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ORIGINAL

ATHLETE MUSCULOSKELETAL INJURY RECOGNITION BASED ON TRANSFER LEARNING MRI SCANNING

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ABSTRACT

Currently, the prevalence of musculoskeletal injuries in high-level competitive athletes is high, and the injuries mainly appear in the neck and lower back. Long training years, looking down during training, and engaging in real-time combat sports are the main risk factors for the occurrence of neck disorders, and therefore, a scientific method is needed to identify signs of musculoskeletal injuries in athletes' MRI scans for early prevention and early intervention. Therefore, in this paper, a network model based on the lightweight network MobilenetV2 is proposed based on the transfer learning method, which ensures high classification accuracy while completing the recognition task with less number of parameters and computation. To address the problem that deep learning models require a large amount of data for training and patient images are difficult to obtain, this paper proposes the RS algorithm, which masks the local features of the 2DMRI images, augments the dataset, and combines it with the two proposed deep migratory learning classification models, TLV2 and TLV2C, in which TLV2 is the MobileNetV2 that fixes the shallow layer and initializes the deep layer after training on the Image Net dataset. network, initialize the deep network and re-train it under MRI dataset. TLV2C redesigns the classifier on the basis of TLV2. The experimental results show that the algorithm proposed in this paper solves the problem of insufficient MRI data, and at the same time is able to identify the signs of musculoskeletal injuries in MRI scans of athletes.

KEYWORDS: Identifying Signs; Musculoskeletal Injury; MRI Scans; Transfer Learning Approach; Deep Learning

1. INTRODUCTION

With the further development of information technology and the ever-increasing demand for diversified sports and entertainment, e-Sports will attract more people's attention and participation (Bakhrom, 2022; Blobel et al., 2021; Liebermann et al., 2002). However, as in the case of other sports, sports injuries have always been a major problem plaguing athletes. Especially among high-level athletes, due to long-term training and competition, athletes will always suffer from injuries related to the sports they engage in, which affect their technical and tactical performance to different degrees and even affect their normal life. It is important to propose preventive measures according to the characteristics of different sports, and reasonable treatment and rehabilitation programmes for the injuries and illnesses suffered will be of positive significance for athletes to maintain a good state of performance and prolong their sporting life (Astaficevs et al., 2020; Miragaia et al., 2019). As a new sport, it is of great practical significance to study the injury and disease situation of e-Sports to help raise the awareness of athletes and enthusiasts of e-Sports in preventing injuries and diseases, and at the same time to help improve the level of e-Sports in China (Adams & Lasseigne, 2018). In general, most of the studies on sports injuries focus on acute injuries caused by high-intensity, high-load and exhaustive sports, such as injuries in athletics and ball games. In sports such as shooting, archery and chess, which require the body to bear large static loads, injuries to the skeletal muscle system are mainly diffuse strain injuries, and these injuries affect the normal training and competition of athletes to a large extent. Injuries in e-sports are mainly caused by repetitive movements or prolonged forced positions during computer operation, resulting in chronic strain injuries of skeletal muscles and muscles. At present, there is no research on sports injuries in e-Sports (Tee et al., 2020; Van Eetvelde et al., 2021). By conducting epidemiological surveys on high-level e-Sports athletes, understanding the occurrence of injuries and analysing the related factors, it can help to provide a basis for the prevention of injuries and illnesses, support the development and implementation of treatment and rehabilitation programmes, and provide a reference for training methods that are still in a state of uncertainty. At the same time, as e-Sports has a large number of enthusiasts, the results of the study can provide information on disease prevention and thus play an active role in national fitness (Milroy et al., 2022; Younes et al., 2021). Occupational Musculoskeletal Injury (OMSI) is often used as a general term to refer to a range of disorders arising from a wide range of occupational activities characterised by repetitive movements, long working hours or forced positions. Skeletal muscle injuries can be divided into acute and chronic injuries according to the course of the disease (Mathey-Andrews et al., 2023; Prall & Ross, 2019). Chronic injuries can be divided into soft tissue, bone and cartilage chronic injuries and peripheral nerve compression injuries. Chronic injuries are the main cause of occupational musculoskeletal injuries. With the process of industrialisation and the increase in mechanisation, automation and specialisation of production, occupationally related skeletal muscle injuries have not decreased, but have gradually changed from a high incidence of acute injuries to a high incidence of chronic injuries caused by repetitive movements and forced positions. In particular, with the widespread use of computers, the number of chronic occupational skeletal muscle injuries among people working with computers has been increasing and has become an important factor that seriously threatens the health of workers, which not only seriously affects their ability to work, but also affects their quality of life. In recent decades, the problem of occupationally related chronic skeletal muscle injuries has become increasingly prominent, affecting half of the occupational population (Filippini et al., 2020; Yong et al., 2022; York & Bell, 2019). As science and technology continue to advance, neuroimaging is increasingly being used to assist doctors in diagnosing diseases. Magnetic Resonance Imaging (MRI) technology can non-invasively visualise various tissues and organs in the human body, and compared to other neuroimaging techniques, MRI images are able to better reproduce the details of the images and capture the changes in the tissue structure of patients with OMSI (Klein et al., 2019). Machine learning has become an indispensable technology in today's medical image processing field, and many excellent classification models have emerged. Migration learning can complete complex feature extraction and solve high-dimensional data problems through computers, which has gradually shown a broad development prospect in today's medical image field, and it is one of the popular directions of today's research (Siouras et al., 2022). Migration makes use of the similarity between the learning target and the known domain, and migrates the network model that has been completed training to the learning target, which can solve the practical problems more quickly and efficiently. The main contributions are as follows:

