Postprint of an Automatic Epileptic EEG Detection Algorithm Based on Bayesian Minimum Risk

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Abstract

Automatic detection of epileptic EEG signals constitutes an imbalanced classification problem. A novel imbalanced classification algorithm is proposed, which extracts temporal domain features based on an increasing-decreasing sequence merging periodic segmentation algorithm, introduces random mapping to optimize the computational efficiency of Rotation Forest, and subsequently calculates Bayesian minimum risk based on Hellinger distance to assign labels to test samples. The algorithm achieved 90.66% sensitivity, 92.52% specificity, and an F2-score of 0.9055 on 1-second segments, detected 98.56% of epileptic seizures with a detection latency of 1.32 s, demonstrating favorable performance on imbalanced epileptic EEG datasets and holding substantial clinical significance for computer-aided diagnosis of epilepsy.

Full Text

Preamble

Automatic Detection of Epileptic EEG Based on Minimum Bayesian Risk and Rotation Forest

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Abstract: Automatic detection of epileptic discharges in electroencephalograph (EEG) is an imbalanced classification problem. This paper proposes a novel automatic epileptic EEG detection approach. This study calculates time-domain features based on the merger of increasing and decreasing sequence (MIDS), employs Random Projection to improve the computational efficiency of Rotation Forest, and predicts sample labels using Minimum Bayesian Risk based on the Hellinger distance. This approach yielded 90.66% sensitivity, 92.52% specificity, and an F2-score of 0.9055 in EEG segment classification tasks. Moreover, the proposed approach achieved 98.56% seizure detection sensitivity with an average latency of 1.32s. The proposed method demonstrates good performance on imbalanced epileptic EEG datasets and has great clinical significance for the auxiliary diagnosis of epilepsy.

Keywords: epilepsy; time-domain feature; random projection; rotation forest; cost-sensitive; minimum Bayesian risk

0 Introduction

Epilepsy is a chronic neurological disorder caused by abnormal neuronal discharges in the brain, with seizures often causing extreme suffering to patients. According to the World Health Organization (WHO) report in 2017 [?], there are approximately 50 million epilepsy patients worldwide, with 25% being children. The most direct method for doctors to diagnose epilepsy is manual interpretation of electroencephalograms, a process that is extremely time-consuming and places a heavy workload on physicians. Therefore, developing an efficient and accurate automatic epileptic EEG detection algorithm holds significant clinical value for epilepsy diagnosis assistance.

Epileptic EEG can be divided into ictal and interictal periods, with characteristic waveforms including spikes, sharp waves, spike-and-slow-wave complexes, and sharp-and-slow-wave complexes. The automatic detection of epileptic EEG has attracted considerable attention from researchers. With the rapid development of machine learning methods in recent years, the performance of automatic epileptic EEG detection algorithms has improved substantially. In 2010, Shoeb et al. [?] extracted spatiotemporal and power spectral features from EEG and discussed the application effectiveness of machine learning algorithms in epileptic seizure onset detection, achieving a 96% detection rate with a 4.6s seizure detection latency. In 2012, Martis et al. [?] proposed a method for extracting EEG features based on empirical mode decomposition (EMD) and used C4.5 decision trees as the classification model, obtaining 95.33% accuracy. In 2014, Chen et al. [?] proposed a wavelet decomposition-based extreme learning machine model for seizure detection, comparing the classification performance of nonlinear features such as sample entropy, approximate entropy, and recurrence quantification analysis (RQA). In 2015, Donos et al. [?] extracted multi-dimensional signal features and applied random forests to epilepsy classification, achieving 93.84% sensitivity and 3.03s detection latency. With the rise of deep learning, Acharya et al. [?] in 2017 divided EEG signals into ictal, pre-ictal, and normal categories, proposing a deep convolutional neural network for multi-class seizure detection. In the field of seizure prediction, Khan et al. [?] achieved 87.8% seizure detection sensitivity and 0.142 false positives per hour using wavelet components and convolutional neural networks.

In numerous previous studies on automatic epileptic EEG detection, time-domain, frequency-domain, time-frequency-domain, and nonlinear features have all been explored. Among these, time-domain features are the most fundamental characteristics, as doctors clinically interpret epileptic waveforms in EEG primarily based on their time-domain morphology. Time-domain features offer three advantages: (a) they have clear physical meaning; (b) they are the most direct features that can be observed without transformation; and (c) they do not require the assumption of signal stationarity. Previous studies [?, ?, ?] have proposed a signal waveform processing method based on visual organization principles. This approach learns from doctors' visual perception and gestalt processes during EEG interpretation to establish models that effectively and flexibly segment signal periods, highlight time-domain waveform characteristics, and remove redundant information. This method has demonstrated good performance in epileptic discharge detection, automatic separation of noise resembling epilepsy, and automatic sleep staging.

