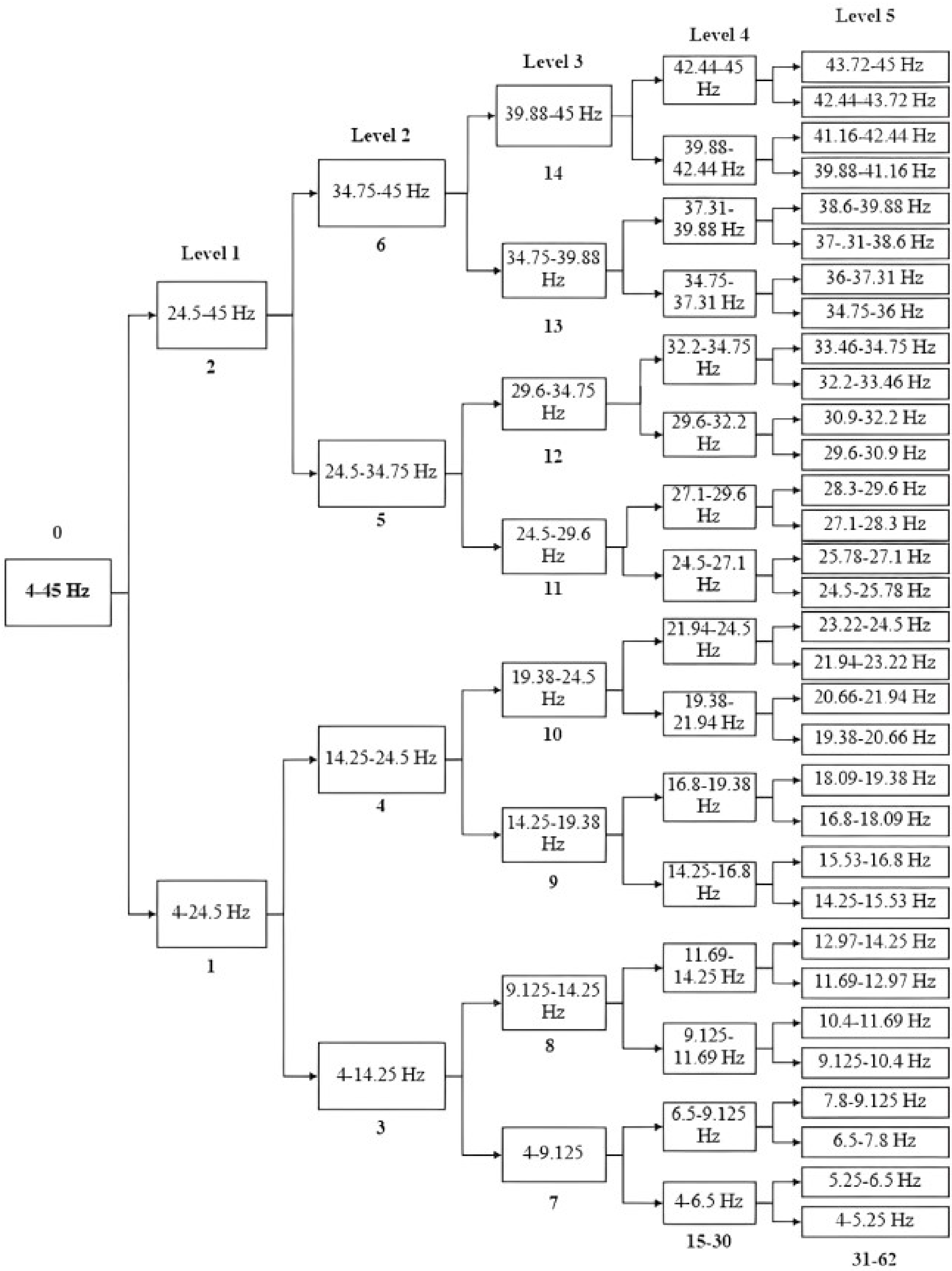

Fig. 4: Replacement of the NN-GRUBBS-DWPT-based outlier signal point at index 312.

