Multi-model decision-making seizure types classification based on transfer learning

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Abstract—**For brain doctors, knowing the type of seizures in patients with epilepsy is conducive to accurate treatment of patients.Although many researchers have done enough research on the prediction and detection of epileptic seizures, there is a lack of research on the classification of seizure types. Therefore, in order to classify the 8 types of epileptic seizures, this article proposes two ideas based on the fusion of multi-models of transfer learning. Extract the MAS features from the 22 montage combined channels, use reliefF for feature selection, and finally convert it to images. Use the following two transfer learning strategies:(1) Transfer learning multi-model feature fusion, (2) Transfer learning multi-model classification probability fusion. On the TUSZ data set of temple university school of medicine, use six pre-trained models of Alexnet, Googlenet, Inception- v3, Resnet18, Vgg16, and Vgg19. The results show that the proposed algorithm are better than the compared algorithms. The probability fusion strategy is adopted to obtain the best classification performance, classification accuracy and F1 score reaching 98.48% and 97.61%, respectively.**

Keywords-Seizure types, Transfer learning, Multi-model, MAS, Support vector machine

I. INTRODUCTION *(HEADING 1)*

Epilepsy is a chronic disease caused by abnormal brain discharge. When a seizure occurs, a certain part of the body or the whole body is transiently involuntarily convulsed (that is, partial seizure or generalized seizure)[1]. Typical epilep- tic seizure type include: lose consciousness(absent), muscles beconme rigid(tonic), intermittent muscle twitches(myoclonic) etc[2 − 4], different types of seizures need to be treated ac- cordingly,therefore, the precise classification of seizure types plays a vital role in the treatment and disease management of patients.

Electroencephalogram (EEG) is an effective method for researchers to obtain brain information, it's one of the im- portant tools for the diagnosis of neurological diseases. In recent decades, in order to help doctors diagnose and treat patients with epilepsy, researchers have proposed many useful methods combining EEG and machine learning technology in the field of epilepsy detection[5–9] and prediction[10–14]. Epilepsy detection is to detect the seizure part of EEG to detect seizures in real time and help doctors free from the heavy work of long-term visual inspection of EEG. As for epilepsy prediction, it can give a warning to the patient before the epileptic seizure, and minimize the impact of the epileptic seizure on the patient.

In order to achieve the purpose of automatically detecting epileptic seizures in EEG, Rout et al[5] integrate Variational Mode Decomposition (VMD), Hilbert Transform (HT) and the proposed error minimization random vector function link network (EMRVFLN) to detect and classify seizures from EEG signals. Janjarasjitt et al[6] perform a discrete wavelet transform from the patient's EEG to obtain details and approx- imate coefficients. Support vector machines (SVM) are used to classify wavelet-based scalp EEG feature vectors as seizures or non-seizures. The average accuracy, sensitivity, and specificity are 0.9687, 0.7299, and 0.9813, respectively. Yao et al[7] uses the Independent Recurrent Neural Network (IndRNN) to construct a new method for seizure/non-seizure classification. This new method gradually expands the time range, thereby extracting temporal and spatial features from the local duration to the entire record. Nandy et al[8] extracts the time domain, spectrum domain, wavelet domain and entropy features in EEG, and uses multi-objective evolutionary algorithm for feature selection. The support vector machine (SVM) classifier optimized by the Bayesian optimization algorithm is used for classification, and the classification accuracy rate is as high as 97.05%. Peng et al[9] proposes a sparse representation-based seizure classification method based on the dictionary learning with homotopy (DLWH) algorithm. This method achieves an average accuracy of 99.5% and 95.06% in the Bonn University database and the CHB-MIT database, respectively.

Precise warnings before epileptic seizures can minimize the harm of epileptic seizures to patients. In order to achieve this goal, researchers have proposed many solutions. Zhang et al[10] used Common Spatial Pattern (CSP) and Convolutional Neural Network (CNN) to propos a new seizure prediction solution , which can warn the occurrence of epilepsy in advance. Liu er al[11] used EEG's time domain and frequency domain to provide two different views for the same data source at the

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same time, and proposed a multi-view convolutional neural network framework to predict the occurrence of epilep- tic seizures. Ozcan et al[12] used spectral power, statistical moments and Hjorth parameters to extract the frequency and time domain features of the EEG signal, and converted it into a series of multi-color images according to the topology of the EEG channel, which is used as the input of the 3D Convolutional Neural Network (3DCNN) , the multi-frame 3DCNN model achieves a prediction sensitivity of 85.7%. In[13] researchers used short-time fourier transform (STFT) to characterize EEG signals and uses it to train the proposed CNN-LSTM neural network in order to capture the spectral, spatial and temporal features within and between EEG seg- ments and classify them as preictal or interictal stage. This method achieved 98.21% sensitivity and 0.13/h false prediction rate (FPR) on the CHB-MIT dataset. In research[14], spike rate is used as the indicator to anticipate seizures in EEG signals. The spike detection step is used during interictal, preictal, and ictal periods of the EEG signal. The maximum spike rate during seizures is used as an index to predict seizures, the proposed method has ensured that the accuracy of seizure prediction for all patients is 92% in the CHB-MIT database.