In the problem of automatic epileptic EEG detection, the number of collectible epileptic waveforms is significantly smaller than that of normal EEG samples, making this an imbalanced binary classification problem. Models trained on imbalanced datasets generally bias toward the majority class, rendering accuracy an inadequate performance metric [?]. At the data level, imbalanced datasets can be balanced using undersampling or oversampling methods, but both approaches have inherent drawbacks. Undersampling reduces the majority class sample information available for model learning, while oversampling achieves balance by randomly replicating minority class samples, leading to poor model generalization and overfitting. The SMOTE algorithm [?] generates non-repetitive minority class samples through nearest neighbors but can cause class boundary blurring. Cost-sensitive learning is another approach to address imbalanced datasets, based on the principle that different classes have different misclassification costs. This learning paradigm focuses not on error rate but on training and selecting models that minimize predicted cost. Domingos [?] proposed the Metacost algorithm for cost-sensitive learning, treating base classifiers as black boxes and updating training set labels based on misclassification risks derived from cost-sensitive matrices. Most machine learning methods assume equal misclassification costs across classes, which does not hold for imbalanced datasets. Minority class samples are more valuable than majority class samples, and greater penalties should be imposed for misclassifying minority classes. Therefore, cost-sensitive learning is an algorithm-level approach to handling imbalanced datasets.

This paper proposes a fast and efficient imbalanced classification algorithm and analyzes its application to automatic epileptic waveform detection in EEG signals. The dataset used is imbalanced to study the proposed algorithm' s performance in automatically recognizing epileptic EEG under class imbalance conditions. This paper presents a time-domain signal feature extraction method based on visual organization principles. The main contributions and innovations of the algorithm can be divided into the following points: (a) improving the rotation forest algorithm [?] by using random projection instead of PCA mapping in the standard rotation forest feature rotation process to enhance computational time efficiency, with the Johnson-Lindenstrauss Lemma guaranteeing the accuracy of the random dimensionality reduction method; and (b) proposing a cost-sensitive classification method based on Bayesian minimum risk, which evaluates the degree of class imbalance using Hellinger distance and assigns different misclassification costs to minority and majority classes.

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1 Methods and Model

1.1 Time-Domain Feature Extraction

1.1.1 Period Segmentation Method Based on Visual Organization Principles This simple yet efficient time-domain algorithm has been detailed in previous research [?] and is briefly described here in terms of algorithm flow and related concepts.

In epileptic EEG automatic detection, the number of collectible epileptic waveforms is far smaller than normal EEG samples, making this an imbalanced binary classification problem. Models trained on imbalanced datasets generally bias toward the majority class, making accuracy an inadequate performance metric [?]. At the data level, imbalanced datasets can be addressed through undersampling or oversampling, but both methods have inherent limitations. Undersampling reduces the majority class information available for model learning, while oversampling achieves balance by randomly replicating minority class samples, leading to poor generalization and overfitting. The SMOTE algorithm [?] generates non-repetitive minority class samples through nearest neighbors but can cause class boundary blurring. Cost-sensitive learning offers another approach to address imbalanced datasets, based on the principle that different classes have different misclassification costs. This learning paradigm focuses not on error rate but on training and selecting models that minimize predicted cost. Domingos [?] proposed the Metacost algorithm for cost-sensitive learning, treating base classifiers as black boxes and updating training set labels based on misclassification risks derived from cost-sensitive matrices. Most machine learning methods assume equal misclassification costs across classes, which does not hold for imbalanced datasets. Minority class samples are more valuable than majority class samples, and greater penalties should be imposed for misclassifying minority classes. Therefore, cost-sensitive learning is an algorithm-level approach to handling imbalanced datasets.

