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Analysis of EEG Signals Between Motor Imaginary Tasks and Rest Condition for Biometric Application

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Abstract

Biometric technology has gained immense popularity as an effective solution for enhancing cybersecurity, specifically in countering financial fraud and security threats. EEG-based authentication is unique among biometric authentication methods due to its unparalleled confidentiality and non-replicability. This study explores the feasibility of using motor imagery tasks and rest conditions for human authentication. Ten physically fit subjects, aged between 20 and 28 years, participated voluntarily in the study. The subjects perform imaginary tasks involving their left and right-hand movement. Each task lasted for two minutes, separated by a one-minute break, and EEG data were collected using the EPOC+ device, which features 14-channel electrodes. The sampling frequency was set at 128 Hz. To extract relevant frequency information, Butterworth bandpass filters were employed to extract the alpha (8-13Hz), beta (14-30Hz), and gamma (30-42Hz) frequency bands. Linear features, such as power spectral density (PSD), were obtained using the Welch Method and the Burg Method, while spectral entropy was used to extract non-linear features. Statistical features mean, median, standard deviation, minimum, and maximum were derived from the PSD, and spectral entropy was used as input for the classifiers. Multiple classifiers, including k-nearest neighbor (KNN), support vector machine (SVM), decision tree and Naive Bayes, were employed for the classification task. The Welch method combined with the support vector machine classifier achieved a higher classification accuracy of 96.83% for the beta waves from channels C3, C4, O1, and O2, corresponding to the frontal and occipital lobes. Interestingly, the rest conditions exhibited a higher classification accuracy of 96.83% compared to the motor-imagery tasks, which achieved 96.04%. The utilization of motor imagery tasks and rest conditions, along with the application of advanced classification techniques, holds promise for the development of robust and reliable biometric systems in cybersecurity.

1. Introduction

Biometric technology has rapidly become a favoured solution for enhancing cybersecurity, particularly in combating financial fraud and security threats [1]. Biometric methods for individual authentication and identification are gaining popularity due to their association with an individual's physiological and behavioural characteristics. Physiological authentication relies on various body parts' forms, such as fingerprints, eye iris, face, and hand geometry. In contrast, behavioural biometrics are based on traits like voice, gestures, keyboard inputs, and signatures. In this system, a person's biometric features are collected and compared with a template stored in the database to identify the person [2].

Despite the scientific evidence confirming the uniqueness of these biometric features for each individual [3], they still possess certain drawbacks and weaknesses. Some technologies, like fingerprint or iris identification, can be falsified or replicated [4], [5]. For instance, experiments suggest that a suspect could create a fake fingerprint using an image of themselves [2]. Consequently, there is a pressing demand for new biometric approaches that overcome these limitations and weaknesses.

Electroencephalography (EEG) has emerged as a promising biometric candidate that is difficult to forge and suitable for continuous authentication. EEG records the brain's electrical activity by measuring small voltage fluctuations on the scalp surface using electrodes [6], [7]. Since brain wave information is not visible on the body's surface, it remains highly confidential, eliminating the risk of information leakage. Although EEG signals have traditionally garnered significant interest within the medical field, they are currently being investigated as a biometric modality for person recognition [8]. Several studies have demonstrated that electroencephalogram signals can reflect unique characteristics that enable individual differentiation [9], [10].

The advantage of EEG lies in the fact that the brain's electrical activity, generated by the nerve cells, is distinct for each individual and remains stable over time [2]. EEG-based biometrics offer greater security compared to conventional biometric systems as they cannot be imitated or artificially generated. Brain activities strongly correlate with a person's unique memory and knowledge, making replication by others impossible. Due to the susceptibility of brain signals to the influence of an individual's mental state, their collection becomes significantly challenging and vulnerable to coercion and force [2]. The use of mental states for authentication may also lead users to stop acting in dangerous situations.

While EEG signals have various advantages, they do have limitations when used in biometrics. It is critical to overcome these constraints in order to ensure the consistency and reliability of EEG-based biometric assessments. To do this, a well-suited experimental protocol built specifically for biometric applications using EEG signals is required. The selection of acceptable qualities is critical in the field of EEG signal properties. This usually entails recognizing and concentrating on specific frequency bands, such as alpha, beta, gamma, and delta. This can improve the utility and effectiveness of EEG biometrics by focusing on these essential elements.

The objective of this study is to design and establish a straightforward EEG biometric protocol centered around imagery tasks, then, followed by a comprehensive analysis of EEG signal features to identify the most appropriate set for enhancing the efficacy and reliability of EEG-based biometric applications. In line with the objective, the work plan includes the development of the EEG biometric protocol, data acquisition, feature extraction and analysis, and systematic evaluation of these features, ultimately leading to the identification of the most appropriate set for improving the efficacy and reliability of EEG-based biometric applications.