Although researchers have combined EEG and machine learning in the field of epilepsy detection and prediction and done sufficient researches. At present, there are few studies on the classification of seizure types. In article [15], Roy et al is the first in the world to propose and discuss the feasibility of using machine learning algorithms to automat- ically distinguish different types of seizures when they are detected. By comparing different machine learning algorithms, a weighted F1 score of up to 90.7% is obtained. Wijayanto et al[16] used the EEG epilepsy corpus (TUSZ) of Temple University Hospital to explore the classification of seizure types. The EEG signal is decomposed by empirical mode decomposition (EMD) to extract the five-level intrinsic mode function (IMF) then calculate the mean, variance, skewness, kurtosis, standard deviation and interquartile range. Support vector machines (SVM) are used for classification with five-fold cross-validation, the best accuracy that can be obtained using the secondary SVM kernel is 95%.

However, because the types of seizures are closely related to the patient's treatment plan and the types of drugs taken, the classification of seizure types deserves more attention and research. In order to solve the above problems, this paper proposes a seizure type classification algorithm with high classification accuracy based on multi-transfer learning model fusion useing Temple Universitys EEG Epilepsy Corpus (TUSZ). This article first uses a band-pass filter to perform basic filtering on the original EEG, and after a specific mon- tage combination, the EEG signal is divided into 19 frequency subbands, and the mean amplitude spectrum(MAS) of each subband is obtained. The REliefF feature selection algorithm is used to filter the extracted features, and the filtered features are converted into images and input into 5 transfer learning models for depth feature extraction. Finally, 5 support vector machines (SVM) are used to classify the depth features extracted by the corresponding transfer learning model, and the probabilities of each category of the five SVMs are averaged, and the category

each category of the five SVMs are averaged, and the category with the largest probability is the final result.

II. METHODOLOGY

A. EEG data set

Multiple types of epileptic seizure data come from epilepsy patient data collected by Temple University Hospital, which is currently the world' s largest EEG open source database[17], representing a grand total of 29.1 years (total duration summed over all EEG channels) of EEG data. This database is equipped with electrodes on the scalp according to the international 10-20 standard with the sampling frequency of 250Hz(87%), 256Hz(8.3%), 400Hz(3.8%), 512Hz(1%). As shown in Fig1, 21 channels including FP1, FP2, F3, F4, etc. are selected according to the montage combination in TableI to eliminate the influence of the reference electrode. According to the

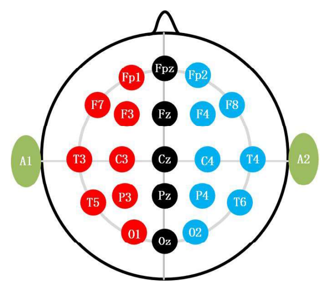


Fig. 1: International 10-20 standard electrode channels

TABLE I: 21 channels montage combinats

montage = 0	FP1-F7	FP1-REF – F7-REF
montage = 1	F7-T3	F7-REF – T3-REF
montage = 2	T3-T5	T3-REF – T5-REF
montage = 3	T5-O1	T5-REF – O1-REF
montage = 4	FP2-F8	FP2-REF – F8-REF
montage = 5	F8-T4	F8-REF – T4-REF
montage = 6	T4-T6	T4-REF – T6-REF
montage = 7	T6-O2	T6-REF – O2-REF
montage = 8	A1-T3	A1-REF – T3-REF
montage = 9	T3-C3	T3-REF – C3-REF
montage = 10	C3-CZ	C3-REF – CZ-REF
montage = 11	CZ-C4	CZ-REF – C4-REF
montage = 12	C4-T4	C4-REF – T4-REF
montage = 13	T4-A2	T4-REF – A2-REF
montage = 14	FP1-F3	FP1-REF – F3-REF
montage = 15	F3-C3	F3-REF – C3-REF
montage = 16	C3-P3	C3-REF – P3-REF
montage = 17	P3-O1	P3-REF – O1-REF
montage = 18	FP2-F4	FP2-REF – F4-REF
montage = 19	F4-C4	F4-REF – C4-REF
montage = 20	C4-P4	C4-REF – P4-REF
montage = 21	P4-O2	P4-REF – O2-REF

function, the TUH data set is divided into several corpus, and the purpose of each corpus is shown in TableII. This paper has carried out a classification research on the 8 types of seizures in the TUSZ corpu, the descriptions of the eight types of seizures are shown in TableIII. According to EEG and clinical manifestations, experts annotated different types of epileptic seizures EEG[18]: focal non-specific seizure (FNSZ), gen- eralized non-specific seizure (GNSZ), simple partial seizure (SPSZ), complex partial seizure (CPSZ), absence Seizure

TABLE II: Each corpus description of TUH data set

Corpus	The function of corpus
TUEG	Total EEG recording
TUAB	Subset of TUEG that have been annotated as normal or abnorma
TUAR	Subset of TUEG that contains annotations of 5 different artifacts
TUEP	subset of TUEG that contains 100 subjects epilepsy and 100 subjects without epilepsy
TUEV	Subset of TUEG that contains six annotation categories such as eye movement and artifact
TUSZ	Subset of TUEG which has manually EEG signals that have been carefully annotated data for seizures
TUSL	Subset of TUEG which contains annotations of slowing events and has been used to study common error modalities in automated seizure detection.