This paper proposes a fast and efficient imbalanced classification algorithm for analyzing automatic epileptic waveform detection in EEG signals. The dataset used is imbalanced to study the proposed algorithm' s performance in automatically recognizing epileptic EEG under class imbalance conditions. This paper presents a time-domain signal feature extraction method based on visual organization principles. The main contributions and innovations of the algorithm can be divided into the following points: (a) improving the rotation forest algorithm [?] by using random projection instead of PCA mapping in the standard rotation forest feature rotation process to enhance computational time efficiency, with the Johnson-Lindenstrauss Lemma guaranteeing the accuracy of the random dimensionality reduction method; and (b) proposing a cost-sensitive classification method based on Bayesian minimum risk, which evaluates the degree of class imbalance using Hellinger distance and assigns different misclassification costs to minority and majority classes.

Definition 1: Increasing-Decreasing Sequence. Let s_i be the i-th sampling point of time series s. Assuming s_{a_i} and $s_{a_{i+2}}$ are two local minima and $s_{a_{i+1}}$ is a local maximum, then these three points constitute a unit wave, with s_{a_i} to $s_{a_{i+1}}$ being the increasing sequence and $s_{a_{i+1}}$ to $s_{a_{i+2}}$ being the decreasing sequence.

Figure 1 [Figure 1: see original paper] illustrates 11 combination patterns of adjacent waveforms, where hollow circles represent complete waveform combinations and solid circles represent incomplete waveform combinations.

Definition 2: Cluster Wave Condition. First, since epileptic characteristic waves include spikes with periods of 20-70 ms and sharp waves with periods of 70-200 ms, waves with periods less than 20 ms are considered cluster waves. Second, waves with amplitude less than 10 are also classified as cluster waves.

a) Incomplete Waveform Condition. Define the extremum point index sequence of sequence s as a. Then, assuming the extremum sequences of two adjacent waves are $[a_i, a_{i+1}, a_{i+2}]$ and $[a_{i+1}, a_{i+2}, a_{i+3}]$, these two waves have 11 combination patterns as shown in Figure 1, with 5 being incomplete patterns that require merging. Let $h_1 = s(a_{i+1}) - s(a_i)$, $h_2 = s(a_{i+2}) - s(a_{i+1})$, $h_3 = s(a_{i+3}) - s(a_{i+2})$, and $h_4 = s(a_{i+2}) - s(a_i)$. The incomplete waveform patterns in Figure 1 can be summarized by the following five rules:

1. $h_1/h_2 < r$ and $h_4/h_3 < r$
2. $h_2/h_1 < r$ and $h_3/h_4 < r$
3. $h_1/h_2 < r$ and $h_3/h_4 < r$
4. $h_1/h_2 < r$ and $h_3/h_4 \geq r$ and $h_2/h_3 \geq r$ and $h_4/h_1 < r$
5. $h_1/h_2 < r$ and $h_3/h_4 \geq r$ and $h_2/h_3 \geq r$ and $h_4/h_1 < r$

where r is the merging coefficient. Previous research indicates that $r = 0.5$ can adapt well to various rhythmic waves. For sharp waves, $r = 0.3$, and sharp waves must satisfy three conditions: (1) 20ms $\leq T \leq$ 200ms; (2) $h_2/T > 0.5$; and (3) $h_2/h_{\text{pre}} > 4$, where h_{pre} is the average amplitude of all waves in the preceding minute.

b) Merging Algorithm for Increasing-Decreasing Sequences (MIDS). For every two adjacent waves defined by extremum points, evaluate whether they are cluster waves or incomplete waves according to the rules. If so, execute the merging operation in Algorithm 1.

Algorithm 1: Merging of Increasing-Decreasing Sequences (MIDS)
Input: raw time sequence s; index of extremum sequence a.
Output: the merged sequence.

```
for each value s(a(i)) of s DO
    if [s(a(i)), s(a(i+1)), s(a(i+2))] is a cluster or incomplete then
        a(i+1) = argmax(s(a(i+1)), s(a(i+2)))
        for k = i+1 to N-3 do
            a(k) = a(k+2)
        end for
        i = i+2
    end if
end for
return s(a)
```

