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Work Fatigue Detection of Search and Rescue Officers Based on Hjorth EEG Parameters

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***Abstract*—Work fatigue can cause a decrease in cognitive function, such as decreased thinking ability, concentration, and memory. A tired brain cannot work optimally, interfering with a person's ability to perform tasks that require complex thinking. In general, to evaluate work fatigue in a person, self-assessment activities using the Perceived Stress Scale (PSS) are the method most often used by researchers or practitioners. However, this method is prone to bias because sometimes people try to hide or exaggerate their tiredness at work. Therefore, we propose to evaluate people's work fatigue based on their EEG data in this study. A total of 25 participants from SAR officers recorded their EEG data in relaxed conditions (pre-SAR operations) and fatigue conditions (post-SAR operations). Recording was performed on the brain's left (fp1 & t7) and right (fp2 & t8) hemispheres. The EEG data is then processed by filtering, artifact removal using ICA method, signal decomposition into several frequency bands, and Hjorth feature extraction (activity, mobility, and complexity). The main advantage of Hjorth parameters compared to other EEG features is its ability to provide rich information about the complexity and mobility of the EEG signal in a relatively simple and fast way. Based on the results of activity feature extraction, feature values will tend to increase during the post-SAR operation conditions compared to the pre-operation SAR conditions. In addition, the results of the classification of pre- and post-operative SAR conditions using Bagged Tree algorithm (10-fold cross validation) show that the highest accuracy can be obtained is 94.8%.**

Keywords—Work Fatigue; Electroencephalography; Brain Hemisphere; Hjorth Parameters; Machine Learning.

I. INTRODUCTION

Work fatigue is a change in the physical or mental condition that can arise due to excessive workload and can occur over short or long periods [1]. Various factors cause work fatigue, including much workload, high work intensity, long working hours, and lack of rest time [2]. When a person experiences protracted work fatigue, the body will experience significant adverse impacts, such as decreased cognitive abilities, unstable emotions, decreased creativity/thinking power, sleep disturbances, and disturbed mental health [3]. Work fatigue can cause a decrease in cognitive function, such as decreased thinking ability, concentration, and memory [4]. A tired brain cannot work optimally, interfering with a person's ability to perform tasks that require complex thinking [5]. Work fatigue can affect a person's emotional balance. A tired brain tends to be more easily affected by stress, anxiety, and depression [6]. It can cause drastic mood swings, such as becoming irritable, anxious, or prone to crying. An exhausted brain can also experience a decline in creativity and innovation [7]. The ability to think smartly or find innovative solutions can be impaired due to burnout, affecting the quality of work and work output [8]. Sustained work fatigue can disrupt a person's sleep patterns, whether sleep deprivation or disturbed [9]. Insufficient or poor-quality sleep can impair cognitive function and overall brain performance [10]. Continuous work fatigue can increase a person's risk of experiencing mental health disorders, such as depression, anxiety, and post-traumatic stress disorder [11]. A brain that is constantly exposed to stress and pressure can have a detrimental effect on a person's mental health [12]. Everyone needs to balance between work and personal life to overcome fatigue at work [13]. In addition, good work time management and avoiding excessive workload can also reduce stress levels which can lead to work fatigue [14].

Brain fatigue is often related to activity in different areas of the brain, especially in the prefrontal cortex, which sits at the front of the brain [15]. The prefrontal cortex is responsible for executive functions such as decision-making, attention and emotional control. In addition, other areas such as the parietal and temporal cortex may also show changes in activity when fatigue occurs, mainly related to decreased attention and sensory processing abilities [16]. Based on the very close relationship between brain activity and fatigue, it is not impossible that work fatigue can be detected using human brain signals [17]. Brain signals are electrical signals generated by human brain activity while thinking or behaving [18]. Brain signals arise because nerve cells communicate with each other through electric currents. The electroencephalogram (EEG) method can measure and record brain signals [19]. This method is used to observe the electrical activity of the scalp using electrodes placed on the scalp [20]. In electrode placement, EEG signal measurement is based on the international standard 10-20, which divides the scalp into several regions, such as Frontopolar, Frontal, Central, Parietal, and Occipital [21]. In addition, brain signals can provide information about brain function, thought patterns, emotions, and other human cognitive activities [22]. Another benefit of brain signals is that they can be used in numerous applications such as scientific research, medical diagnosis, and developing brain-computer interface technologies [23].