TABLE III: Description and total count of different types of seizures in the TUH EEG Seizure Corpus

Type	Name	Description	Events
FNSZ	Focal Non-Specific Seizure	Focal seizures which cannot be specified by its type	992
GNSZ	Generalized Non-Specific Seizure	Generalized seizures which cannot be further classified into one of the groups below	415
SPSZ	Simple Partial Seizure	Partial seizures during consciousness; Type specified by clinical signs only	44
CPSZ	Complex Partial Seizure	Partial Seizures during unconsciousness; Type specified by clinical signs only	342
ABSZ	Absence Seizure	Absence discharges observed on EEG; patient loses consciousness for a few seconds	99
TNSZ	Tonic Seizure	Stiffening of body during seizure (EEG effects disappears)	67
TCSZ	Tonic Clonic Seizure	At first stiffening and then jerking of body	50
MYSZ	Myoclonic Seizure	Myoclonous jerks of limbs	3

(ABSZ), tonic Seizure (TNSZ), tonic clonic seizure (TCSZ) and myoclonic seizure (MYSZ).

B. Feature extraction and selection

1) Feature extraction: The data directly collected by EEG acquisition equipment contains a lot of noise, such as contact electrode noise, 50Hz power frequency interference, etc. The presence of noise will affect the analysis of the original EEG signal. So pass the original EEG signal through a 0-70 Hz band pass filter and a 50 Hz notch filter for basic filtering, combine the filtered montages shown in TableI to filter out the reference electrode interference.

The EEG signal reflects the scalp potential difference between electrodes at different positions on the scalp surface. Describing EEG according to the rhythmic activity of frequency-divided frequency bands has become the standardization of epilepsy analysis, and the effectiveness of this method has been verified in many researches[19]. The rhythm waves of human brain electricity mainly include: δ rhythm (1-3Hz), θ rhythm (4-7Hz), α rhythm (8-13Hz), β rhythm (14-30Hz), low γ rhythm (30-70Hz). In order to characterize the characteristics of each type of seizure, this paper calculates the mean amplitude spectrum(MAS) on each frequency band of the EEG[20].

First, the 22 montage combined EEG channels are converted from the time domain to the frequency domain by discrete fourier transform(DFT). As shown in Fig2, we found that the MAS characteristics of different seizure symptoms are quite different in the low frequency range. At the same time, the main frequency of EEG is concentrated in low frequency(0-70HZ), and it is easily interfered by high frequency noise[21]. So the filtered EEG signal only retains the frequency information of 0-70 Hz, which is divided into 19 frequency subbands, among them, each frequency band of δ rhythm, θ rhythm and α rhythm is divided into 3 sub-bands, and each frequency band of β rhythm and low γ rhythm is divided into 5 sub-bands. Secondly, calculate the amplitude of each frequency sub-band for 22 channels, and calculate the mean amplitude spectrum of 19 frequency sub-bands for each channel. Finally, the MAS feature with a size of 22×19 is obtained as the feature of each frame of the EEG signal. Perform the above operations on each frame of signal, and the duration of each frame of signal is 1 second, the calculation of MAS features is shown in algorithm1:

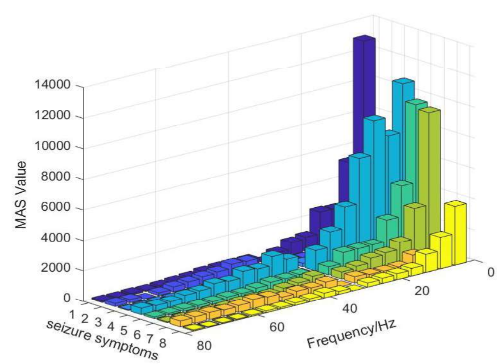


Fig. 2: MAS distribution of 8 types of seizures.

The DFT of the EEG frame signal x(n) is expressed as formula(1):

$$X_k = \sum_{n=0}^{N-1} x(n) e^{-\frac{2\pi j}{N} kn} \tag{1}$$

Algorithm 1: MAS feature extraction

Require: EEG signal length N, Sampling frequency fs, Montage channel number 22

Ensure: MAS feature

1: Each EEG segment contains a total of M frames

2: M = floor(N/fs)

3: for i = 1 to M −1 do

4:Take two frames of signal data as X,with a

5: step length of 1 second

6: for j = 1 to 22 do

7: $$MAS = \sum_{l=1}^{19} mean(P_l(X(i)_j))$$

8: Where P_l is the DFT of a frequency sub-band

9: end for

10: end for

11: Obtained M −1 MAS features

Where N represents the frame length, k=0,...,N-1,by executing algorithm1 on 22 channels, the MAS feature of 418 dimensions(22 × 19) is obtained.

2) Feature selection: When using the extracted features to train machine learning or deep learning models, if the featuredimension is insufficient, it is easy to cause data overlap, and all classifiers will not work; if the feature dimension is too large, it may consume a lot of time and computing resources. In different types of epileptic seizures, not all frequency sub-band MAS features have obvious differences. By eliminating the redundant features in the MAS, not only the classification accuracy of the model can be improved, but also the calculation overhead can be reduced and the training time can be shortened.

ReliefF algorithm is an efficient feature selection algorithm proposed by Kononeill[22]. It is an improved algorithm for improving the relief algorithm that cannot perform multiclass tasks. When the ReliefF algorithm deals with multi-class problems, it randomly takes a sample R from the training sample set each time, and then finds k near hits of R from the sample set of the same class as R. Find k nearest neighbor samples (near Misses) in the sample set, and then update the weight of each feature.

