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Analisis Perbandingan Kinerja DWT dan SWT dalam Pengenalan Emosi Berbasis EEG Menggunakan XGBoost

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Abstract

Emotion recognition from electroencephalography (EEG) signals is crucial for human-computer interaction and diagnosing emotional disorders. This study evaluates the impact of feature extraction methods on the performance of XGBoost in classifying emotions in game players using EEG data. It compares the efficacy of Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT) combined with XGBoost, aiming to identify the most effective feature extraction method for improving emotion classification accuracy. Using the GAMEEMO dataset, which includes preprocessed EEG signals from game players, three scenarios were analyzed: XGBoost without feature extraction, XGBoost with DWT, and XGBoost with SWT. The results demonstrate that DWT significantly enhances classification performance, achieving higher accuracy, precision, and recall compared to SWT and no feature extraction. DWT's ability to capture rapid frequency changes in EEG signals is a key factor in its superior performance. Future work should focus on refining data preprocessing techniques, exploring additional feature extraction methods, and optimizing XGBoost hyperparameters to further enhance emotion recognition accuracy. This research provides valuable insights into the comparative effectiveness of different wavelet transform methods for EEG-based emotion classification, emphasizing the potential of DWT for improved performance.

Keywords: *EEG-based Emotion Recognition, XGBoost Classification, Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Feature Extraction Techniques*

Abstrak

Pengenalan emosi dari sinyal electroencephalography (EEG) sangat penting untuk interaksi manusia-komputer dan diagnosis gangguan emosional. Studi ini mengevaluasi dampak metode ekstraksi fitur terhadap kinerja XGBoost dalam mengklasifikasikan emosi pada pemain game menggunakan data EEG. Penelitian ini membandingkan efektivitas Discrete Wavelet Transform (DWT) dan Stationary Wavelet Transform (SWT) yang dikombinasikan dengan XGBoost, dengan tujuan mengidentifikasi metode ekstraksi fitur yang paling efektif untuk meningkatkan akurasi klasifikasi emosi. Menggunakan dataset GAMEEMO, yang mencakup sinyal EEG yang telah diproses dari pemain game, tiga skenario dianalisis: XGBoost tanpa ekstraksi fitur, XGBoost dengan DWT, dan XGBoost dengan SWT. Hasilnya menunjukkan bahwa DWT secara signifikan meningkatkan kinerja klasifikasi, mencapai akurasi, presisi, dan recall yang lebih tinggi dibandingkan SWT dan tanpa ekstraksi fitur. Kemampuan DWT untuk menangkap perubahan frekuensi cepat dalam sinyal EEG adalah faktor kunci dalam kinerja superiornya. Penelitian selanjutnya harus berfokus pada penyempurnaan teknik prapemrosesan data, eksplorasi metode ekstraksi fitur tambahan, dan pengoptimalan hiperparameter XGBoost untuk lebih meningkatkan akurasi pengenalan emosi. Penelitian ini memberikan wawasan berharga tentang efektivitas komparatif berbagai metode transformasi wavelet untuk klasifikasi emosi berbasis EEG, menekankan potensi DWT untuk kinerja yang lebih baik.

Kata Kunci: *Pengenalan Emosi Berbasis EEG, Klasifikasi XGBoost, Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Teknik Ekstraksi Fitur*

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1. Introduction

Human emotion recognition is crucial for human-computer interaction and is a key research area in cognitive science, computer science, and psychology [1], [2]. Emotions, characterized by distinct physiological rhythms and changes, are vital for studying emotional reactions [1]. Computer-aided recognition of emotions from electroencephalography (EEG) signals is essential for diagnosing emotional disorders in neurology and psychiatry [3]. EEG-based emotion recognition methods, however, often neglect the spatial correlation between electrodes[2]. Alakus et al. [4] identified a gap in providing brain signals based on computer games and alternative EEG signals aided by aural/visual stimuli. EEG signals are complex and have limitations such as low signal-to-noise ratio, uncertain brain areas for specific reactions [2], [5] and noise from eye blinks, heartbeats, and muscle movements [6]. Thus, EEG-based emotion recognition remains challenging.