6. 3.3. Classification

The least squares support vector machine (LSSVM) classifier is delivered as an improvement of support vector machine (SVM) classifiers (Suykens & Vandewalle, 1999; Mustaffa & Yusof, 2018). This paper is using LSSVM classifier for analyzing data and recognizing patterns which are used for classification and regression analysis in DEAP dataset. It was suggested that resolving a system of linear equations might resolve the issue of the SVM's equality constraint. Compared to SVM, LSSVM is simpler to train and requires less computing work (Boolchandani, Ahmed, & Sahula, 2011; Hamad, Houssein, Hassanien, & Fahmy, 2016; Bai et al., 2023). Therefore, the three standard kernels associated with SVM-based classifiers are typically employed to avoid the optimization issue of hyperplane construction that naturally arises in large-scale data. Radial Basis Function, linear, and multi-layer perception comprise these kernel functions (RBF). RBF is frequently used as a kernel function of LSSVM because of its favorable characteristics (Pelckmans et al., 2003; Guo et al., 2012; Ahmad, Al-Qammaz, & Yusof, 2016).

Therefore, this study typically utilized the multiclass classification using LSSVM along with RBF kernel for classifying of 3-levels of valence and 3-levels of arousal. Thus, the two parameters, γ (regularization parameter) and σ (smoothing parameter), were tuned using the grid search algorithm where the LSSVM toolbox that is provided by Pelckmans et al., 2003) is used. In the classification process, 70% of the data were dedicated to training data, while the rest were committed to testing. K-fold cross-validation was performed during the training procedure to train the model effectively. Optimizing the k-fold proportion to the data used in this study was achieved by conducting several tests with varying k-fold numbers, specifically k=5, k=10, k=15, and k=20. The characteristics obtained were then assigned three levels each for valence and arousal. The number of folds that shows the best classification result is selected for further process.

3.4. Evaluation Criteria

The average classification accuracies were obtained upon testing each feature extraction method. Other evaluation criteria taken into consideration include Standard Deviation (SD), Precision, F-score, and Area Under Curve (AUC) (Goutte & Gaussier, 20005; Fawcett, 2006; Nguyen, Bouzerdoum, & Phung, 2009; Zhou, Yi, Wang, & Li, 2023). The accuracy of a classification model is determined by dividing the number of correct decisions by the total number of cases, as shown in equation (10). This equation considers the true positive and negative points (TP and TN, respectively) and the false positive and negative points (FP and FN, respectively). The standard deviation is a measure of variability that indicates the spread of the dataset and its relationship to the mean. Equation (11) shows how to calculate the standard deviation, which is determined by considering the TP, TN, FP, and FN. Specificity is another metric used to evaluate a classification model, which is calculated by dividing the number of true negative decisions by the total number of actual negative cases, as shown in equation (12).

On the other hand, sensitivity is calculated by dividing the number of true positive decisions by the total number of actual positive cases, as shown in equation (13). Precision and recall are two additional metrics used to evaluate a classification model. Precision is determined by dividing the number of relevant classes retrieved by the total number of irrelevant and relevant classes retrieved, as shown in equation (14). The recall is calculated by dividing the number of appropriate classes retrieved by the total number of proper classes, as shown in equation (15). The F-score is a weighted average of precision and recall, and it can be calculated using equation (16). The F-score ranges from 0 to 1, with 1 indicating perfect accuracy. The receiver operating characteristic (ROC) curve plots the true positive rate (TPR) against the false positive rate (FPR), as shown in equation (17). The area under the ROC curve (AUC) measures how well the model performs, with a higher AUC indicating better performance.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

$$SD = \frac{TP+TN}{TP+TN+FP+FN} \quad (11)$$

$$Specificity = \frac{TN}{FP+TN} \quad (12)$$
$$Sensitivity = \frac{TP}{TP+FN} \quad (13)$$
$$Precision = \frac{TP}{TP+FP} \quad (14)$$
$$Recall = \frac{TP}{TP+FN} \quad (15)$$
$$Fscore = 2.\frac{p.r}{p+r} \quad (16)$$
$$\mathrm{TPR} = \frac{TP}{TP+FN},\ \mathrm{FPR} = \frac{FP}{FP+TN} \quad (17)$$