(1) In this paper, we propose a network model based on the lightweight network Mobilenet V2, which ensures high classification accuracy while completing the recognition task with less number of parameters and computation. (2) In this paper, we propose the RS algorithm, which masks the local features of 2DMRI images, augments the dataset, and combines it with two proposed deep migration learning classification models, TLV2 and TLV2C. The experimental results show that the algorithm proposed in this paper solves the problem of insufficient MRI data, and at the same time is able to identify signs of musculoskeletal injuries in the MRI scans of athletes.

2. Methodology

2.1 Transfer Learning

Transfer learning is widely used in the field of deep learning. It uses the similarity between the learning target and the known domain to transfer the trained network model to the learning target, which can solve practical problems more quickly and efficiently. Regarding transfer learning, there are two main basic areas, one is the source domain and the other is the target domain. The source domain represents the domain that has been mastered, and the target domain represents the domain that will be learned. Usually there is a certain degree of similarity between the source domain and the target domain. During the process of knowledge transfer, the difference in data distribution between the two domains should be weakened. The shallow network in the convolutional neural network is mainly responsible for extracting basic information of the image, such as contours, texture, etc. Deep networks are mainly responsible for extracting high-level discriminative information between images. When the source domain data is not similar to the target domain data, as long as it has common attributes of basic graphics such as textures and edges, it is eligible for migration. The shallow network of the source domain model can be directly migrated to the target domain model. The shallow network is only responsible for extracting the texture, edge and other information of the image, while the deep network cannot directly use the source domain because the target domain and source domain data are too different. The network parameters in the model need to retrain the deep convolution parameters to extract high-level discriminative information in the target domain. In this article, the ImageNet data set is selected as the pre-training data, and the shallow parameters of the trained model are applied to the classification and recognition of occupational musculoskeletal injury (OMSI) images. The transfer learning in this article is shown in Figure 1.

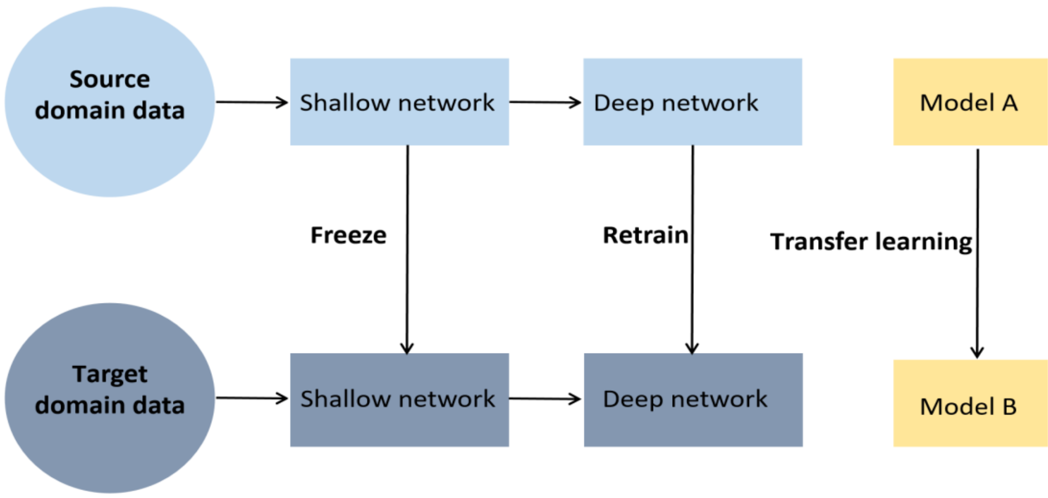

Figure 1: Schematic diagram of transfer learning.