Where diff(A,R_1,R_2) represents the difference between samples R_1 and R_2 on feature A, and $M_j(C)$ represents the jth nearest neighbor sample in class C / ∈ class(R). The overall steps of the reliefF algorithm are as follows, where D, m, δ , k T represent training set, sampling times,feature weight threshold, number of nearest neighbor samples,feature weight respectively.

- Set all feature weights to 0, and T is an empty set.
- from 1 to m do:
- Randomly select a sample R from D, find the k nearest neighbors Hj(j = 1,2,..,k) of R from the sample set of R, and find the k nearest neighbors Mj(C) from each sample set of different classes.
- for A=1 to N(all features), use formula(2) to update the weights.

$$W(A) = \frac{W(A)-\sum_{j=1}^{k} diff(A,R,H_j)+}{mk} + \frac{\sum_{C\notin class(R)} [\frac{p(C)}{1-p(class(R))}\sum_{j=1}^{k} diff(A,R,M_j(C))]}{mk} \quad (2)$$

- Sort the weights in descending order, and select the desired features according to the weights.

After weights are assigned by the reliefF feature selection algorithm, the weight map shown in Fig3 is obtained after the MAS feature is sorted. According to the weight arrangement, the final MAS feature is selected.

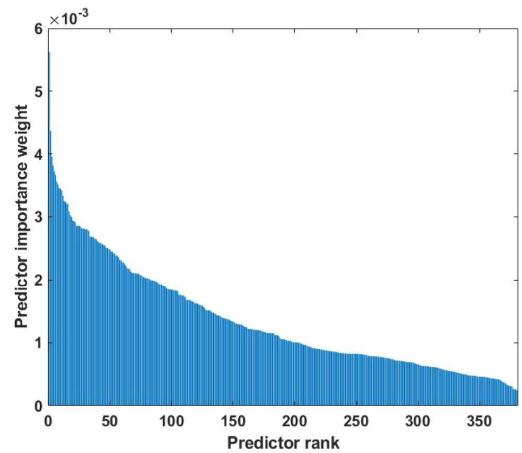


Fig. 3: MAS feature weights after sorting.

The original EEG needs to be input into the classification model for classification after feature extraction and selection. This article uses the deep convolutional neural network and requires 2D image input, so the MAS features are converted into images. The sample image of the 8 types of epilepsy are shown in Fig4:

C. Support Vector Machines

Support Vector Machine (SVM) has been widely used for classification method for pattern recognition, seizure detection,seizure prediction, and many other applications[23]. The purpose of SVM is to find a hyperplane to divide the two types of samples to maximize the sample interval. A linearly separable problem is shown in Fig5: Point A is closer to the hyperplane than point B, indicating that the probability of correct classification of point B by this classifier is greater than the probability of correct classification of point A.

The point closest to the hyperplane is called the “support vector” . Ideally, SVM will find the hyperplane with the largest distance between the hyperplane and the support vector from all the hyperplanes that can be correctly classified as the optimal hyperplane.

The basic SVM is a two-class model, when the actual task is multi-class, multiple SVMs are needed at this time.

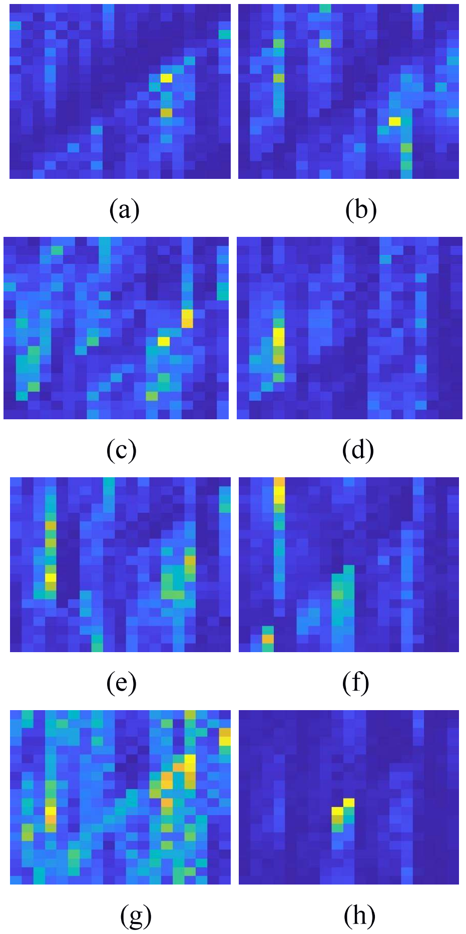


Fig. 4: The MAS feature image of: (a) ABSZ, (b) CPSZ, (c) FNSZ, (d) GNSZ, (e) MYSZ, (f) SPSZ, (g) TCSZ, (h) TNSZ.

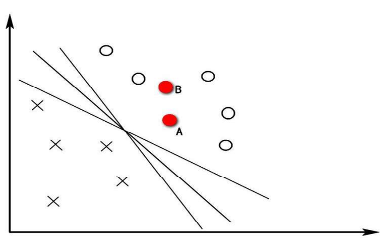


Fig. 5: Linearly separable SVM model

If the number of classifications is m, then any two classes are combined to form a two-class SVM, a total of m(m1)/2 two-class SVMs need to be trained to meet the m-class classification requirements, and finally the voting method is used to determine the final result.