Wang et al. [24] analyzed driving fatigue using EEG signals in their research. A total of 20 people who experienced driving fatigue recorded their brain signals (EEG) using Neuroscan32 EEG. The Li fatigue scale and the Borg CR-10 scale were used to determine the people to be research subjects. This scale can measure a person's level of driving fatigue and label data for the classification process. Then the EEG data is processed into several signal features such as Entropy Wavelet and Spectral Entropy. To distinguish conditions between driving fatigue or not, Wang et al. use the same classifier, namely SVM. Based on the classification results using SVM, an accuracy rate of 90.7% was obtained (when the classification was performed using the entropy wavelet feature) and 81.3% (when the classification was carried out using the spectral entropy feature). The EEG frequency characteristics can be used to observe a person's driving fatigue.

Research conducted by Zhang et al. [25] also tried to reveal the driver's mental fatigue based on a person's EEG signal. In their study, the EEG signal was decomposed into three different bands (alpha, beta, and theta) and analyzed in the domain of frequency, time, and non-linear features. The methods used for signal feature selection include Logistic Regression, ARFE Logistics, and one-way analysis. Based on the overall test results, the Gaussian SVM classifier has the highest accuracy in the process of detecting mental fatigue, namely 79.33% (combination of features on TD, FD, and NL), 79.09% (TD and FD), 78.45% (TD and NL), and 79.32% (FD and NL). In addition, Chen et al. [26] also explored the effect of fatigue on people's EEG signals. A total of 14 subjects were selected for the EEG signal recording process. Then the signal decomposition is carried out into four different bands, delta, theta, alpha, and beta, using the Wavelet method (WPT). Based on observations, there are differences in brain connectivity function when a person is in a state of alert and fatigue (for the alpha and beta bands). Although the connectivity function in the frontal-parietal area tends to be weak. For the classification process, the SVM method is used to distinguish alert and fatigue conditions with an accuracy of 94.4%, a precision of 94.3%, and a sensitivity of 94.6%. Tuncer et al. [27] in their research tried to analyze EEG-based driving fatigue. The approach used is to extract multilevel generator features and statistics simultaneously. Each level is composed of one-dimensional discrete wavelet transform (1D-DWT). In addition, ReliefF and iterative neighborhood component analysis (RFINCA) are used in feature selection. Based on the experimental results, this approach produces accurate EEG classification.

Based on previous research, we intend to detect work fatigue based on EEG signals but with a different approach. This study will extract the EEG signal features using the Hjorth parameter approach (activity, mobility, and complexity). The results of this Hjorth parameter are then used as input for the process of classifying fatigue conditions or not. Classification uses several conventional machine learning algorithms such as SVM, Bagged Tree, K-NN, and Naive Bayes. We hypothesize that the features of the Hjorth EEG signal can differentiate the state of occupational fatigue in humans. In addition, the level of signal accuracy can also be improved by this proposed approach.

II. METHODOLOGY

To obtain a pattern of EEG-based fatigue conditions, several steps were carried out in this study, including EEG data collection, initial data processing, feature extraction using the Hjorth parameter, and data classification. The stages of EEG data collection consist of participant selection and EEG recording before and after the SAR operation. The EEG data then goes through pre-processing, such as filtering, artifact removal, and signal decomposition, to get a clean signal (not affected by noise). Hjorth parameters, including activity, mobility, and complexity, are used to obtain data patterns in the signal feature extraction process. For the classification stage, several classifiers are used, such as SVM, Bagged Tree, K-NN, and Naive Bayes. The Fig. 1 is a block diagram related to the stages in this research.

