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***Article***

# RBEBT: A ResNet-Based BA-ELM for Brain Tumor Classification

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**Abstract:** Brain tumor refers to the formation of abnormal cells in the brain. It can be divided into benign and malignant. The main diagnostic methods for brain tumors are plain X-ray film, Magnetic resonance imaging (MRI), and so on. However, these artificial diagnosis methods are easily affected by external factors. Scholars have made such impressive progress in brain tumors classification by using convolutional neural network (CNN). However, there are still some problems: (i) There are many parameters in CNN, which require much calculation. (ii) The brain tumor data sets are relatively small, which may lead to the overfitting problem in CNN. In this paper, our team proposes a novel model (RBEBT) for the automatic classification of brain tumors. We use fine-tuned ResNet18 to extract the features of brain tumor images. The RBEBT is different from the traditional CNN models in that the randomized neural network (RNN) is selected as the classifier. Meanwhile, our team selects the bat algorithm (BA) to optimize the parameters of RNN. We use five-fold cross-validation to verify the superiority of the RBEBT. The accuracy (ACC), specificity (SPE), precision (PRE), sensitivity (SEN), and F1-score (F1) are 99.00%, 95.00%, 99.00%, 100.00%, and 100.00%. The classification performance of the RBEBT is greater than 95%, which can prove that the RBEBT is an effective model to classify brain tumors.

**Keywords:** Brain tumor; randomized neural network; bat algorithm; ResNet

## 1 Introduction

Brain tumor refers to the formation of abnormal cells in the brain. It can be divided into benign and malignant. The cause of the brain tumor is not clear. The etiological investigation can be divided into environmental factors and host factors. At present, the main diagnostic methods of brain tumors are plain X-ray film, Magnetic resonance imaging (MRI), and so on. However, these artificial diagnosis methods are easily affected by external factors, such as fatigue, emotion, and so on. At the same time, the early symptoms of brain tumors are not obvious and are easy to be ignored. Now more and more researchers try to use the artificial intelligence to diagnose brain tumors.

Rehman et al. [1] designed a new deep learning method for the classification of brain tumors. Firstly, a 3D convolutional neural network (CNN) was proposed to extract the features. Then, these features were passed to the feed-forward neural network for classification. The new deep learning method got 98.32%, 96.97%, and 92.67% accuracy on the 2015, 2017, and 2018 BraTS datasets, respectively. Deepak et al. [2] proposed a new combination that was based on the CNN and support vector machine (SVM). They used CNN to extract features, and the SVM was used for the classification. Finally, they obtained 95.82% accuracy. Mzoughi et al. [3] explored a 3D CNN to classify the brain tumor. The intensity normalization and adaptive contrast enhancement were used to deal with the data heterogeneity. The final accuracy was 96.49%. Kesav et al. [4] proposed a novel RCNN method for the classification of brain tumors. In the proposed method, there were two channels to classify the brain tumors. Srinivas et al. [5] designed a new model (CNN-KNN) to classify brain tumors. KNN used the features which were extracted by CNN for classification. They got 96.25% accuracy on the test set. Belaid et al. [6] used the pre-trained CNN model (VGG-16) to classify brain tumors and got 96.5% accuracy. Sarkar et al. [7] proposed a 2D CNN to detect brain tumors based on MRI. The 2D CNN method achieved 91.3% accuracy. Agarwal et al. [8] classified the brain MRI images based on the pre-trained VGG16. They got 90% test accuracy. Salçin [9] utilized the faster R-CNN to classify and detect brain tumors. The faster R-CNN could achieve 91.66% accuracy. Hossain et al. [10] used a Fuzzy C-Means clustering algorithm to extract features. There were six classifiers used in this method. Finally, the CNN was implemented to improve the performance. The accuracy was 97.87% based on this method. Hemanth et al. [11] proposed the BPNN for the segmentation of brain tumors images. Nayef et al. [12] introduced a new method (LVQNN) to classify brain tumors. Chen et al. [13] proposed the LRC to classify brain tumors. Zhang, et al. [14] proposed a new model to deal with the accurate interaction of soft tissue. The new model was based on the BP neural network. Sun et al. [15] introduced the fine-tuned VTC which was based on the light CNN with feature optimization. Xiao et al. [16] proposed the novel model (TReC) to detect brain diseases on MRI. The TReC was based on ResNet and Convolutional block attention module.