4. Experimental Results

This section describes the results obtained from the undertaken experiments. Whereby a multiclass classification problem is addressed by the proposed model in the experiments. The extracted features were classified into three levels of valence (V) and three levels of arousal (A) emotional states. The results of a classification experiment comparing two techniques, the proposed NN-Grubbs-DWPT and the original DWPT, are presented in Table 2. The experiment involved two sets of data, Data 1 and Data 2. It measured the performance of each technique by calculating the Min, Max, and Mean values of Valence and Arousal under different numbers of folds (k=5, k=10, k=15, and k=20). For the Original DWPT Data 1 and 2, the Min values for valence ranged from 20.83% to 23.61%, with Mean values ranging from 41.56% to 41.17%. The Min values for arousal ranged from 36.11% to 23.61%, with Mean values ranging from 53.06% to 43.41%. On the other hand, for the NN-Grubbs-DWPT Data 1 and 2, the Min values for valence ranged from 27.78% to 23.61%, with Mean values ranging from 44.55% to 44.46%. The Min values for arousal ranged from 30.56% to 25%, with Mean values ranging from 54.579% to 49.16%.

These results suggest that the NN-Grubbs-DWPT technique performed better than the Original DWPT, as evidenced by the higher Min and Mean values obtained for the former. Furthermore, it was found that the NN-Grubbs-DWPT with k=20 achieved the highest maximum accuracy for valence and arousal classification on Data 1, with accuracy values of 62.50% and 73.61%, respectively. Meanwhile, in Data 2, using NN-Grubbs-DWPT with k=10 for valence classification resulted in the highest maximum accuracy, with accuracy values of 63.89% and 69.44% for valence and arousal classification, respectively, with k values of 5, 10, and 15. Finally, the LSSVM classifier was used to train the data using the best k-folds. The accuracy results for categorizing valence and arousal emotions, including the lowest accuracy (min), maximum accuracy (max), mean accuracy, standard deviation (SD), precision, F-score, and area under the curve (AUC), are presented in the following section.

Table 2. Classification results based on different K-fold numbers.

Algorithm / Data Set	K-Fold	Min	Max	Mean
Original DWPT Data 1	K=5	20.83	56.94	41.90
	K=10	26.39	59.72	41.77
	K=15	25	55.56	41.73
	K=20	26.39	56.94	41.56
Original DWPT Data 2	K=5	23.61	58.33	41.08
	K=10	23.61	56.94	40.98
	K=15	23.61	58.33	41.03
	K=20	22.22	58.33	41.17
NN-Grubbs-DWPT Data 1	K=5	27.78	61.11	44.55

	K=10	25	61.11	44.67
	K=15	26.39	59.72	44.56
	K=20	25	62.50	44.76
NN-Grubbs-DWPT Data 2	K=5	23.61	61.11	44.46
	K=10	26.39	63.89	44.46
	K=15	27.78	59.72	44.36
	K=20	26.39	61.11	44.48

On another side, Table 3 shows the results of the classification experiments conducted on Data 1 and Data 2 using both the original DWPT and NN-Grubbs-DWPT methods. The accuracy %, SD (Standard Deviation), precision, recall, F-score, and AUC (Area Under the Curve) values are shown for the emotional dimensions of valence and arousal. For the original DWPT method, the maximum accuracy values for valence and arousal on Data 1 are 59.72% and 70.83%, respectively. The mean accuracy for valence and arousal is 41.77% and 53.06%, respectively, and the standard deviation for both dimensions is 4.94% and 5.18%, respectively. The precision, recall, and F-score values for valence and arousal are 0.58, 0.47, 0.48, 0.24, 0.33, and 0.28, respectively. The AUC values for valence and arousal are 0.65 and 0.50, respectively.

For the NN-Grubbs-DWPT method, the maximum accuracy values for valence and arousal on Data 1 are 62.50% and 73.61%, respectively. The mean accuracy for valence and arousal is 44.76% and 54.69%, respectively, and the standard deviation for both dimensions is 5.29% and 5.55%, respectively. The precision, recall, and F-score values for valence and arousal are 0.60, 0.60, 0.60, 0.53, 0.44, and 0.44, respectively. The AUC values for valence and arousal are 0.71 and 0.59, respectively. In Data 2, the NN-Grubbs-DWPT method showed a maximum accuracy of 63.89% for valence and 66.67% for arousal classification.