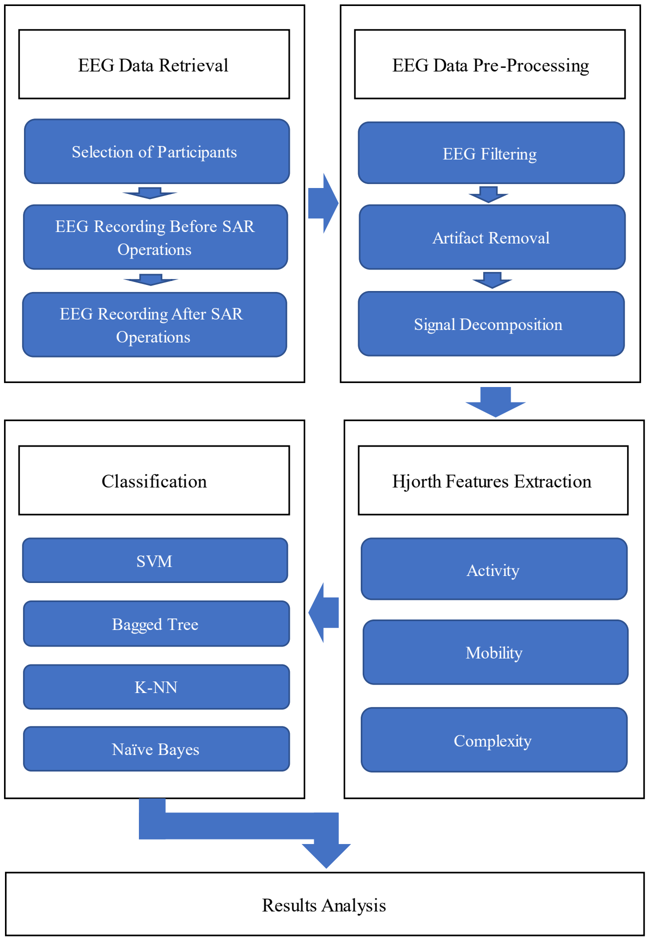

Fig. 1. Methodology of the research

A. *EEG Data Retrieval*

In this study, EEG data measurements were carried out on participants from SAR officers. These participants were chosen because they have high busyness and work pressure in carrying out their duties. It is hoped that the EEG patterns related to work fatigue can be obtained properly. Participants who participated in this study had an average age of 29.5 years, with 25 participants. Participants in this study were aged between 25-35 years old (average age 29.5 years). All participants were male and employed by the National Search and Rescue Agency. In this case, the researcher also obtained direct and written consent from each participant before the data collection process was carried out.

The device used for participant EEG recording was OpenBCI UltraCortex (Fig. 2). This device was chosen because of its compact shape and can be used anywhere. In addition, this tool also uses a dry type of electrode for EEG recording [29]. This electrode type is relatively practical and can shorten the device preparation process. This OpenBCI device has a default recording channel of up to 8 channels [30]. However, in this study, researchers only used four specific channels: the frontopolar (FP1 & FP2) and the temporal (T7 & T8) areas. The frontopolar is located in an area known as the prefrontal lobe. This area is closely related to high-level executive functions, such as planning, decision-making, problem-solving, self-monitoring, and behavior control [31]. In addition, frontopolar also plays a role in working memory, emotional regulation, and other cognitive processes [32]. In comparison, the Temporal is the area on the side of the brain. This area concerns sensory processing, hearing, facial recognition, short and long-term memory, and language comprehension [33]. The temporal lobe also has a vital role in processing emotions and making decisions related to affective aspects [34]. The Fig. 3 is a display regarding the location of the electrode installation in the area/channel on the human head.

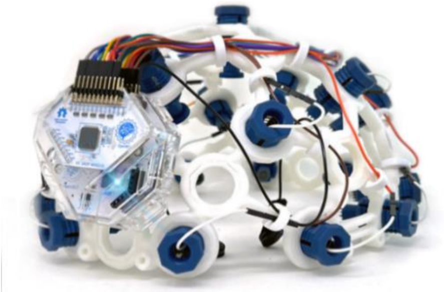

Fig. 2. EEG OpenBCI UltraCortex [28]

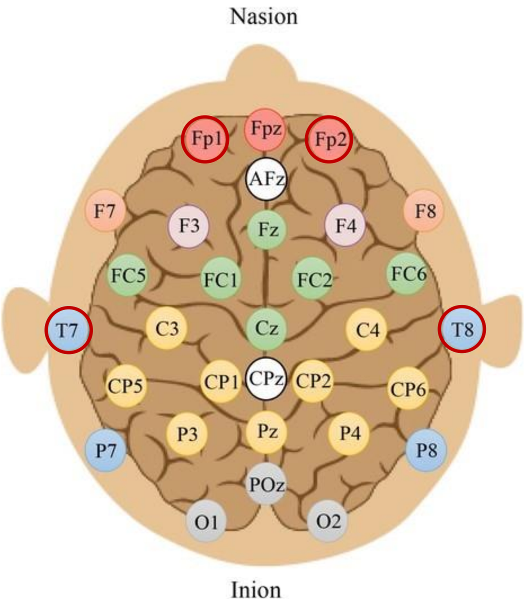

Fig. 3. EEG recording channels [35]

Before and after the EEG recording is carried out, participants will be required to complete the Perceived Stress Questionnaire (PSQ). The Stress Perception Questionnaire is a set of questions to measure participants' perceptions and responses to mental/work fatigue [36]. This questionnaire collects data on how participants interpret and responds to situations that cause mental/work fatigue in their activities [37]. In this study, the questionnaire will be used to validate the recorded EEG data and label signal features used in classification. The EEG recording process will be carried out under two conditions: pre-SAR and post-SAR operations. EEG recording was carried out for 5 minutes for each condition. Fig. 4 and Fig. 5 is the EEG recording process before and after SAR operations.

