IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 8 May 2024, accepted 26 May 2024, date of publication 29 May 2024, date of current version 29 July 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3406932

RESEARCH ARTICLE

Exploring Skin Potential Signals in Electrodermal Activity: Identifying Key Features for Attention State Differentiation

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This work was supported in part by the Sichuan Science and Technology Program under Grant 2023YFSY0041, in part by the Key Research and Development Program of Zhejiang Province under Grant 2021C01039, in part by the Zhejiang basic public welfare research project under Grant LGF22F030003, and in part by The Leading Goose Research and Development Program of Zhejiang Province under Grant 2022C01136.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Clinical Research Ethics Committee of the First Affiliated Hospital, Zhejiang University School of Medicine with under Approval No. 2022, IIT Consent Letter No. 568.

ABSTRACT Assessing changes in human attention states via noninvasive physiological signals poses a significant challenge. Research has often associated the migration of mitochondrial superoxide radicals with electrical skin signals and physiological state. This study proposes a novel method to identify meaningful features for discerning variations in attention states by examining skin potential (SP) signals from specific features. This research project began with gathering SP signals. Next, Wavelet Packet Transform (WPT) and other approaches are applied to conduct an energy analysis across various frequency bands, which allows for the extraction of time- and frequency-domain features from the SP signals, and the potential of these features to differentiate human attention states is then examined via regression-based classifiers. Feature selection refinement is accomplished through statistical tests and Linear Support Vector Machines (SVM) with Recursive Feature Elimination (RFE). The focus is on the discriminative power of a selected set of primary features to distinguish human attention states. The designed experiment revealed significant variations in SP signal features when the subjects experienced shifts in their attention states. These features encompass measures such as first- and second-order derivative sequences, wavelet energy, wavelet coefficient, and power spectral density in different frequency bands. The core significance of this research lies in its focus on the feature selection of the SP signal, which yields a set of highly impactful features contributing to the distinction of attention states. This study underscores the potential of classifier models to effectively distinguish attention states, particularly through the examination of critical features, such as the wavelet energy of SP signals within certain frequency bands. These features may be relevant to several psychological mechanisms that reinforce the relationship between physiological signals and cognitive state. The insights derived from this investigation deepen the comprehension of human attention states and set the groundwork for more granular future explorations of SP signals.

INDEX TERMS Electrodermal activity, feature selection, machine learning, SP signal, attention, wavelet.

The associate editor coordinating the review of this manuscript and approving it for publication was Sotirios Goudos.

I. INTRODUCTION

Attention is one of the most intricate mechanisms within the human cognitive system [1], and plays a crucial role in an individual's capacity to concentrate and engage in purposeful tasks over an extended period [2]. It is widely recognized as indispensable for accurately comprehending human activities, and research has consistently demonstrated that lower attention significantly undermines learning effectiveness [3], [4]. Consequently, the detection of shifts in attention state has become vital, particularly in fields like training programs to improve concentration, reducing accidents caused by driver fatigue, and managing attention deficits in children. [5]. However, traditional methods, such as direct observation, surveys, and interviews, are hindered by credibility, lack of objectivity, inefficiency, and resource wastage [6], [7]. Consequently, their limitations restrict the development of broader applications, rendering them impractical for implementation.

In the quest for more reliable, convenient, and instantaneous methods for identifying attention, the exploration of diverse attention detection strategies has been inspired, especially non-contact methods [8]. Predominantly reliant on facial recognition technologies, these approaches have made significant progress in attention analysis [9], [10]. Although numerous non-contact methods for determining attention levels exist, they face challenges in maintaining accuracy, coping with artificial expressions, and handling environmental interference. These methods often struggle with feature extraction owing to variability in scale, angle, and occlusion in facial images, thereby compromising their accuracy [11]. Coupled with high computational costs and slow detection speeds, real-time applications have become problematic. Further, reliance on handcrafted features in traditional face detectors results in lower flexibility and reliability, thus underperforming in unpredictable scenarios [11]. So there is a pressing demand for a more robust and less disruption-prone method. This has led researchers towards contact methods that pivot physiological signals, such as electroencephalography (EEG) patterns, heart rate variability, eye movements, and skin conductance responses [12]. For neurological measures like EEG, functional magnetic resonance imaging (fMRI), and positron emission tomography (PET), despite their effectiveness in assessing brain activity, they are often hampered by invasiveness, high costs, susceptibility to motion artifacts, complexity of data interpretation, variable resolution, individual differences, lack of portability, and setup inconvenience. Among physiological signals, electrodermal activity (EDA) has emerged as a promising avenue because of its positive correlation with attention levels and its ability to provide real-time data with a quicker and more sensitive indication of changes in attention states [13], [14].

The basis of EDA signals corresponds to the activity of the autonomic nervous system (ANS), intricately reflecting the sympathetic "fight or flight" and parasympathetic "rest and digest" responses [15]. EDA data can be acquired through two primary methodologies: skin resistance (SR) and skin potential (SP). Although both SP and SR changes exhibit a correlation, this interrelationship undergoes variations under different conditions, such as individual sex and the nature of stimulation received [16], [17], [18]. A unique feature of SP signals is the complexity of their waveforms, which may have additional psychological implications [19], [20]. This complexity, alongside the sensitivity of SP to the activity of superoxide free radicals produced during cellular metabolic processes in the skin, potentially renders SP a more valuable tool than SR for psychophysiological research [21], [22]. SP not only reflects sweat gland activity, such as SR, but also provides a wider snapshot of physiological responses [23]. This broad spectrum of captured responses becomes particularly noticeable during periods of intense mental activity, where increases in sympathetic nervous system activity correspond to observable changes in SP [24]. The advantages of SP over SR can be further demonstrated in practical applications. For instance, the measurement of SP involves a simpler setup and does not require the injection of current into the body. Additionally, SP signals display less sensitivity to variations in both electrode and skin impedance, and respond more swiftly to stress stimuli [25], [26]. The sensitivity of SP to cellular metabolic processes and the influence of the neurotransmitter acetylcholine offers a comprehensive representation of ANS activity and serves as an effective measure of an individual's attention level [21], [27], [28]. Various pathways, such as hypothalamic control, contralateral and basal ganglion influences, and reticular formation in the brainstem integrate multiple central mechanisms into the EDA signal. This integration provides SP signals with a uniquely holistic view of an individual's attention state [22], [28], [29].

The intricacy and multidimensionality of SP signals make machine learning (ML) classification models an indispensable tool in attention recognition and feature selection [30]. ML models excel in dissecting high-dimensional, nonlinear data and unearthing complex patterns that often elude traditional statistical methods [31]. This exceptional ability allows ML models to offer a comprehensive understanding of an individual's attention state by concurrently processing diverse features of SP signals, including features from the time, frequency, and time-frequency domains. ML models are instrumental in feature selection, helping identify and select the most relevant features for attention detection from a sea of possible candidates. This process reduces the data dimensionality, prevents model overfitting, and enhances model interpretability. Moreover, the capability of ML models for real-time responses is invaluable in situations requiring immediate feedback, such as learning environments or fatigue prevention systems [14], [32]. In addition, it can inherently benefit from an iterative learning process, which increases the accuracy and reliability of attention detection with increased exposure to data over time.

Our study proceeds to a detailed examination of the construction of classifiers, selection of features, and refinement of an effective machine learning model for practical applications. This approach aligns with our research's core methodology, in which we utilize Random Forest (RF), Gradient Boosting Decision Trees (GBDT), and XGBoost classifiers for more than just data classification. These classifiers are also used to evaluate and select SP features, thereby enhancing our understanding of the inherent patterns in the data and enabling us to create a streamlined, efficient model suitable for real-world use. This is particularly important in wearable devices, where computational resources are limited. Thus, our methodological approach focuses on developing a model that balances accuracy and practical feasibility, ensuring that our findings are theoretically significant and applicable in real-world situations. The result is a lean, potent Support Vector Machine (SVM) classifier that utilizes a carefully chosen set of key features to differentiate between attention states. This model represents a significant advancement in wearable technology applications and provides a scalable and accessible solution for continuous real-time attention monitoring.