The mean accuracy for valence and arousal is 44.46% and 49.09%, respectively, and the standard deviation for both dimensions is 5.33% and 5.51%, respectively. The precision, recall, and F-score values for valence and arousal are 0.61, 0.61, 0.61, 0.68, 0.68, and 0.68, respectively. The AUC values for valence and arousal are 0.64 and 0.76, respectively. Also in Data 2, the original DWPT method showed a maximum accuracy of 58.33% for valence and 63.89% for arousal classification. The mean accuracy for valence and arousal is 41.17% and 43.72%, respectively, and the standard deviation for both dimensions is 5.25% and 5.57%, respectively. The precision, recall, and F-score values for valence and arousal are 0.56, 0.54, 0.54, 0.63, 0.61, and 0.60, respectively. The AUC values for valence and arousal are 0.59 and 0.67, respectively.

Table 3. Classification results for original DWPT and NN-Grubbs-DWPT of data 1 and data 2.

Method	**Dimension**	**Accuracy % (min-max)**	**Accuracy % (mean)**	**SD**	**Precision**	**Recall**	**F-score**	**AUC**
NN-Grubbs-DWPT	Data 1 V	25-62.50	44.76	5.29	0.60	0.60	0.60	0.71
NN-Grubbs-DWPT	Data 1 A	33.33-73.61	54.69	5.55	0.53	0.44	0.44	0.59

NN-Grubbs-DWPT	Data 2 V	26.39-63.89	44.46	5.33	0.61	0.61	0.61	0.64
NN-Grubbs-DWPT	Data 2 A	31.94-66.67	49.09	5.51	0.68	0.68	0.68	0.76
Original DWPT	Data 1 V	26.39-59.72	41.77	4.94	0.58	0.47	0.48	0.65
Original DWPT	Data 1 A	36.11-70.83	53.06	5.18	0.24	0.33	0.28	0.50
Original DWPT	Data 2 V	22.22-58.33	41.17	5.25	0.56	0.54	0.54	0.59
Original DWPT	Data 2 A	26.39-63.89	43.72	5.57	0.63	0.61	0.60	0.67

In assumption, the NN-Grubbs-DWPT method showed better accuracy, precision, recall, F-score, and AUC results than the original DWPT method for both Data 1 and Data 2. On the other hand, Figure 5 serves as a visual representation of the comparison between the performance of the NN-GRUBBS-DWPT algorithm and the traditional DWPT algorithm. This comparison is made through various evaluation measures, such as precision, recall, F-score, and AUC, to demonstrate the improved performance of the NN-GRUBBS-DWPT algorithm. Figure 5 not only presents a comparison between the minimum and maximum values obtained by each algorithm, but it also aims to demonstrate the superior performance of the NN-GRUBBS-DWPT algorithm over the traditional DWPT algorithm. The line chart in Figure 5 displays the trends in the data, showcasing how the accuracy or AUC scores change with different methods or dimensions (i.e., Data1 or Data2). The line chart also helps to clarify the patterns of various methods, highlighting the differences or similarities between the patterns for different dimensions of data and algorithms. The left half of the line represents the results obtained using the proposed NN-GRUBBS-DWPT algorithm, while the right half represents the results obtained using the traditional DWPT algorithm. As seen in Figure 5, the line's left side exhibits higher differences than the right side, emphasizing the improved performance of the NN-GRUBBS-DWPT algorithm over the traditional DWPT algorithm.

