Comparison of Different Spectral Analysis Methods with an Experimental EEG Dataset

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Electroencephalogram (EEG) signals are low-amplitude electrical signals that measure the electrical activity between electrodes from the scalp and neurons in the brain. Successful studies have been carried out in many different areas for the detection of many neurological diseases, especially epilepsy, using EEG signals. In this study is aimed to compare different spectral analysis methods on EEG data. For this purpose, three different feature vectors were created by calculating power spectrum densities between 1-49 Hz using three different spectral analysis methods: Periodogram, Welch, and Multitaper. The performances of the three spectral analysis methods were compared by classifying them with the Support Vector Machine (SVM) algorithm using the created feature vectors. The accuracy rate of the Periodogram and SVM model was 92.30 %, the accuracy rate of the Welch and SVM model was 96.16 %, the accuracy rate of the Multitaper and SVM model was 94.48 %. The model with the highest performance is the classification model that effectively combines the Welch method and the SVM algorithm.

***Keywords**:* *Spectral analysis, EEG, Welch, Periodogram, Multitaper*

1. Introduction

The electrical activity between brain neurons is linked to motor, cognitive, perceptual, and emotional processes. From the scalp, EEG monitors brain messages and electrical activity. The normal electrical activity of the brain is an auxiliary test in the diagnosis of many neurological problems, especially epilepsy. Although it has not been fully revealed yet, it is known that a large amount of information is stored in these signals obtained from the human brain [1].

EEG is a completely painless and harmless examination method. In addition, EEG is preferred due to its lower cost and less equipment requirement compared to other neuroimaging techniques such as magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI), computed tomography (CT), and functional near infrared spectroscopy (fNRIS) [2]. Because of its portability, noninvasive nature, relatively simple and inexpensive equipment, EEG is the most widely used technique in the clinic. Therefore, findings obtained using EEG signals can be easily exported for daily clinical use [3]. Clinical analysis of EEG signals aids in disease management and prognosis. Thanks to the latest developments in biomedical signal processing, multi-resolution analysis of EEG signals is possible in the diagnosis of diseases [4]. A number of signal processing methods are applied to analyze EEG signals by converting them from time domain to frequency domain.

Spectral analysis is a method of examining the characteristic of EEG signals according to frequency and estimating how the power of a signal is distributed. In spectral analysis is aimed to reveal the repetitive and hidden behaviors of the signal. The distribution and characteristics of EEG signals in frequency space can be found with power spectrum density [5]. Spectral analysis on EEG can be performed in a wide frequency range, as well as in defined sub-bands of the EEG signal. EEG signals are basically divided into five frequency bands: delta (δ), theta (θ), alpha (α), beta (β) and gamma (γ) [6]. For a long time, power spectrum estimate approaches have been utilized in the study of EEG signals. There are many studies in the literature using spectral analysis methods and EEG data, epileptic seizure detection [7-9], sleep disorder detection [10], biometric verification [11], classification of mental tasks [12] and detection of major depressive disorder [13]. In order to estimate the power spectrum intensities of EEG signals, it is seen that Periodogram [11], Welch [8, 10] and Multitaper [9] methods are widely used.

In this study is aimed to compare different spectral analysis methods on experimental EEG dataset. For this purpose, three different feature vectors were created by calculating power spectrum densities between 1-49 Hz using three different spectral analysis methods: Periodogram, Welch and Multitaper. The performances of the three spectral analysis methods were compared using the created feature vectors and SVM algorithm.

2. Materials and Methods

In the study, three different spectral analysis methods, namely Periodogram, Welch and Multitaper, were compared on EEG dataset. The general block diagram of the study is given in Figure 1.