Building on the groundwork laid by Li's group on emotion recognition through SP signals [19], this study leverages the effectiveness of ML classification models for extracting, analyzing, and interpreting the multifaceted features within SP signals and the deeper meaning of the selected main features in human physiological signals. The objective is to promptly and efficiently differentiate between diverse attention periods through a specific useful feature from SP signals. In addressing the complex problem of differentiating attention states, our study only focuses on attention concentration, which means that attention would be simplified into lower dimensions for presented different states. Our approach does not emphasize the precise score at a specific point but rather the overall tendency towards one of these two ends of the attention spectrum. This perspective aligns with the cognitive understanding of attention as a crucial aspect of human engagement in tasks and activities, as highlighted in the introduction [1], [2]. With the idea of simplified attention, the feature exploration from SP for attention shifting and the classification model based on machine learning for distinguishing shifting attention can be found. By simplifying the complex nature of attention evaluation into a binary classification model, we aim to overcome the challenges faced by non-contact methods, such as accuracy issues owing to variability in facial recognition [11], and establish a foundation for more efficient and reliable attention state detection.

This approach underscores the versatility and adaptability of ML models in feature selection and attention state differentiation, thereby demonstrating the potential of SP signals to unravel the intricacies of human attention states. We developed a robust methodology that addresses special features and classification results of SP signals suitable for wearable technology. This approach significantly enhances the detection of attention states, providing a precise, efficient alternative to existing methods. Additionally, our research lays a foundational framework for future explorations into the physiological aspects of attention, potentially improving real-time monitoring and management of attention-related disorders. This integration of machine learning and feature selection marks a notable advancement in applying physiological signal analysis to practical settings.

II. MATERIALS AND METHODS

A. PARTICIPANTS

Participants were selected based on specific inclusion criteria: they were between the ages of 18 and 65 years, in a good mental state, and had no diagnosis of Palmar Hyperhidrosis. Our study involved attention state monitoring experiments conducted on qualified participants, resulting in 97 sets of valid data. This study was conducted in strict accordance with the principles of the Declaration of Helsinki and the protocol was approved by the Clinical Ethics Committee of the First Affiliated Hospital of Zhejiang University. All participants provided written informed consent before trial commencement.

The participants were placed in a bright, quiet environment, with the temperature maintained at approximately 26 °C to ensure comfort. A proper seating posture was ensured to facilitate focus and reduce potential discomfort. To aid the participants during the experiment, a guide was presented at the site to direct them step-by-step through various stages of the experiment. This systematic approach ensured the validity of the collected data and maintained the integrity of the experiments.

B. SP SIGNAL ACQUISITION DEVICE

For SP data collection, we utilized a portable hardware device measuring 10 cm in length, 6 cm in width, and 3 cm in height, designed and developed by Li et al. using emotion recognition with equipment similar to that in a previous study [19]. This compact design allowed for easy transport and unobtrusive applications during the experiment. The device is connected via Bluetooth to transmit the collected data from the human body directly to a smartphone terminal.

Equipped with a high impedance and a high common-mode rejection ratio, the device effectively reduces the interference caused by the instability of the human body resistance. The device has two channels, a measurement channel (red) and a reference channel (white), connected to the inside of the wrist and the fingertip of the middle finger using electrode patches [19], [21]. The SP signals from the human body were amplified through a differential amplifier module and input into an active low-pass filter module for low-pass filtering, reducing the interference caused by the power frequency. In the main control module, the digital signal is adjusted by subtracting the changed amplitude and dividing it by the differential amplification multiple to obtain the desired SP signal.

Furthermore, a custom mobile application developed in our lab facilitates the interface between the hardware device and data collection. It connects to the hardware device via

Bluetooth, and records and displays the changes in the body's SP signals in real time. As the SP signals were recorded, the app presented a real-time waveform diagram showing signal changes over time (see Figure 1), providing an intuitive visual interface for data collection. After data collection was concluded, the data were saved locally on the smartphone in CSV format for easy extraction and further analysis.

FIGURE 1. Device and app interface.

C. SIGNAL PROCESSING TOOLS

Data analysis for this study was conducted using a combination of software tools to ensure a robust and accurate interpretation of our findings.

The primary programming environment was Python 3.9.12, a versatile platform offering a myriad of libraries renowned for their applications in data science and signal processing, particularly utilizing scikit-learn (sklearn) for the implementation of ML algorithms [33], [34]. Additionally, HeartPy is a specialized library for heart rate variability analysis, with a particular emphasis on its time-domain and frequency-domain modules for EDA signal processing [34]. These modules facilitate data preprocessing, feature extraction, model construction, and validation.

We used MATLAB R2022a's Signal Processing and Wavelet Toolbox for analyzing [35], preprocessing, and extracting features from our data, especially facilitating the decomposition and reconstruction of signals using wavelet techniques, aiding in the extraction of time-frequency features. GraphPad Prism version 9.5.0 was also used as a tool for creating scientific graphs and conducting statistical analyses [36].

Together, these software tools form an integrated environment for signal processing, ML, and statistical analysis to uncover the complex patterns present in the SP data.

D. EXPERIMENT

Participants were situated in a bright, quiet environment with the temperature controlled at approximately 26 °C to ensure optimal comfort and concentration. Each participant was seated comfortably with the experimenter at hand to guide them through each step of the experiment.

The flow of the experiment, depicted in Figure 2, involves four main steps.

1. The participants were equipped with Bluetooth noise-canceling headphones, and two electrode patches were attached: one to the pulp of the middle finger and the other to the inner right side of the left wrist. Our Bluetooth hardware device was connected physically to the two electrode patches and via Bluetooth to the smartphone application. At this stage, a live waveform graph of the participant's physiological electrical signal is visible on the smartphone screen. Participants were instructed to sit quietly for 5 min while the experimenter clicked on the "Start Test" button on the app interface, initiating music playback through the headphones.

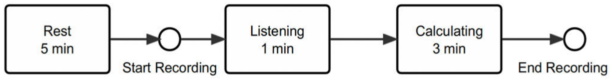

FIGURE 2. Block diagram of experimental procedures.

2. A 60-second strong music segment was continuously played to the participants, who were instructed to immerse themselves as much as possible in the strong rhythm of the music. Simultaneously, the smartphone application continuously recorded participants' SP signals.

3. After the 60-second music segment, the experimenter paused the music playback. The participants were then asked to solve mental arithmetic problems on the screen for continuous three minutes. Participants were required to concentrate fully on solving these calculations.

4. At the end of three minutes, the experimenter signaled the participants to stop the test and pressed the "End Test" button on the app. Subsequently, the participants were asked to complete a post-test questionnaire.

The questionnaire required participants to self-assess their state of attention during the experiment, rating it on a scale of 1 to 5. A score of 1 indicated a state of inattention, whereas a score of 5 represented a state of full attention. Participants were asked to evaluate their attention level during both phases of the experiment: the music-listening phase and arithmetic arithmetic-solving phase. The self-evaluation scores provided a subjective gauge of the participants' attention level during the different phases of the experiment, supplementing the objective physiological data collected.

E. DATA PREPROCESSING AND DATASET CONSTRUCTION

The transmission of SP signals via Bluetooth can occasionally deviate from the 20 Hz sampling rate, although such instances are infrequent (probability less than 0.1%). To compensate for this, we employed the cubic spline interpolation method for data completion [37]. Previous studies have often normalized the data during signal preprocessing to account for variations in the amplitude range among different participants' physiological signals [38]. However, considering that normalization can potentially affect the data's extreme value distribution, certain frequency domain features, and the correlation study of individual SP signals, we opted for selective normalization treatment during the time- and frequency-domain feature analysis phase based on the characteristic properties of the features.