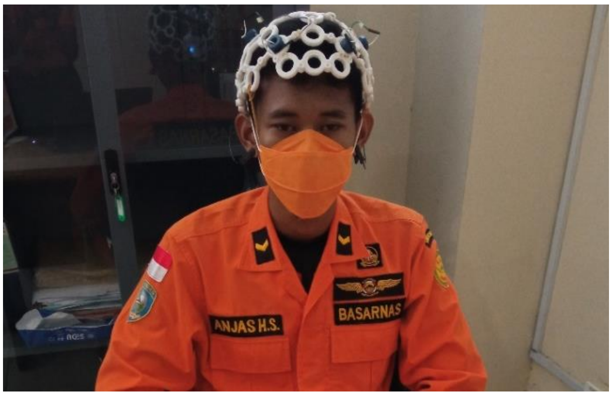

Fig. 4. EEG recording before SAR operation

Fig. 5. EEG recording after SAR operation

B. EEG Data Pre-Processing

Pre-processing on EEG is the initial step to obtain a signal free from noise or artifacts [38]. Pre-processing involves filtering, artifact removal, and signal decomposition into several sub-bands [39]. EEG signal filtering removes unwanted frequency components or noise from the EEG signal, improving signal quality and focusing on the relevant components [40]. This study applied the Butterworth filter type to the EEG data from the previous recording. The main advantage of the Butterworth filter is that the frequency response is very smooth and does not show ripples in the passband and stopband [41]. This is important in EEG processing as it preserves the authenticity of the signal without introducing distortions or artefacts that may affect further analysis. In addition, Butterworth filters can be designed with various orders, which allows flexibility in determining the slope of the transition between the passband and stopband, according to the needs of the analysis [42]. The filter is also effective in removing unwanted noise and artefacts from EEG signals, such as high-frequency components caused by external interference or physiological artefacts [43]. Its stability and predictability make the

Butterworth filter an ideal choice in maintaining the integrity of EEG data during the filtering process [44].

In addition to filtering, removing artifacts can be done using the ICA method. Using ICA in EEG aims to separate the EEG signal into independent components [45]. By separating the EEG signal into independent components, ICA allows the process of identifying brain activity to be more specific [46]. It can also assist in further understanding and analysis of brain function, relationships between brain components, and identifying brain responses to certain stimuli or conditions [47]. The working principle of ICA is to assume that different signal sources (including artifacts and brain signals) are independent of each other. ICA processes the mixed EEG signal and produces independent components that represent the original sources. Artifacts such as eye blinks, muscle movements, or electrical noise from devices often appear as independent components that can be identified based on their spatial or temporal characteristics [48]. Once these components are identified, they can be removed or separated from the original EEG signal, allowing for a more accurate analysis of the actual brain activity [49]. Thus, ICA becomes a powerful tool in purifying EEG data from various sources of noise or artifacts without destroying the essential information of the brain signal [50].

After the EEG signal is clean from noise or artifacts, the next step in pre-processing the EEG signal is decomposing the signal into several sub-bands. This process will separate the EEG signal into five different types of frequency sub-bands, including alpha, beta, gamma, theta, and delta [51]. Each sub-band has a different frequency range from one another. Alpha has a frequency range between 8-12Hz, the beta has a frequency range of 12-25, and gamma has a frequency range between 25-45Hz. In contrast, delta and theta have a frequency range of 0.5-4Hz and 4-8Hz, respectively [52]. Band decomposition techniques typically use bandpass filters that separate the signal into specific frequency bands. This decomposition helps in identifying and separating different types of brain activity, as well as in detecting certain anomalies or patterns that may not be visible in the raw EEG signal [53]. As such, band decomposition is an important tool in EEG analysis, allowing for a more in-depth understanding of the various neurophysiological processes occurring in the brain [54].

