Classifining Seizure patients based on EEG Signals

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Abstract:

This study presents a comparative analysis of three classification methods—Radial Basis Function (RBF), k-Nearest Neighbors (KNN), and Support Vector Machine (SVM)—for detecting seizures in EEG signals from the MIT-CHB scalp dataset. We focused on five subjects, each with five seizure cases and one non-seizure case. Preprocessing steps included signal segmentation and epoch creation, followed by feature extraction using Shannon entropy, variance, min, max, and mean. Features were normalized and selected using a t-test with a p-value threshold of 0.001. The classifiers were evaluated on accuracy, sensitivity, and specificity under various conditions, including variations in sigma for RBF, training/test size ratios, and p-value thresholds. Our findings indicate that [insert key result], demonstrating the strengths and limitations of each method in the context of EEG signal classification. These insights contribute to the development of more accurate and reliable seizure detection systems.

Keywords: **EEG, seizure detection, RBF network, k-NN, SVM, feature extraction, classification, MIT-CHB dataset, machine learning, signal processing.**

I. Introduction:

Epilepsy is a chronic neurological disorder characterized by recurrent, unprovoked seizures. Effective management of epilepsy relies heavily on the accurate and timely detection of these seizures, primarily through electroencephalogram (EEG) monitoring. EEG is a non-invasive method that records electrical activity of the brain and is widely used for diagnosing and monitoring neurological disorders.

Despite advancements in EEG technology, the accurate classification of seizure and non-seizure states remains a challenging task. Traditional visual inspection by neurologists is time-consuming and subjective, highlighting the need for automated and reliable seizure detection systems. Machine learning techniques have emerged as powerful tools for this purpose, offering the potential to enhance the accuracy and efficiency of seizure detection.

The MIT-CHB scalp EEG database is a widely used resource for developing and testing seizure detection algorithms. It contains comprehensive EEG recordings from pediatric subjects, including detailed annotations of seizure events. This study utilizes a subset of the MIT-CHB dataset, focusing on five subjects with a balanced number of seizure and non-seizure cases.

In this paper, we present a comparative study of three machine learning classifiers—Radial Basis Function (RBF), k-Nearest Neighbors (KNN), and Support Vector Machine (SVM)—for the classification of seizure and non-seizure EEG signals. The objectives of this study are threefold: (1) to preprocess and segment the EEG data into meaningful epochs, (2) to extract and select relevant features, and (3) to evaluate the performance of each classifier under various conditions.

The preprocessing phase involves segmenting the EEG signals into 10-minute intervals, with epochs created from 16-second segments of the signal. Features such as Shannon entropy, variance, minimum, maximum, and mean are extracted from these epochs. The features are then normalized using z-score normalization, and a t-test is applied to select features with a p-value below 0.001 for each subject.

The classification phase employs three different methods: RBF, KNN, and SVM. The RBF network's hidden layer neurons are determined using k-means clustering, validated by silhouette scores, while KNN and SVM parameters are optimized through standard techniques. Each classifier's performance is measured in terms of accuracy, sensitivity, and specificity. Additional evaluations include varying the sigma parameter for the RBF method, adjusting the training/testing size ratios, and modifying the p-value threshold for feature selection.

The results of this study provide insights into the effectiveness of each classification method and suggest optimal conditions for their application. By comparing these methods, we aim to identify the most promising approach for seizure detection, ultimately contributing to the development of more robust and accurate EEG-based diagnostic tools.

II. Preprocessing:

The preprocessing of EEG data is a crucial step in preparing the signals for effective classification. This section outlines the procedures for data reading, segmentation, epoch creation, feature extraction, normalization, and feature selection.

Data Reading:

The MIT-CHB scalp EEG dataset was utilized for this study. This dataset comprises EEG recordings from pediatric subjects, with detailed annotations indicating the start and end times of seizures. For this analysis, data from five subjects were selected, each subject having five seizure cases and one non-seizure case.