Each test was conducted over a span of four minutes (97 samples in total), and at a sampling rate of 20 Hz, we obtained 4800 sampling points of the SP signal for each trial. During the single test, the moments when the music started and stopped were annotated with time tags using the mobile app. This procedure effectively divided the entire process into two distinct regions: one minute of music disturbance and three minutes of calculation tasks. From Figure 3, which depicts the initial SP signal (a) and the magnitude scalogram of the wavelet transform (WT) (b), it can be inferred that there may be discernible differences between the two stages according to our initial observations. In this study, a fixed-length segmentation strategy for processing physiological signals was employed, which is consistent with previous research [39], [40]. To capture the representative signal features from each stage, we chose to use a 50-second signal segment (1000 sampling points) to strike a balance between obtaining a view of the signal characteristics within each stage and ensuring the precision of our analysis. This structured approach helps isolate and analyze the distinct phases of the experiment, allowing for a reliable comparison across different periods and participants.

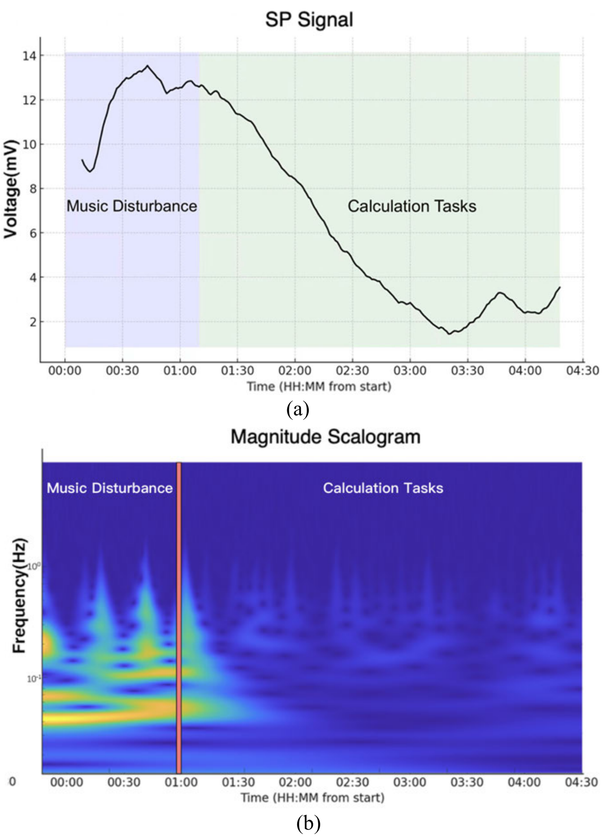

FIGURE 3. **(a) Initial SP signal (b) Magnitude scalogram of WT.**

F. FEATURE EXTRACTION

According to previous research and analysis [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [28], [29], a total of 29 features were extracted in this study for music disturbance and calculating parts, which include 9 time domain features, eight frequency-domain features, and 12 time-frequency domain features listed in Table 1.

TABLE 1. **29 features extracted.**

Domain	Feature Category
Time domain	Mean, Median, Standard Deviation, First Derivative of Mean, Standard Deviation of First Derivative, Second Derivative of Mean, Standard Deviation of Second Derivative, Minimum Ratio, Maximum Ratio
Frequency domain	Signal Energy, Spectral Power [0-0.625Hz] $\delta = \frac{5}{32}$, Minimum Spectral Power, Maximum Spectral Power, Variance of Spectral Power
Time-frequency domain	Mean Wavelet Coefficient, Standard Deviation of Wavelet Coefficient, Relative Wavelet Energy

1) TIME DOMAIN FEATURES

A predominant observation throughout the course of the experiment was that the SP signals of most participants demonstrated a pronounced downward trend when transitioning from music disturbance to performing an arithmetic calculation task. The consistent pattern was characterized by either steady reductions in SP over time or fluctuations with an overall declining trend, approximating the characteristics of a first-order function. This empirical finding informed the selection of parameters for the time-domain feature analysis, including the median, mean, standard deviation, variance, and root mean square of the amplitude. The minimum and maximum ratios of the sample were also considered (Equations 4.1, 4.2), where x_{min} and x_{max} denote the peak and trough positions within the sample frequency band signal, respectively, and x_{length} represents the number of data segment sampling points. Considering the relatively pronounced declining trajectory of the potential signal, the first- and second-order derivative sequences of the sample were also computed, along with their corresponding means, medians, and standard deviations, augmenting the suite of time-domain features. The specific contributions of these time-domain features are elaborated in Chapter 3.

$$Ratio_{min} = \frac{x_{min}}{x_{length}} \tag{4.1}$$

$$Ratio_{max} = \frac{x_{max}}{x_{length}} \tag{4.2}$$

2) FREQUENCY DOMAIN FEATURES

Following time-domain feature extraction, frequency-domain features were obtained using Welch's method (Figure 4), which is an approach that enhances signal analysis in noisy environments. Welch's method involves segmenting the signal into overlapping segments, applying a Fourier Transform to each, and then averaging the power spectra of these segments. This procedure effectively reduces noise, leading to a more stable and accurate estimation of the power spectral density of the signal, thereby providing a reliable foundation for our frequency-domain feature analysis [41]. In Figure 4, the left part of the x-axis is extracted from a dataset window of one-minute (00:00 – 01:00) length during the music disturbance stage, and the right part is extracted from a dataset window of one-minute (02:30 – 03:30) length during the calculation stage within a sample.

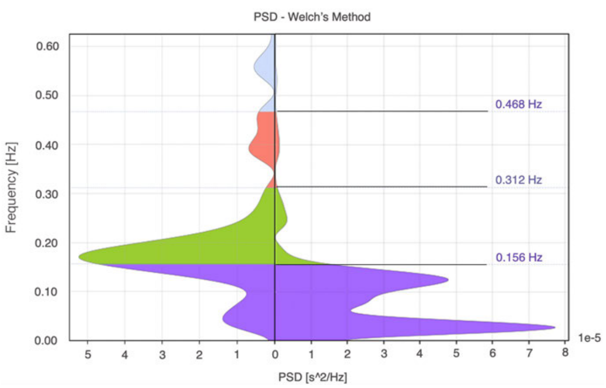

FIGURE 4. Power spectral density of different frequency bands.

The dataset window from 2:30 to 3:30 during the calculation stage was selected for analysis to represent a typical period within the longer calculating phase, assuming that it reflects the sustained attention state characteristic of this stage, following the initial adaptation period post-music-disturbance stage. In accordance with the bandwidth partitioning in Wavelet Packet Decomposition (WPD) (2.6.3), the frequency spectrum was divided into four segments: 0-5/32 Hz, 5/32-5/16 Hz, 5/16-15/32 Hz, and 15/32—5/8 Hz. Figure 5 is a typical WPD method akin to bisection to meticulously divide the frequency spectrum. The visual representation in the figure clarifies the segmentation process and showcases the unique energy patterns within each band. Signals under 5/32-5/16 Hz and 15/32—5/8 Hz are taken out as visualization examples. Differences in the power distribution across these spectral bands were evident between the music disturbance and calculation stages. Spectral analysis indicated relatively minimal power beyond 0.625 Hz, which is likely attributed to noise [20]. Furthermore, the extracted frequency-domain features included the spectral power of each band, minimum and maximum spectral powers, total energy within the 0-0.625 Hz range, and variance of spectral band powers, offering a capture of the frequency-domain characteristics of SP signals to distinguish and comprehend attention states.