2.2 RS data augmentation algorithm

During the training of a convolutional neural network, if the data set is too small, the model will not be able to learn sufficient features and the model will be less robust. Due to the particularity of medical images, it is relatively difficult to collect images. In order to obtain sufficient data, a series of methods such as rotation, horizontal flipping, mirror flipping, noise addition, and exposure are usually used to expand the data set. Network models trained with a larger number of data sets have better robustness and generalization capabilities than network models trained with a smaller number of data sets. At different stages of OMSI, structural changes will occur in different regions and to varying degrees. This article uses this mechanism as a classification feature. This paper proposes a RS data amplification algorithm to uniformly amplify pre-processed 2DMRI images. Method and detailed steps: The size of the 2DMRI data occlusion block used in the experiment is set to 108×108. A point P is randomly selected on the 2D slice image. Point P is the centre of the square occlusion block, and the coordinates are *(X, Y)*. Since The occlusion block is inside the image, so the value range of its coordinates simultaneously satisfies: $X-54 \geq 0,\ X+54 \leq 360,\ Y-54 \geq 0,\ Y+54 \leq 360$, and the value range is $54 \leq X \leq 306$ and $54 \leq Y \leq 306$. Point *P* randomly appears within the value range and blocks some features in the image. As shown in Figure 2, when amplifying the data, point *P* randomly appears on the 2DMRI image, and the square block blocks local lesion features. A 2DMRI image is randomly blocked 9 times, and finally 9 images can be obtained through a 2DMRI slice.

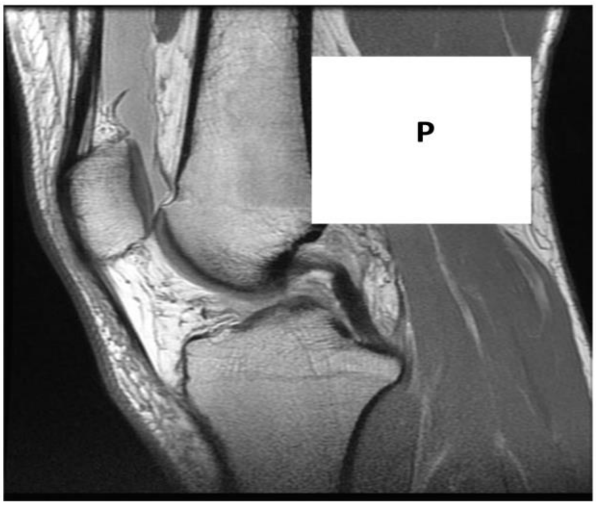

Figure 2: Schematic diagram of the RS algorithm processing process.

The RS algorithm proposed in this article has the following three advantages: (1) The RS algorithm can preserve most of the global semantic information, ensure that the features are relatively continuous in space, and avoid the problem of over-dispersion of features caused by shearing the image. (2) Compared with methods such as rotation, horizontal flipping, mirror flipping, noise addition, and exposure, the data set amplified by the RS algorithm can make the network more sensitive to global features. When dealing with classification tasks where local lesions are not obvious, the model has stronger classification ability. (3) The RS algorithm combined with deep transfer learning can solve the problem of insufficient data sets and improve the robustness of the network model. Figure 3 is a 2DMRI image processed by the RS algorithm.

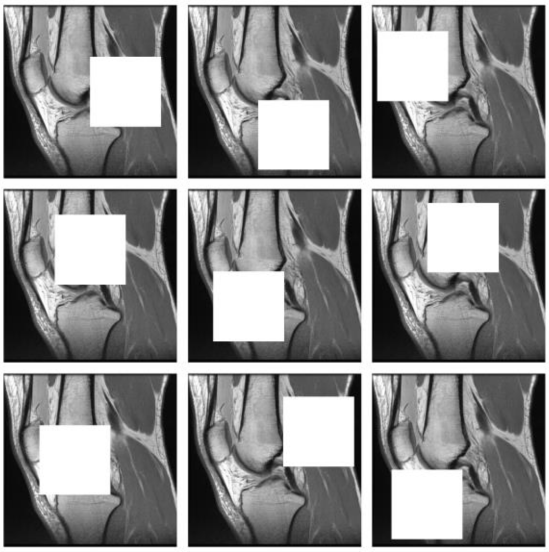

Figure 3: 2DMRI images after augmentation with RS algorithm.