The EEG data was read using appropriate Python libraries designed for handling EEG data. The signals were sampled at a frequency of 256 Hz. The summary text files accompanying the dataset provided the exact timings of seizure events, which were crucial for subsequent segmentation.

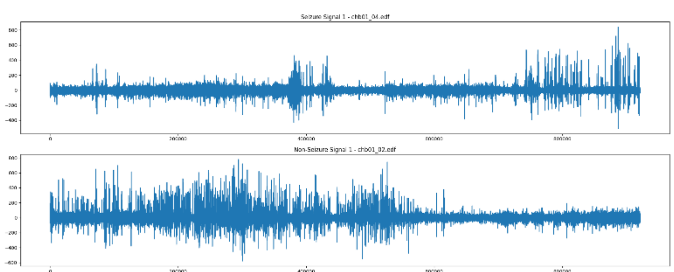

Figure 1 Raw Signal of two sample from each class. Top Image show Seizure Case and Bottom Image show Non-Seizure Case

Segmentation:

Segmentation involved extracting specific time windows from the continuous EEG recordings. For each seizure case, a 10-minute segment preceding the seizure onset was cropped from the data. This choice was made to capture the pre-ictal phase, which is indicative of an impending seizure.

For the non-seizure data, segments were selected randomly from periods without any seizure events. To maintain balance, the number of non-seizure segments was matched to the number of seizure segments for each subject.

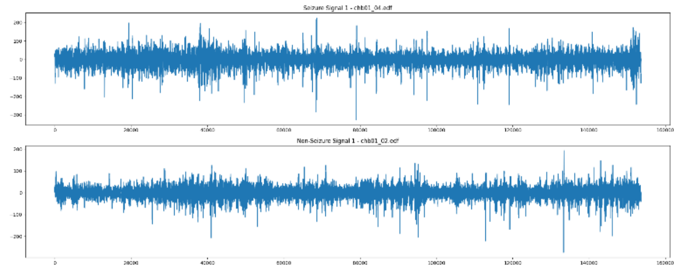

Figure 2 Segmented Signal of two sample from each class. Top Image show Seizure Case and Bottom Image show Non-Seizure Case

Epoch Creation:

After segmentation, each 10-minute segment was divided into smaller epochs of 16 seconds. This was done to create uniform time windows that facilitate feature extraction and classification. Each 10-minute segment yielded 37 epochs (600 seconds / 16 seconds per epoch).

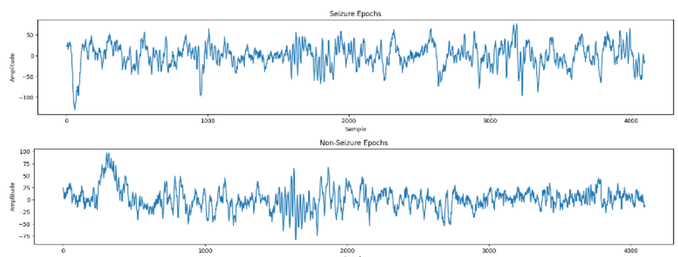

Figure 3 Epochs of two sample from each class. Top Image show Seizure Case and Bottom Image show Non-Seizure Case

Feature Extraction:

Feature extraction was performed on each epoch to derive meaningful statistical measures that could distinguish between seizure and non-seizure states. The features extracted included:

1. **Shannon Entropy:** Measures the complexity or irregularity of the signal.
2. **Variance:** Indicates the signal's dispersion.
3. **Minimum:** The lowest amplitude value in the epoch.
4. **Maximum:** The highest amplitude value in the epoch.
5. **Mean:** The average amplitude value of the epoch.

Normalization:

The extracted features were normalized using z-score normalization to ensure that each feature had a mean of 0 and a standard deviation of 1. This step helps in mitigating the effect of varying scales among different features.