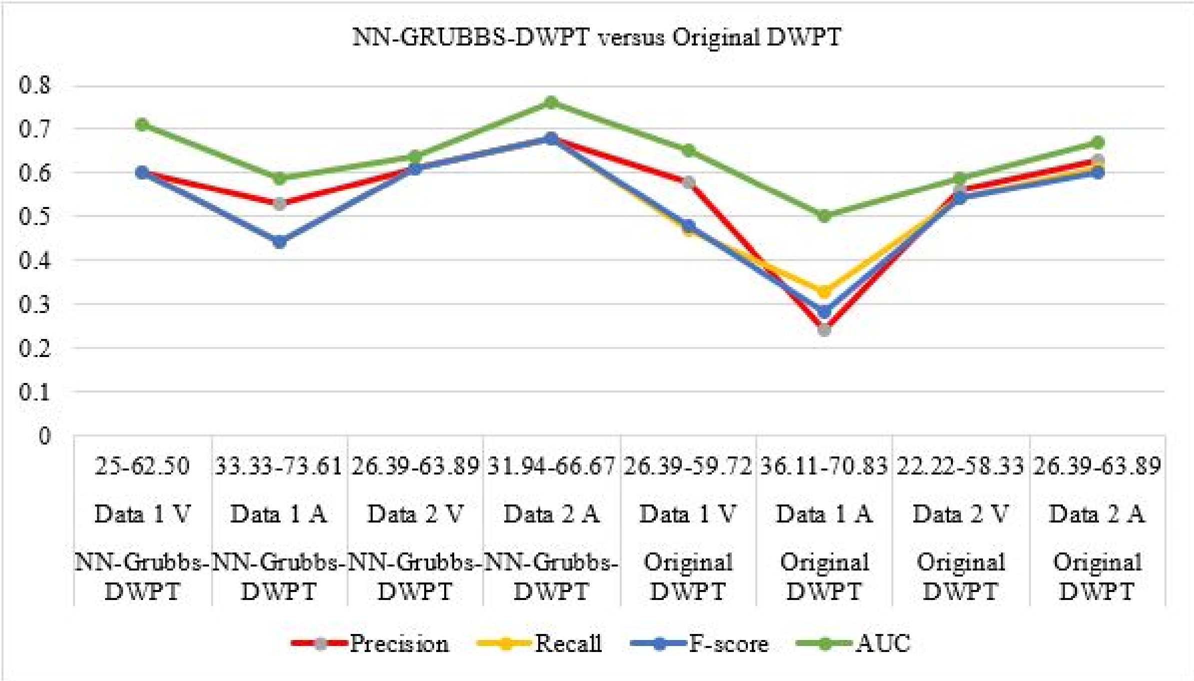

Fig. 5: A comparison of the performance of the NN-GRUBBS-DWPT algorithm and the original DWPT algorithm.

Moreover, Figure 6 likely illustrates the difference in the theta bands (4-6.5 Hz) obtained from two different subjects (subject number 7 [Image a] and subject number 1[Image b]) of the pre-processed DEAP dataset, using the original DWPT and NN-Grubbs-DWPT algorithms. The EEG signals were taken from the Fp1 channel and Trial 1. The x-axis presents the time domain in microseconds (ms), and the y-axis presents the micro (µV) voltages. This comparison aims to show the impact of outliers on the original DWPT algorithm and how the NN-Grubbs-DWPT algorithm eliminates these outliers, resulting in improved classification performance.

The Figure 6 demonstrates that a result of the NN-Grubbs-DWPT performance approach (the left side of both Images a and Image b) effectively removes the outliers present in the signal when using the original DWPT (the right side of both Images a and Image b), respectively. These outliers/noises can negatively impact the classifier's performance. By removing these outliers, the NN-Grubbs-DWPT method can provide improved classification performance, as shown in the above results.