2. Methodology

The methodology in this study involves a few stages of work, i. data acquisition, ii. Signal pre-processing, iii. feature extraction, and v. machine learning classification. All the details about the works are described below.

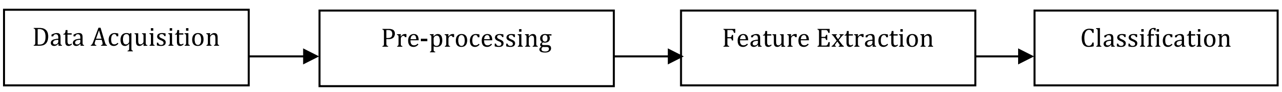


Fig. 1 *Block diagram of methodology*

2.1 Data Acquisition

Ten subjects who meet the specific study criteria, such as being right-handed and within the age range of 20 to 27 years old, having no mental problems or brain injuries, and having had sufficient sleep before the experiment, are carefully selected to ensure consistency and minimize confounding variables, thus yielding reliable results. The subjects were required to fill out the informed consent form to provide consent to collect their EEG signals and acknowledge the safety measures implemented in the experiment. Additionally, the subjects were requested to fill out the demography form to facilitate result analysis.

This experiment utilized the Emotive Epoch X brain wear device, an EEG device, to collect EEG signals from the subjects. The EEG cap of this device contains 14 electrode channels, namely AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4, which are used to record the EEG signals. These electrodes are placed specifically to its specific brain area, as shown in Fig. 2 [11]. The sampling frequency for recording is set at 128 Hz. Electrodes are strategically placed on the subject's scalp to achieve optimal results, and electrode gel is applied to enhance conductivity and ensure stable electrode attachment, effectively reducing impedance below 5kΩ for all channels. Clear instructions are given to the subjects to minimize body movements during the experiment and to remain relaxed until the EEG recording begins, ensuring data consistency and integrity by reducing potential sources of noise or interference.

The experimental protocol involves imaginary and resting tasks. The imaginary task consists of task 1: clench right hand and task 2: clench left hand, each lasting 2 minutes. These tasks were chosen for their simplicity, ease of performance, and inclusivity, promoting robust EEG signal analysis for biometric identification purposes. Before starting the experiment, a 1-minute pre-experiment resting phase with closed eyes is provided to establish a baseline measurement of the EEG signals, acting as a control condition to properly compare and analyze the subsequent EEG data during the imaginary task. This resting phase is considered as resting task.

(a) (b)

Fig. 2 *(a) Emotive epoch X set and its function features; (b) The electrodes placement*

2.2 EEG Signal Processing

Visual examination cannot comprehend the EEG signal because it is complicated, unpredictable, and non-stationary. The EEG signals must therefore be investigated using advanced signal processing to extract the brain signal's hidden information. The three primary steps of signal processing are pre-processing, feature extraction, and classification.

2.2.1 Pre-Processing

The Butterworth filter, selected for its flat frequency response and lack of ripple, is utilized in the pre-processing stage. Unlike other filters, the Butterworth filter does not exhibit a roll-off of minus 20dB per pole or passband ripple. Its characteristics are mathematically defined by the cutoff frequency and the number of poles [12]. For the purpose of analysis, the Butterworth filter is employed to achieve a flat frequency response. Before filtering, the raw signal contains all frequencies, and it is necessary to filter the signal to isolate specific frequency bands. The frequency bands of interest are as follows: theta signals range from 4Hz to 8Hz, alpha signals range from 8Hz to 13Hz, beta signals range from 13Hz to 30Hz, and gamma signals range from 30Hz to 40Hz.In this study, normalisation of the signal is done to obtain accurate results. Normalization of signals is an essential and fundamental process in signal processing, carrying significant importance across various applications. The primary objective of normalizing signals is to enable effective comparisons and analyses of data that possess different scales or units.

2.2.2 Feature Extraction

In this study, there are two linear analyses and two nonlinear analyses to extract the features from the EEG signals. For the linear analysis method, power spectral density (PSD) using the Welch method and the Burg method are used to extract the power spectral density (PSD). For non-linear analysis, spectral entropy had been used.

The Welch method is utilized to compute and sequence the signal while reducing noise. This method provides a high signal-to-noise ratio. It reduces the estimated power spectra in exchange for reducing the frequency resolution [11], [13]. By changing the Bartlett method in two aspects, an improved estimator was obtained which is Welch's method. The two aspects allowed the data segments in Welch's method to overlap and windowed each data segment prior to computing the periodogram. It is also an improved version of the periodogram.