Feature Selection:

Feature selection was conducted using a t-test to identify features that significantly differed between seizure and non-seizure epochs. Features with a p-value less than 0.001 were retained for each subject, ensuring that only the most relevant features were used in the classification phase.

After completing the feature extraction and selection process, we obtained the following dataset shapes for each subject: chb01 with a shape of (9384, 4), chb08 with a shape of (7820, 3), chb16 with a shape of (7616, 2), chb03 with a shape of (7820, 4), and chb14 with a shape of (11424, 3). These dimensions indicate the number of epochs and the selected features for each subject. Specifically, chb01 and chb03 retained four features, chb08 and chb14 retained three features, and chb16 retained two features. This variability reflects the individualized nature of EEG data and the effectiveness of the feature selection process in identifying the most relevant features for seizure detection per subject.

In summary, the preprocessing phase involved meticulous steps to ensure that the EEG data was properly segmented, epochized, and prepared for feature extraction. Normalization and feature selection further refined the data, making it suitable for accurate classification in the subsequent steps. Figures 2 and 3 provide visual representations of these preprocessing steps, while tables summarize the quantitative aspects of the data at each stage.

III. Methods

Dataset:

The dataset used for this study is the MIT-CHB scalp EEG dataset, which includes EEG recordings from pediatric subjects. We selected data from five subjects (chb01, chb03, chb08, chb14, and chb16). Each subject has five seizure cases and one non-seizure case.

Preprocessing:

Data Reading and Segmentation:

The EEG data was read at a sampling rate of 256 Hz. For each seizure case, a 10-minute segment preceding the seizure onset was extracted to capture the pre-ictal phase. For non-seizure data, segments of equal length were selected randomly from periods without seizures, ensuring a balanced dataset.

Epoch Creation:

Each 10-minute segment was divided into epochs of 16 seconds. This resulted in 37 epochs per segment (600 seconds / 16 seconds per epoch). Epochs from both seizure and non-seizure segments were created for further analysis.

Feature Extraction:

From each epoch, five statistical features were extracted:

1. **Shannon Entropy (H):**
   Measures the complexity of the signal.

   $$H = -\sum_{i=1}^{n} p_i \log(p_i)$$

   where p_i is the probability of amplitude iii in the epoch.

2. **Variance (σ^2):**
   Indicates the signal's dispersion.

   $$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$$

   where x_i are the amplitude values and μ is the mean amplitude.

3. **Minimum (min):**
   The lowest amplitude value in the epoch.

4. **Maximum (max):**
   The highest amplitude value in the epoch.

5. **Mean (μ):**
   The average amplitude value of the epoch.

   $$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Normalization:

The extracted features were normalized using z-score normalization:

$$z = \frac{x - \mu}{\sigma}$$

where x is a feature value, μ is the mean of the feature, and σ is the standard deviation.

Feature Selection:

Feature selection was performed using a t-test to identify features that significantly differed between seizure and non-seizure epochs. Features with a p-value less than 0.001 were retained. The final dataset shapes were as follows:

- chb01: (9384, 4)
- chb03: (7820, 4)
- chb08: (7820, 3)
- chb14: (11424, 3)
- chb16: (7616, 2)

Classification:

Three classification methods were employed: Radial Basis Function (RBF) Network, k-Nearest Neighbors (k-NN), and Support Vector Machine (SVM). Each method was applied per subject, and the performance metrics (accuracy, sensitivity, and specificity) were calculated.

1. Radial Basis Function (RBF) Network:

The RBF network consists of an input layer, a hidden layer with RBF neurons, and an output layer. The number of neurons in the hidden layer was determined using k-means clustering, optimized by the silhouette score.

The RBF function is given by:

$$\phi(x) = \exp(-\frac{||x-c||^2}{2\sigma^2})$$

where x is the input, c is the center of the RBF neuron, and σ is the spread parameter.

2. k-Nearest Neighbors (k-NN):

The k-NN algorithm classifies a sample based on the majority class among its kkk nearest neighbors in the feature space. The Euclidean distance was used to measure proximity between samples.