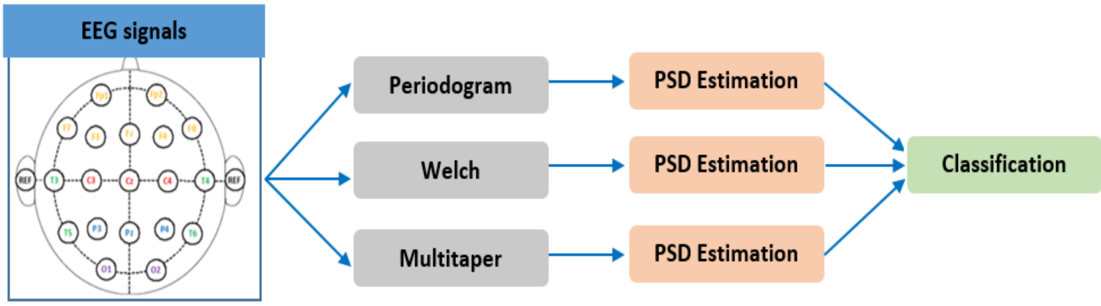

Figure 1. *The general block diagram of the study*

A. Dataset:

The experimental EEG dataset that is used in this study was obtained from physionet.org, a huge repository website for data scientists and machine learning practitioners [14]. EEG signals were recorded from 36 subjects (27 females, 9 males) before and during mental arithmetic tasks by a neurophysiologist specialized in EEG visual examination. The Bioethics Commission of the Education and Scientific Center of the Taras Shevchenko National University of Kyiv "Institute of Biology and Medicine" accepted the EEG dataset utilized. Each participant gave written informed consent in accordance with the World Medical Association (WMA) Declaration of Helsinki. Inclusion criteria of the participants in the study; normal or corrected-normal visual acuity, normal color vision, and the absence of clinical signs of mental or cognitive impairment, verbal or nonverbal learning difficulties. Exclusion criteria were psychoactive drug use, alcohol or drug addiction, and presence of neurological or psychiatric complaints [15].

B. Experiment design:

EEG signals were recorded using the Neurocom EEG 23-channel system, 21 channels and 2 reference ear electrodes. Participants are given the arithmetic task of subtracting two numbers serially during the experiments. Each trial begins with verbally subtracting the 2-digit number from the 4-digit number (example: 3141 – 42). All recordings are 60 second artifact-free EEG segments. EEG recordings of each participant were taken before and during the mental arithmetic task. Figure 2 shows how all electrodes were placed on the scalp using the international 10/20 technique.

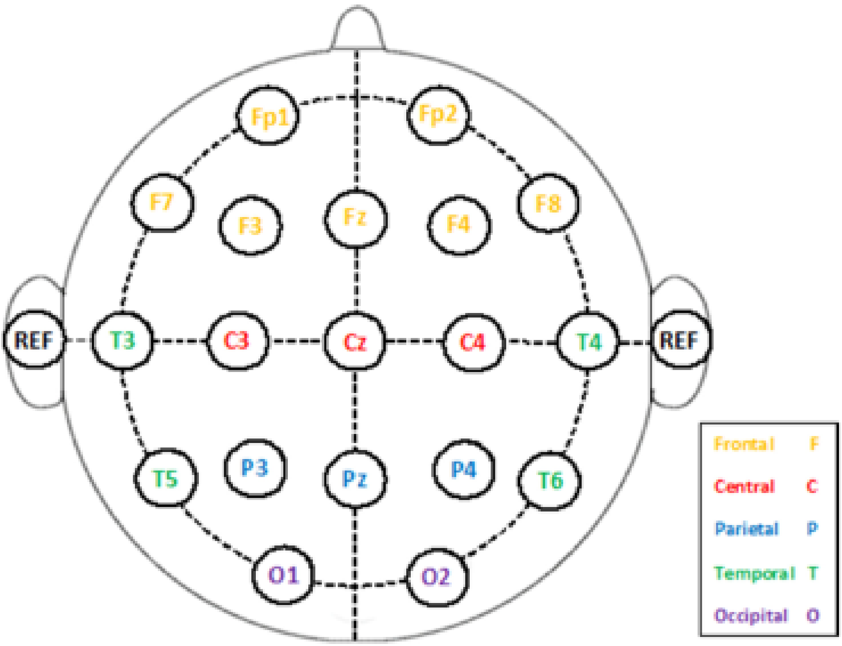

***Figure 2**. Electrodes positioning for the international 10-20 system*

C. Training and Test Datasets

In the study, the Holdout method was used while the dataset was divided into test and training datasets. In the holdout method, a certain amount of sample is separated as test dataset, the remaining data is used as training dataset. There are 4536 pieces of data in total in the dataset. In order to control the performance of the classification models, these data are divided into 2/3 as training dataset (3024) and 1/3 as test dataset (1512) by holdout method. The model is trained using the training dataset and the performance of the model is evaluated using the test dataset.