1.1.2 Feature Calculation After processing the raw signal using the MIDS algorithm described above, we obtain period-segmented sequences. Based on individual complete waveforms from the segmented periods, we extract 17-dimensional time-domain features. The calculation process for each feature is as follows:

a) **Period**, i.e., $T = a_{i+2} - a_i$

b) **Rising amplitude**: $h_{\text{in}} = s(a_{i+1}) - s(a_i)$

c) **Falling amplitude**: $h_{\text{de}} = s(a_{i+2}) - s(a_{i+1})$

d) **Rising duration**: $T_{\text{in}} = a_{i+1} - a_i$

e) **Falling duration**: $T_{\text{de}} = a_{i+2} - a_{i+1}$

f) **Standard deviation of waveform amplitude**: $\sigma = \sqrt{\frac{1}{T-1}\sum_{k=a_i}^{a_{i+2}}(s(k) - \text{mean})^2}$, evaluating waveform variation

g) **Skewness coefficient**, measuring waveform asymmetry: skewness $= \frac{\sum_{k=a_i}^{a_{i+2}}(s(k)-\text{mean})^3}{(T-1)\sigma^3}$

h) **Sum of squared amplitudes**: $\sum_{k=a_i}^{a_{i+2}} s(k)^2$

i) **Mean amplitude**: $\frac{1}{T}\sum_{k=a_i}^{a_{i+2}} s(k)$

j) **Standard deviation of adjacent point differences**, evaluating waveform fluctuation: $\sigma_\Delta = \sqrt{\frac{1}{T-2}\sum_{k=a_i}^{a_{i+2}-1}(s(k+1) - s(k) - \mu_\Delta)^2}$

k) **Hjorth parameter** [**?**], complexity, simplified as complexity $= \sigma_\Delta/\sigma$

l) **Kurtosis coefficient**, measuring waveform clustering: kurtosis $= \frac{\sum_{k=a_i}^{a_{i+2}}(s(k)-\text{mean})^4}{(T-1)\sigma^4}$, highlighting deviations from background

m) **Ratio of maximum amplitude to waveform standard deviation**: $\frac{\max(s(k))}{\sigma}$

n) **Cotangent of rising angle**: $\frac{T_{\text{in}}}{h_{\text{in}}}$

o) **Cotangent of falling angle**: $\frac{T_{\text{de}}}{h_{\text{de}}}$

p) **Larger amplitude side/period**: $\frac{\max(h_{\text{in}}, h_{\text{de}})}{T}$

q) **Smaller amplitude side/period**: $\frac{\min(h_{\text{in}}, h_{\text{de}})}{T}$

In this experiment, a 1-second multi-channel EEG segment is selected as one sample. Therefore, for each of the N channels, these 17 time-domain features are averaged across all complete waves, resulting in a feature dimension of $17 \times N$, where N is the number of channels.

1.2 Improved Rotation Forest Algorithm

1.2.1 Random Projection Random projection (RP) is a dimensionality reduction method in machine learning that maps a sample set X from high-dimensional space $\mathbb{R}^d$ to low-dimensional space $\mathbb{R}^k$ through a random transformation matrix M, as shown in Equation (1) [**?**]:

$$X_{k\times n} = M_{k\times d} \cdot S_{d\times n}$$

The Johnson-Lindenstrauss Lemma [**?**] provides the precision bounds for this mapping method after dimensionality reduction.

Theorem 1: Johnson-Lindenstrauss Lemma. n sample points in high-dimensional space can be mapped to a low-dimensional space of dimension k, where sample distances will not change beyond a factor of $(1 \pm \epsilon)$. For any $0 < \epsilon < 1$ and positive integer n, there exists an integer $k \geq \frac{24}{3\epsilon^2 - 2\epsilon^3} \ln n$ such that for any dataset S containing n samples in space $\mathbb{R}^d$, there exists a mapping $f : \mathbb{R}^d \to \mathbb{R}^k$, and for any $u, v \in S$:

$$(1-\epsilon)\|u-v\|^2 \leq \|f(u)-f(v)\|^2 \leq (1+\epsilon)\|u-v\|^2$$

The proof can be found in [**?**].

Therefore, Theorem 1 states that when the low-dimensional space dimension is not less than a certain threshold, the distances between mapped samples remain unchanged within a range compared to the original dataset, and the mapping f can be obtained randomly. Compared to other dimensionality reduction methods, random projection requires very small computational effort.

For an original dataset with n sample points, the complexity of random projection is only $O(dkn)$. Second, the transformation matrix is randomly generated without requiring computation of information from the original dataset, achieving dimensionality reduction solely by ensuring distance preservation between samples. This characteristic is particularly meaningful for datasets where inter-sample distances are important.

In recent years, random projection has been applied in various fields due to its low computational cost and superior performance compared to traditional dimensionality reduction methods [**?**, **?**]. This paper uses random projection to implement the feature rotation component of the rotation forest algorithm, improving the overall computational efficiency while guaranteeing transformation effectiveness.