Above reviewing the aforementioned research, scholars have done much impressive progress in brain tumors classification. However, there are several problems: (i) There are many parameters in CNN, which require much calculation. (ii) The brain tumor data sets are relatively small, which may lead to the overfitting problem in CNN.

Our team proposes a novel model (RBEBT) for the automatic classification of brain tumors to solve these above problems. We want to propose a model which can achieve great classification performance in small brain tumors data set. The main contributions of this paper are summarized as: (i) Our team proposes a new model that can accurately classify brain tumors. (ii) A new classifier is proposed to classify the brain tumor faster and more accurately than the traditional CNNs. (iii) The proposed novel model has superior classification to state-of-the-art methods.

The rest structure of this paper is as follows: We introduce the public brain tumor data set in Section 2. The details of the proposed model are presented in Section 3. Several experiments, results, and the corresponding discussions are shown in Section 4. Section 5 is mainly about the conclusion.

## 2 Materials

We obtain the brain tumor images from the public data set on the Harvard Medical School website (https://www.med.harvard.edu/aanlib.). There are five types on this website: normal brain, cerebrovascular disease, neoplastic disease, degenerative disease, and infectious disease. In this paper, our team classifies this public data set into two categories: the normal brain and the abnormal brain. Some images of this public data set are presented in Fig. 1.

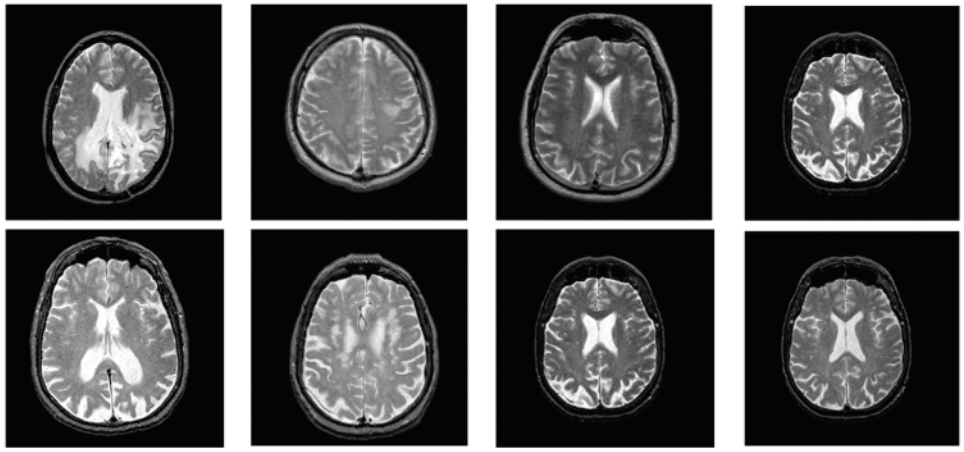


**Figure 1:** Samples in the public brain tumor data set

## 3 Methodology

### *3.1 Proposed RBEBT*

For image recognition and classification, extracting key features from images is one of the most important steps. Before, people tried to extract features from images by hand, but manually extracting features needs a lot of time and energy, and the results were not very satisfactory. The continuous development of machine learning in computers [17] has been applied to image classification and achieved great success. A sea number of CNN models have been proposed, such as AlexNet, VGG, MobileNet, ResNet, and so on. Scholars use these CNN models to classify and segment brain tumors. Nevertheless, there are some problems: (i) These proposed CNN models are generally tested on large data sets. However, brain tumors' data sets are relatively small, which can lead to overfitting problems. (II) CNN model contains many layers and parameters, so it may take a long time to complete the training. Our team proposes a novel model (RBEBT) to deal with these problems as mentioned above. The pipeline of the proposed model is shown in Fig. 2.

In the RBEBT, we use fine-tuned ResNet18 to extract the features of brain tumor images. The RBEBT is different from the traditional CNN models in that the randomized neural network (RNN) is selected as the classifier. The training time of RNN is shorter than that of the CNN models because of the simpler structure of RNN. What's more, it is not easy to produce overfitting problems on small data sets in RNN. However, it may also cause some other problems because the parameters in the RNN are random, such as redundant nodes. We use the bat algorithm (BA) to optimize it to get the ideal parameters. The five-fold cross-validation is chosen to verify the superiority of the RBEBT.