If there is a number of data representing each class and the dataset is evenly distributed, the Holdout method is widely used [16]. In the study, the number of representations belonging to each class is distributed adequately and evenly.

D. Spectral Analysis:

Spectral analysis methods show how a stationary, random and finite-length signal is distributed over the frequency band. In spectral analysis is aimed to reveal the repetitive and hidden behaviors of the signal [5]. Power spectral density describes the power distribution of a signal over the frequency range. Periodogram, Welch and Multitaper spectral analysis methods are widely used to estimate the power spectral density.

Periodogram method is the simplest form of spectral analysis methods. The Periodogram is applied directly to the EEG signals. It is the most basic form of extraction of signals and power spectra. It is calculated as in Equation 1. $\varphi(w)$ represents the power spectrum density, N is the sample number of the signal, y(t) is the spectrum of the signal, and w is the frequency which is the power spectrum density.

$$\vartheta_{(\mathrm{w})} = \frac{1}{N}\left|\sum\nolimits_{t=1}^{N} y(t)e^{-j\omega t}\right|^{2} \tag{1}$$

The Welch method is a form of calculation that finds the weighted sum of the periodograms of the overlapping windows of the signal. In the method, the signal is windowed to create overlapping segments. Then the square size of the Discrete Fourier Transform (DFT) is calculated for each segment. Finally, the average PSD for each separated segment gives the Welch periodograms [17]. The Welch method is calculated as in Equation 2.

In Equation 2, P is the number of windowed segments, $\hat{I}^{p}_{xx}(\omega)$ is the Periodogram calculated per windowed segment, and $\hat{I}^{W}_{xx}(\omega)$ is the average of the periodograms.

$$\hat{I}^{W}_{xx}(\omega) = \frac{1}{P}\sum_{p=0}^{p-1} \hat{I}^{p}_{xx}(\omega). \tag{2}$$

The Multitaper method is used to obtain the power spectral density by carrying the information contained in a signal into the frequency space. The power spectrum is created by distributing the average power of a signal over certain frequency values in the signal. The spectral density of the Multitaper method is calculated by Equation 3. The K in Equation 3 represents the number of filters to be used and $hK{-}n$ the filter impulse [18].

$$\vartheta_{(\mathrm{w})} = \left|\sum\nolimits_{n=1}^{K} h_{K-n}y(n)e^{-j\omega n}\right|^2 \tag{3}$$

3. Experimental Results

In this study, feature vectors were created by calculating the power spectrum densities of the EEG signals on the experimental EEG dataset with three different spectral analysis methods. The performance of classification models created with these feature vectors and SVM machine learning algorithm has been compared. The spectral power densities of the frequencies between 1-49 Hz of the EEG signals recorded from 36 participants were calculated using Periodogram, Welch and Multitaper spectral analysis methods. The raw 10-second EEG signals of mental workload and resting states from the Fp1 channel are given in Figure 3. Raw EEG signals from other channels have similar characteristics.