D. Convolutional neural network

Due to its excellent feature learning ability, convolutional neural networks (CNN) are widely used for multi-classification tasks based on image samples. The general structure of a CNN is: convolutional layer - pooling layer - fully connected layer - Dropout layer - Softmax layer. The convolutional layer performs a convolution operation to perform preliminary calculations on the input sample feature maps, and then the pooling layer selects and filters the feature maps calculated by the convolutional layer, and finally performs nonlinear combination in the fully connected layer.This study uses alexnet, googlenet, inceptionv3, resnet18, vgg16, vgg19 to solve the problem of classification of 8 types of seizures. The detailed network structure (depth, number of layers, etc.) of several CNN models and the representative Alexnet network structure are shown in TableIVand Fig6 respectively:

TABLE IV: Structure of the pretrained networks used for this study

network name	Depth	Number of layers	Image input size
Alexnet	8	25	227*227
Googlenet	22	144	224*224
Inceptionv3	48	316	299*299
Resnet18	18	72	224*224
Vgg16	16	41	224*224
Vgg19	19	47	224*224

In order to solve the problem of classification of epileptic seizure types, this paper uses transfer learning to extract the deep features of MAS and tries the idea of multi-model fusion. The specific ideas are as follows:

(1)Use multiple pre-trained networks to extract features, merge the features together, and use an SVM classifier for classification.

(2)Using multiple pre-trained networks to extract features, each pre-training network corresponds to an SVM classifier, and the class with the largest mean output probability of multiple classifiers is the final result.

1)*Transfer learning multi-model feature fusion:* Since the pre-trained network takes a lot of time and computational cost to achieve satisfactory performance, it cannot be directly applied to the classification of epileptic seizures, transfer learning precisely solves this problem. The pre-trained network has a strong calculation and selection effect on image features, this article uses it for deep feature extraction. Transfer learning can replace the last three layers extraction. Transfer learning can replace the last three layers of the pre-trained model with the fully connected layer, softmax layer, and output layers required for epilepsy types classification. Use the weights that have been trained by the pre-training network and freeze them, only by training the weights of the fully connected layer after replacement, the required depth features can be obtained with a small computational cost.

Fig. 6: The structure of Alexnet

The proposed seizure type classification flow chart based on transfer learning multi-model feature fusion is shown in Fig7, the main steps are as follows:

- Frame the filtered EEG signal, and extract the MAS feature of each frame signal.
- Use reliefF feature selection algorithm for feature selection.
- Convert the selected feature frames into images.
- Choose pre-trained networks suitable for seizure classification.
- Replace the fully connected layer, softmax layer and output layer of the selected pre-trained networks.
- After replacing the layer, freeze the previous weights, use the pre-trained networks to extract the depth features output by the MAS feature at the fully connected layer, and combine them together.
- Train the SVM classifier with the combined features, and test the proposed algorithm by classifying the test date set.

2) Transfer learning multi-model probability fusion: In addition to the idea of fusing the features extracted by multiple transfer learning pre-training networks into the SVM classifier learning, another idea of this article is to integrate the probability of multiple SVM. classifiers. Each pre-training network has different depth feature extraction capabilities for the eight types of MAS features. For example, the alexnet network may be more effective for the depth feature of ABSZ, and VGG16 is more effective for the depth feature extraction of CPSZ, this may cause unbalanced classification accuracy, with low classification accuracy for some classes and high classification accuracy for another classes.

In order to make the proposed classification algorithm meet the high classification accuracy of the overall and single class at the same time, this paper presents the idea of classification probability fusion of transfer learning multi-classification model. Probability fusion adopts Dempster-Shafer(DS) envidence theory, the theory of evidence was introduced in the 1970s by G. Shafer[24] after the expansion of seminal works of A. Dempster[25]. This theory can be considered as a generalization of the probability theory.The flow chart of the proposed transfer learning multi-model probability fusion algorithm is shown in the Fig8, the main steps of the algorithm are:

- Frame the filtered EEG signal, and extract the MAS feature of each frame signal.
- Use reliefF feature selection algorithm for feature selection.
- Convert the selected feature frames into images.
- Choose pre-trained networks suitable for seizure classification.
- Replace the fully connected layer, softmax layer and output layer of the selected pre-trained networks.
- After replacing the layer, freeze the previous weights, use the pre-trained networks to extract the depth features output by the MAS feature at the fully connected layer, and use it to train the corresponding SVM classifier.
- Calculate the mean probability of which class each sample belongs to by multiple SVM classifiers, and the class with the largest mean is the final result. Test the proposed algorithm by classifying the test date set.

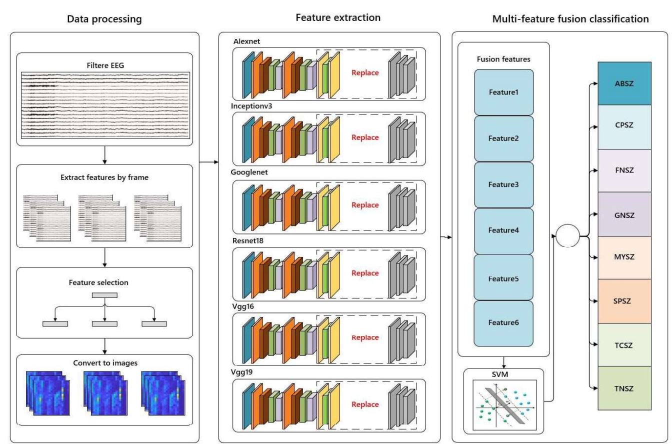


Fig. 7: Flow chart of seizure type classification based on transfer learning multi-model feature fusion.