C. Hjorth Features Extraction

Hjorth is an EEG analysis method used to explain important information or parameters related to activity in the brain [55]. The Hjorth method can analyze EEG signals in the time and frequency domain with three primary parameters: activity, mobility, and complexity [56]. Activity parameters can represent the EEG signal's total energy characteristics and indicate the brain activity level. Activity can be described as the variance or energy value of the EEG signal in the time domain [57]. So that the higher the activity value of the Hjorth parameter, the higher the level of brain activity [58]. The mobility parameter can represent brief changes in EEG signals and indicate rapid changes in brain activity [59]. So that the higher the mobility value of the Hjorth parameter, the faster changes in brain activity [60]. The complexity parameter can represent the level of randomness or complexity of the EEG signal [61]. The higher the complexity value, the higher the randomness or signal complexity level [62]. The main advantage of Hjorth parameters over other EEG features is their ability to provide rich information about the complexity and mobility of EEG signals in a relatively simple and fast way [63]. This makes Hjorth parameters particularly useful in real-time applications and systems that require fast and efficient calculations, such as disease detection or cognitive analysis [64].

The following is the formulation of Hjorth's activity, mobility, and complexity parameters.

$$Activity = var(y(t)) \tag{1}$$

$$Mobility = \sqrt{\frac{var\left(\frac{dy(t)}{dt}\right)}{var(y(t))}} \tag{2}$$

$$Complexity = \frac{Mobility\left(\frac{dy(t)}{dt}\right)}{Mobility(y(t))} \tag{3}$$

Where, $y(t)$ is the signal in time domain and dt is the derivative of the signal $y(t)$.

D. Classification

In this study, several classifiers are used to classify EEG data, including SVM, Bagged Tree, K-NN, and Naive Bayes. SVM is a supervised learning method generally used to divide two classes or classify data based on the optimal hyperplane between the two classes [65]. Hyperplane can function as a barrier that maximally separates two data classes and tries to minimize errors in the classification process [66]. The advantage of SVM compared to other classifiers is its ability to handle high-dimensional data sets [67]. In addition, SVM is also tolerant of data outliers and can handle non-linear data using the kernel [68]. However, SVM can also have a complex structure in terms of computation, especially in the process of determining its parameters [69]. The following is the formulation of the SVM method kernel.

Gaussian:

$$K(x_1, x_2) = exp\left(-\frac{\|x_1 - x_2\|^2}{2\sigma^2}\right) \tag{4}$$

Linear:

$$K(x_1, x_2) = x_1^{\mathrm{T}} x_2 \tag{5}$$

Polynomial:

$$K(x_1, x_2) = (x_1^{\mathrm{T}} x_2 + 1)^{\rho} \tag{6}$$

Sigmoid:

$$K(x_1, x_2) = tanh(\beta_0 x_1^{\mathrm{T}} x_2 + \beta_1) \tag{7}$$

Where, x is data, σ is the width of the kernel, ρ is the order of the polynomial, and β_0, β_1 is the mercer kernel.

The bagged tree is a machine-learning method that combines multiple decision trees to improve data classification or prediction performance [70]. This method performs voting output from a collection of decision trees to obtain an optimal learning model [71]. The advantages of the Bagged Tree method are its ability to overcome data noise, reduce variance in the classification process, and can work independently/parallel [72]. In dealing with noise data, Bagged Tree will take random sample data and combine the classification results from many trees [73]. So, this will automatically reduce the effect of noise or outlier data and can increase the reliability of the classification model [74]. In addition, Bagged Tree can also overcome the problem of overfitting and tends to be suitable for distributed computing processes [75]. Following are some of the essential functions used in Bagged Tree-based learning.

Classification Error Rate:

$$E = 1 - \max_{k}(\hat{p}_{mk}) \tag{8}$$

Gini Index:

$$G = \sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk}) \tag{9}$$

Cross-Entropy:

$$D = -\sum_{k=1}^{K} \hat{p}_{mk} \log \hat{p}_{mk} \tag{10}$$

Bagging:

$$\hat{f}_{bag}(x) = \frac{1}{B}\sum_{b=1}^{B} \hat{f}^{*b}(x) \tag{11}$$

Where, $\hat{p}_{mk}$ is the proportion of k^{th}-class training observations in the m^{th} region and $\hat{f}_{bag}$ is the bagging function.