3) TIME-FREQUENCY DOMAIN FEATURES

Time-frequency domain feature analysis of physiological signals has been emphasized in many related studies [42]. Emphasizing time-frequency domain analysis through WPD can achieve a multidimensional perspective of the complex dynamics of attention levels within SP signals. This refined wavelet transformation method optimizes the frequency spectrum representation for precise feature extraction [43]. This is pivotal because of the non-stationary nature of SP signals, providing high-resolution analysis in both the time and frequency domains, and enhancing classification performance through detailed signal representation. The features we especially focused on were the relative wavelet energy percentage and statistical measures of wavelet coefficients across various frequency bands (0-5/32 Hz, 5/32–5/16 Hz, 5/16-15/32 Hz, and 15/32–5/8 Hz).

Given the criticality of WPD in elucidating SP signals, selection of an appropriate mother wavelet for feature extraction is paramount. The Daubechies wavelet of order five (DB5) was used in this study, given its successful applications in various recent physiological signal studies employing WT [44]. The impact of using different mother wavelets is discussed in Section IV. Figure 5 shows two of the four nodes used in this study as time-frequency domain features.

G. CLASSIFIER CONSTRUCTION

Three different classifiers–Random Forest (RF), Gradient Boosting Decision Tree (GBDT), and Extreme Gradient Boosting (XGBoost)–were employed in this study to construct attention state models [45]. RF is an ensemble learning method that offers robustness through decision-tree aggregation. GBDT is a powerful ML technique that creates a model in the form of an ensemble of weak prediction models, typically, decision trees. XGBoost is a more advanced implementation of the GBDT algorithm optimized for both computational speed and model performance [46]. Each classifier is particularly adept at handling the high dimensionality of features, making them well-suited for the task of complex attention state classification based on SP signals. The parameters are listed in Table 2.

Special considerations were given to data division and validation to maintain the integrity and reliability of the study. A total of 97 samples and 194 data slices were collected from the 37 participants. These were divided into training and testing sets in a ratio of 7:3. Importantly, to avoid data dependence that could stem from individual participant SP signal characteristics, the original data from each participant were divided proportionally. This measure aimed to minimize the occurrence of the same participant's data in both the training and testing sets, thereby establishing a relatively participant-independent physiological state classification model.

Furthering the accuracy of the model [47]. This step ensured that the model was not only trained but also

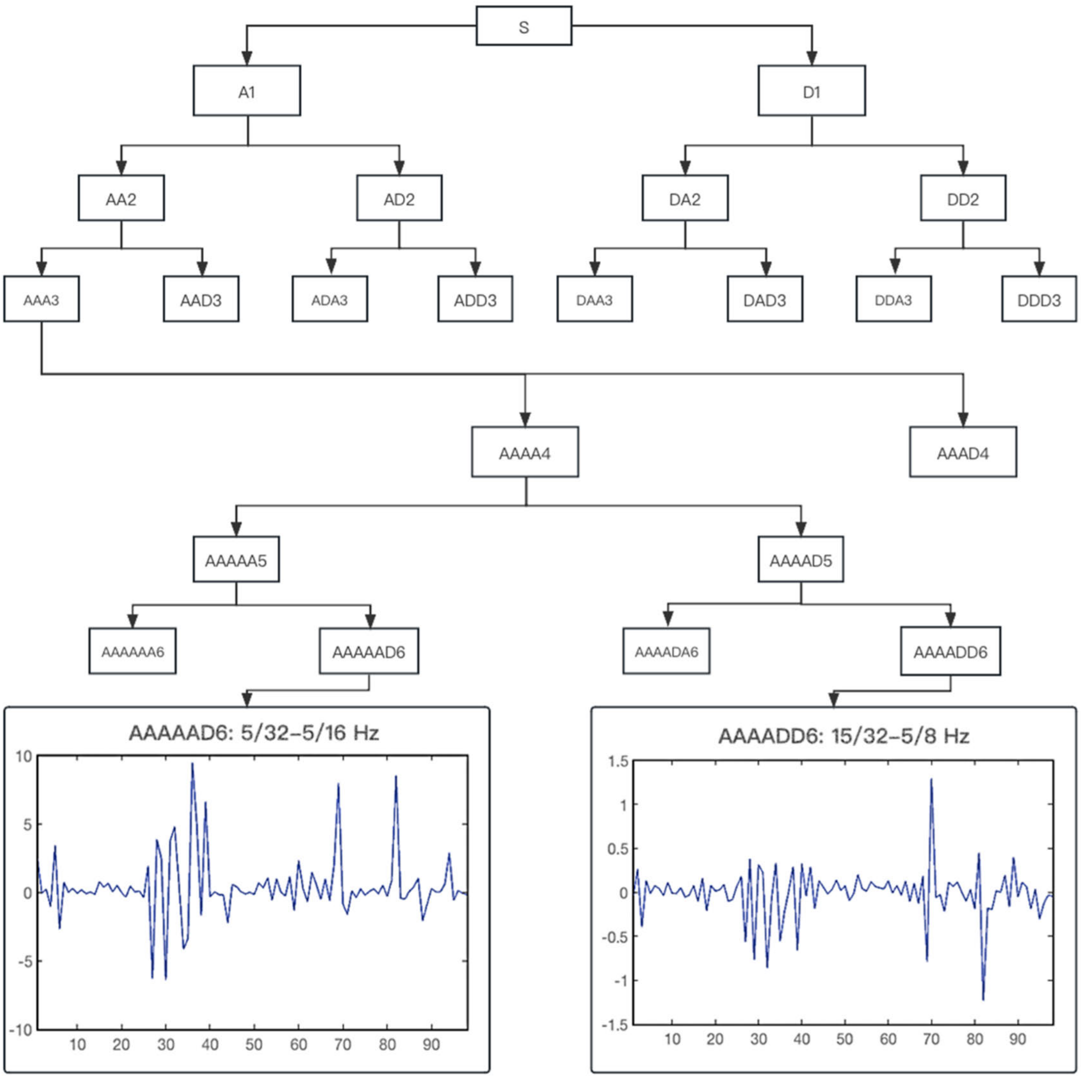

FIGURE 5. **Wavelet packet decomposition.**

validated on multiple subsets of data, offering a more robust estimation of the model's generalizability. These methodological choices help guarantee a comprehensive evaluation of the classifiers' ability to differentiate attention states using SP signals, contributing significantly to the ongoing research on attention state differentiation.

H. FEATURE SELECTION

Our feature selection process aims to accurately distinguish attention states from SP signals. It incorporates a multi-tiered approach that synergies statistical and machine learning methodologies for a holistic analysis.

Initially, tree-based models, including RF, GBDT, and XGBoost, were employed to assess the importance of various features. This step served as the cornerstone of our feature selection strategy, leveraging the intrinsic capability of these models to rank features based on their contribution to classification accuracy. The output from these models provided a preliminary yet robust indication of feature significance, setting the stage for further validation.

Subsequently, a paired t-test was applied to statistically validate the importance of features identified by the tree-based models [31], [48]. This statistical evaluation, ideal for within-subject designs, allowed us to account for individual differences across participants by focusing on mean feature differences between attention states. The selection of features with statistically significant differences ensured that our subsequent analyses were grounded in features with proven discriminative power.

The final refinement of our feature set was accomplished through the use of a Support Vector Machine (SVM) with a linear kernel, incorporating a Recursive Feature Elimination (RFE) strategy [49], [50]. This phase involved iteratively eliminating the least significant features and retraining the SVM to identify a concise set of features with the highest

TABLE 2. Results for nine selected features.