The Burg method aims to minimize forward and backward prediction errors by utilizing the Levinson-Durbin recursion. This method estimates reflection coefficients directly instead of calculating autocorrelation [14]. The advantages of the Burg method include its ability to resolve closely spaced sinusoids in low noise level signals, estimate short data records accurately, and ensure the computational efficiency of stable autoregressive (AR) models [15].

The spectral entropy method is utilized as a feature extraction technique to assess the complexity and irregularity present in the frequency content of a signal [16]. It offers a metric to determine the distribution of power or energy across various frequency components. Within EEG biometric applications, spectral entropy finds application in quantifying the distinctive spectral characteristics of EEG signals, enabling the extraction of pertinent features for identification or authentication purposes.

2.2.3 Classification

After extracting the features from the previous stage, the next step is to analyse and classify the data using a classifier. The data is divided into training data and testing data for this purpose. The training data is used to train the classifier and teach it to recognize patterns in the data, while the testing data is used to evaluate the classifier's ability to accurately classify new data instances. In this study, four supervised learning classifiers are utilized: support vector machine (SVM), k-nearest neighbors (KNN), decision tree, and Naive Bayes.

The KNN algorithm is a supervised machine learning algorithm used for classification and regression tasks. It is a non-parametric approach that classifies data based on the majority of its k-Nearest Neighbors without making any assumptions [17]. In this algorithm, a new data point is assigned a value based on its similarity to the training data sets [18]. The number of neighbors, K, needs to be predetermined before running the algorithm, and the optimal value of K is determined by minimizing the error rate [19].

The SVM classifier is employed to distinguish data points from different classes by finding the best hyperplane. It aims to maximize the margin between the classes in order to achieve optimal separation. The SVM classifier utilizes a kernel function to handle non-linear classification problems and can handle both linear and non-linear decision boundaries [20].

The decision tree classifier is a supervised classification technique that involves dividing a complex problem into subproblems and recursively generating a tree structure. The tree is built using features from the input training dataset, and rules are extracted from the tree to classify test data. The branching of nodes in the decision tree is determined using entropy, which measures the impurity or uncertainty of a node.

The Naive Bayes classifier is an algorithm used to classify data based on observed features. It is a powerful and efficient machine-learning method that has been applied to various classification tasks. By leveraging Bayes' theorem with the assumption of feature independence, the Naive Bayes classifier calculates the probability of a data instance belonging to a particular class. To process the data using the Naive Bayes classifier, the algorithm estimates the prior probability of each class and the conditional probability of each feature given the class. These probabilities are computed separately for each feature due to the assumption of feature independence. This simplifies the overall computation and allows the algorithm to scale well even with large datasets.

3. Result and Discussion

This section presents the results from the analysis of frequency bands and the classification performance evaluation. Discussion on the results is delivered.

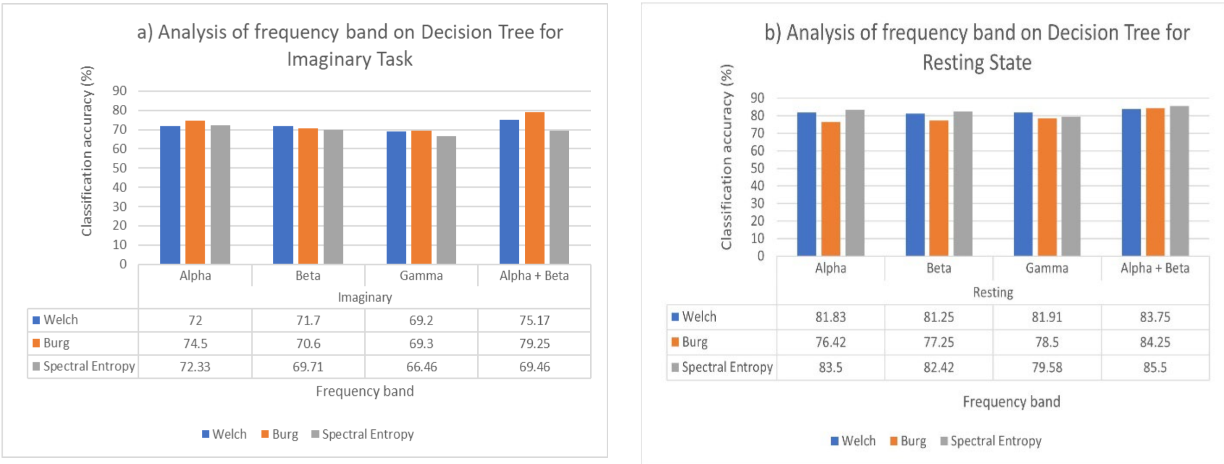
3.1 Frequency Band Analysis of the Imaginary and Resting Task Features

Results of analysis based on Welch, Burg, and spectral entropy EEG signal features are shown in Fig. 3 to Fig. 6. Each of the figures demonstrates the imaginary and resting task. Each feature involved four frequency bands, alpha, beta, gamma, and alpha-beta.