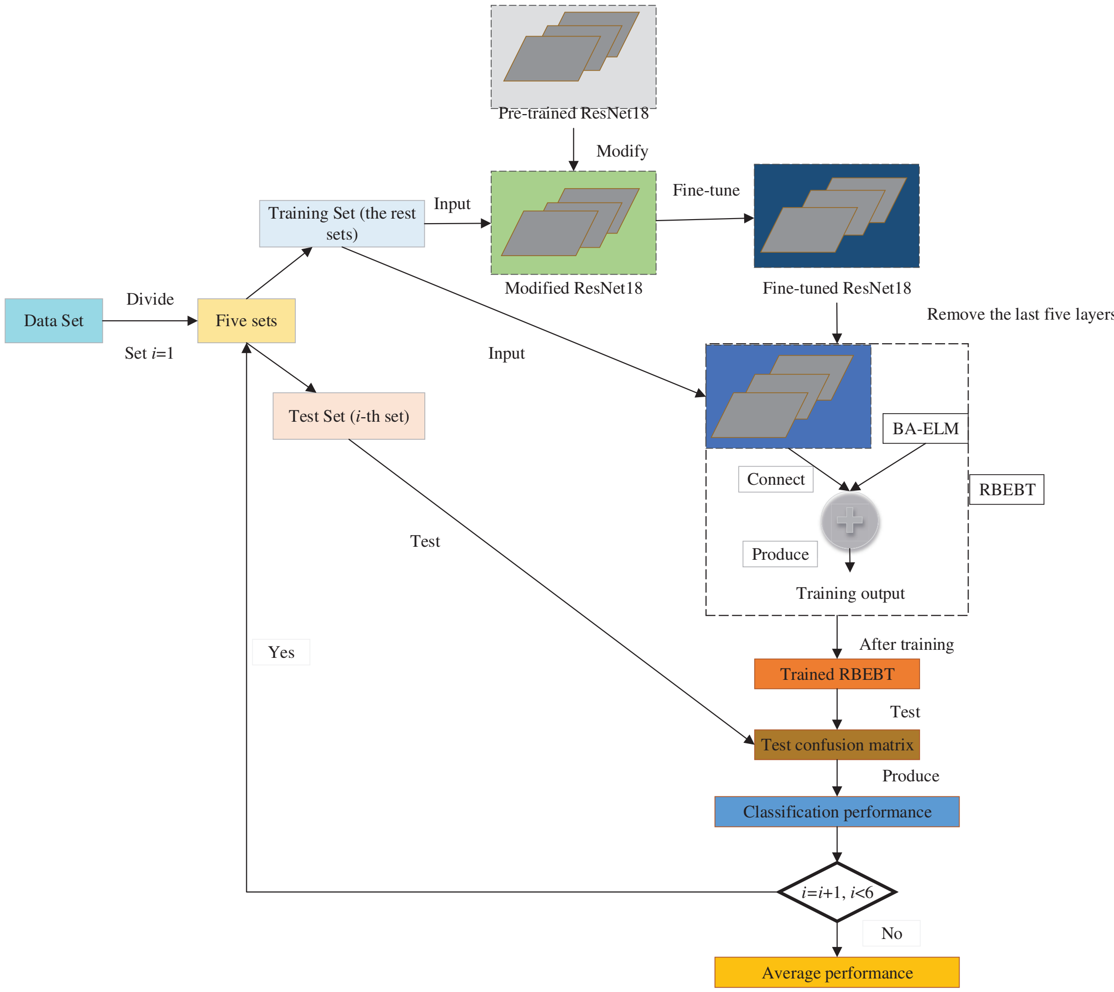


**Figure 2:** The pipeline of the proposed model

### *3.2 Backbone of the Proposed RBEBT*

Scholars hope that the increasing number of layers in the CNN models could improve the performance. However, the increase in the number of layers leads to the problem of gradient explosion. Many methods have been proposed to alleviate such problems, such as batch normalization (BN). However, gradient degradation has not been well solved. He et al. [18] coped with the gradient degradation problem by the residual connection, as shown in Fig. 3. The formula of the residual connection is as follows:

$$R(x) = T(x) - x \tag{1}$$

where $x$ is the input, $T(x)$ is the learned feature, and $R(x)$ is learned from the residual connection. The conversion of the above formula is shown as:

$$T(x) = R(x) + x \tag{2}$$

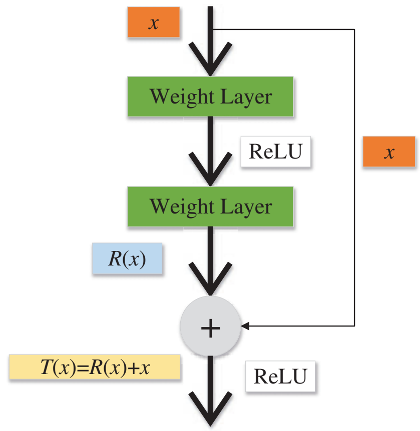


**Figure 3:** The structure of the residual connection

The data set in this paper is classified into two categories, but the output nodes of the pre-trained ResNet18 are 1000. In this paper, our team classifies this public data set into two categories. Therefore, we fine-tune the ResNet18, as given in Fig. 4. Fully connected and batch normalization are abbreviated as FC and BN, respectively. Then, we replace the last five layers of fine-tuned ResNet18 (ReLU, BN, FC2, Softmax, and Classification layer) with the RNN.

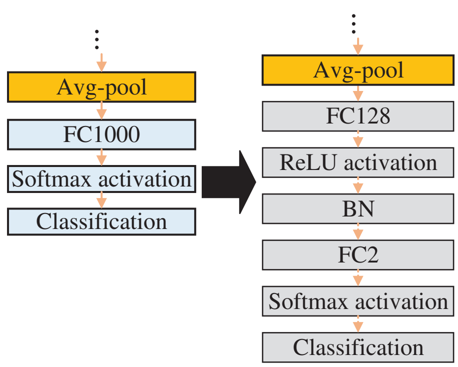


**Figure 4:** The fine-tuned ResNet18

### *3.3 Classifier Optimization*

This paper chooses the RNN as the classifier. The advantages of RNN are to shorten the training time and avoid the overfitting problem. RNN used in this paper is the extreme learning machine (ELM). The structure of ELM is presented in Fig. 5.

Given a data set with the $i$-th sample as $(\boldsymbol{x}_i, \boldsymbol{y}_i)$, the calculation steps of ELM are as follows:

$$\boldsymbol{x}_i = (x_{i1}, \ldots, x_{in})^{\mathrm{T}} \in \mathrm{R}^n, i = 1, \ldots, N, \tag{3}$$

$$\boldsymbol{y}_i = (O_{i1}, \ldots, O_{im})^{\mathrm{T}} \in \mathrm{R}^m, i = 1, \ldots, N, \tag{4}$$

where $n$, $m$ represents the input and output dimension, respectively.

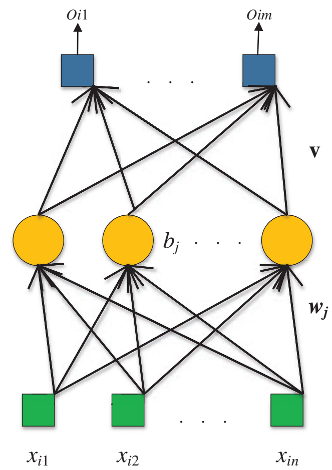


**Figure 5:** The structure of extreme learning machine (ELM)

The formula of the output matrix of the hidden layer is shown as:

$$\mathbf{Q}_{\mathbf{ELM}(i)} = \sum_{j=1}^{r} f\left(\boldsymbol{w}_j \boldsymbol{x}_i + b_j\right), i = 1, \ldots, N. \tag{5}$$

where $r$ is the number of hidden nodes, the weight vector is given as $\boldsymbol{w}_j$, the bias of the j-th hidden node is $b_j$, and $f$ is the sigmoid function.