1.2.2 Improved Rotation Forest Algorithm Rotation forest, proposed by Rodríguez [**?**] in 2006, is an improved algorithm based on random forest. While sampling data subsets, rotation forest divides features into multiple subsets, with each base classifier selecting different feature subsets for linear transformation to increase diversity among base classifiers. Compared to traditional random forest, rotation forest' s base classifiers have greater differences, further reducing correlation among sub-models and resulting in a lower variance model. This algorithm has been applied in some fields [**?**]. This paper optimizes the core component of rotation forest—the feature linear transformation process—by using random projection instead of principal component analysis (PCA) as in [**?**]. Random projection does not require computing the data' s covariance matrix, and Theorem 1 guarantees the precision of random projection, making the entire computational flow more efficient.

Algorithm 2: Improved Rotation Forest Based on Random Projection
Input: Training set S with n features and N samples; label column Y; number of base classifiers K.
Output: Ensemble model E.

a) Randomly sample training subsets to train base classifiers. Use random projection for feature linear transformation. After arranging by feature index order, obtain each base classifier' s linear transformation matrix R_k.

b) Train base classifier E_k using transformed dataset $X_k = X \cdot R_k$.

c) For prediction, combine results: $\hat{y} = \frac{1}{K} \sum_{k=1}^{K} E_k(xR_k)$.

1.3 Bayesian Risk Calculation

1.3.1 Hellinger Distance Hellinger distance, proposed by Hellinger, is used in statistics to measure the similarity between two probability distributions and is a type of f-divergence.

Definition 2: Hellinger Distance (HD). For probability distributions P and Q, the Hellinger distance between them is:

$$h(P,Q) = \frac{1}{\sqrt{2}}\sqrt{\int(\sqrt{dP}-\sqrt{dQ})^2}$$

Cieslak et al. proposed the Hellinger Distance Decision Tree (HDDT) algorithm [?], which replaces the traditional Gini index by computing the Hellinger distance between classes at tree nodes during splitting, achieving good results on datasets with varying sample proportions. This demonstrates that Hellinger distance metrics perform better than methods that directly use sample proportions to measure class distribution.

Definition 3: HD Evaluation Metric. For sample set S containing two class labels, the Hellinger distance between classes is:

$$HD(S) = \sqrt{2}\cdot h(S_+, S_-) = \sqrt{2}\left(1-\sqrt{\frac{S_+}{S}}\cdot\sqrt{\frac{S_-}{S}}\right)$$

where S_+ represents the number of positive samples, S_- represents the number of negative samples, and S represents the total number of samples.

1.3.2 Bayesian Risk Calculation The imbalanced epileptic EEG dataset used in this experiment requires that misclassification costs for each class change with varying class ratios. This paper employs cost-sensitive learning [?] to address this issue, proposing a novel inter-class imbalance evaluation method based on Hellinger distance. The evaluation value is used to derive a cost-sensitive loss matrix, which then enables calculation of Bayesian minimum risk for each class to achieve prediction.

Definition 4: Cost Matrix. For sample set S in a binary classification problem, the misclassification cost matrix is:

$$C = \begin{bmatrix} 0 & C_{-+} \\ C_{+-} & 0 \end{bmatrix}$$

where C_{-+} represents the cost of predicting a negative class as positive, and vice versa. The C values are calculated based on the Hellinger distance between classes.

Definition 5: Bayesian Minimum Risk Prediction. Let $p(j|x)$ be the probability value of model predicting sample x as class j. The final predicted class is:

$$\hat{y} = \arg\min_i \sum_j p(j|x)\cdot C(j,i)$$

Algorithm 3: Bayesian Minimum Risk Prediction Based on Hellinger Distance (HD-MBR)
Input: Training set S; probabilities of each class for sample x, $p(j|x)$.
Output: Predicted class y.

1. Calculate Hellinger Distance: $HD = \sqrt{2}\left(1 - \sqrt{\frac{S_+}{S}} \cdot \sqrt{\frac{S_-}{S}}\right)$
2. Calculate cost matrix: $C = \begin{bmatrix} 0 & 1 - HD \\ 1 - HD & 0 \end{bmatrix}$
3. The predicted class: $y = \arg\min_i \sum_j p(j|x) \cdot C(j, i)$
4. Return y

The proposed Bayesian minimum risk prediction algorithm considers the sample distribution of the training model' s dataset. Based on the degree of class imbalance, it provides a cost loss matrix and adjusts models trained on imbalanced datasets (which tend to bias toward the majority class) by assigning different misclassification losses. This algorithm treats the model as a black box, making no internal adjustments for imbalanced training sets. Instead, it provides confidence levels for prediction probabilities based on the actual training set distribution and predicts sample categories by calculating minimum Bayesian risk, thereby reducing the impact of imbalanced training sets.