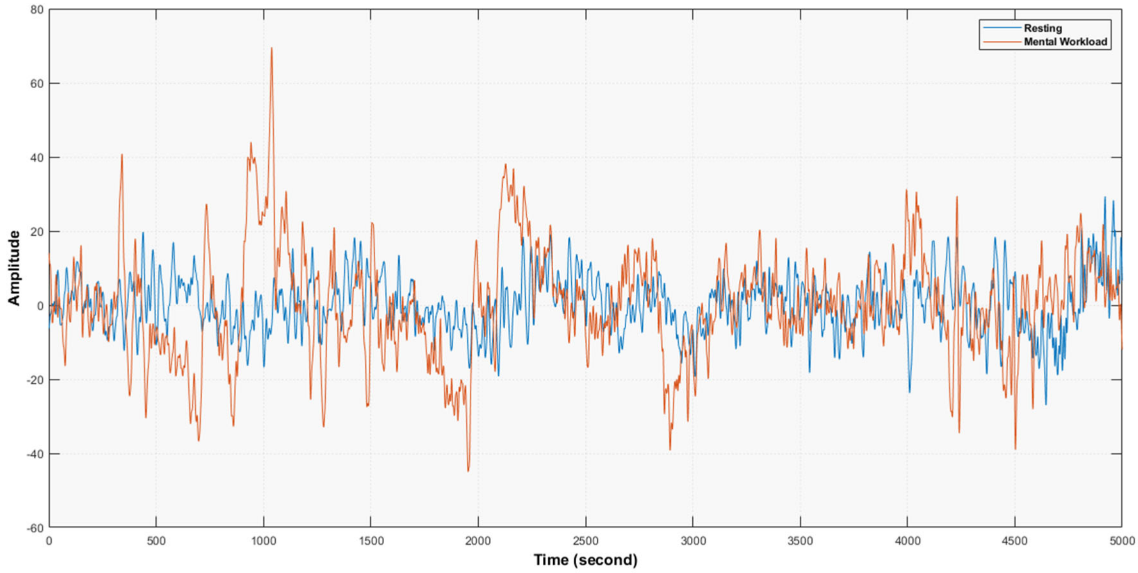

Figure 3. *Raw EEG signal graph*

The power spectral density values obtained from the Fp1 channel using the Periodogram method of mental workload and resting states are given in Figure 4. Power spectral density values obtained from other channels also have similar characteristics.

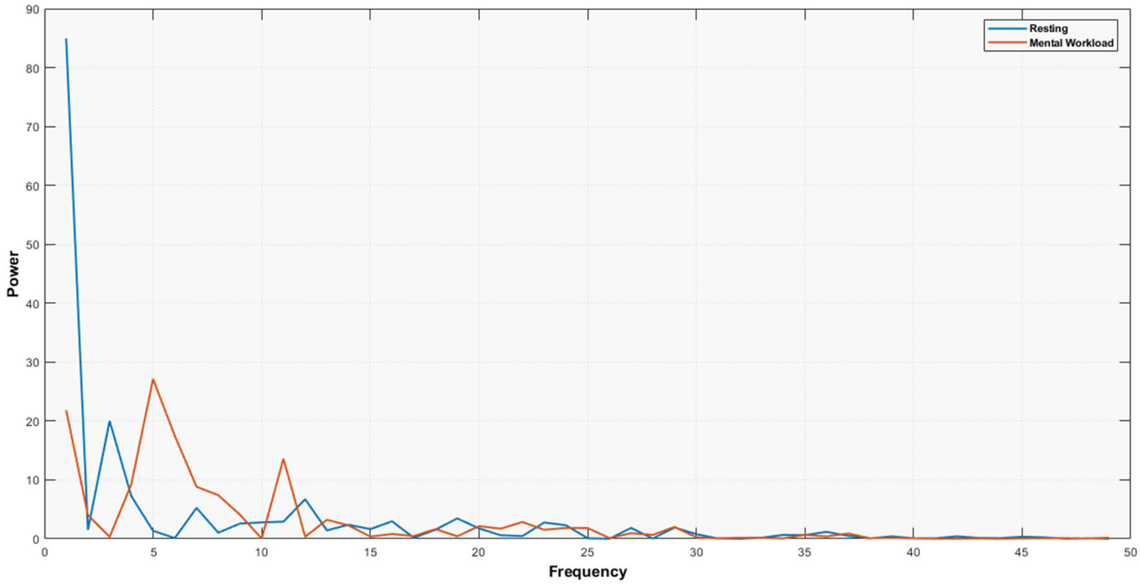

Figure 4. *Power spectral density graph calculated by the Periodogram*

In the Welch method, the window length is ¼ of the data size and the "Noverlap" parameter is ½ of the window length were selected. The power spectral density values obtained from the Fp1 channel using the Welch method of mental workload and resting states are given in Figure 5.