For decision tree classifier, it is observed that for imaginary tasks, the combination of alpha and beta frequency bands achieves the highest accuracy. Specifically, using the Burg feature extraction method, the accuracy value reaches 79.25%. Similarly, for the resting state, the combination of alpha and beta frequency bands achieves the highest accuracy of 85.5% when employing the spectral entropy method. For the imaginary task, the SVM classifier achieves the highest accuracy when focusing on the beta frequency band, with a value of 96.04%. This suggests that the beta frequency range is particularly effective in accurately classifying motor imaginary tasks. Similarly, for resting conditions, the SVM classifier achieves the highest accuracy of 96.83% when analysing EEG signals in the beta frequency range. The KNN classifier shows that for motor imaginary tasks, the Burg feature extraction method with the alpha + beta frequency band achieves the highest accuracy, with a value of 74.21%.

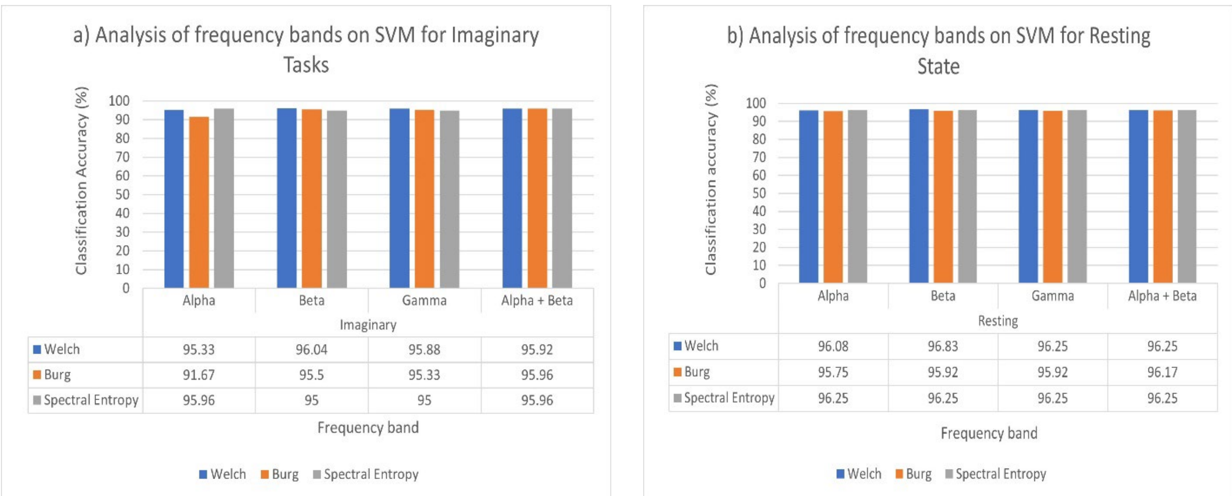
On the other hand, for the resting condition, the Welch feature extraction method with the gamma frequency band yields the highest accuracy, reaching 70.25%. When analysing the Naive Bayes classifier, it is found that for motor imaginary tasks, the Burg feature extraction method with the combination of the alpha and beta frequency bands achieves an accuracy of 67.25%. Regarding the resting conditions, the Sample Entropy feature extraction method with the combination of the alpha and beta frequency band obtains the highest accuracy of 68.42%.

The findings indicate that the beta frequency band emerges as the most suitable frequency band for EEG-based biometric applications. It consistently yields the highest accuracy values for both motor imaginary and resting state tasks across different classifiers and feature extraction methods. For instance, in the support vector machine classifier, the beta frequency band achieves accuracy values ranging from 95.92% to 96.83% for motor imaginary tasks and 96.08% to 96.83% for resting state tasks. These results imply that the beta frequency band captures crucial neural patterns relevant to distinguishing individuals in both task conditions. Thus, leveraging the information encoded in the beta frequency band can lead to the development of effective and accurate biometric systems, contributing to advancements in the field of EEG-based biometrics and its applications in various domains.