3. Support Vector Machine (SVM):

The SVM classifier finds the optimal hyperplane that separates seizure and non-seizure data with the maximum margin. The decision function for SVM is:

$$f(x) = \sum_{i=1}^{N} \alpha_i \, y_i K(x_i, x) + b$$

where α_i are the support vectors, y_i are the class labels, K is the kernel function, and b is the bias term.

Evaluation Metrics:

The classifiers were evaluated using the following metrics:

- **Accuracy (ACC):** The proportion of correctly classified samples.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Sensitivity (SEN):** The ability to correctly identify seizure epochs.

$$SEN = \frac{TP}{TP + FN}$$

- **Specificity (SPE):** The ability to correctly identify non-seizure epochs.

$$SPE = \frac{TN}{TN + FP}$$

where TP is true positives, TN is true negatives, FP is false positives, and FN is false negatives.

Parameter Evaluation:

- **Sigma Variation in RBF Network:**
  The effect of varying the sigma parameter (σ) in the RBF network was evaluated. The values of σ tested were -0.5, -0.25, 0.25, and 0.5.

- **Training vs. Testing Size:**
  The impact of different training vs. testing size ratios was analyzed. The test sizes considered were 0.4, 0.2, 0.1, and 0.05.

- **P-value Threshold for Feature Selection:** The influence of different p-value thresholds (0.01, 0.001, 0.0001) for feature selection was assessed to understand its effect on classifier performance.

In summary, this study provides a comprehensive comparison of three classification methods for EEG-based seizure detection, detailing preprocessing steps, feature extraction, and selection processes, along with thorough evaluation of classifier performance under various conditions.

IV. Results:

RBF Network Results:

The RBF network's performance varied across different subjects. For instance, with sigma set to 0, the accuracy ranged from 0.4311 to 0.6191, with sensitivity and specificity also showing considerable variation. Subject chb01 achieved the highest accuracy of 0.6191, with a sensitivity of 0.6516 and specificity of 0.5841, indicating a relatively balanced performance. On the other hand, subject chb16 had the lowest accuracy at 0.4311, sensitivity at 0.4660, and specificity at 0.3972, suggesting that the model struggled to differentiate between seizure and non-seizure events for this subject. The number of optimal hidden neurons also varied, generally being around 2 or 3 for different subjects.

Table 1 RBF Classification Results

Subject	Optimal Hidden Neurons	**Acc**	**Sen**	**Spe**
chb01	2	0.6191	0.6516	0.5841
chb08	2	0.4962	0.4557	0.5387
chb16	2	0.4311	0.4660	0.3972
chb03	2	0.5556	0.6111	0.4987
chb14	3	0.5348	0.3295	0 .7322

KNN Results:

The KNN classifier demonstrated a generally strong performance across subjects. The optimal k values varied, with subject chb01 having an optimal k of 9 and an accuracy of 0.7203. Sensitivity and specificity for this subject were 0.6495 and 0.7965, respectively, indicating the model's strong ability to correctly identify non-seizure events. Subject chb08, with an optimal k of 1, had an accuracy of 0.7078, suggesting that the nearest neighbor approach worked well for this subject. Sensitivity and specificity for chb08 were 0.6841 and 0.7326, respectively. However, subject chb14 showed lower accuracy at 0.5895, indicating that the model's performance was more variable across different subjects.

Table 2 KNN Classification Results

Subject	Optimal k	Acc	Sen	Spe
chb01	9	0.7203	0.6495	0.7965
chb08	1	0.7078	0.6841	0.7326
chb16	9	0.6102	0.4980	0.7193
chb03	8	0.7212	0.6301	0.8148
chb14	1	0.5895	0.6518	0.5296

SVM Results:

The SVM classifier's performance was also subject-dependent, with accuracies ranging from 0.5427 to 0.6953. For example, subject chb01 had the highest accuracy of 0.6953, with sensitivity and specificity of 0.5591 and 0.8418, respectively, showing a strong ability to correctly identify non-seizure events. However, subject chb16 had an accuracy of 0.5486, sensitivity of 0.3515, and specificity of 0.7400, indicating that while the model was good at identifying non-seizure events, it struggled with detecting seizures. This variability underscores the importance of parameter tuning and the potential need for subject-specific models.