III. Results and Analyses

In this section, we will discuss the experimental results of the proposed two ideas on TUH EEG Seizure Corpus. By comparing the experimental results on TUH EEG Seizure Corpus, the final seizure type classification algorithm is selected, and the latest comparison algorithm results are compared to prove the advancement and effectiveness of the proposed algorithm.

A. *Performance evaluation*

So as to evaluate the performance of the proposed seizure type classification algorithm, precision, sensitivity and F1 score are used, and their definitions and functions are:

(1)Precision

Precision can reflect the proportion of samples classified as a certain seizure type, and it can reflect the ability of the proposed algorithm to avoid misclassification. The calculation formula is:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

(2)Sensitivity

Sensitivity can reflect the proportion of samples of a certain seizure type that are detected as that type, and can reflect the ability of the algorithm to avoid missing classification. The calculation formula is:

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

(3)F1 Score

The F1 score is a performance index that combines precision and sensitivity. An algorithm may have high accuracy or sensitivity, but another index may be very low. Such an algorithm is useless, therefore, an excellent algorithm should have a higher F1 score, the formula for calculating the F1 score is:

$$F1 = \frac{2 * Precision * Sensitivity}{Precision + Sensitivity} \tag{5}$$

Here, TP, FP, FN represent the true positive, false positive and false negative rates, respectively.

B. *Result on feature fusion*

In the transfer learning multi-model feature fusion experiment proposed in this article, alexnet, googlenet, inceptionv3, resnet18, vgg16, vgg19 were used to extract the depth features of the MAS feature at the fully connected layer. The depth feature of MAS obtained by each model is 8 dimensions, fuse the 48 dimensions deep features extracted from the 6 models and send them to SVM for training. For the data set division, the division ratio of the training data set and the test data set is 4:1. In the training data set, use 5-fold cross-validation for model tuning to find the hyperparameter value that makes the classification model's generalization performance optimal. After finding, retrain the model on all training sets, and use the independent test data set to make a final evaluation of model performance.

In order to explore the influence of the kernel on the classification performance of SVM, the Linear kernel, Quadratic kernel, and Gaussian kernel are used for experiments. The experimental results of each kernel function take the average of five experimental results to ensure the reliability of the results. The performance of proposed method can be seen in TableV:

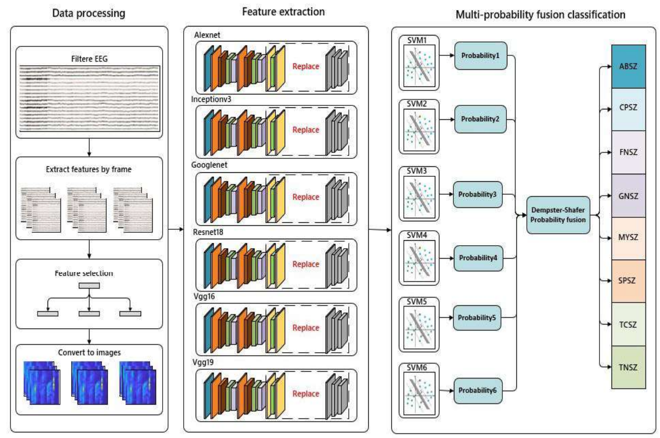


Fig. 8: Flow chart of seizure type classification based on transfer learning multi-model probability fusion.

Linear kernel SVM has obtained the best classification performance, and it’ s confusion matrix is shown in Fig9. So as to verify that the classification performance of transfer learning multi-model feature fusion is better than single-model classification, Fig10 shows the F1 score comparison between them. It can be seen that the highest F1 score of a single model is Vgg19, reaching 94.54%, but the F1 score after multi-model feature fusion is higher, reaching 95.35%.

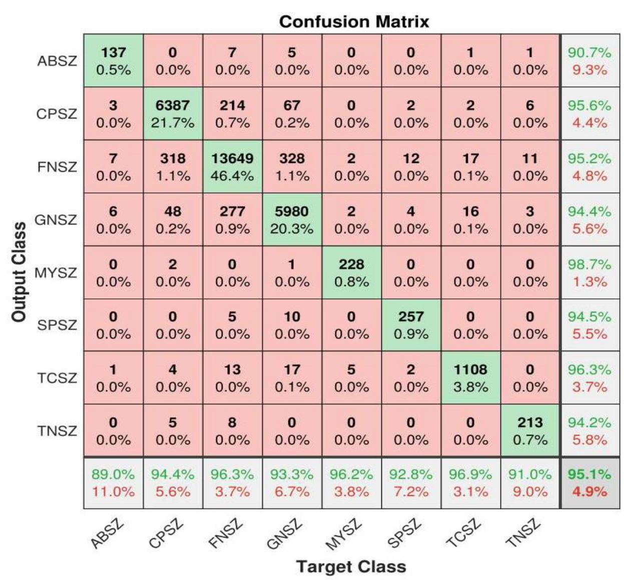


Fig. 9: Confusion matrix of Liner kernel SVM(feature fusion).

TABLE V: Feature fusion experiment results of different SVM kernel.