Common algorithms involve preprocessing, feature extraction, and classification techniques [6]. Preprocessing extracts crucial brain activity from recorded *noise* [7]. Feature extraction reduces data complexity [8] while retaining essential information [9]. Popular methods include Wavelet Transform (WT), Fourier Transform (FT), Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA) [10]. This research uses WT due to its versatile time-frequency analysis technique that allows localization of signals in time or space, separating them from noise [11], effectively removes noise and detects artifacts like eye blinks and spikes [12], [13]. Despite some limitations, such as ringing and shift variance, WT is a strong choice for EEG-based emotion recognition due to its multi-resolution analysis and noise removal capabilities [14], [15]. There are three main types of WT: Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), and Stationary Wavelet Transform (SWT). DWT and SWT are useful for signal decomposition and noise removal [16], [17]. SWT maintains resolution, potentially offering better performance in certain applications [17]. Studies show SWT sometimes outperforms DWT in denoising tasks [17], [18], [19]. Several studies combine DWT and SWT with algorithms like SVM [18], CNN [20], and ANN [21] for optimal EEG signal classification.

This study uses XGBoost for classifying game players' emotions due to its effectiveness in handling imbalanced datasets and high accuracy in addressing overfitting issues. XGBoost outperforms other methods in multi-class EEG signal classification, achieving 88.80% accuracy and being 3.7 times faster in training [22]. It effectively handles imbalanced datasets [23] but is less sensitive in seizure detection [24]. Compare to Gradient Boost and AdaBoost, Gradient Boost offers high classification accuracy but is complex to understand and can increase overfitting risk [25]. AdaBoost shows resilience to changes in test sample ratios and subject numbers [26] but may decrease performance [27].

This study aims to understand the impact of feature extraction methods on XGBoost performance, compare the performance of Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT) with XGBoost, and identify the best feature extraction method for emotion classification from EEG data to improve emotion recognition performance in game players. Therefore, three scenarios were conducted: evaluating XGBoost performance without feature extraction, with feature extraction using DWT, and with feature extraction using SWT. This research aims to provide a more efficient and accurate solution for processing game players' EEG signals and recognizing and classifying their emotions.

2. Research Methodology

2.1. Wavelet Transform (WT)

Wavelet Transform (WT) is a mathematical technique that decomposes a signal into components at various scales, providing a time-frequency representation. Unlike Fourier Transform, which analyzes signals in terms of frequency only, WT offers both time and frequency information, making it suitable for non-stationary signals like EEG. WT's ability to perform multi-resolution analysis helps in identifying relevant features while reducing noise and artifacts [28].

2.1.1. Discrete Wavelet Transform (DWT)

An essential tool for time-frequency signal analysis, providing better temporal resolution than traditional transforms like Fourier [29]. Utilizing discretely sampled wavelets, the DWT is pivotal in numerical and functional analysis [30]. It decomposes signals into multilevel subbands, including approximation and detailed components. Its diverse applications range from image compression and video enhancement to robotics, biometrics, medical assessment, power systems, and telecommunications [30]. The transform is computed using the pyramid algorithm with wavelet and scaling filters [31]. Extensions of the DWT include the Discrete Wavelet-Packet Transform (DWPT) for more refined analysis and the Discrete Shapelet Transform (DST) for joint time-frequency-shape analysis [29].

2.1.2. Stationary Wavelet Transform (SWT)

Stationary Wavelet Transform (SWT) is a significant tool in signal processing with broad applications. In seismic data analysis, SWT maintains the original data length at each wavelet scale, enhancing resolution and reducing noise [32]. For spectrum sensing in cognitive radio systems, SWT offers superior edge detection in wideband signals, facilitating efficient spectrum allocation [33]. In fault diagnosis of rotating machinery, SWT excels over the Discrete Wavelet Transform (DWT) by detecting potential defects in motor bearings [34]. Its translation-invariant property makes SWT especially useful in brain MRI feature extraction, addressing DWT limitations when minor movements occur between scans [35].