2.3 Model framework

2.3.1 MobileNetV2

Mobile NetV1 network is proposed by Google company in 2017, is a lightweight convolutional neural network, compared with the ordinary convolutional neural network model, its biggest feature is the traditional convolution operation completed decomposition, through the depth of the separable convolution, greatly reducing the number of network parameters and the amount of computation, improve the network computational efficiency, Figure 4 shows the depth of convolution calculation process.

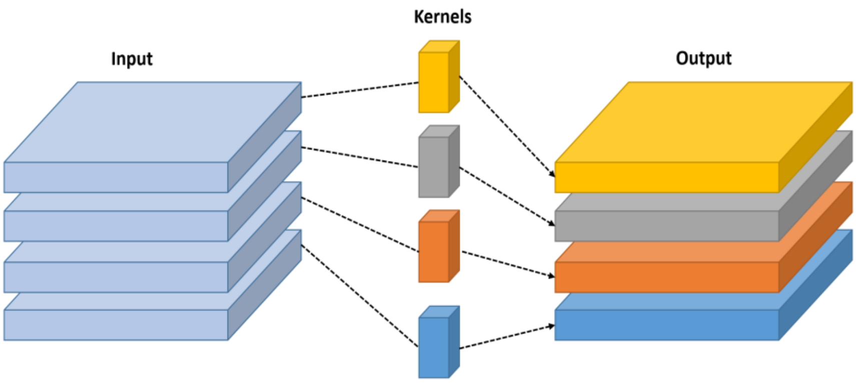

Figure 4: Schematic diagram of the convolution calculation process.

As shown in Figure 4, in depth convolution, each channel of the input feature map has a one-to-one correspondence with the convolution kernel. In depth convolution operation, each channel of the input image is operated on its corresponding single convolution kernel. The output feature map is then fused with channel information through 1×1 point-by-point operation. The block diagram of ordinary convolution and depth-separable convolution network is shown in Figure 5.

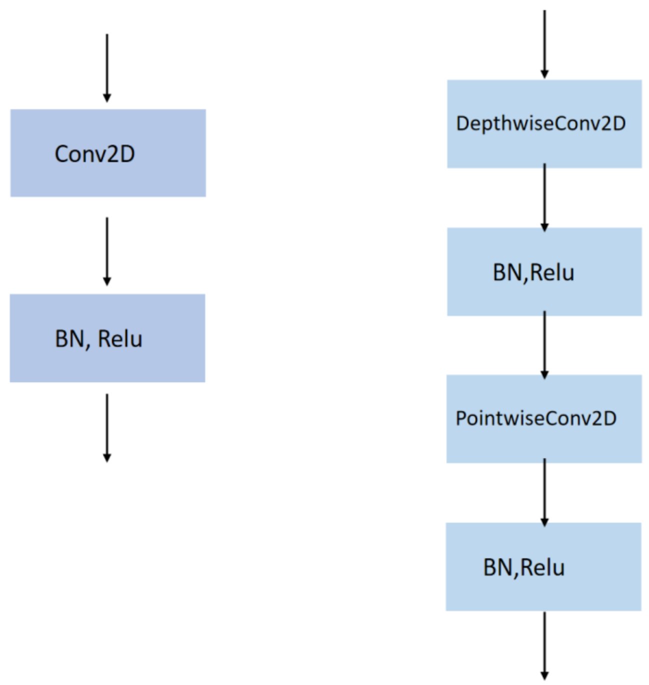

Figure 5: Schematic representation of a regular convolutional and deep separable convolutional network.