Accuracy	Linear	Quadratic	Gaussian
Trial1	95.80%	95.50%	94.68%
Trial2	95.66%	94.66%	94.92%
Trial3	95.05%	94.35%	95.22%
Trial4	96.01%	95.03%	94.87%
Trial5	95.21%	95.13%	95.02%
average	95.55%	94.93%	94.94%
Sensitivity	Linear	Quadratic	Gaussian
Trial1	94.11%	94.38%	93.86%
Trial2	94.35%	94.52%	94.12%
Trial3	94.68%	94.13%	94.46%
Trial4	95.22%	94.26%	94.06%
Trial5	94.68%	94.56%	93.87%
average	94.61%	94.37%	94.07%
Precision	Linear	Quadratic	Gaussian
Trial1	96.01%	96.53%	95.62%
Trial2	96.21%	95.12%	95.96%
Trial3	95.98%	95.02%	96.15%
Trial4	96.51%	95.18%	95.73%
Trial5	95.84%	95.33%	95.93%
average	96.11%	95.44%	95.88%
F1 Score	Linear	Quadratic	Gaussian
Trial1	95.05%	95.44%	94.73%
Trial2	95.27%	94.82%	95.03%
Trial3	95.33%	94.57%	95.30%
Trial4	95.86%	94.72%	94.89%
Trial5	95.26%	94.94%	94.89%
average	95.35%	94.90%	94.97%

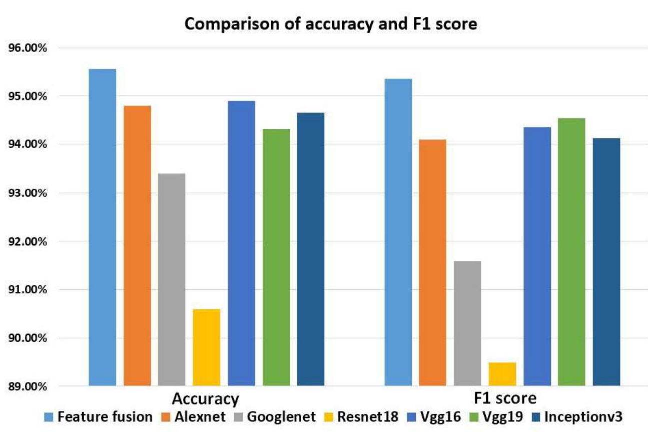


Fig. 10: F1 score and accuracy of multi-model feature fusion and single-model classification.

TABLE VI: Probability fusion experiment results of different SVM kernel.

Accuracy	Linear	Quadratic	Gaussian
Trial1	98.42%	98.38%	98.62%
Trial2	98.43%	98.42%	98.60%
Trial3	97.31%	98.42%	98.29%
Trial4	98.50%	98.35%	98.33%
Trial5	98.37%	98.28%	98.55%
average	98.21%	98.38%	98.48%
Sensitivity	Linear	Quadratic	Gaussian
Trial1	97.92%	98.21%	98.64%
Trial2	98.11%	98.32%	98.72%
Trial3	98.08%	98.37%	98.63%
Trial4	97.96%	98.69%	98.58%
Trial5	98.01%	98.50%	98.68%
average	98.02%	98.42%	98.65%
Precision	Linear	Quadratic	Gaussian
Trial1	96.00%	96.33%	96.66%
Trial2	96.56%	95.96%	96.85%
Trial3	95.84%	96.14%	96.34%
Trial4	96.30%	95.86%	96.96%
Trial5	96.45%	95.89%	96.15%
average	96.23%	97.14%	96.59%
F1 Score	Linear	Quadratic	Gaussian
Trial1	96.95%	97.26%	97.64%
Trial2	97.33%	97.12%	97.78%
Trial3	96.95%	97.24%	97.47%
Trial4	97.12%	97.25%	97.76%
Trial5	97.23%	96.80%	97.40%
average	97.12%	97.13%	97.61%

C. *Result on probability fusion*

For the transfer learning multi-model probability fusion experiment, the same 6 pre-trained networks are used, the 48dimensional MAS deep features extracted by the pre-trained network train 6 SVM classifiers respectively. Use the same data set division and 5-fold cross-validation for model tuning to find the hyperparameter value. The performance comparison of the proposed probabilistic fusion algorithm under the three kernel is also discussed. It can be seen from TableVI that when SVM uses the linear kernel function, the best classification performance is obtained, it' s confusion matrix is shown in Fig11.

Similarly, in order to verify that the probability fusion algorithm performs better than the single model, Fig12 shows the comparison the F1 score of them. It can be seen that the F1 score after multi-model probability fusion is higher, reaching 97.61%.

D. Comparison algorithm

In order to verify the advancement and effectiveness of the proposed algorithm, two latest seizure classification algorithms are compared[15, 16].

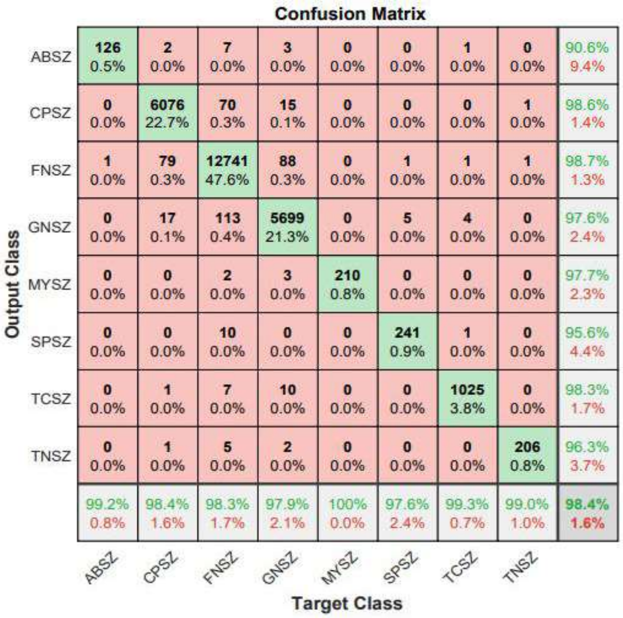


Fig. 11: Confusion matrix of linear kernel SVM(probability fusion).