2.2. XGBoost

XGBoost is a gradient boosting algorithm that enhances model performance by combining the predictions of multiple weak models. It is known for its efficiency and accuracy in handling large datasets and complex problems. In the context of EEG-based emotion recognition, XGBoost can improve classification performance by addressing issues such as overfitting and dataset imbalance [36].

2.3. GAMEEMO Dataset

The GAMEEMO dataset, developed by Alakus et al. [4], provides a comprehensive collection of EEG signals recorded from participants engaged in various computer games. This dataset is notable for its use of portable EEG devices, allowing for data collection in a naturalistic gaming environment rather than a controlled laboratory setting. This setup captures a broad spectrum of emotional responses, enhancing the authenticity of the recorded data. Emotions within the dataset are annotated using both arousal and valence dimensions, as well as positive and negative labels. This multi-dimensional labeling supports a range of emotion recognition tasks by offering nuanced insights into emotional experiences. In addition to its rich annotations, the GAMEEMO dataset includes a comparative analysis of portable versus traditional EEG devices, providing valuable information on the performance and reliability of portable EEG technologies. This comparison is essential for evaluating the practical utility of portable devices in real-world applications.

2.4. Type, Nature, and Approach of Research

The research focuses on measuring the performance of emotion classification algorithms using EEG data from game players, making a quantitative approach highly appropriate. This research is applied in nature, aimed at solving practical issues by improving the performance of emotion classification algorithms based on EEG data. The study not only emphasizes theoretical development but also the application of technology and methods to create effective and efficient solutions for emotion recognition in game players. An experimental approach with a quasi-experimental design is utilized, allowing manipulation of independent variables (Wavelet Transform feature extraction and XGBoost usage) and observation of their effects on the dependent variable (emotion classification performance on EEG data).

2.5. Data Collection Method

The study utilizes the publicly available GAMEEMO dataset introduced by Alakus et al. (2020), widely used for EEG-based emotion recognition research. This dataset is chosen for its relevant characteristics, such as the use of portable EEG devices, various game genres to elicit different emotions, and preprocessed data quality to remove artifacts, ensuring its suitability for EEG-based emotion recognition analysis. Alakus et al. (2020) highlight a gap in providing brain signals based on computer games and alternative EEG signals with aural/visual assistance, making this dataset relevant to address that gap.

2.6. Data Analysis Method

EEG data preprocessing, feature extraction using Wavelet Transform, training and testing the emotion classification model using XGBoost, and evaluating the model's performance. The collected EEG signals undergo filtering to remove movement artifacts and other noise using a 5th order sinc filter, followed by downsampling from 2048 Hz to 128 Hz to reduce data size and facilitate subsequent analysis. Feature extraction is performed using two types of Wavelet Transform: Discrete Wavelet Transform (DWT) for capturing rapid frequency changes and Stationary Wavelet Transform (SWT) for retaining time and frequency information without downsampling.

The extracted features are used to train and test the XGBoost emotion classification model, with training using the training data and testing using the testing data to assess classification performance based on the extracted features. Model performance is evaluated using metrics from the Confusion Matrix, including Accuracy, Precision, and Recall, to assess how well the model classifies emotions based on EEG data. The XGBoost model's performance is compared based on the three types of Wavelet Transform feature extractions (DWT and SWT) to evaluate the effectiveness of each in enhancing emotion classification performance. Conclusions are drawn by comparing the results of the optimized XGBoost model evaluation with the performance of emotion classification based on the three types of Wavelet Transform feature extractions, confirming the research hypothesis on the proposed method's effectiveness.

2.7. Research Workflow

The first stage involves identifying the research problem and objectives, starting with defining the research scope and conducting an in-depth literature review to identify knowledge gaps or issues. Relevant literature is reviewed to understand the solutions, shortcomings, and suggestions provided, leading to a problem statement formulation for research. The next stage involves obtaining and preparing the GAMEEMO dataset [4]. Preprocessing includes data cleansing, filtering, or downsampling if necessary. The dataset is then split into training and testing data, with an 80% training and 20% testing data ratio. Various scenarios are determined to provide solutions to the research problem:

2.7.1. First Scenario: to obtain the XGBoost performance results without feature extraction. The XGBoost model is trained using 80% original training data without feature extraction and tested using 20% original testing data without feature extraction.