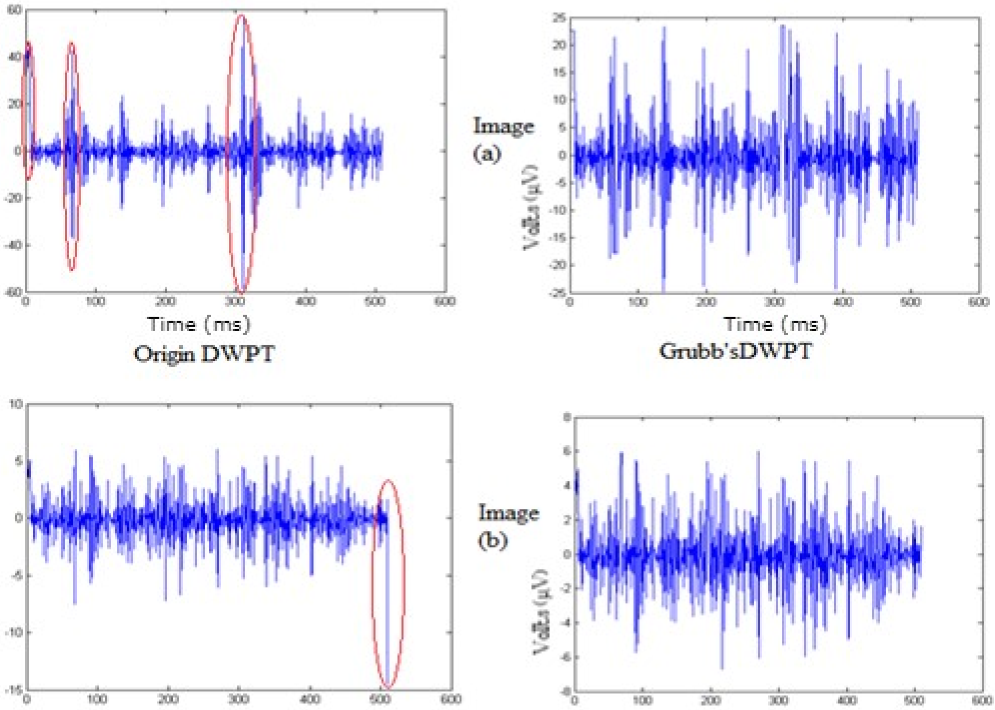

Fig. 6: Theta bands of the original DWPT and NN-Grubbs-DWPT (4–6.5 Hz).

5. Discussion

One of the most popular methods for recognizing emotions is the analysis of electroencephalogram signals, but the current accuracy of the techniques used remains an open area of study. A promising algorithm for extracting EEG features is the DWPT algorithm, introduced in the literature. Despite that, the main objective of this study is to enhance the performance of the reliable DWPT algorithm for more efficient classification of EEG-based emotions. Indeed, the excellence of the DWPT-based feature extraction method in this study agreed with many in previous studies compared to many feature extraction methods in the literature. One of the main limitations of other algorithms for feature extraction is that they cannot effectively capture the complex and non-stationary nature of EEG signals, unlike DWPT. Traditional Fourier transform-based techniques assume that the signals are linear and stationary, which is not the case with EEG signals. DWT is computationally efficient and requires fewer computations, but the limited decomposition may not provide enough information about the signal for some applications. DWPT, on the other hand, provides a more detailed representation of the signal, particularly for complex signals like EEG, which contain multiple frequency components. DWPT can decompose EEG signals into sub-bands with different frequency ranges, enabling a more accurate signal representation.

Additionally, DWPT effectively captures the time-frequency characteristics of EEG signals and removes noise and artifacts. It can also provide a better Signal Noise Ratio (SNR) than other algorithms, making it more suitable for analyzing EEG signals with low amplitude and high noise. Several studies have shown the advantages of using DWPT for EEG signal analysis, including higher classification accuracy for EEG-based emotion recognition and better performance for motor imagery-based BCI compared to other time-frequency analysis methods.

However, the presence of outliers in the DWPT decomposition can have a negative impact on the quality of the extracted features, making it challenging to classify emotions accurately. To address this issue, this study proposed a new DWPT-based feature extraction method called the NN-Grubbs-DWPT, which has been shown to outperform the original DWPT algorithm. The NN-Grubbs-DWPT combines nearest neighbor replacement and Grubbs' test to detect and remove outliers in the DWPT decomposition tree. The method was tested on two sub-datasets of the DEAP database, and the extracted features were classified using the LSSVM classifier, resulting in nine different human emotions. The results showed that NN-Grubbs-DWPT outperforms the original DWPT method regarding several evaluation criteria, including precision, AUC, and F-score.