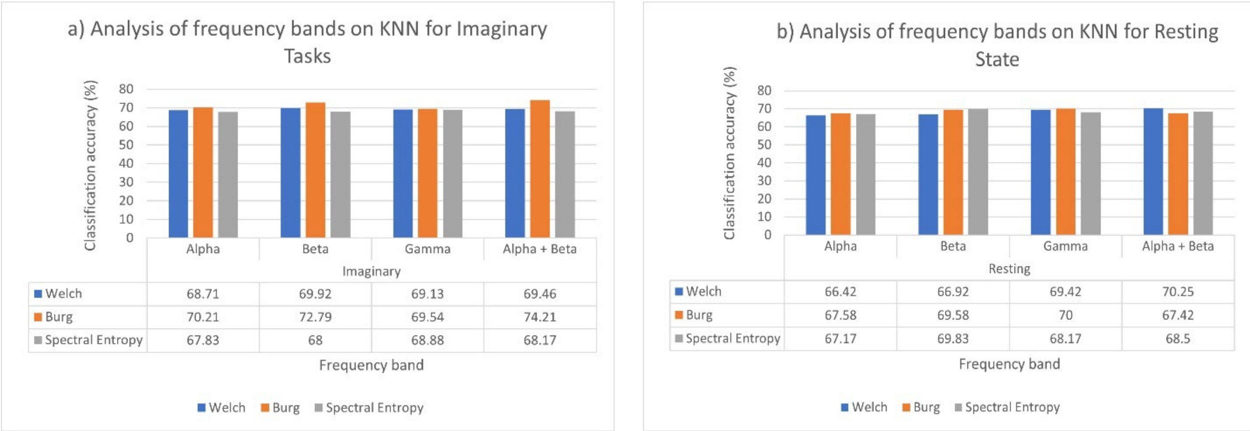
(a) **(b)**

Fig. 3 *Analysis of frequency band on decision tree for (a) Imaginary task; (b) Rest conditions*



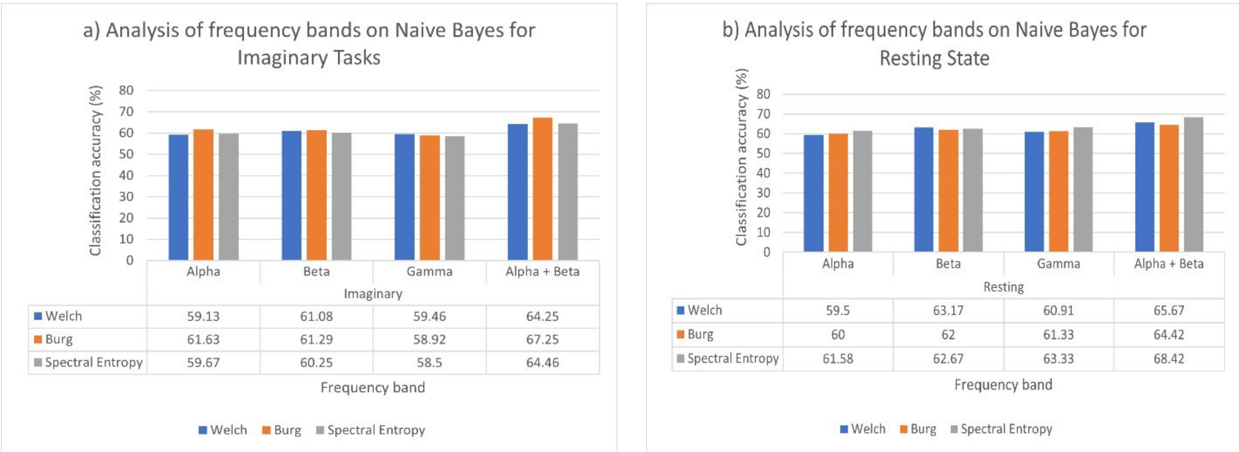
(a) **(b)**

Fig. 4 *Analysis of frequency band on support vector machine for (a) Imaginary task; (b) Rest conditions*



(a) **(b)**

Fig. 5 *Analysis of frequency band on k-nearest neighbor for (a) Imaginary task; (b) Rest conditions*



(a) **(b)**

Fig. 6 *Analysis of frequency band on Naive Bayes for (a) Imaginary task; (b) Rest conditions*

3.2 Feature Performance Evaluation

This study evaluates the performance of different machine learning techniques for biometric applications using EEG signals. In order to assess the performance of the classifiers the accuracy, sensitivity, specificity, and F1 score of these techniques were obtained and are presented in Fig. 7,8 and 9. These performance metrics were presented relative with the different frequency bands (alpha, beta, gamma, alpha + beta) of the EEG.

The accuracy metric reflects the overall correctness of the classification results, while sensitivity and specificity provide insights into the classifier's ability to correctly identify positive and negative instances, respectively. By examining these performance features, we can gain a comprehensive understanding of how well each machine learning technique performs in distinguishing individuals based on EEG signals.