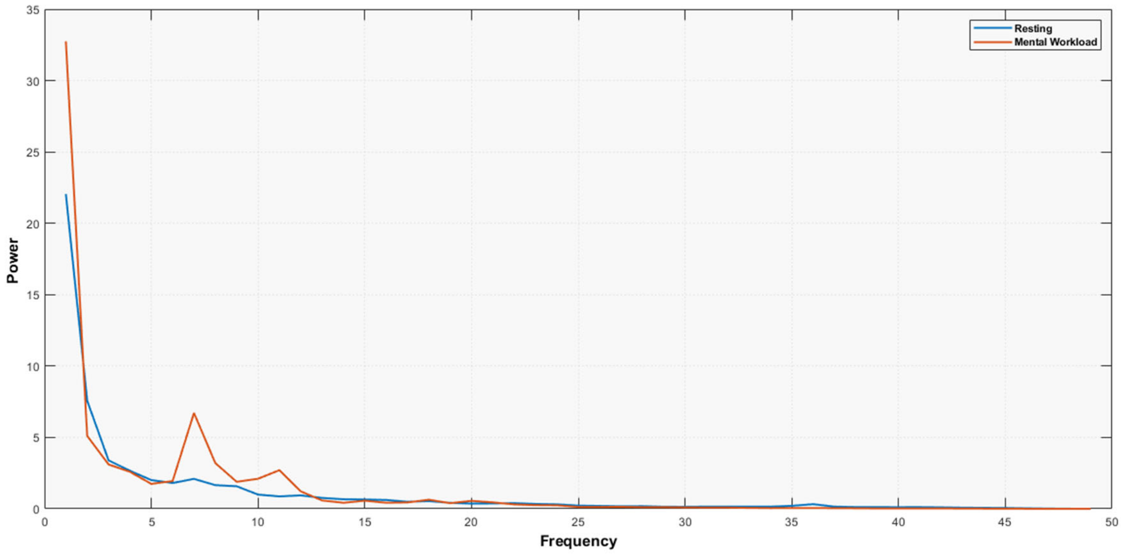

Figure 5. *Power spectral density plot calculated by the Welch*

The power spectral density values obtained from the Fp1 channel using the Multitaper method are given in Figure 6.