Table 3 SVM Classification Results

Subject	Accuracy	Sensitivity	Specificity
chb01	0.6953	0.5591	0.8418
chb08	0.5965	0.3358	0.8702
chb16	0.5486	0.3515	0.7400
chb03	0.6618	0.5038	0.8238
chb14	0.5427	0.3795	0.6996

Parameter Evaluation Results:

1. Changing Sigma:

The RBF network's performance was sensitive to changes in the sigma parameter. For instance, with sigma set to -0.50, the accuracy for subject chb01 was 0.5706, but increased to 0.6287 when sigma was set to -0.25. Sensitivity and specificity also improved with this change. For subject chb08, a similar pattern was observed where accuracy increased from 0.5217 to 0.5320 when sigma was adjusted from -0.50 to 0.25. However, for some subjects, such as chb16, changes in sigma did not lead to significant improvements, indicating that other factors might be at play affecting the model's performance.

Table 4 RBF Result with different Sigma Value

Subject	Sigma	Acc	Sen	Spe
chb01	-0.50	0.5705	0.4635	0.6858
chb08	-0.50	0.5217	0.2247	0.8335
chb16	-0.50	0.5072	0.3821	0.6287
chb03	-0.50	0.5441	0.4103	0.6813
chb14	-0.50	0.5085	0.3741	0.6377
chb01	-0.25	0.6286	0.6690	0.5851
chb08	-0.25	0.4846	0.3895	0.5845
chb16	-0.25	0.4560	0.4727	0.4398
chb03	-0.25	0.5524	0.5404	0.5647
chb14	-0.25	0.5330	0.3214	0.7364
chb01	0.25	0.6169	0.6413	0.5907
chb08	0.25	0.5319	0.5118	0.5530
chb16	0.25	0.4304	0.4487	0.4126
chb03	0.25	0.5677	0.6641	0.4689
chb14	0.25	0.5382	0.3419	0.7270
chb01	0.50	0.6137	0.6289	0.5973
chb08	0.50	0.5562	0.5443	0.5688
chb16	0.50	0.4422	0.4260	0.4579
chb03	0.50	0.5767	0.7007	0.4494
chb14	0.50	0.5396	0.3437	0.7278

2. Changing Test Size:

Adjusting the test size also impacted the classifiers' performance. For instance, with a test size of 0.1, subject chb01 achieved an accuracy of 0.6852, sensitivity of 0.5774, and specificity of 0.7814. Increasing the test size to 0.5 resulted in a lower accuracy of 0.6162, suggesting that a smaller test size might be more effective for certain subjects. Subject chb08 saw a similar pattern, with higher accuracy and sensitivity at a smaller test size. These results indicate that the proportion of data used for testing can significantly influence model performance and should be carefully considered.