Based on Fig 7, 8, and 9, the support vector machine (SVM) consistently demonstrated high accuracy, sensitivity, specificity, and F1 score across all frequency bands. The SVM achieved accuracy values ranging from 95.33% to 96.042%, with the beta frequency band consistently achieving the highest accuracy scores. This indicates that the SVM classifier is highly effective in accurately classifying motor imaginary tasks and rest conditions using EEG signals, making it a suitable choice for biometric applications.

The SVM classifier also achieved high sensitivity values ranging from 92.83% to 95.42%, consistently exhibiting the highest sensitivity. This suggests that the SVM classifier can effectively detect motor imaginary tasks and rest conditions, capturing important patterns in the EEG signals. Furthermore, the SVM classifier demonstrated excellent specificity values ranging from 91.83% to 99.25%. The beta frequency band consistently achieved the highest specificity, indicating the classifier's ability to correctly identify individuals in both motor imaginary tasks and rest conditions.

Comparing the performance of other classifiers, the decision tree, k-nearest neighbors (KNN), and Naive Bayes classifiers, it is evident that the SVM classifier consistently outperforms them in terms of accuracy, sensitivity, and specificity. These findings highlight the suitability of the SVM classifier, particularly when considering the beta frequency band, for biometric applications using EEG signals. The k-fold cross-validation with a value of 10 was applied to avoid any bias inherent in the training and testing datasets. The results of this validation approach for the SVM classifier applied to the beta frequency band using the Welch method revealed an accuracy of 0.9604, a sensitivity of 0.9922, and a specificity of 0.9327. The high accuracy, sensitivity, and specificity achieved by the SVM classifier indicate its potential for reliable identification or authentication purposes based on EEG signals. Therefore, this analysis underscores the importance of leveraging the SVM classifier and the beta frequency band in EEG-based biometric applications. The consistent performance of the SVM classifier across different classifiers and frequency bands provides compelling evidence of its effectiveness and reinforces its value for biometric identification or authentication based on EEG signals.

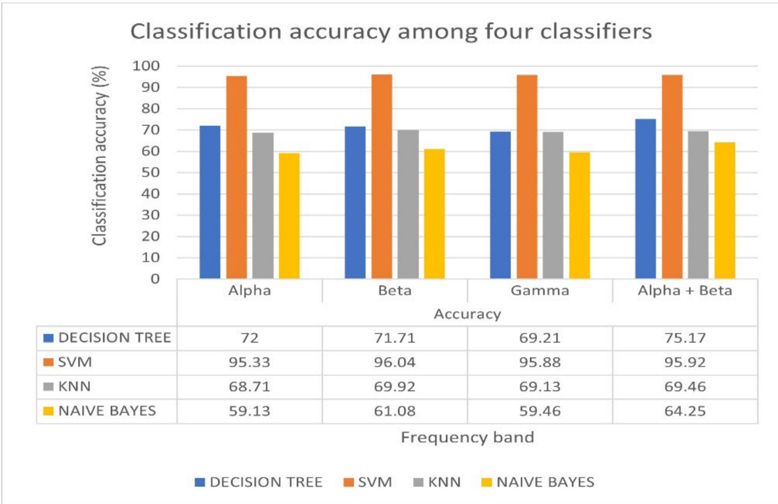


Fig. 7 *Classification accuracy among five classifiers using Welch method*

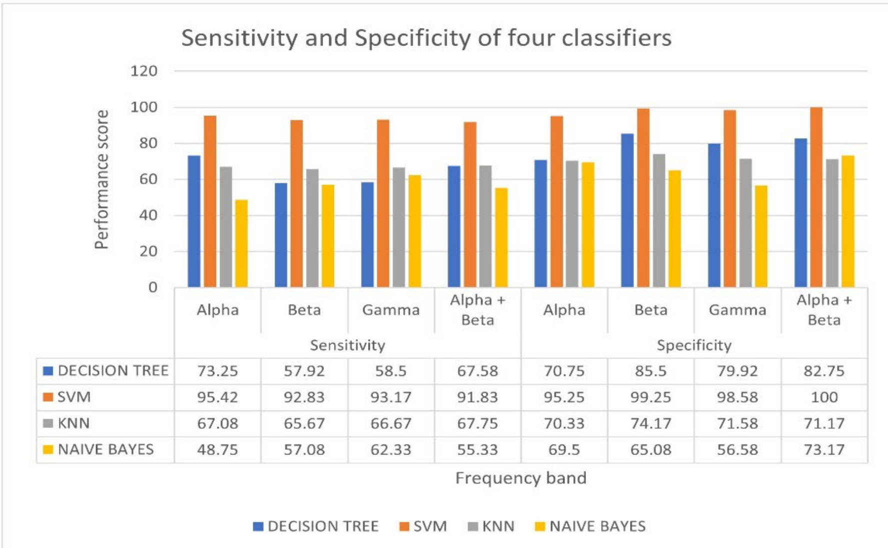


Fig. 8 *Classification sensitivity and specificity among five classifiers using Welch method*