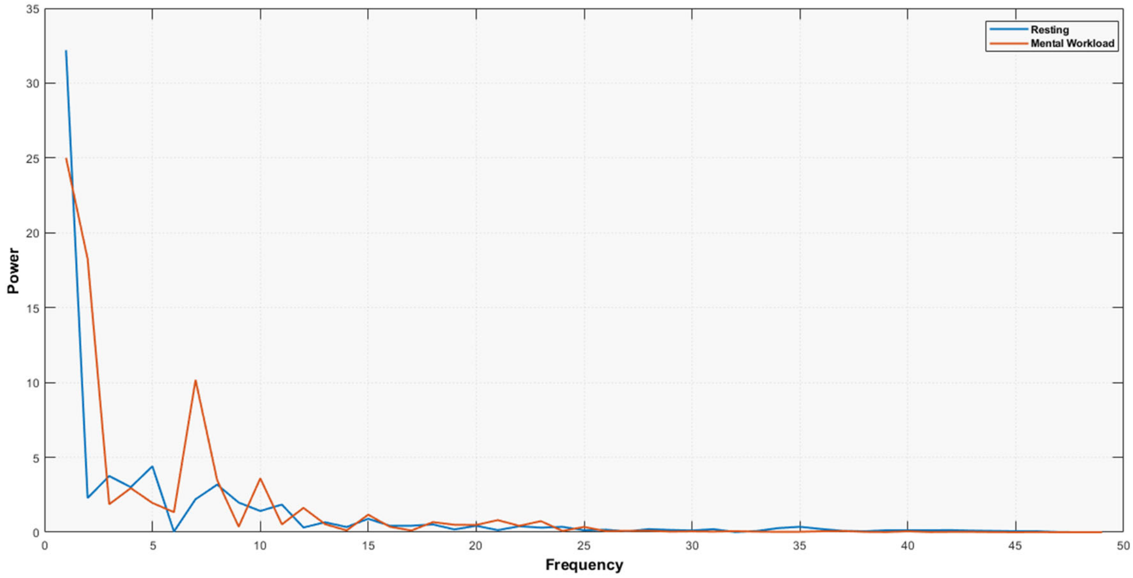

***Figure 6**. Power spectral density plot calculated by the Multitaper*

In the study, three different experiments were carried out using the Periodogram, Welch and Multitaper methods. In all experiments, SVM machine learning algorithm was used together with these methods. The experimental EEG dataset consists of EEG signals from 36 subjects, 21 channels, resting and mental workload tasks, with a sampling frequency of 500. To these data (36 subject x 21 channels x 2 situations = 1512), the number of feature vectors was increased by using the amplifying augmentation method. The primary goal of data augmentation is to provide enough data for the model to make more accurate predictions. Data augmentation eliminates the overfitting problem of the model. Using the data augmentation method, the feature vector numbers were multiplied by the factors of 0.98 and 1.02. Thus, the number of feature vectors has been increased threefold. These represent variations in the amplitude of brain waves depending on factors such as electrode-tissue impedance [19-20]. As a result, there are 4536 data (1512 x 3) in total in the dataset with data augmentation.

In order to control the performance of the classification models, these data were divided into 2/3 training dataset (3024) and 1/3 test dataset (1512) using the holdout method. While the model was trained with the training dataset, the success of the model was checked with 1512 independent test datasets. Kernel function "rbf" was chosen in SVM algorithm. The parameters in the confusion matrix of the experiments in which different spectral analysis methods were used are given in Table 1.

***Table 1.** The parameters in the confusion matrix of the experiments in which different spectral analysis methods*

Experiments	**Method**	**Classification**	**Confusion matrix parameters**					
			TP	FP	FN	TN	FP+FN	TP+TN
Experiment 1	Periodogram	SVM	725	53	68	666	121	1391
Experiment 2	Welch	SVM	731	8	50	723	58	1454
Experiment 3	Multitaper	SVM	745	2	85	680	87	1425

When Experiment 1, Experiment 2 and Experiment 3 are examined in Table 1, the highest number of correctly classified data belongs to the Welch method, one of the spectral analysis methods. In the confusion matrix of Experiment 2 using Welch and SVM algorithm, TP value is 731, FP value is 8, FN value is 50, TN value is 723, total number of incorrectly classified samples (FP+FN) is 58, and total number of correctly classified samples (TP+TN) is 1454. The results of Experiment 2, where the feature vectors extracted by the Welch method and the SVM machine learning algorithm are used, have the highest number of correctly classified samples.

Using these parameters obtained from the confusion matrix, sensitivity, specificity, precision, f1-score, MCC and accuracy model performance criteria are calculated. The performances of the models are evaluated using these performance criteria. According to the experiments, the performance results of the classification models are given in Table 2:

Table 2. *Performance analysis of classification models*

Experiments	Classification models	Model performance evaluation					
		Sensitivity	Specificity	Precision	F1- score	MCC	Accuracy
Experiment 1	Periodogram + SVM	0.914	0.926	0.931	0.923	0.839	92.30%
Experiment 2	Welch + SVM	0.936	0.989	0.989	0.961	0.924	96.16%
Experiment 3	Multitaper + SVM	0.897	0.997	0.997	0.944	0.890	94.48%

When the performance analyzes of the classification models are examined in Table 2, the highest performance belongs to the Welch and SVM classification model, in which the power spectral density values obtained by the Welch method are used. In Experiment 2, the performance analysis results of the Welch and SVM classification model were calculated as 0.936 sensitivity, 0.989 specificity, 0.989 precision, 0.961 f1 score, 0.924 MCC, and 96.16% accuracy. The values of the model performance criteria should be close to 1. The fact that these values are close to 1 indicates that the model does not have a random success [21]. In Figure 7, the performance analysis results of the SVM algorithm according to the spectral analysis methods are given.