2.7.2. Second Scenario: to obtain the XGBoost performance results using DWT feature extraction. Feature extraction is conducted on 80% training data and 20% testing data. The XGBoost model is trained using training data with DWT feature extraction and tested using testing data with DWT feature extraction.

2.7.3. Third Scenario: to obtain the XGBoost performance results using SWT feature extraction. Feature extraction is conducted on 80% training data and 20% testing data. The XGBoost model is trained using training data with SWT feature extraction and tested using testing data with SWT feature extraction.

The fourth stage is to evaluate the results. At this stage, evaluation is conducted using a confusion matrix to analyze the performance of the classification algorithm with various scenarios previously conducted. Evaluation is done to assess the extent to which the model can accurately classify emotions based on EEG data. The evaluation results are compared between different feature extraction methods and optimization algorithms tested. The final stage is discussion and conclusion drawing. At this stage, the evaluation results from various scenarios are discussed and analyzed to see the strengths and weaknesses of each feature extraction method and optimization algorithm. After that, conclusions are drawn by comparing the evaluation results of the model optimized with XGBoost against the performance of emotion classification based on the three types of Wavelet Transform feature extractions used. These conclusions will confirm the research hypothesis about the effectiveness of the proposed method.

3. Results and Discussion

In this study, an evaluation was conducted on the impact of applying feature extraction using XGBoost on EEG data to improve the performance of emotion classification in game players. The research process involved several main stages, starting with data collection, preprocessing, feature extraction, model training and testing, and performance evaluation. The script used includes the following steps:

3.1. Data Collection

The dataset used is GAMEEMO, an EEG dataset for emotion recognition in the context of gaming. This dataset consists of EEG signals that have been processed to remove artifacts and is used for training and testing the model.

3.2. Preprocessing Data

EEG data is processed to remove noise and perform downsampling to make the data size more manageable. This process includes filtering and downsampling. In this process, an FIR (Finite Impulse Response) filter is used with the firwin function from the *scipy.signal* library. FIR filters are designed to remove specific frequencies from the signal, such as high-frequency noise or low-frequency artifacts. Downsampling is performed using the decimate function from the *scipy.signal* library, which reduces the signal's sampling frequency by a certain factor (q). In this case, the filtered data is downsampled from 2048 Hz to 128 Hz.

3.3. Feature Extraction

Feature extraction is performed using both Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT). Features are extracted for each type of transformation for further analysis.

3.3.1. Feature Extraction Using Discrete Wavelet Transform (DWT):

Discrete Wavelet Transform (DWT) is used to decompose EEG signals into multiple frequency levels to capture important information that might be lost in the time domain. This process involves the use of wavelet filters that segment the signal into different frequency components, such as detail and approximation. The coefficients produced from this process are then used as features for the classification model.

3.3.2. Feature Extraction Using Stationary Wavelet Transform (SWT)

Stationary Wavelet Transform (SWT) offers the advantage of preserving the temporal position information of the signal, which is particularly useful in EEG signal analysis.

3.4. Model Training and Evaluation

At this stage, model training and evaluation are performed. The process begins by configuring the model with specified parameters. After configuring these parameters, the model is trained using the prepared training data, and predictions are made on the test data once the model has been trained. The testing phase begins after the model is trained and involves evaluating the model's performance on unseen data. For each scenario, the training and testing data are separated, and the model is trained and tested. The accuracy, precision, and recall values are calculated for each scenario, which are then used to compare the effectiveness of different feature extraction methods. These results reveal how well the XGBoost model performs with features extracted using various techniques, providing a clear picture of the model's performance in classifying EEG data.

3.5. Research Result

The performance evaluation results of the XGBoost model for each feature extraction scenario are shown in the table below:

Table 1. Table of the comparation result

Scenario	Accuracy	Precision	Recall
No Feature Extraction	0.0000	0.4348	0.0000
DWT	0.1304	0.5217	0.1304
SWT	0.0435	0.4928	0.0435

From the table above, it can be observed that the model without feature extraction (No Feature Extraction) performs very poorly, with very low accuracy and recall. In contrast, the model using DWT shows better results compared to SWT, in terms of accuracy, precision, and recall.