Feature	P value	Significantly different
Time-domain Standard Deviation (feature 2)	0.0054	Yes
First-order Differentiation in Time Domain (feature 3)	0.0897	No
Standard Deviation of First-order Differentiation (feature 4)	0.3636	No
Wavelet Energy in 0 - 0.15625 Hz (feature 11)	0.0189	Yes
Mean Wavelet Coefficient in 0.15625 – 0.3125 Hz (feature 12)	0.2420	No
Wavelet Energy in 0.15625 – 0.3125 Hz (feature 14)	<0.0001	Yes
Mean Wavelet Coefficient in 0.3125 – 0.46785 Hz (feature 15)	0.1574	No
Wavelet Energy in 0.3125 – 0.46785 Hz (feature 17)	<0.0001	Yes
Standard Deviation of Wavelet Coefficient in 0.46785 – 0.625 Hz (feature 19)	<0.0001	Yes

predictive value for attention states [51], [52]. The RFE method, bolstered by the preliminary feature ranking from tree-based models and statistical validation through paired t-tests, allowed for a meticulous distillation of the most informative features.

This comprehensive approach to feature selection—beginning with tree-based model evaluations, validated through statistical analysis, and finalized with SVM and RFE—ensures that our model is based on features with high predictive power and statistical significance. The fusion of machine learning insights and statistical validation underscores the robustness of our method in identifying key SP signal features for attention state differentiation.

I. EFFICIENT ML MODEl FOR PRACTICE

The culmination of our study led to the development of an efficient ML model designed for real-world application, especially within the domain of wearable technology. The linear SVM was chosen for its proficiency in binary classification tasks and unparalleled feature selection efficiency. This model utilizes a refined set of significant features—primarily features 11 and 17—to unlock the potential of SP signal analysis for attentive state monitoring in everyday settings.

The model's development was guided by a rigorous feature selection process, as outlined in Section H, aiming to craft a tool that is both rapid in training and lightweight enough for deployment on wearable devices. These devices, characterized by their limited computational capacities, necessitate models that promise swift diagnostic capabilities and maintain high accuracy with minimal feature requirements. Such a model is ideal for integration into wearable technology, enabling real-time, on-the-go attention state monitoring without taxing the device's processing power.

Emphasizing a targeted feature set, the model sets a precedent for deploying sophisticated ML techniques in wearable technologies for attention monitoring. Its practical application is further accentuated by a 2D graphical representation, which elucidates the decision boundaries between features 11 and 17, reinforcing the model's operational viability and ease of interpretation.

In essence, this model represents a significant stride towards integrating SP signal analysis into wearable technologies, paving the way for innovative attention monitoring solutions. It epitomizes a judicious combination of advanced feature selection and model efficiency, offering a blueprint for future explorations in the domain of real-time physiological monitoring.

III. RESULTS

In exploring distinguishing attention states, this study meticulously unfolds through a sequence of pivotal analytical stages, which is crucial for understanding our methodology and subsequent insights. Despite the established correlation between SP signals and attention shifts, the underlying physiological mechanisms remain largely uncharted. This gap underscores the importance of our exploration into the SP feature space as a pioneering step towards laying the foundational work for understanding how specific features of SP signals correlate with attention states [14], [16]. Initially, the evaluation of three sophisticated classifiers, RF, GBDT, and XGBoost, via a rigorous ten-fold cross-validation process, established the groundwork. This stage assesses their capacity to differentiate attention states based on SP signals, setting the stage for a deeper dive into the essence of feature selection. Following this, we leveraged the importance of the permutation feature as a cornerstone for our feature selection phase, underpinning our analysis with a paired t-test for statistical validation of the selected features. This approach not only sharpens our focus on the most indicative features of attention states but also seamlessly integrates into the subsequent refinement using an SVM. The RFE method plays a critical role in streamlining the feature set to the most impactful elements. This meticulous process culminates in the development of a highly efficient SVM model that encapsulates our findings into a pragmatic classifier designed for real-world applications. This progression from classifier evaluation through strategic feature selection to the crafting of an efficient machine learning model for practice illustrates our methodological approach. It emphasizes the balance between computational efficiency and the complex analysis required for real-time attention monitoring, which is particularly relevant for developing wearable devices. Through this structured narrative of our results, we aimed to provide a comprehensive overview of our methodological rigor and the significant strides made in differentiating attention states.

A. CLASSIFIER PERFORMANCE

We first evaluated the performance of three classifiers, RF, GBDT, and XGBoost, each validated through a ten-fold cross-validation. The three classifiers, RF, GBDT, and XGBoost, play a distinctive role in feature selection from SP signals [53]. RF, an ensemble of decision trees, provides a robust assessment of feature importance through the decrease in average impurity across trees, favoring universally informative features [54]. GBDT, which leverages boosting techniques, iteratively corrects ensemble errors, with feature importance emerging from each feature's contribution to the overall model performance [55]. XGBoost, a refined gradient boosting library, highlights feature splitting near tree roots, thus identifying key contributors to predictive outcomes. These classifiers were tested for their ability to differentiate attention states using features selected from SP signals.

This new clarity in feature identification led us to compare multiple algorithms to ensure the robustness and reliability of our findings. The RF classifier achieved an accuracy of 0.7339 and an AUC score of 0.85, demonstrating its robustness for classifying different attention states. GBDT followed, with an accuracy of 0.7096 and an AUC of 0.8, showing reasonable efficacy. XGBoost outperformed both, with the highest accuracy of 0.7506 and AUC of 0.87, indicating its superior capability in discerning attention states.

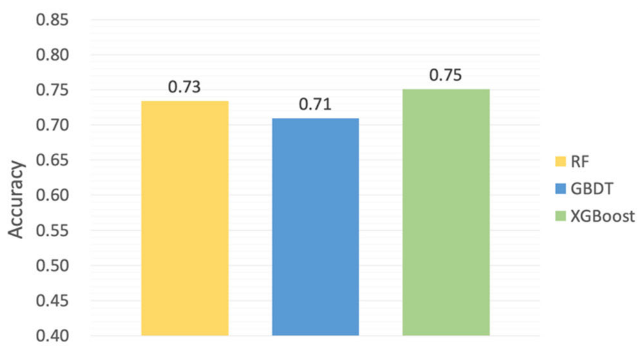

FIGURE 6. Accuracy of three classifiers.

To assess these models further, Receiver Operating Characteristic (ROC) curves and Area Under Curve (AUC) values were employed as performance metrics [56]. These metrics provide a comprehensive evaluation of the classifiers, with ROC curves visualizing the performance and AUC values quantifying the overall predictive capacity. The combined analysis of these metrics reaffirmed the effectiveness of our models in accurately identifying the different attention states. Further discussions on a detailed comparison of the models' performances are provided in the subsequent subsections.

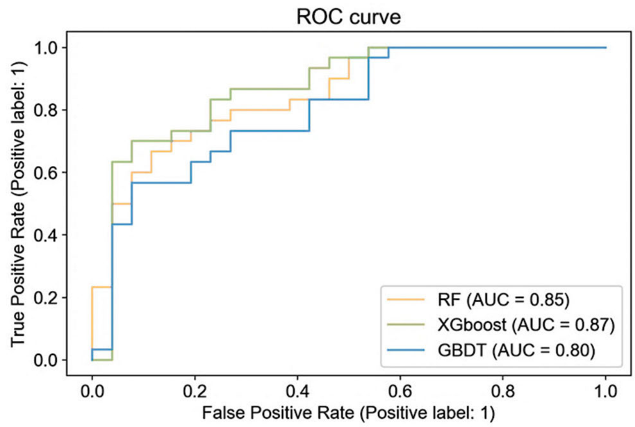

FIGURE 7. ROC curve and AUC value.