K-NN is a learning method used for classification or prediction. This method has a working principle of finding the nearest K neighbors from data samples that do not yet have labels [76]. Then the KNN method will use the majority of labels from the neighbors as the result of the data class or prediction [77]. The advantages of KNN compared to other types of classifiers are its superficial characteristics and do not require complex learning mechanisms [78]. The KNN method is considered simple because it is easily understood and implemented by users [79]. In addition, KNN does not require a complex learning mechanism because it only stores training data and the distance between k data during the classification or prediction process [80]. The following is the distance function formula used to calculate the K-NN.

$$E_d = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{12}$$

$$Man_d = \sum_{i=1}^{k}|x_i - y_i| \tag{13}$$

Where, E_d is the Euclidean Distance and Man_d is the Manhattan Distance.

Naive Bayes is a classifier based on the Bayes theorem or independent assumptions about its features [81]. In Naive Bayes, all existing features are considered mutually independent of their class [82]. While these assumptions are rarely encountered in the real life, Naive Bayes can yield reasonably good results in many cases [83]. The following is the formula for the Naive Bayes classifier.

$$P(n \mid m_1, \dots, m_j) = \frac{P(m_1,\dots,m_j \mid n)\, P(n)}{P(m_1,\dots,m_j)} \tag{14}$$

Where, $P(n \mid m_1, \dots, m_j)$ is the posterior probability, $P(m_1, \dots, m_j \mid n)$ is the probability of features value, $P(n)$ is the prior probability, and $P(m_1, \dots, m_j)$ is the marginal probability. The advantages of Naive Bayes are its simple and efficient structure, stability against limited training data, and straightforward interpretation [84].

E. Evaluation Matrices

Evaluation matrices are an important tool in measuring the performance of machine learning models, as they provide metrics that can be used to evaluate how well the model works in predicting or classifying data [85]. Some commonly used evaluation matrices include accuracy, precision, recall, and F1-score. Accuracy measures the percentage of correct predictions out of total predictions, but can be less effective if the dataset is not balanced [86]. Precision measures how many positive predictions are actually positive, while recall measures how much of the total positive data was correctly predicted. F1-score combines precision and recall into one metric to give a more balanced picture of model performance, especially when there is a trade-off between the two.

III. Results and Discussions

This study performed EEG signal feature extraction based on the Hjorth parameter. In the Hjorth EEG method, three main parameters are used to describe the EEG signal: activity, mobility, and complexity of Hjorth. These features are also reviewed from several EEG signal sub-bands, such as Alpha, Beta, and Gamma. Meanwhile, the EEG observation channel was carried out on the left (fp1 & t7) and right hemispheres of the head (fp2 & t8). The conditions compared in this study were the conditions before & after the participants carried out SAR operations and the fatigue conditions of the SAR officers who were trying to be analyzed based on their EEG (Fig. 6 and Fig. 7).

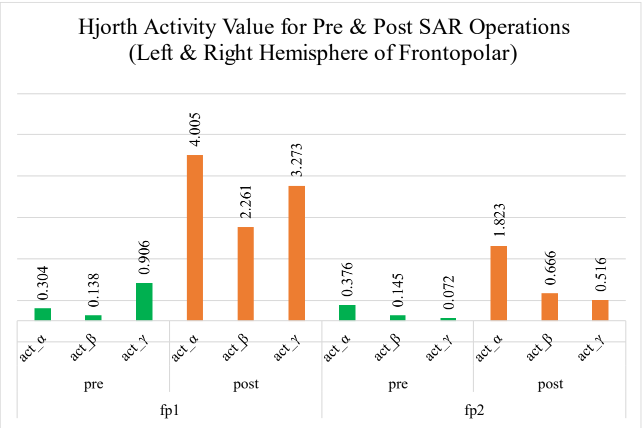

Fig. 6. Hjorth Activity (Left & Right Hemisphere of Frontopolar)

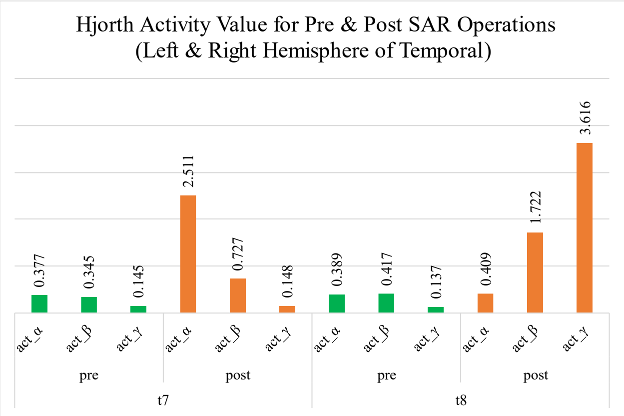

Fig. 7. Hjorth Activity (Left & Right Hemisphere of Temporal)