The study's findings demonstrate that outliers harm the quality of the extracted features in DWPT, and eliminating this noise is necessary to obtain better and more reliable classification results. The NN-Grubbs-DWPT method improved classification performance by partially removing the outliers in the decomposition tree and outperforming the original DWPT method and LSSVM in various evaluation criteria. The proposed method's ability to identify and eliminate outliers in the decomposition tree has positively impacted the quality of the information obtained through the feature extraction process. On another side, although the NN-Grubbs-DWPT algorithm is superior in performance, the time required for its implementation was not a primary focus of our study.

On another side, interparticipant variability is a common issue in EEG-based emotion recognition, especially when using complex models in subject-independent approaches. Studies such as Liu & Sourina (2014) and Jirayucharoensak et al. (2014) have demonstrated this phenomenon, which results can be shown as low accuracy results. However, compared to similar works, the authors Liu & Sourina (2014) achieved an accuracy of 53.7% for recognizing up to 8 emotions using an EEG-based algorithm tested on a subset of 6 subjects from the DEAP dataset. On the other hand, the study of Jirayucharoensak et al. (2014) proposed a deep learning network based on stacked autoencoders achieving 49.52% and 46.03% accuracy for classifying valence and arousal levels, respectively. The authors claimed that using principal component-based covariate shift adaptation improves classification accuracy by 5.55% and 6.53% and that the DLN outperforms SVM and naive Bayes classifiers in performance.

As a result, the NN-Grubbs-DWPT method introduced in this study effectively improves the quality of extracted features and the classification performance in emotion recognition systems. The proposed method's ability to detect and remove outliers in the DWPT decomposition tree has been shown to improve the extracted features' quality and increase the emotion classification's accuracy. The results of this study suggest that the NN-Grubbs-DWPT method has great potential for use in practical applications of emotion recognition systems. Unlike other methods that usually used for very limited tasks, the proposed algorithm (NN-GRUBBS-DWPT) achieved reliable accuracy on very complex aforementioned classification tasks with rates 62.5% and 73.61% based on Data 1 and 63.89% and 66.67% based on Data 2 respectively.

6. Conclusion

In conclusion, the study presented in this paper aimed to improve the accuracy of emotion recognition from EEG signals by addressing the issue of outliers in the decomposition tree produced by the DWPT algorithm. The proposed NN-GRUBBS-DWPT method used nearest neighbor replacement and Grubbs' test to detect and remove outliers, improving the extracted features' quality and overall classification performance. The experiments on two sub-datasets from the DEAP database showed that the proposed method outperformed the original DWPT algorithm regarding maximum valence and arousal accuracy, reaching 62.5% and 73.61% based on Data 1 and 63.89% and 66.67% based on Data 2. Meanwhile, the model achieves an average accuracy of 44.76% and 54.69% on Data 1 and 44.46% and 49.09% for valence and arousal, respectively.

Despite the promising results of this study, there are still several areas for improvement in EEG-based emotion recognition. One crucial challenge is to produce an efficient representation of the DWPT decomposition tree, as the decomposition level, wavelet filter, coefficient, and entropy type can all impact the performance of DWPT. Additionally, future research may aim to enhance the Grubbs-DWPT replacement method for outliers, as outliers in the decomposition tree can still negatively impact the quality of the extracted features. Another direction for future work could be to explore alternative methods for feature extraction and classification in EEG-based emotion recognition to improve the system's accuracy and robustness. Overall, this study highlights the importance of addressing outliers in EEG signal processing and demonstrates the potential of the NN-GRUBBS-DWPT method for improving emotion recognition accuracy in HCI applications.

In summary, to enhance human emotion recognition from may unique EEG signals, the proposed approach employs the Discrete Wavelet Packet Transform technique. However, compared to prior methods of human emotion recognition, the use of nearest neighbour replacement and Grubbs' test in order to identify and remove the outliers in the DWPT decomposition tree will help to ultimately perfect the extraction of the features representing the quality and the end classification accuracy. Therefore, the proposed approach known as NN-GRUBBS-DWPT not only enhances the current methodologies but also provides a foundation for other works to be carried out in the human emotion research. One critical methodology by which human emotion recognition is distinguished for the eradication of the outlier value.

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