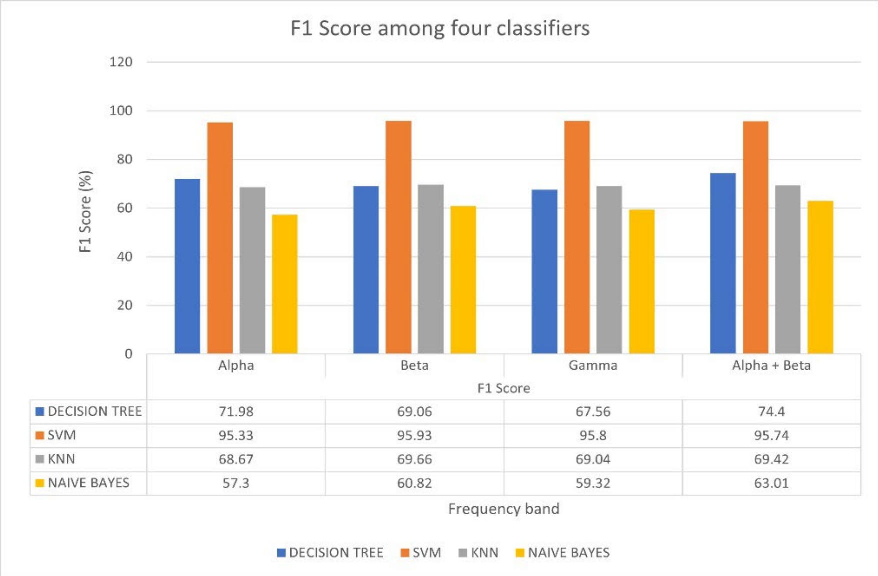


Fig. 8 *F1 score among five classifiers using Welch method*

4. Conclusion

In conclusion, the proposed experimental protocol yielded a high classification rate, with the SVM classifier achieving an accuracy of 96.04% for the motor imaginary state and 96.83% for the resting state. The findings revealed that the beta frequency band, followed by a combination of alpha and beta bands, exhibited the highest accuracy in distinguishing between the two conditions. This analysis provided valuable insights into the specific frequency ranges that exhibited distinctive characteristics related to the imaginary and rest conditions. The SVM classifier consistently demonstrated high specificity, sensitivity, and accuracy across all frequency bands. This finding suggests that SVM is a suitable machine-learning technique for biometric applications using the proposed performance features. The proposed experimental protocol ensured a higher classification rate, while the analysis of frequency bands shed light on the specific frequency ranges that exhibited discriminative characteristics. The evaluation of performance features using different machine learning techniques demonstrated the effectiveness of SVM in achieving high accuracy, sensitivity, and specificity.

This EEG biometric study contributes to the field by developing a simpler methodology based on mental imagery activities. It provides a comprehensive analysis of EEG signal properties, identifying the most appropriate ones to improve the effectiveness and dependability of EEG-based biometric applications. By accomplishing this, the work paves the door for more practical and precise biometric identity and authentication systems, possibly enhancing security and accessibility in a variety of fields such as healthcare, technology, and beyond.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Thenmoli Manogar, Saidatul;* ***data collection:*** *Thenmoli Manogar;* ***analysis and interpretation of results:*** *Thenmoli Manogar, Saidatul Ardeenawatie, Marni Azira;* ***draft manuscript preparation:*** *Thenmoli Manogar, Saidatul, Mohammad Shahril, Roy Francis Navea. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Chin, T. Z., Saidatul, A., & Zunaidi, I. (2019). Exploring EEG based Authentication for Imaginary and Non-imaginary tasks using Power Spectral Density Method. *IOP Conference Series. Materials Science and Engineering*, *557*(1), 012031. https://doi.org/10.1088/1757-899x/557/1/012031

[2] Shams, T. B., Hossain, M. S., Mahmud, M. F., Tehjib, M. S., Hossain, Z., & Pramanik, M. (2022). EEG-based Biometric Authentication Using Machine Learning: A Comprehensive survey. *ECTI Transactions on Electrical Eng. / Electronics and Communications*, *20*(2), 225–241. https://doi.org/10.37936/ecti-eec.2022202.246906

[3] Zeynali, M., & Seyedarabi, H. (2019). EEG-based single-channel authentication systems with optimum electrode placement for different mental activities. *Biomedical Journal*, *42*(4), 261–267. https://doi.org/10.1016/j.bj.2019.03.005