The calculation of final output weight ($\mathbf{v}$) is as follows:

$$\mathbf{v} = \mathbf{Q}^{+}_{\mathbf{ELM}}\mathbf{Y}, \tag{6}$$

However, the parameters assigned at random may not be the optimal solution. Our team selects the bat algorithm (BA) to optimize it. Suppose the velocity of the $u$-th bat is $l^t_u$ and the position is $p^t_u$ at the time $t$.

$$f_u = f_{\min} + (f_{\max} - f_{\min})\alpha \tag{7}$$

$$l^{t+1}_u = l^t_u + (p^t_u - p_*)f_u \tag{8}$$

$$p^{t+1}_u = p^t_u + l^t_u \tag{9}$$

where $f_{\max}$, $f_{\min}$, and $f_u$, are the maximum, minimum, and current frequency, respectively, $\alpha \in [0, 1]$ is randomized, $p_*$ is the best position at present.

The optimal position will be updated as:

$$p_{\text{new}} = p_{\text{old}} + \beta s^t \tag{10}$$

where $\beta \in [0, 1]$ is randomized, the loudness is $s^t$.

The emission rate and loudness will be generated when the $u$-th bat gets the prey:

$$s^{t+1}_u = 0.9 s^t_u \tag{11}$$

$$h^t_u = h^0_u(1 - \mathrm{e}^{-0.99t}) \tag{12}$$

### *3.4 Evaluation*

Five-fold cross-validation is chosen to verify the superiority of the RBEBT. In this paper, the abnormal brain and the normal brain are defined as the positive and the negative, respectively. Five indexes are selected in this paper, which are accuracy (ACC), specificity (SPE), precision (PRE), sensitivity (SEN), and F1-score (F1). Their equations are shown as below:

$$\begin{cases} \mathrm{ACC} = \dfrac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \\ \mathrm{SPE} = \dfrac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \\ \mathrm{PRE} = \dfrac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \\ \mathrm{SEN} = \dfrac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \\ \mathrm{F1} = \dfrac{2 \times \mathrm{TP}}{2\mathrm{TP} + \mathrm{FP} + \mathrm{FN}} \end{cases}, \tag{13}$$

## 4 Results and Discussion

### *4.1 The Classification Performance of the RBEBT*

The five-fold cross-validation is chosen to verify the superiority of the RBEBT, as shown in Tab. 1. Average and standard deviation are abbreviated as Avr and Std, respectively. The ACC, SPE, PRE, SEN, and F1 are 99.00%, 95.00%, 99.00%, 100.00%, and 100.00%. The results of the RBEBT are greater than 95%, which can prove that the RBEBT is an effective model to classify brain tumors.

**Table 1:** The classification performance

| Methods | Fold | ACC | SPE | PRE | SEN | F1 |
|---|---|---|---|---|---|---|
| RBEBT (Ours) | F 1 | 0.97 | 0.75 | 0.97 | 1.00 | 0.99 |
| | F 2 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | F 3 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | F 4 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | F 5 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | Avr | 0.99 | 0.95 | 0.99 | 1.00 | 1.00 |
| | Std | ±0.01 | ±0.10 | ±0.01 | ±0.00 | ±0.01 |
| AlexNet-BA-ELM | F 1 | 0.97 | 1.00 | 1.00 | 0.97 | 0.99 |
| | F 2 | 0.87 | 0.25 | 0.92 | 0.94 | 0.93 |
| | F 3 | 0.95 | 0.50 | 0.95 | 1.00 | 0.97 |
| | F 4 | 0.95 | 0.50 | 0.95 | 1.00 | 0.97 |
| | F 5 | 0.95 | 0.50 | 0.95 | 1.00 | 0.97 |
| | Avr | 0.94 | 0.55 | 0.95 | 0.98 | 0.97 |
| | Std | ±0.03 | ±0.24 | ±0.02 | ±0.02 | ±0.02 |

(Continued)