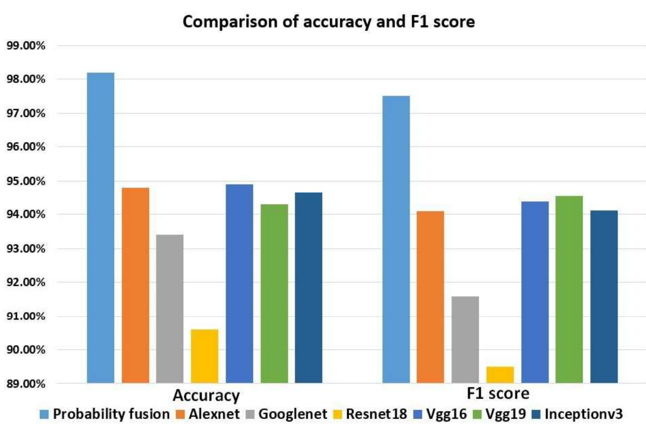
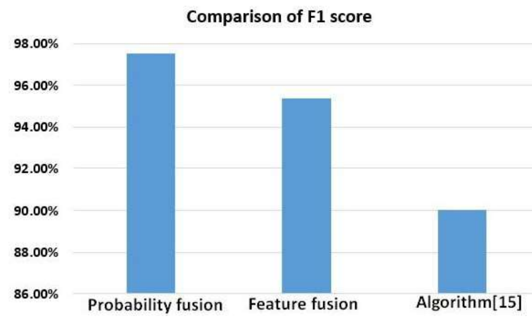


Fig. 12: F1 score and accuracy of multi-model probability fusion and single-model classification.

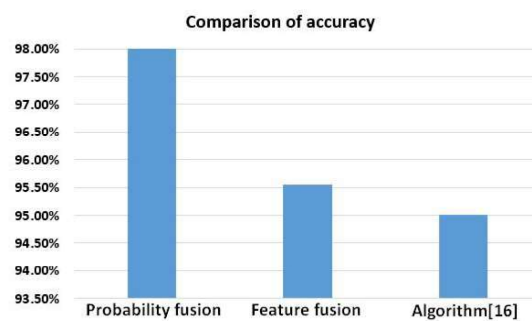
In[15], the author is the first to explore the use of machine learning technology in the classification of automatic seizure types. This technology could support automatic seizure type logging in digital seizure diaries. Such seizure diaries could then be used to improve the performance of clinical trials through more efficient and reliable patient monitoring for endpoint detection, adherence control, and patient retention.

In[16], the author decomposes the EEG signal through empirical mode decomposition (EMD) to extract the five-level intrinsic mode function (IMF). The feature extraction is completed by calculating the mean, variance, skewness, kurtosis, standard deviation and interquartile range. A secondary kernel support vector machine (SVM) is used for classification with five-fold cross-validation.

The two comparison algorithms use the same TUH data set(TUSZ) as this article. Algorithm[15] used the F1 score to evaluate the performance of the classification algorithm, while algorithm[16] used the accuracy rate. Therefore, the two model fusion methods proposed in this article compare F1 scores with algorithm[15], and compare accuracy with algorithm[16].



(a)



(b)

Fig. 13: Comparison of the proposed transfer learning multimodel fusion algorithm and the comparison algorithm in (a) accuracy (b) F1 score.

As shown in Fig13, Fig(a) shows the comparison results of the F1 scores of proposed two fusion algorithms and algorithm[15]. It can be clearly seen that the F1 scores of the two fusion algorithms are higher than algorithm[15]. Compared to the feature fusion , the probability fusion algorithm got a higher F1 score, reaching 97.61%. Fig(b) shows the comparison results of the accuracy of proposed two fusion algorithms and algorithm[16]. Like the F1 score comparison result, the accuracy of the two proposed fusion algorithms is better than that of algorithm[16]. Among them, probability fusion algorithm is the highest, reaching 98.48%. feature fusion and algorithm[16] are 95.55% and 95.00% respectively.

IV. CONCLUSIONS

This study proposes an 8-classification problem to classify seizure types using multi-CNN model fusion. The

MAS features extracted from the EEG time series are selected by the reliefF algorithm. Then converted them into images, which are used as the input of CNN. Use transfer learning algorithm, and 6 pre-trained networks to extract the deep features of MAS. The extracted features are fed into 6 SVM classifiers and the classification probabilities obtained are fused. The highest accuracy rate of 98.48% and F1 score of 97.61% are obtained. Experimental results show that the proposed algorithm is better than the comparison algorithm.

The entire experiment was completed on a computer equipped with Nvidia Rtx2080Ti GPU and Matlab R2020b. The relevant code has been uploaded to Github at: https: //github.com/Roarmomo/My Code.

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