B. FEATURE SELECTION DETAILS

The permutation feature importance was the chosen method for feature ranking because of its model-agnostic nature. This technique evaluates the decrease in performance after shuffling each feature, thereby measuring the importance of each feature based on the deterioration of the model's performance [57]. Unlike GINI importance, or Mean Decrease Impurity, which is biased towards preferring variables with more categories, permutation importance provides a fair comparison for both continuous and high-cardinality categorical variables, making it suitable for our study [58]. The top five features for each of the three models based on permutation importance are illustrated in Figure 8, with each column representing a unique feature and its relative importance demonstrated through the corresponding bar length. Nine features were selected for their prominence: feature 2 (time-domain standard deviation), feature 3 (first-order differentiation in the time domain), feature 4 (standard deviation of first-order differentiation), feature 11 (wavelet energy between 0–0.15625 Hz), feature 12 (mean wavelet coefficient between 0.15625 – 0.3125 Hz), feature 14 (wavelet energy between 0.15625 – 0.3125 Hz), feature 15 (mean wavelet coefficient between 0.3125 – 0.46785 Hz), feature 17 (wavelet energy between 0.3125 and 0.46785 Hz), and feature 19 (standard deviation of wavelet coefficient between 0.46785 and 0.625 Hz).

The statistical method paired t-test results indicated that out of the nine features initially selected, five of them–std_time (feature 2), wavelet energy in the 0–0.15625 Hz band (feature 11), wavelet energy in the 0.15625 – 0.3125 Hz band (feature 14), wavelet energy in the 0.3125–0.46785 Hz band (feature 17), and std_wavelet in the 0.46785–0.625 Hz band (feature 19)–presented p-values less than 0.05, thereby deeming them statistically significant, solidifying the robustness of our feature selection approach [31], [48]. Each p-valve is listed in Table 2.

To further refine our feature selection, we employed an SVM, a renowned and robust classifier widely utilized in physiological signal research, especially binary classification [49]. To conduct feature selection, an RFE strategy with

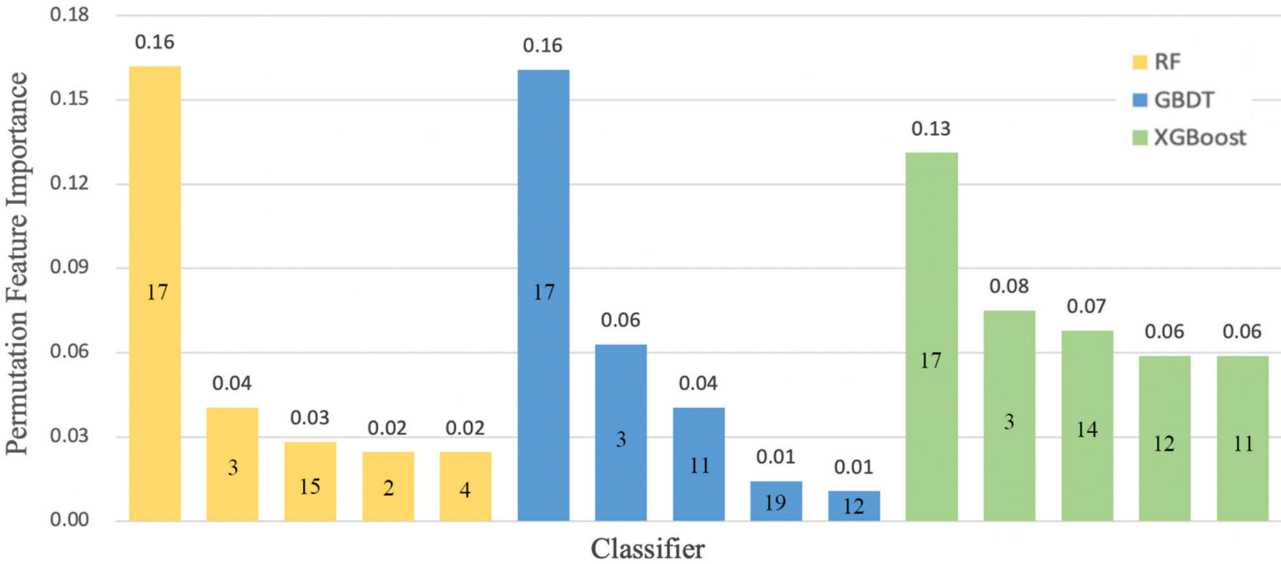

FIGURE 8. Permutation feature importance.

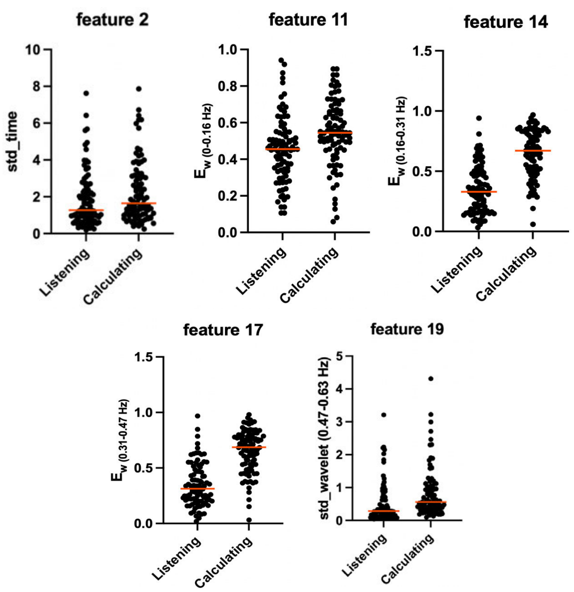

FIGURE 9. Paired t-test of each feature.

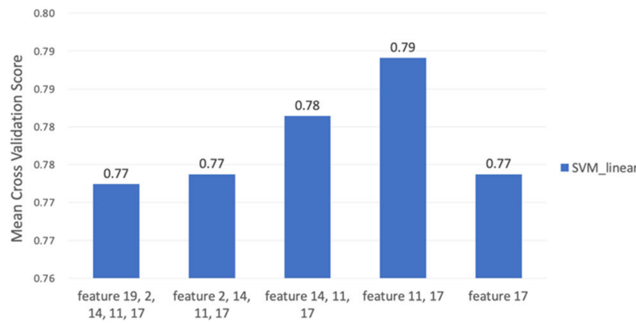

FIGURE 10. Mean cross-validation score for each iteration.

an SVM was utilized [51]. The final set of features was deemed to be the most informative for the classification task.

C. SVM PERFORMANCE

Beginning with features 19, 2, 14, 11, and 17, an SVM model was trained, yielding a mean validation score of 0.772436. The feature with the least weight is then removed iteratively, and the SVM model is retrained. After removing Feature 19, the remaining features 2, 14, 11, and 17 yielded a score of 0.773718. Upon further pruning of the features, sets 14, 11, and 17 gave a score of 0.78141, while features 11 and 17 gave a score of 0.789103. Finally, training using Feature 17 alone yielded a score of 0.773718. The feature weights for each iteration are listed in Table 3. An effective feature selection procedure was established to show that the most crucial features from SP signals necessary to differentiate attention states are wavelet energy at 0–0.15625 Hz (feature 11) and wavelet energy at 0.3125 – 0.46785 Hz (feature 17).

Following diligent iterative refinement using SVM's RFE strategy, two salient features, features 11 and 17, were identified (wavelet energy in 0–0.15625 Hz (feature 11) and wavelet energy in 0.3125 – 0.46785 Hz (feature 17)). These features display the most robust discriminative power in differentiating attention states, as affirmed by the SVM model's performance. To further illustrate the potent discriminative ability of these features, a visualization showing the decision boundaries of the SVM model in the space defined by features 11 and 17 was provided. Figure 11 visually demonstrates the classification performance of the SVM with a linear kernel applied to differentiate between two distinct

TABLE 3. Results for nine selected features.