**Table 1:** Continued

| Methods | Fold | ACC | SPE | PRE | SEN | F1 |
|---|---|---|---|---|---|---|
| MobileNet-BA-ELM | F 1 | 0.95 | 0.50 | 0.95 | 1.00 | 0.97 |
| | F 2 | 0.95 | 0.50 | 0.95 | 1.00 | 0.97 |
| | F 3 | 0.97 | 0.75 | 0.97 | 1.00 | 0.99 |
| | F 4 | 0.97 | 0.75 | 0.97 | 1.00 | 0.99 |
| | F 5 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | Avr | 0.97 | 0.70 | 0.97 | 1.00 | 0.98 |
| | Std | ±0.02 | ±0.19 | ±0.02 | ±0.00 | ±0.01 |
| ResNet50-BA-ELM | F 1 | 0.90 | 0.75 | 0.97 | 0.91 | 0.94 |
| | F 2 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | F 3 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | F 4 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | F 5 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | Avr | 0.98 | 0.95 | 0.99 | 0.98 | 0.99 |
| | Std | ±0.04 | ±0.10 | ±0.01 | ±0.03 | ±0.02 |
| VGG-BA-ELM | F 1 | 0.92 | 1.00 | 1.00 | 0.91 | 0.96 |
| | F 2 | 0.95 | 0.75 | 0.97 | 0.97 | 0.97 |
| | F 3 | 0.97 | 1.00 | 1.00 | 0.97 | 0.99 |
| | F 4 | 0.90 | 0.00 | 0.90 | 1.00 | 0.95 |
| | F 5 | 0.97 | 1.00 | 1.00 | 0.97 | 0.99 |
| | Avr | 0.94 | 0.75 | 0.97 | 0.97 | 0.97 |
| | Std | ±0.03 | ±0.39 | ±0.04 | ±0.03 | ±0.02 |
| ResNet18-ELM | F 1 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | F 2 | 0.97 | 0.75 | 0.97 | 1.00 | 0.99 |
| | F 3 | 0.97 | 1.00 | 1.00 | 0.97 | 0.99 |
| | F 4 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | F 5 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | Avr | 0.99 | 0.95 | 0.99 | 0.99 | 0.99 |
| | Std | ±0.01 | ±0.10 | ±0.01 | ±0.01 | ±0.01 |
| Fine-tuned ResNet18 | F 1 | 0.90 | 1.00 | 1.00 | 0.89 | 0.94 |
| | F 2 | 0.72 | 1.00 | 1.00 | 0.69 | 0.81 |
| | F 3 | 0.72 | 1.00 | 1.00 | 0.69 | 0.81 |
| | F 4 | 0.69 | 1.00 | 1.00 | 0.663 | 0.79 |
| | F 5 | 0.64 | 0.75 | 0.96 | 0.63 | 0.76 |
| | Avr | 0.73 | 0.95 | 0.99 | 0.71 | 0.82 |
| | Std | ±0.09 | ±0.10 | ±0.02 | ±0.09 | ±0.06 |

### *4.2 Comparison of Different Backbones*

In this paper, we test five different backbone models, which are ResNet18, AlexNet, MobileNet, ResNet50, and VGG. The results are shown in Tab. 1 and Fig. 6. ResNet18 as the backbone model can obtain the best results than the other four backbone models.

The ResNet18 can deal with the problem of gradient explosion by residual connection. Other backbone models may meet the problem of gradient explosion. Therefore, our model can achieve the best performance than other models.

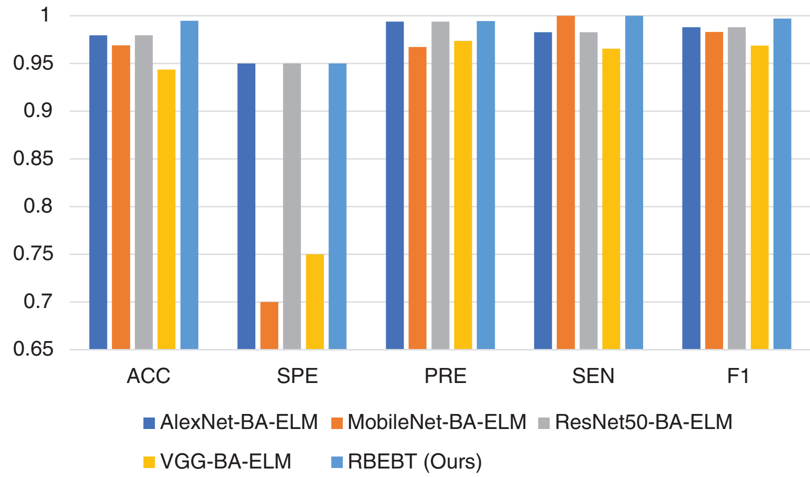


**Figure 6:** The comparison of five different backbone models

### *4.3 Effects of Optimization*

To prove the superiority of our network, we compare the proposed RBEBT with the fine-tuned model and the model with only RNN. The results are shown in Tab. 1. The comparison figure is given in Fig. 7. We can conclude that the optimized network (RBEBT) will achieve better classification performance through comparison.