There are several problems with MobileNetV1. First of all, when the activation function Relu function has fewer input channels, it will discard the part less than 0, causing damage to the features. Therefore, in low-dimensional space, it is not as effective as the linear activation function. Secondly, there is no feature reuse. When running deep convolution operations, the filters and channels are in one-to-one correspondence. When the weight of a network node is zero, under the action of the Relu function backpropagation (Jia & Zhao, 2023), all inputs to this network node The output of is always 0, causing the training process to do useless work at this node. The calculation equation of the Relu function is as follows:

$$Relu = \max(x, 0)\begin{cases} 0, & x < 0 \\ x, & x > 0 \end{cases} \quad (1)$$

In response to the above problems, MobileNetV2 has made improvements on the basis of V1, mainly as follows: (1) Increase the number of network channels and increase the dimension before the deep convolution layer. And directly remove the second Relu function to avoid the Relu function from damaging the features when the output dimension is low (Tuazon, 2023). (2) Introduce the inverted residual mechanism. In V1, since there is no residual structure, feature loss will occur during transmission, so the inverse residual structure is used in V2 to superimpose the input and output tensors. The bottleneck layer structure in V2 is shown in Figure 6.

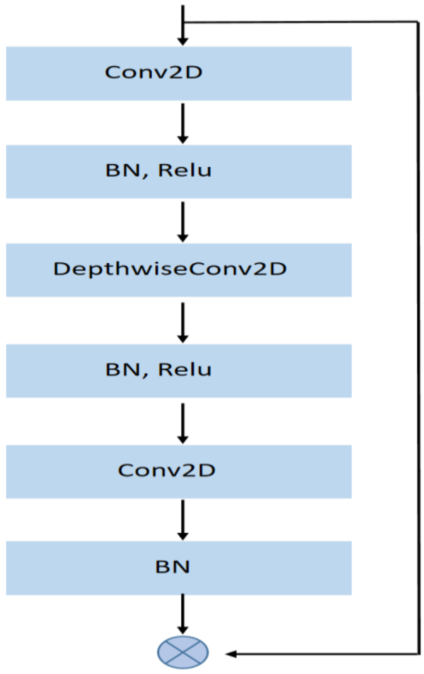

Figure 6: Schematic diagram of the bottleneck layer structure.

The input to the residual module in MobileNetV2 is a low-dimensional feature map, and if the traditional ResNet residual unit is used to compress the input before convolution and finally upscaling, it will further reduce the dimensionality of the input information of the deep convolution layer. Before the V2 deep convolutional layer, a dimension-up convolutional layer is added to expand the input into high-dimensional data, and then the deep convolution operation is performed, which is finally projected into a low-dimensional output. By this method, the input dimension of the deep convolutional layer can be increased to obtain more adequate features (Javed Awan et al., 2021).

2.3.2 TLV2 and TLV2C network models

In this paper, we use a deep transfer learning network, retaining the shallow structure in the MobileNetV2 network, freezing the shallow network parameters, initialising the deep network parameters and classifiers, and re-training on the MRI dataset to complete the OMSI recognition. The shallow layer of the convolutional neural network is responsible for extracting the basic information of the image, such as contours, colours, shapes, etc., while the deep layer is mainly responsible for extracting the high-level discriminative information between images. In the MobileNetV2 network model, there are 17 bottleneck layers, and in this paper, through experimental comparisons, it is determined that using the last 5 bottleneck layers to extract OMSI image features achieves a higher classification accuracy (Namiri et al., 2020). Therefore, two MobileNetV2 network models based on deep migration learning are designed. The training modes of TLV2 and TLV2C are shown in Fig. 7, where the blue part indicates the first 12 bottleneck layers trained and frozen under ImageNet dataset, and the green part indicates the deep network trained under MRI data after initialisation. where the structure of the TLV2C network model is shown in Table 1. where t denotes the expanded dimension in the residual block, c denotes the number of output channels, n denotes how many bottleneck layers were repeated, and s denotes the step size (Kim et al., 2023).