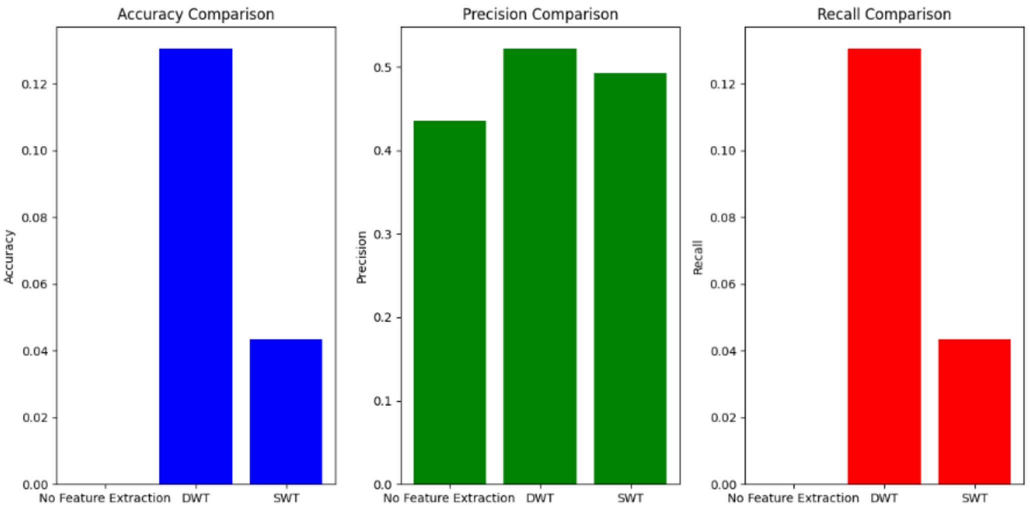

Figure 1. A bar chart representation of the comparison

3.6. Discussion

The results indicate that applying feature extraction can have a significant impact on the classification model's performance. The XGBoost model trained with features extracted using DWT showed the best performance compared to the model using SWT and the model without feature extraction.

3.6.1. How does feature extraction impact the performance of the XGBoost model for emotion recognition using EEG data: The performance of the XGBoost model varies significantly with different feature extraction techniques. Without feature extraction, the model achieved a poor performance with an accuracy of 0.0000, precision of 0.4348, and recall of 0.0000. This highlights that raw EEG data alone is insufficient for effective emotion classification, emphasizing the necessity of feature extraction to improve model performance. Applying Discrete Wavelet Transform (DWT) led to substantial improvements. The model using DWT had an accuracy of 0.1304, precision of 0.5217, and recall of 0.1304. DWT captures important frequency changes in the EEG signals, which enhances the model's ability to recognize emotions. In comparison, the model using Stationary Wavelet Transform (SWT) performed worse, with an accuracy of 0.0435, precision of 0.4928, and recall of 0.0435. This suggests that DWT is more effective in extracting relevant features for emotion recognition compared to SWT.

3.6.2. Which feature extraction method—DWT or SWT—provides better performance for emotion recognition from EEG data: The results clearly indicate that DWT outperforms SWT in emotion recognition from EEG data. DWT achieved higher accuracy and precision compared to SWT, suggesting that DWT is better at capturing the essential characteristics of the EEG signals relevant to emotion classification. The lower performance of SWT could be due to its inability to effectively capture the necessary patterns without downsampling, which may lead to less relevant feature extraction.

3.6.3. The impact of not using feature extraction on the XGBoost model's ability to classify emotions: The absence of feature extraction resulted in very poor model performance. The XGBoost model with no feature extraction had an accuracy and recall of zero, indicating that it could not effectively classify emotions from raw EEG data. This underscores the critical role of feature extraction in improving the model's classification capabilities. Raw EEG signals alone do not provide sufficient information for effective classification, highlighting the importance of employing feature extraction techniques to enhance model performance.