Table 5 All Results over Different Test size

Model	Subjct	Test Size	Acc	Sen	Spe
RBF	chb01	0.40	0.6254	0.6558	0.5947
KNN	chb01	0.40	0.7213	0.6611	0.7821
SVM	chb01	0.40	0.7112	0.5535	0.8704
RBF	chb08	0.40	0.4744	0.4409	0.5083
KNN	chb08	0.40	0.6825	0.6588	0.7065
SVM	chb08	0.40	0.6023	0.3462	0.8616
RBF	chb16	0.40	0.4305	0.4980	0.3643
KNN	chb16	0.40	0.6265	0.6311	0.6219
SVM	chb16	0.40	0.5470	0.3754	0.7156
RBF	chb03	0.40	0.5661	0.6124	0.5190
KNN	chb03	0.40	0.7087	0.6580	0.7604
SVM	chb03	0.40	0.6550	0.4952	0.8179
RBF	chb14	0.40	0.5336	0.3395	0.7234
KNN	chb14	0.40	0.5759	0.6498	0.5036
SVM	chb14	0.40	0.5479	0.4776	0.6166
RBF	chb01	0.20	0.6190	0.6515	0.5840
KNN	chb01	0.20	0.7202	0.6495	0.7964
SVM	chb01	0.20	0.6952	0.5590	0.8418
RBF	chb08	0.20	0.4961	0.4556	0.5386
KNN	chb08	0.20	0.7078	0.6841	0.7326
SVM	chb08	0.20	0.5965	0.3358	0.8702
RBF	chb16	0.20	0.4311	0.4660	0.3971
KNN	chb16	0.20	0.6102	0.4980	0.7192
SVM	chb16	0.20	0.5485	0.3515	0.7399
RBF	chb03	0.20	0.5556	0.6111	0.4987
KNN	chb03	0.20	0.7212	0.6300	0.8147
SVM	chb03	0.20	0.6617	0.5037	0.8238
RBF	chb14	0.20	0.5347	0.3294	0.7321
KNN	chb14	0.20	0.5894	0.6517	0.5296
SVM	chb14	0.20	0.5426	0.3794	0.6995
RBF	chb01	0.10	0.6325	0.6746	0.5839
KNN	chb01	0.10	0.7273	0.6924	0.7678
SVM	chb01	0.10	0.6932	0.5793	0.8252
RBF	chb08	0.10	0.4936	0.4761	0.5117
KNN	chb08	0.10	0.7391	0.7117	0.7676
SVM	chb08	0.10	0.5805	0.3333	0.8381
RBF	chb16	0.10	0.4055	0.4375	0.3730
KNN	chb16	0.10	0.6364	0.7083	0.5634
SVM	chb16	0.10	0.5446	0.3567	0.7354
RBF	chb03	0.10	0.5498	0.6059	0.4893
KNN	chb03	0.10	0.7301	0.6871	0.7765
SVM	chb03	0.10	0.6534	0.5000	0.8191
RBF	chb14	0.10	0.5433	0.3357	0.7304
KNN	chb14	0.10	0.6045	0.6863	0.5307
SVM	chb14	0.10	0.5363	0.3413	0.7121
RBF	chb01	0.05	0.6127	0.6539	0.5603
KNN	chb01	0.05	0.7191	0.6653	0.7874
SVM	chb01	0.05	0.6723	0.5323	0.8502
RBF	chb08	0.05	0.4680	0.4240	0.5100
KNN	chb08	0.05	0.7698	0.7434	0.7950
SVM	chb08	0.05	0.5959	0.3298	0.8500
RBF	chb16	0.05	0.3805	0.4213	0.3369
KNN	chb16	0.05	0.6194	0.5228	0.7228
SVM	chb16	0.05	0.5433	0.3553	0.7445

RBF	chb03	0.05	0.5677	0.6262	0.5027
KNN	chb03	0.05	0.7519	0.7233	0.7837
SVM	chb03	0.05	0.6445	0.5048	0.8000
RBF	chb14	0.05	0.5611	0.3582	0.7401
KNN	chb14	0.05	0.5874	0.4813	0.6809
SVM	chb14	0.05	0.5576	0.3656	0.7269

1. Changing p-value:

The classifiers' performance also varied with changes in the p-value used for feature selection. For example, with a p-value of 0.01, subject chb01 had an accuracy of 0.6815, sensitivity of 0.5734, and specificity of 0.7829. Increasing the p-value to 0.1 slightly decreased the accuracy to 0.6628, indicating that a more stringent feature selection process might benefit performance. For subject chb08, a p-value of 0.01 resulted in an accuracy of 0.6041, which decreased to 0.5824 with a p-value of 0.1. This suggests that careful tuning of the p-value is necessary to optimize the classifiers' performance for each subject.