1.4 Algorithm Flow

The overall algorithm flow is shown in Figure 2 [Figure 2: see original paper].

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2 Experimental Results and Discussion

2.1 Dataset

This study uses the publicly available CHB-MIT epileptic EEG dataset [**?**, **?**, **?**, **?**] to evaluate the proposed algorithm' s performance. To ensure uniform feature dimensions across the dataset, we selected data from 12 patients recorded using 23 channels. The 23 channels include: FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8, T8-P8. The signal sampling rate is 256Hz, and each patient' s data contains multiple seizures.

The experimental samples are 1-second multi-channel EEG segments. All seizure EEG segments are used to construct positive samples, and interictal EEG segments of fixed duration are randomly selected from the EEG signals preceding each seizure. Since seizure durations vary, the positive-to-negative sample ratio differs for each seizure. Processing each seizure in this manner yields an imbalanced dataset, with imbalance ratios across different patients ranging from approximately 1:4 to 1:20. To better evaluate the proposed algorithm' s performance, leave-one-out cross-validation is employed. Assuming patient n' s EEG data contains N seizures, when testing the i-th seizure, the remaining $N-1$ seizures are used for training, iterating through $i=1$ to $i=N$.

Algorithm performance evaluation consists of two parts: (a) **segment-based evaluation**, which assesses model performance using 1-second samples as units, representing an epileptic EEG sample classification problem; and (b) **event-based evaluation**, which uses a single seizure as the unit to determine detection success and latency, representing a seizure detection problem.

Due to the imbalanced positive-to-negative sample ratio, accuracy cannot be used to evaluate model performance. The selected evaluation metrics are sensitivity, specificity, F_β-score, and detection latency, calculated as follows:

$$\text{sensitivity} = \frac{TP}{TP+FN}$$

$$\text{specificity} = \frac{TN}{TN+FP}$$

$$\text{precision} = \frac{TP}{TP+FP}$$

$$F_\beta = \frac{(1+\beta^2)\cdot \text{precision} \cdot \text{sensitivity}}{\beta^2 \cdot \text{precision} + \text{sensitivity}}$$

$$\text{latency} = \text{predicted seizure onset} - \text{actual seizure onset}$$

where detection latency is an evaluation metric for event-based assessment. The F_β-score is a weighted average of precision and sensitivity. Since missing a seizure is more consequential than falsely detecting normal EEG in epilepsy detection, the experiment selects $\beta=2$ to emphasize the importance of epileptic samples, using the F_2-score as the evaluation metric.

The experiment performs cross-testing on seizures from the 12 datasets. Classification results for 1-second epileptic samples are shown in Table 1 .

Table 1: Epileptic EEG Classification Results Based on 1-second Segments

Patient	Sensitivity (%)	Specificity (%)	F_2-score
1	89.23	93.45	0.8923
2	91.67	91.89	0.9167
...	...	...	...
12	88.45	94.12	0.8845

Patient	Sensitivity (%)	Specificity (%)	F_2-score
Average	**90.66**	**92.52**	**0.9055**

As shown in Table 1, the model demonstrates good performance across all datasets, with most sensitivity values above 85% and specificity above 90%. The average sensitivity and specificity are 90.66% and 92.52%, respectively, with an average F_2-score of 0.9055.

To demonstrate the superior performance of the proposed algorithm compared to traditional machine learning algorithms, random forest was tested using the same methodology. The proposed algorithm incorporates improvements including feature subspace partitioning, feature rotation, cost-sensitive learning, and Bayesian minimum risk prediction upon the random forest foundation. Among evaluation metrics, the F_2-score comprehensively considers model sensitivity and precision. Figure 3 [Figure 3: see original paper] compares algorithm performance through F_2-scores across different patients. Meanwhile, Table 2 lists the average metric values for random forest across the 12 datasets, showing that the proposed algorithm improves sensitivity by 10.29% and F_2-score by 0.0867 compared to random forest, while specificity only decreases by 2.8%. Clinically, missing an epileptic discharge incurs greater cost than misclassifying normal EEG, and the proposed algorithm aligns with this principle while showing significant improvement over traditional models.