3.6.4. How do preprocessing steps such as downsampling and filtering affect the model’s performance: Preprocessing steps, including downsampling and filtering, are crucial for preparing the EEG data for feature extraction and model training. Filtering helps to remove noise and artifacts from the EEG signals, ensuring that the data used for feature extraction is clean and relevant. Downsampling reduces the data size and computational complexity, making the model training process more efficient. Proper preprocessing ensures that the extracted features are accurate and representative of the underlying patterns in the EEG data, thereby improving the model's performance. Inadequate preprocessing can lead to poor data quality, which negatively impacts the effectiveness of feature extraction and model training.

3.7. Limitation and Future Works

The study revealed several limitations affecting the performance of the emotion recognition model based on EEG data. Firstly, the model's overall performance remained relatively low, particularly in scenarios without feature extraction and with Stationary Wavelet Transform (SWT). This indicates that both raw data and the feature extraction methods used may not be fully effective. Additionally, the quality of the EEG data and the parameters selected for the XGBoost model could be suboptimal, impacting the results. The feature extraction methods, Discrete Wavelet Transform (DWT) and SWT, may not capture all relevant information from the EEG signals, leading to limited model accuracy.

To address these limitations, several areas of improvement are suggested. Enhancing data preprocessing through advanced filtering and cleaning techniques could improve data quality and model performance. Exploring alternative feature extraction methods, such as Continuous Wavelet Transform (CWT), may yield better results in capturing important signal characteristics. Applying more comprehensive hyperparameter tuning could optimize model performance. Additionally, utilizing larger and more diverse datasets could help in developing a more robust and accurate model. Implementing regularization techniques may also reduce overfitting and improve generalization. These steps are essential for advancing emotion recognition models and achieving more accurate classification outcomes.

4. Conclusion

This study aimed to evaluate the effectiveness of feature extraction using Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT) on EEG data to improve the performance of emotion classification models, specifically using XGBoost. The primary research questions focused on determining whether these feature extraction methods could enhance the accuracy of emotion recognition from EEG signals and comparing their performance against a baseline model without feature extraction. The results of the study indicate that feature extraction significantly impacts the performance of the emotion classification model. The model with DWT-based features demonstrated superior performance compared to the models without feature extraction and with SWT-based features. This suggests that DWT is more effective in capturing relevant information from EEG signals for emotion classification. However, the overall performance of the models, including the DWT-enhanced model, was lower than expected, indicating room for improvement.

The effectiveness of feature extraction is evident as the DWT-enhanced model outperformed the baseline and SWT-enhanced models. This suggests that DWT is a viable method for extracting meaningful features from EEG data for emotion classification. Despite this improvement, the overall accuracy, precision, and recall of the models were relatively low, indicating potential issues with data quality, the chosen feature extraction methods, or the parameters used for the XGBoost model. Additionally, the need for improved methods is underscored, as the study highlights the necessity of exploring alternative feature extraction techniques, improving data preprocessing methods, and conducting comprehensive hyperparameter tuning to enhance model performance. The study found that DWT can improve the accuracy of emotion recognition models compared to no feature extraction and SWT. However, the improvement was not substantial enough to meet high-performance standards, indicating that while DWT is beneficial, further enhancements are necessary. Additionally, the comparison revealed that DWT is more effective than SWT in extracting features for emotion classification from EEG data. The DWT-enhanced model achieved higher accuracy, precision, and recall compared to the SWT-enhanced model.

To address the limitations identified in this study and enhance the performance of emotion recognition models, the following recommendations are made: First, implement more advanced filtering and cleaning techniques to improve the quality of the EEG data. Second, explore other feature extraction methods such as Continuous Wavelet Transform (CWT), which might capture more relevant features from the EEG signals. Third, conduct thorough hyperparameter tuning to optimize the XGBoost model's performance. Fourth, use larger and more diverse datasets to improve the robustness and generalizability of the model. Lastly, apply regularization techniques to reduce overfitting and enhance model generalization. These steps are crucial for advancing the field of affective computing and developing more accurate and reliable emotion recognition models using EEG data. By addressing these areas, future research can build on the findings of this study and contribute to more effective emotion classification systems.

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