Table 1 All Results over Different P-Value for Feature Selection

Model	Subject	Pvalue	Acc	Sen	Spe
RBF	chb01	0.01	0.6249	0.6688	0.5812
KNN	chb01	0.01	0.7314	0.7029	0.7598
SVM	chb01	0.01	0.7144	0.5940	0.8342
RBF	chb08	0.01	0.5115	0.4701	0.5534
KNN	chb08	0.01	0.6988	0.6683	0.7297
SVM	chb08	0.01	0.6464	0.4409	0.8545
RBF	chb16	0.01	0.4350	0.4863	0.3873
KNN	chb16	0.01	0.6430	0.5245	0.7531
SVM	chb16	0.01	0.5459	0.3692	0.7101
RBF	chb03	0.01	0.5524	0.6440	0.4680
KNN	chb03	0.01	0.7199	0.6293	0.8034
SVM	chb03	0.01	0.6560	0.5106	0.7899
RBF	chb14	0.01	0.5304	0.2975	0.7538
KNN	chb14	0.01	0.5794	0.6595	0.5025
SVM	chb14	0.01	0.5330	0.3208	0.7367
RBF	chb01	0.001	0.6100	0.6276	0.5917
KNN	chb01	0.001	0.7202	0.6799	0.7622
SVM	chb01	0.001	0.6750	0.5313	0.8241
RBF	chb08	0.001	0.4929	0.4401	0.5473
KNN	chb08	0.001	0.6988	0.6721	0.7263
SVM	chb08	0.001	0.5856	0.3341	0.8443
RBF	chb16	0.001	0.4160	0.4345	0.3958
KNN	chb16	0.001	0.6233	0.5151	0.7410
SVM	chb16	0.001	0.5262	0.3589	0.7082
RBF	chb03	0.001	0.5511	0.6005	0.5006
KNN	chb03	0.001	0.7320	0.6877	0.7774
SVM	chb03	0.001	0.6668	0.5056	0.8318
RBF	chb14	0.001	0.5194	0.2911	0.7428
KNN	chb14	0.001	0.5855	0.4707	0.6978
SVM	chb14	0.001	0.5417	0.2982	0.7800
RBF	chb01	0.0001	0.6281	0.6691	0.5854
KNN	chb01	0.0001	0.7266	0.7045	0.7497
SVM	chb01	0.0001	0.7005	0.5991	0.8063
RBF	chb08	0.0001	0.4859	0.4398	0.5339
KNN	chb08	0.0001	0.6924	0.6591	0.7271
SVM	chb08	0.0001	0.5786	0.3195	0.8485
RBF	chb16	0.0001	0.4179	0.4115	0.4250
KNN	chb16	0.0001	0.6305	0.6963	0.5584
SVM	chb16	0.0001	0.5531	0.3651	0.7592
RBF	chb03	0.0001	0.5549	0.6106	0.4980
KNN	chb03	0.0001	0.7231	0.6826	0.7645
SVM	chb03	0.0001	0.6585	0.5183	0.8020
RBF	chb14	0.0001	0.5260	0.2859	0.7621
KNN	chb14	0.0001	0.5921	0.4730	0.7092
SVM	chb14	0.0001	0.5404	0.2727	0.8038

VI. Conclusion:

The results indicate that the performance of classifiers in EEG-based epilepsy detection is highly subject-dependent and sensitive to parameter changes. The KNN classifier generally performed well across subjects, but the optimal k value varied. The SVM classifier showed good performance but was highly dependent on the parameter C. The RBF network's performance was particularly sensitive to changes in the sigma parameter.

Overall, the choice of classifier and parameter tuning should be tailored to each subject and dataset to achieve the best performance. These findings underscore the importance of personalized approaches in developing effective models for EEG-based epilepsy detection.

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