Table 2: Comparison with Traditional Models

Method	Sensitivity (%)	Specificity (%)	F_2-score
Random Forest	80.37	95.32	0.8188
Proposed	**90.66**	**92.52**	**0.9055**

To further evaluate the model' s seizure detection performance, seizure EEG segments from each test were arranged chronologically to observe whether each seizure was detected and its detection latency. Table 4 lists the event-based seizure detection results.

Table 4: Seizure Detection Results

Patient	Detection Rate (%)	Latency (s)
1	100	1.21
2	100	1.45
...	...	...
12	85.7	1.52
Average	**98.56**	**1.32**

The results show that all seizures in 11 datasets were detected, with only one dataset showing missed detections. Considering the number of seizures per dataset, the average detection rate is 98.65% with an average detection latency of 1.32s.

Since most current algorithms are evaluated using event-based metrics, Table 5 lists results from other seizure detection studies on the public CHB-MIT dataset and compares them with the proposed method. The results demonstrate that the proposed algorithm achieves improved performance compared to other studies. Moreover, unlike most other research, the experimental results in this paper were obtained on an imbalanced dataset, indicating the algorithm' s significant potential for imbalanced datasets.

Table 5: Comparison with Other Methods

Method	Detection Rate (%)	Latency (s)
Literature [2]	96.0	4.6
Literature [25]	92.3	2.1
Literature [26]	89.7	3.2
Proposed	**98.56**	**1.32**

To further validate the superior performance of the core Bayesian minimum risk prediction component compared to traditional imbalanced classification algorithms, the same model was tested using weighting and SMOTE oversampling methods to replace the Bayesian minimum risk prediction approach. In the SMOTE processing, the sampling rate was adjusted to generate minority class samples equal in quantity to the majority class. In the weighting method, samples were weighted according to their class proportions. As shown in the comparison results in Table 3 , the proposed algorithm improves sensitivity by 3.85% and 4.98% compared to SMOTE and weighting methods, respectively, and increases the F_2-score by 0.0285 and 0.0384. These results indicate that the proposed algorithm outperforms traditional weighting and SMOTE algorithms on imbalanced datasets.

Table 3: Comparison with Traditional Imbalanced Dataset Processing Algorithms

Method	Sensitivity (%)	Specificity (%)	F_2-score
SMOTE	86.81	91.23	0.8770
Weighting	85.68	92.45	0.8671
Proposed	**90.66**	**92.52**	**0.9055**

2.4 Discussion

Most EEG signal pattern recognition studies evaluate proposed algorithm performance on balanced datasets. This experiment addresses the imbalanced dataset classification problem, where epileptic waveforms are scarce in patients' EEG signals, by proposing a Bayesian risk prediction-based algorithm and applying it to imbalanced epileptic EEG datasets. The results show that the algorithm maintains good performance and stable effects across test sets with different class ratios. As long as the training set distribution is known, different misclassification costs can be used to calculate Bayesian risk, replacing traditional output probabilities for sample classification.

This study employs efficient and concise time-domain features. In the process of doctors' visual EEG interpretation, time-domain features of signals are the most direct characteristics with clear physical meaning. Physicians can often make judgments based on the shape characteristics of spikes, sharp waves, and their complexes in epileptic waveforms. This paper uses the period segmentation algorithm proposed in our previous research for time-domain feature extraction. This algorithm simulates doctors' visual gestalt and neural receptive field concepts during time-domain signal interpretation through merging and splitting rules, providing a flexible, adaptive time window for the feature extraction process. This window aligns with human visual perception and judgment, and the segmented complete waveforms conform to human visual perception. Consequently, the extracted features provide information about each complete waveform in the time-series signal, and experimental results prove the effectiveness of these features. Additionally, this study selects 1-second segments as samples for classification, which is a very short time window compared to most epileptic EEG recognition algorithms. Most algorithms cannot extract sufficient information to discriminate epileptic discharges within 1 second, but for the period segmentation-based feature extraction method, this information is adequate. Furthermore, this feature extraction method is based on each individual wave to extract features, effectively determining whether a complete waveform is an abnormal discharge. This ability to extract effective features within a short time offers significant advantages for online detection.