Based on the Hjorth EEG activity feature extraction results (Fig. 6 and Fig. 7), a striking difference was obtained between the EEG activity values before and after SAR operations. EEG activity values after SAR operations tend to be higher than pre-SAR operations, which occurs in all observation sub-bands or channels. These results show that the level of activity or energy in the EEG signal tends to increase after people carry out activities that drain their energy and mind, such as SAR operations. In the Hjorth activity feature, the EEG signal pattern shows a clear difference in describing each condition. However, due to the mobility and complexity features of Hjorth, the EEG signal patterns cannot be clearly distinguished for each condition. Following are the results of the Hjorth EEG mobility (Fig. 8 and Fig. 9) and complexity feature extraction (Fig. 10 and Fig. 11).

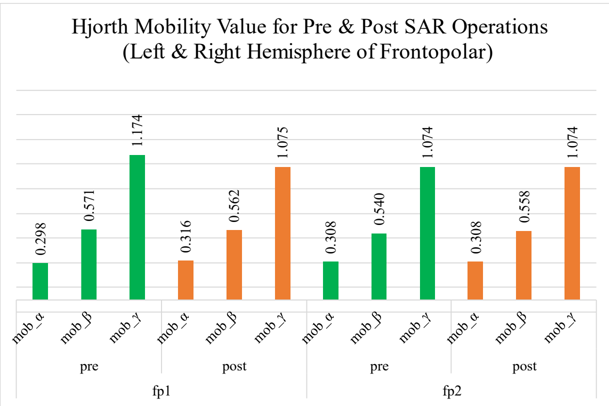

Fig. 8. Hjorth Mobility (Left & Right Hemisphere of Frontopolar)

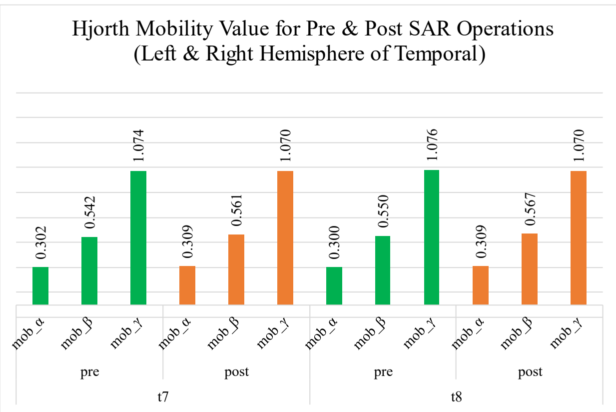

Fig. 9. Hjorth Mobility (Left & Right Hemisphere of Temporal)

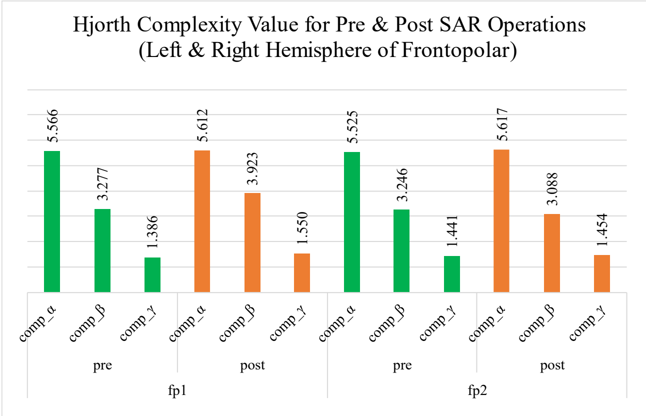

Fig. 10. Hjorth Complexity (Left & Right Hemisphere of Frontopolar)

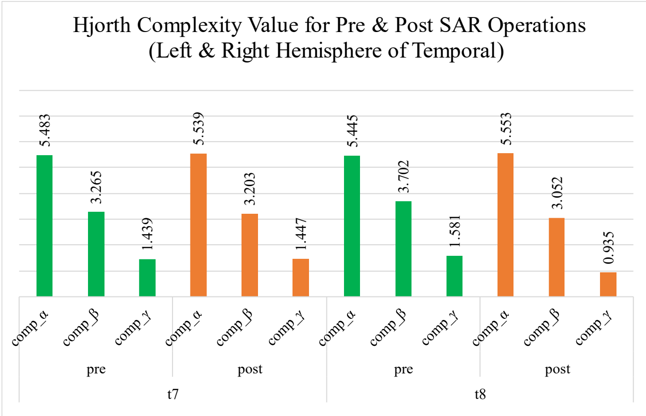

Fig. 11. Hjorth Complexity (Left & Right Hemisphere of Temporal)