Feature	19	2	14	11	17	Feature numbers
Literation 1	-0.3371	0.1273	0.7126	1.4172	4.3063	5
Literation 2		-0.0266	0.5292	1.3001	4.0983	4
Literation 3			0.4617	1.4601	4.2059	3
Literation 4				1.3217	4.7520	2
Literation 5					4.5950	1

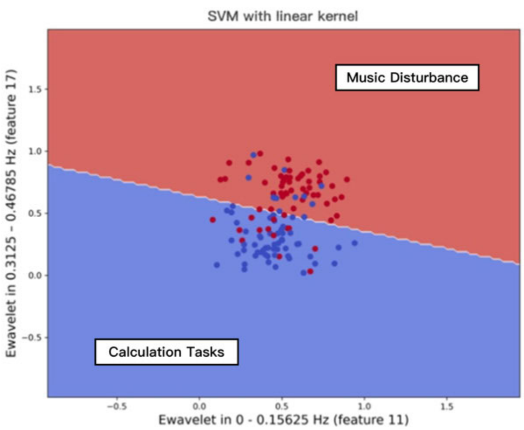

FIGURE 11. SVM results with linear kernel and features 11&17.

attention states: music disturbance and calculation tasks. The x-axis represents the feature derived from the wavelet energy within the 0 - 0.15625 Hz band (Feature 11), while the y-axis corresponds to the wavelet energy within the 0.3125 - 0.46785 Hz band (Feature 17). Each red dot within the red region indicates a correct prediction of the music disturbance stage, whereas blue dots in the blue region accurately classify instances of the calculation tasks. The decision boundary, represented by a solid straight line, clearly demarcates the separation between the two attention states, underscoring the SVM's efficacy in utilizing these features for robust discrimination. This delineation highlights the model's ability to leverage subtle variations in SP signal characteristics to effectively distinguish between the cognitive demands of listening to music and engaging in calculation tasks. This vivid depiction not only underscores the robustness of these features in segregating attention states but also powerfully illustrates how a simple linear model can effectively classify different attention states with high efficiency and accuracy using just two key extracted features. This presentation highlights the model's capability to provide clear and intuitive insights into the classification task, demonstrating its practical applicability in distinguishing between complex cognitive states.

IV. DISCUSSION

A. INSIGHTS ON SPECIFIC SP FEATURES

The two most informative features identified from the WPD of SP signals, the wavelet energy in the frequency bands of 0–0.15625 Hz (feature 11) and 0.3125 – 0.46875 Hz (feature 17), potentially reflect the specific physiological or psychological mechanisms underlying attention states. These features occupy distinct non-overlapping frequency bands, suggesting that they capture different facets of the attention state.

The wavelet energy from 0–0.15625 Hz (feature 11), situated in the very low-frequency band, potentially corresponds to slower tonic changes in EDA, which are associated with underlying states, such as stress or arousal [59]. The tonic shifts in signals are linked to overall arousal, cognitive, and emotional states, and are generally influenced by factors causing a long-term alteration in an individual's physiological arousal level [60]. Within the scope of attention, these factors might include sustained focus on a specific task or stimulus or overall levels of alertness or engagement. The prominence of this feature in classifying attention states indicates that the tonic aspects of SP, as represented by low-frequency fluctuations in SP, are critical in distinguishing between different levels of attention.

In contrast, the wavelet energy from 0.3125 – 0.46875 Hz (feature 17), encompassing a higher frequency band, may correspond to rapid phasic shifts in SP that are associated with immediate reactions to specific stimuli or events. Phasic fluctuations in SP signals might be linked to immediate changes in arousal caused by discrete events, stimuli, or tasks [59]. These changes tend to be more rapid and transient, reflecting an individual's immediate response to specific attention-demanding events or tasks. Consequently, the wavelet energy from 0.3125 – 0.46875 Hz (Feature 17) could capture the variability in these immediate event-related responses across different attention states. The significance of this feature in classifying attention states suggests that these rapid event-related changes in SP play a substantial role in the physiological differentiation of attention states.

However, the specific physiological or psychological mechanisms that these two features reflect remain speculative at this point and should be a focus for future research. Nonetheless, the fact that these frequency-based features were selected as the most informative for classifying attention states highlights the potential of the WPD of SP signals as a promising approach for attention state analysis. This provides additional evidence supporting the hypothesis that specific frequency bands of the SP signal can have distinctive relevance to attention states, thus opening novel avenues for future investigations in this field.

In summary, the identification of these two informative features in the specific frequency bands of the SP signal represents a significant step forward in the quest to differentiate attention states based on physiological signals. It also underscores the potential of ML methods for feature selection in physiological signal analysis given their ability to sift through complex, multidimensional datasets and identify the most informative patterns [30].

B. CLASSIFIER PERFORMANCE DISCUSSION

The efficacy of the three classifiers, RF, GBDT, and XGBoost, in accurately differentiating attention states using SP signals sheds light on their inherent operational strengths. Remarkably, all three classifiers achieved accuracy scores above 0.73 after a ten-fold cross-validation, indicating their performance in this complex task [47].

RF, known for its ensemble nature, is particularly robust [61]. The creation of multiple decision trees and the subsequent aggregation of their outputs effectively mitigated the risk of overfitting, a crucial aspect when dealing with small sample sizes [62]. RF's inherent randomness of RF in the feature selection for individual trees may have contributed to its substantial performance, thereby delivering an AUC of 0.85. The more advanced gradient boosting methods GBDT and XGBoost also presented substantial results. These algorithms operate by learning from their predecessors in an iterative fashion, continually introducing new trees to correct the mistakes of those that came before. While this methodology has the potential to result in overfitting, particularly when dealing with limited datasets, our study showed consistency across all ten cross-validations, which suggests that this overfitting concern was managed to some extent [63]. Specifically, GBDT and XGBoost posted accuracy scores of 0.7906 and 0.7506, respectively, and XGBoost exhibited a particularly commendable AUC of 0.87, indicating strong model performance in differentiating between attention states.

Notably, the feature-selection process was executed using a linear SVM. SVM, known for its robustness, was instrumental in fine-tuning our feature selection, particularly in the high-dimensional context of physiological signals. The two most relevant features (11 and 17) identified through the iterative feature elimination process using SVM aligned with the performance results of our classifiers. This synergy further attests to the robustness of our approach and generalizability of our results, despite the relatively small sample size.

However, it is important to bear in mind that each classifier has its unique strengths and limitations. These insights should guide future research efforts, particularly when dealing with limited datasets. By acknowledging and learning from the limitations of this study, future studies can strive to assemble larger sample sizes and explore other potential classifiers to further bolster the reliability and generalizability of attention state classification based on SP signals.

C. WAVELET CHOICE AND ITS IMPACT ON CLASSIFICATION ACCURACY

The selection of mother wavelets is a critical component in WPD and plays a substantial role in the efficiency of the subsequent classification. For this study, the exploration was conducted on mother wavelets, including Daubechies 5 (db5), Haar, Symlet 5 (sym5), and Coiflet 1 (coif1).

The Daubechies 5 (db5) wavelet achieved the highest accuracy of 78.9% in 10-fold cross-validation, underscoring its effectiveness among the selected mother wavelets. This can be attributed to its approximation of real-world signals and superior localization in both the time and frequency domains. In contrast, Haar, Symlet 5 (sym5), and Coiflet 1 (coif1) wavelets resulted in accuracies of 77.4%, 75.8%, and 72.7%, respectively. Despite their lower accuracy, these wavelets still presented satisfactory results. They possess unique properties, such as Haar's clear delineation between signal details and a good balance between the time and frequency localization offered by sym5 and coif1. However, the Discrete Meyer (dmey) wavelet is not suitable for this specific application, possibly because of its unique characteristics, including infinite support, which may not be in harmony with the nature of the studied physiological signals.