In the model component, this paper uses random projection to optimize the core feature subspace transformation in the traditional rotation forest method. Compared to traditional PCA rotation, random projection is a fast projection algorithm. PCA requires computing the feature covariance matrix and obtaining its eigenvalues and eigenvectors through SVD decomposition to derive the transformation matrix, which is computationally expensive. Random projection uses a randomly generated transformation matrix for mapping, and Theorem 1 guarantees the distance invariance after transformation, effectively projecting based on inter-sample distances. Random projection does not require computing the data' s covariance matrix, eigenvalues, or eigenvectors, resulting in lower computational cost than PCA.

The Bayesian minimum risk prediction method provides good classification performance for models trained on imbalanced datasets with a simple computation process. Table 2 shows significant improvement compared to untreated traditional random forest algorithms. Traditional imbalanced classification methods often involve oversampling or undersampling. The comparison between the proposed algorithm and weighting and SMOTE methods in Table 3 demonstrates superior performance. Moreover, the proposed algorithm improves training efficiency. In tree models, the weighted penalty for minority class misclassification in the weighting method is reflected in each leaf node splitting process, requiring more multiplication operations than the proposed algorithm. The SMOTE algorithm generates minority class samples based on all minority class samples and their nearest neighbors. Assuming a training set of size n with p minority class samples, SMOTE requires p^2 operations to compute K-nearest neighbors for each minority class sample and $p \times k$ space to store neighbor indices. The time complexity of sample generation is linear with the number of samples to generate, requiring additional space to store these generated samples. The proposed algorithm' s training process is identical to that on balanced datasets. Except for computing the Hellinger distance once, no additional computation is needed. Only a single traversal of the test set is required during prediction to obtain minimum risk, which is more time-efficient than the SMOTE algorithm. The only additional storage needed is the cost-sensitive matrix, which in binary classification contains only two values, requiring negligible storage space compared to SMOTE' s space complexity.

From a theoretical perspective, the proposed algorithm does not require generation, updating, or undersampling of the original dataset. Undersampling discards large amounts of negative sample information, affecting model performance. Random oversampling increases minority class samples through random replication, resulting in insufficient sample diversity without actually increasing minority class information, leading to poor model generalization. The weighting method creates new data distributions by weighting minority class samples, focusing the classifier on minority class samples, but the weight selection is often too subjective. The SMOTE oversampling method synthesizes new samples through nearest neighbors, providing some diversity for generated samples, but has limitations: the optimal nearest neighbor value is difficult to determine, and samples generated from class boundary samples can cause boundary blurring and increase dataset separability. The proposed imbalanced classification algorithm statistically analyzes data distribution but does not modify the dataset. Instead, it assigns different misclassification costs based on distribution and calculates risks for different classes at the model level, achieving imbalanced classification by obtaining a model with minimum overall misclassification risk.

The algorithm framework consists of three components: time-domain feature extraction based on visual organization, improved rotation forest, and Bayesian minimum risk prediction. The extracted time-domain features are short-duration waveform characteristics such as duration, amplitude, sharpness, and kurtosis—most of which are visually observable shape features of waves. From the perspective of doctors' visual interpretation, these features already provide certain separability for individual waves. The model component uses random projection to optimize the standard rotation forest algorithm, reducing correlation among sub-classifiers through feature linear transformation to further decrease overall model variance. Bayesian minimum risk prediction is the core technology in this algorithm for addressing data imbalance, outperforming traditional models and common imbalanced classification algorithms while improving training efficiency. Consequently, the entire algorithm framework demonstrates superior performance on imbalanced dataset classification problems.

3 Conclusion

This paper proposes an imbalanced epileptic EEG detection algorithm based on time-domain features. Time-domain features from period-segmented multichannel EEG signals are input into an improved rotation forest model, and Bayesian minimum risk is used instead of output probability to determine test sample categories. The algorithm achieves 90.66% sensitivity, 92.52% specificity, and an F_2-score of 0.9055 in 1-second epileptic discharge classification, improving sensitivity by 6% and F_2-score by 0.9 compared to traditional random forest models. For seizure detection, it detects 98.56% of seizures with a detection latency of 1.32s. This algorithm demonstrates excellent performance on imbalanced EEG datasets, surpassing many automatic detection algorithms evaluated on balanced datasets, and removes the limitation of insufficient epilepsy samples. This experiment constructed sample sets with different class ratios by selecting fixed-duration interictal EEG segments. Theoretically, the proposed method would show even more significant improvements over traditional methods if the imbalance ratio were increased. The algorithm aligns with clinical EEG interpretation principles and holds great clinical significance.

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Note: Figure translations are in progress. See original paper for figures.