[4] Puengdang, S., Tuarob, S., Sattabongkot, T., & Sakboonyarat, B. (2019, January). EEG-based person authentication method using deep learning with visual stimulation. In *2019 11th International Conference on Knowledge and Smart Technology (KST)* (pp. 6-10). IEEE. https://doi.org/10.1109/kst.2019.8687819

[5] Rojas, G., Álvarez, C., Montoya, C., De La Iglesia-Vayá, M., Cisternas, J., & Gálvez, M. (2018). Study of Resting-State Functional Connectivity Networks using EEG Electrodes Position as seed. *Frontiers in Neuroscience*, *12*. https://doi.org/10.3389/fnins.2018.00235

[6] Wilaiprasitporn, T., Ditthapron, A., Matchaparn, K., Tongbuasirilai, T., Banluesombatkul, N., & Chuangsuwanich, E. (2020). Affective EEG-Based person identification using the deep learning approach. *IEEE Transactions on Cognitive and Developmental Systems*, *12*(3), 486–496. https://doi.org/10.1109/tcds.2019.2924648

[7] Kang, J., Jo, Y. C., & Kim, S. (2018). Electroencephalographic feature evaluation for improving personal authentication performance. *Neurocomputing*, *287*, 93–101. https://doi.org/10.1016/j.neucom.2018.01.074

[8] Miyake, T., Nozomu, K., & Nakanishi, I. (2020). Wavelet Transform and Machine Learning-Based Biometric Authentication Using EEG Evoked by Invisible Visual Stimuli. IEEE REGION 10 CONFERENCE (TENCON), (pp. 573-578). https://doi.org/10.1109/tencon50793.2020.9293772

[9] Lai, C. Q., Ibrahim, H., Suandi, S. A., & Abdullah, M. Z. (2022). Convolutional Neural Network for Closed-Set Identification from Resting State Electroencephalography. *Mathematics*, *10*(19), 3442. https://doi.org/10.3390/math10193442

[10] Rahman, A., Chowdhury, M. E. H., Khandakar, A., Kıranyaz, S., Zaman, K. S., Reaz, M. B. I., Islam, M. T., Ezeddin, M., & Kadir, M. A. (2021). Multimodal EEG and keystroke dynamics based biometric system using machine learning algorithms. *IEEE Access*, *9*, 94625–94643. https://doi.org/10.1109/access.2021.3092840

[11] BerciK, J., Giacalone, D., & Doležal, M. (2021). Advances in Aromatization/Aromachology in different environments. In *MDPI eBooks*. https://doi.org/10.3390/books978-3-0365-2298-2

[12] Ong, Z. Y., Saidatul, A., & Zunaidi, I. (2018). Power Spectral Density Analysis for Human EEG-based Biometric Identification. *International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA)*, (pp. 1-6). https://doi.org/10.1109/icassda.2018.8477604

[13] Valsaraj, A., Madala, I., Garg, N., Patil, M., & Baths, V. (2020c). Motor Imagery Based Multimodal Biometric User Authentication System Using EEG. *International Conference on Cyberworlds (CW)*, (pp. 272-279). https://doi.org/10.1109/cw49994.2020.00050

[14] Shrivastava, H., & Tcheslavski, G. V. (2018). On the potential of EEG for biometrics: combining power spectral density with a statistical test. *International Journal of Biometrics*, *10*(1), 52. https://doi.org/10.1504/ijbm.2018.090128

[15] Hu, L. (2019). EEG signal processing and feature extraction. In *Springer eBooks*. https://doi.org/10.1007/978-981-13-9113-2

[16] Ong, Z. Y., Saidatul, A., Vijean, V., & Zunaidi, I. (2019). Non Linear Features Analysis between Imaginary and Non-imaginary Tasks for Human EEG-based Biometric Identification. *IOP Conference Series. Materials Science and Engineering*, *557*(1), 012033. https://doi.org/10.1088/1757-899x/557/1/012033

[17] Bablani, A., Edla, D. R., & Dodia, S. (2018). Classification of EEG Data using k-Nearest Neighbor approach for Concealed Information Test. *Procedia Computer Science*, *143*, 242–249. https://doi.org/10.1016/j.procs.2018.10.392

[18] Harrison, O. (2019, July 14). Machine Learning Basics with the K-Nearest Neighbors Algorithm. *Medium*. https://towardsdatascience.com/machine-learning-basics-with-the-k-nearest-neighbors-algorithm-6a6e71d01761

[19] "K-Nearest Neighbor(KNN) Algorithm for Machine Learning - Javatpoint." Retrieved July 26, 2020, from https://www.javatpoint.com/k-nearest-neighbour-algorithm-for-machine-learning

[20] Ashfaque, J. M., & Iqbal, A. (2019). Introduction to support vector machines and kernel methods https://www. researchgate. net/publication/332370436