Based on these results, db5 was selected as the preferred mother wavelet. The relatively high classification accuracy and its ability to closely approximate real-world signals make it an optimal choice for the SP signal's time-frequency domain features [64]. These findings highlight the importance of careful wavelet selection, emphasizing that it is not only application-specific, but also data-specific. The correct choice of mother wavelet also plays a critical role in harnessing the full potential of wavelet-based feature extraction and applications.

D. CONSIDERATION OF NEURAL NETWORK MODELS VERSUS FEATURE-BASED ANALYSIS

In our study, although the use of neural network models with raw SP signals was considered, we opted for a feature-based approach using machine learning classifiers. This decision was based on several key considerations. First, neural networks, particularly deep learning models, often function as a 'black box,' providing limited interpretability regarding underlying connections or principles. This aspect conflicts with our objective, not just to build a high-accuracy model, but also to identify and understand specific features of SP signals and their potential link to physiological states.

Moreover, owing to their complexity and representational learning capacity, deep learning models are more susceptible to overfitting, especially when working with a relatively limited dataset, as in our case. In contrast, our chosen method allows for a more transparent analysis, in which each feature's contribution to the model can be quantitatively assessed and understood. The feature-based approach of machine-learning classifiers inherently emphasizes the identification and evaluation of distinct signal characteristics, directly linking observable features to varying attention states. By leveraging the principles of machine learning, such as feature importance and model interpretability, we can systematically isolate and understand which aspects of SP signals are most influential

TABLE 4. Average and standard deviation of self-evaluated scores for predicted phase 1 & 2.

	Predicted Results		
	Corrected	Incorrected	p-value
Phase 1	2.12 (0.68)	2.21 (0.73)	0.6644
Phase 2	4.20 (0.70)	3.79 (0.80)	0.0952
p-value	<0.0001	<0.0001	

in distinguishing attentional shifts. This not only enhances the model's accuracy but also provides a clearer, more direct pathway to correlate specific signal features with underlying physiological mechanisms. This approach aligns better with our goal of elucidating the physiological relevance of specific SP signal features, facilitating a more insightful and interpretable connection to attentional states.

Thus, although neural network models offer significant power in pattern recognition and classification tasks, their lack of transparency and potential for overfitting led us to favor a feature-based approach in this specific context.

E. DIFFERENTIATING LEVELS OF ATTENTION

To explore subjective attention awareness, the self-evaluation scores were regrouped into a confusion matrix, depending on the best-model prediction (Table 4). The self-evaluation score of Phase 2 was significantly higher than that of Phase 1 in corrected predictions, which were 4.20 and 2.12 ($p< 0.05$), respectively. In this comparison, the predicted target "phase 2" corresponds to a higher subjective attention level. Moreover, the average self-evaluation score of the incorrect prediction tends to be higher than that of the corrected prediction in phase 1, which is 2.21 versus 2.12. Higher subjective attention awareness also makes model misjudgment easier. A similar condition was found in phase 2, in which the corrected prediction was higher than the incorrect prediction (4.20 vs 3.79). Although there were no significant differences between the corrected and incorrect phases, the trend for the misjudgment of the model is the same as subjective attention awareness, which is higher in phase 1, would make the model easily predict it to phase 2, and for someone who gave lower self-evaluation scores in phase 2, would make the model predict the results to phase 1. This finding implies that the attention level in phase two might have a higher concentration status.

In the other aspect, the attention level is also correlated with the model-selected features (Table 5), especially for the feature 14, 17, and 19. The energy of the wavelet between 0.15625 Hz and 0.46785 Hz and the standard deviation in the 0.46785 – 0.625 Hz range were correlated with self-evaluation scores. This is an important finding that has not been reported in previous studies. Although the physiological meaning of this bandwidth is still unknown, this result implies that the SP signal might be an easier evaluation tool for measuring attention level. Further research on SP signals

TABLE 5. Spearman's correlation between self-evaluation scores and model-selective features.

	Correlation	p-value
std_time (feature 2) *	0.1569	0.033
$E_{wavelet}$ in 0 - 0.15625 Hz (feature 11) *	0.1828	0.013
$E_{wavelet}$ in 0.15625 – 0.3125 Hz (feature 14) **	**0.5072**	< 0.0001
$E_{wavelet}$ in 0.3125 – 0.46785 Hz (feature 17) **	**0.5330**	< 0.0001
std_wavelet in 0.46785 – 0.625 Hz (feature 19) **	**0.2812**	0.0001

* p-value < 0.05   ** p-value < 0.001

and attention levels, such as EEG performance and clinical assessment of attention, should be conducted.

F. LIMITATION AND FUTURE STUDY

Although our research provides valuable insights into differentiating attention states using SP signals and discovering features with significant discriminatory power, it is important to acknowledge certain limitations. First, the sample size of our study, although adequate for preliminary analysis, is relatively small and lacks diversity in terms of racial representation. This limitation may affect the generalizability of our findings to a broader population. In addition, our study primarily focused on distinguishing between the two attention states within a one-dimensional model. However, this approach does not utilize traditional definitions or methods to measure the depth of attention states, such as explicitly defining what constitutes high or low attention.

The conceptual framework of our study was designed to investigate the presence of differing attention states, rather than to provide a comprehensive measurement of attention levels. Consequently, our findings should be interpreted as a foundational step in understanding attentional states through physiological signals. In future studies, we aim to expand our sample size and include a more diverse population with more specifically designed experiments to enhance the representativeness and applicability of our results. Moreover, we plan to delve deeper into the quantification and definition of attention states, exploring traditional and novel methods to measure and categorize the levels of attention. This proposition opens up a promising avenue for future research and applications, such as education, cognitive science, and user experience design, where understanding and adapting to different levels of attention can be pivotal. Future work is anticipated to build upon our current findings, offering a more nuanced and detailed understanding of attentional states and their physiological markers.

V. CONCLUSION

The study achieved an impressive overall accuracy exceeding 75% in effectively classifying varying attention states from music disturbance to calculation. It provides valuable insights into distinguishing human attention states with SP signals, with a particular emphasis on unique features within specific frequency bands. Notably, the wavelet energy at 0–0.15625 Hz and 0.3125 – 0.46875 Hz emerged as the most informative, suggesting the potential biological relevance of these frequencies to attentional states.

To arrive at these key findings, the research process embarked on an extensive set of 30 features derived from the time, frequency, and time-frequency domains via WPD. A sequence of feature selection methods, including RF, GBDT, and XGBoost for Permutation Feature Importance, were applied, leading to the identification of nine significant features. The subsequent utilization of statistical methods further streamlined the feature set to five, and the final phase engaged RFE in conjunction with a linear SVM. The latter was pivotal in identifying the two outstanding features, the wavelet energy in the 0–0.15625 Hz range (Feature 11) and the wavelet energy in the 0.3125 – 0.46875 Hz range (Feature 17). The efficacy of the feature selection process, coupled with the robustness of the SVM in managing high-dimensional data, emphasizes the reliability of the results.

The insights gained through this research significantly augment the understanding of human attention states and underline the potential of SP signals as promising tools for attention state differentiation. The identification of specific frequency bands of importance in SP signals coupled with the robustness of the employed classifiers and feature selection methods paves the way for more precise and intricate future studies in this domain.

The implications of these findings extend to neurophysiology research, with promising applications in real-world scenarios such as attention-based human-computer interaction, mental state monitoring, and the clinical diagnosis of attention-related disorders. In conclusion, this study presents a novel and promising approach for attention state differentiation, providing a solid foundation for further exploration in this evolving field.

ACKNOWLEDGMENT

The authors extend their heartfelt gratitude to all the volunteers who participated in the experiment.

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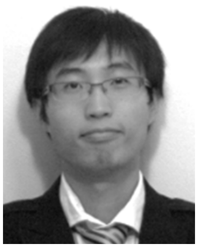

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