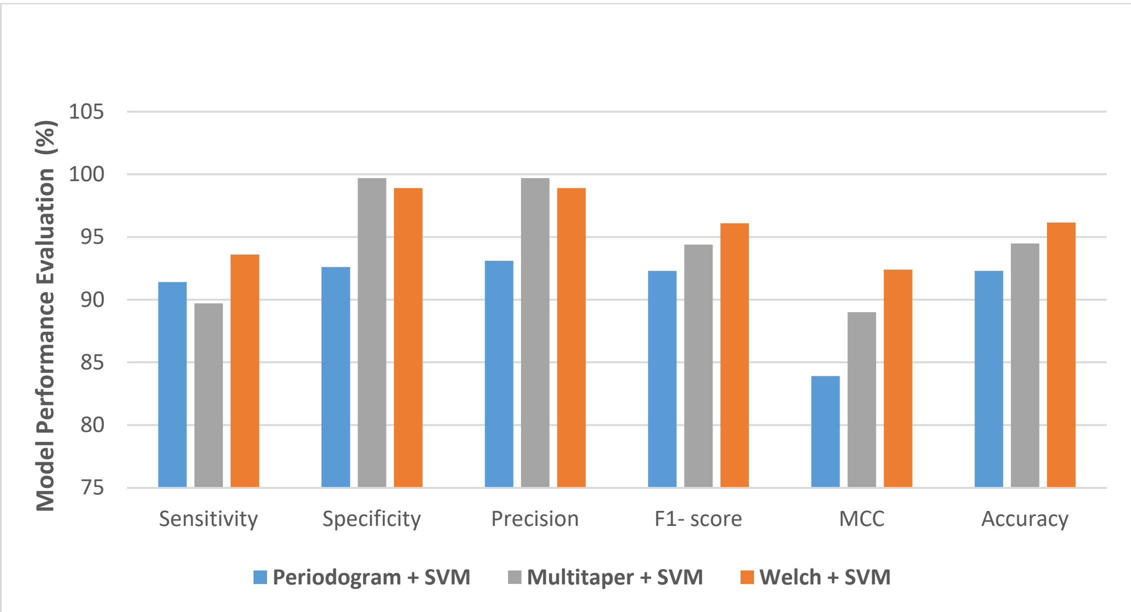

***Figure** 7. Performance results of classification algorithms according to spectral analysis methods*

Of the three spectral analysis methods, Periodogram, Welch and Multitaper, whose performance results were compared, the Welch method showed the highest accuracy in this EEG dataset. The sensitivity, f1-score, MCC and accuracy values of the model performance criteria of the Welch and SVM classification model were higher than the other classification models.

4. Conclusion

As a result, the performances of Periodogram, Welch and Multitaper spectral analysis methods on EEG signals were compared. Three separate experiments were carried out using the power spectral densities calculated with the Periodogram, Multitaper and Welch spectral analysis methods. In the experiments, firstly, feature vectors were obtained by calculating the power spectrum densities of the EEG signals between 1-49 Hz with these spectral analysis methods. The results obtained using these feature vectors and the SVM algorithm were analyzed according to the model performance criteria. The classification model constructed with the Welch technique spectral analysis method and SVM algorithm has the best performance, according to the experimental results. Performance analysis results of the Welch and SVM classification model were calculated as 0.936 sensitivity, 0.989 specificity, 0.989 precision, 0.961 f1 score, 0.924 MCC, and 96.16% accuracy. The fact that these values are close to 1 indicates that the model does not have a random success. It is thought that the proposed model will support classification studies and show high performance by applying it to different EEG datasets.

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