Regarding mobility and complexity features, there is no apparent difference in signal features during pre- and post-SAR operations. It occurs in all sub-band frequencies and EEG observation channels. Based on these results, the mobility and Hjorth complexity features are not very suitable for observing differences in people's levels of work fatigue. Although in theory, the features of mobility and complexity are used to express the level of dynamics and variability of human brain activity [87]. In addition, the classification process uses several scenarios and machine learning algorithms to prove that the Hjorth activity feature is more effective than the mobility and complexity features for distinguishing fatigue conditions. From the results of the classification that has been carried out, it is clear that the highest accuracy (94.8%) is obtained when the classification (fatigue and relaxed) is carried out using the Hjorth activity feature and the Bagged Tree algorithm. When classification is done with all features (activity, mobility, and complexity) (Table I), the accuracy is 90.6%. Meanwhile, when the classification was carried out using mobility and complexity features, the accuracy obtained only reached 64.8% and 64.6%.

The Hjorth activity parameter can represent the level of activity or energy in the EEG signal [88]. It is automatically related to the amplitude or strength of the signal. In addition, activity parameters can also be seen as total energy or signal strength over a specific period. Therefore, the higher the activity feature value, the greater the energy contained in the EEG signal or indicating the human brain's activity level [89]. Meanwhile, the mobility parameter represents changes in

EEG signals or signal shifts at specific frequencies [90]. Therefore, the higher the mobility value, the faster the change or transition of wave patterns that occur in the EEG signal. In addition, mobility can also provide information related to brain activity dynamics or flexibility [91]. The complexity parameter can represent the complexity of the EEG signal [92]. It relates to the diversity of EEG wave patterns such as alpha, beta, gamma, delta, and theta. Thus the higher the complexity value, the more diverse the wave patterns seen in the EEG signal. In addition, complexity can also provide information regarding the variability of brain activity.

TABLE I. CLASSIFICATION ACCURACY OF FATIGUE AND RELAXED CONDITIONS BASED ON HJORTH FEATURES

Activity Hjorth				
Parameter	SVM	BT	K-NN	NB
Training	76.1%	93.8%	88.2%	63.4%
Testing	73.8%	94.8%	89.1%	62.0%
Mobility Hjorth				
Parameter	SVM	BT	K-NN	NB
Training	62.6%	63.1%	66.4%	59.1%
Testing	63.1%	64.8%	61.6%	59.2%
Complexity Hjorth				
Parameter	SVM	BT	K-NN	NB
Training	65.2%	65.8%	65.7%	60.7%
Testing	60.9%	64.6%	63.1%	60.1%
All Hjorth Features				
Parameter	SVM	BT	K-NN	NB
Training	68.3%	92.6%	70.0%	66.2%
Testing	69.1%	90.6%	67.4%	70.2%

IV. CONCLUSION

This study focuses on finding EEG signal patterns for normal conditions (pre-SAR operation) and fatigue (post-SAR operation) through feature extraction based on Hjorth parameters such as activity, mobility, and complexity. In addition, a classification process using a machine learning algorithm is also carried out to prove that the pattern obtained is accurate enough to represent each condition. Based on the feature extraction results, different Hjorth activity values were obtained between the pre and post-SAR operations. The Hjorth EEG activity feature value after SAR operation tends to be higher than the pre-SAR operation conditions. It proves that the activity level or energy in the EEG signal (Hjorth activity parameter) tends to increase after people carry out activities that drain their energy and mind, such as SAR operations. However, due to the mobility and complexity features of Hjorth, signal patterns cannot be clearly distinguished for each condition. In addition, from the results of the classification that has been carried out, the highest accuracy (94.8%) is obtained when the classification (pre and post-SAR operations) is carried out using the Hjorth activity feature and the Bagged Tree algorithm. To strengthen the findings in this study, in future research, the authors will add the amount of EEG data analyzed to make the results more accurate. The parameters contained in the classifier will also be evaluated to improve the performance of the classification results further.

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