The ELM can get better classification performance in small data set because of its simpler structure. What's more, the BA is selected to optimize the ELM. Based on these reasons, the RBEBT can get better results than the fine-tuned ResNet18 and ResNet18-ELM.

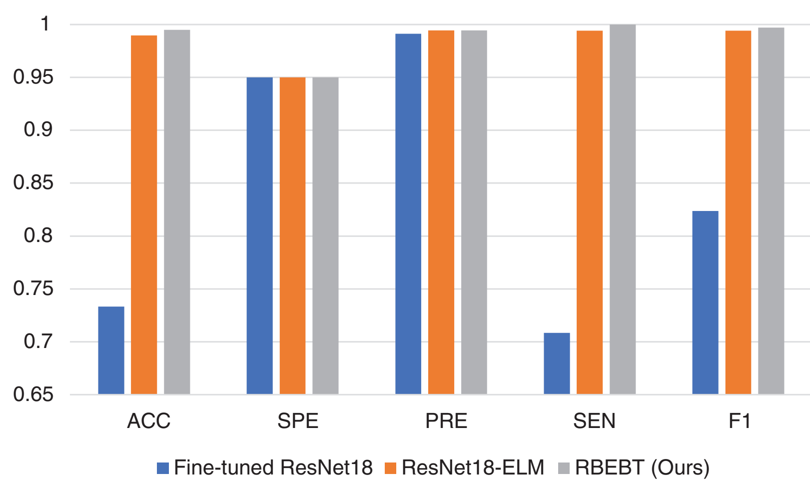


**Figure 7:** Effects of optimization

### *4.4 Comparison with Other State-of-the-Art Methods*

The proposed RBEBT is compared with seven other state-of-the-art methods, which are 3D-CNN [1], SVM-CNN [2], KNN-CNN [5], 2D-CNN [7], BPNN [11], LVQNN [12], and LRC [13], as shown in Tab. 2. In conclusion, the classification performance of our network is better than the other seven methods, which proves the superiority of our network.

**Table 2:** Comparison with other state-of-the-art methods

| Methods | ACC | SPE | PRE | SEN | F1 |
|---|---|---|---|---|---|
| 3D-CNN [1] | 98.32 | – | – | – | – |
| SVM-CNN [2] | 95.82 | 99.30 | 97.30 | – | – |
| KNN-CNN [5] | 96.25 | – | 96.67 | – | 96.25 |
| 2D-CNN [7] | 91.30 | – | – | – | – |
| BPNN [11] | 57.23 | 54.50 | 91.71 | 57.54 | 70.72 |
| LVQNN [12] | 60.05 | 61.00 | 93.08 | 59.94 | 72.92 |
| LRC [13] | 95.74 | 58.50 | 95.47 | 100.00 | 97.68 |
| **RBEBT (Ours)** | **99.00** | **95.00** | **99.00** | **100.00** | **100.00** |

Note: Bold means the best results, - means not available.

In the RBEBT, we use fine-tuned ResNet18 to extract the features of brain tumor images and select ELM as the classifier. The fine-tuned ResNet18 can extract features accurately and ELM has good performance in small data sets. Therefore, the RBEBT can produce better classification performance than other methods.

## 5 Conclusion

In this paper, our team proposes a novel model (RBEBT) for the automatic classification of brain tumors. We use fine-tuned ResNet18 to extract the features of brain tumor images. The RBEBT is different from the traditional CNN models in that the RNN is selected as the classifier. The parameters assigned at random may not be the optimal solution. Our team selects the BA to optimize it. We use five-fold cross-validation to verify the superiority of the RBEBT. The ACC, SPE, PRE, SEN, and F1 are 99.00%, 95.00%, 99.00%, 100.00%, and 100.00%. The classification performance of the RBEBT is greater than 95%, which can prove that the RBEBT is an effective model to classify brain tumors.

The limitations of this paper are: (i) The data set used in this paper is small; (ii) There are only two categories in this paper. In the future, we will apply our model to more public brain tumors data sets to verify its classification performance. Meanwhile, our team will try more methods, such as VIT, U-Net, etc. In addition, we will test our model in other diseases classification.

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**Conflicts of Interest:** The authors declare that they have no conflicts of interest to report regarding the present study.

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