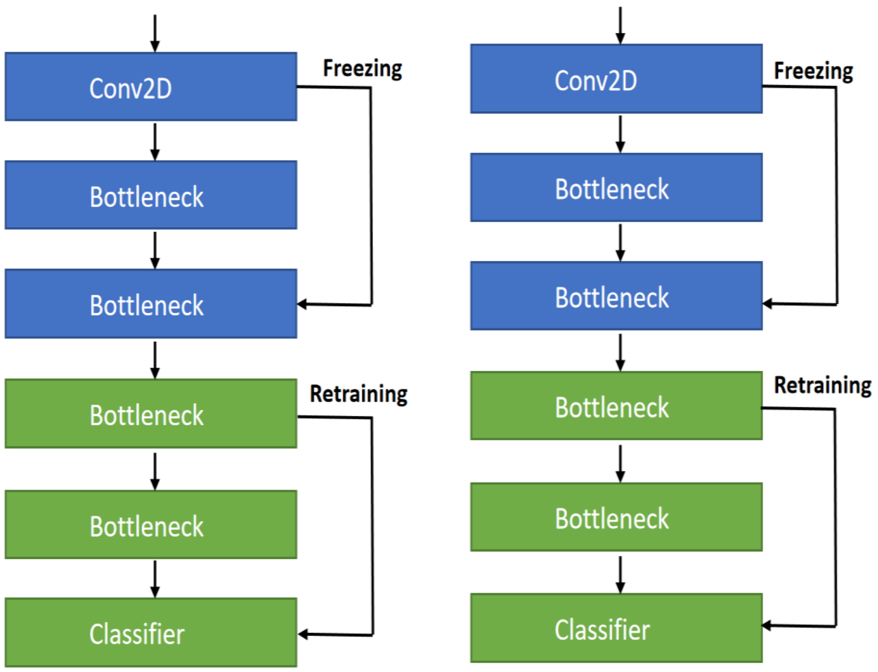

Figure 7: Schematic diagram of the training methods of TLV2 and TLV2C.

Table 1(a): The structure of the TLV2C network model.

INPUT	OPERATOR	T	C	N	S
224×224×3	Conv2D	-	32	1	2
112×112×2	Bottleneck	1	16	1	1
112×112×16	Bottleneck	6	24	2	2
56×56×24	Bottleneck	6	32	3	2
28×28×32	Bottleneck	6	64	4	2
14×14×64	Bottleneck	6	96	3	1
14×14×96	Bottleneck	6	160	3	2
7×7×160	Bottleneck	6	320	1	1
7×7×320	Conv2D 1*1	-	192	1	1
7×7×192	Conv2D 3*3	-	64	1	1

Table 1(b): The structure of the TLV2C network model.

INPUT	OPERATOR	T	C	N	S
5×5×64	AvgPool	-	-	1	-
1×1×64	Conv2D	-	k	-	-

3. Experiment and Results

3.1 Dataset

The OMSI recognition model based on deep learning is limited by the insufficient dataset, and data augmentation is generally used to expand the dataset, and a sufficient number of datasets can improve the robustness of the convolutional neural network and improve the performance of the OMSI recognition model. In this paper, the RS algorithm is used to expand each slice to 9 slices, which expands the number of datasets by 9 times, and finally obtains the number of images of OMSI as 8910, the number of images of MCI as 8649, and the number of images of NC as 9594, which is a total of 27153 MRI images for the network model training and testing. In the experiments of this paper, the MRI dataset is proportionally divided into testset and trainset, with about 75% of the data volume of the training set and 25% of the data volume of the test set. The two datasets are randomly divided and there is no cross use. At the same time, the age and gender of the samples in the two datasets are kept as consistent as possible, so as to avoid the interference of other factors on the experimental results, and the detailed division of the datasets is shown in Table 2.

Table 2: Information on the number of data packets.

TYPE	TRAINING SET	TEST SET	VALIDATION SET
OMSI+NC	13878	4626	18504
MCI+NC	13682	4561	18243

3.2 Experimental setup

Software development environment: The experiments in this paper are designed on a deep learning framework based on Tensorflow, and the development language is Python3.6. Hardware development environment: The experiments in this paper are run on a NVIDIA Ge Force RTX2070S with 8GB graphics memory, which has the Tensor Core function module to improve network computation speed during the training of the deep migration learning model. learning model training process to improve the network computation speed.

3.3 Experimental results and analysis

In this section, the RS algorithm was experimented to compare with the ordinary enhancement methods, which include two kinds of amplification methods, namely rotation and flip, for ordinary data enhancement. In order to ensure experimental rigour, the experiments in this section are built on the TLV2 network model, and the comparative analysis of the two types of data enhancement methods is completed by the three evaluation indexes of Acc, Spe and Sen in the classification experiments of OMSIvs.NC and MCIvs.NC. In this section, 990 OMSI, 961 MCI and 1066 NC pre-processed 2D slices are selected as the data before amplification. These three types of data are augmented by 9 times using the RS algorithm, and they are also augmented by 9 times using the two data enhancement methods of rotation and flip. Finally, 8910 OMSI images, 8649 MCI images and 9594 NC images were obtained by both enhancement methods as the comparative experimental data, and the experimental results are shown in Table 3 and 4.

Table 3: Classification results of two types of amplification methods on TLV2 network (OMSIvs.NC).

MODEL	ACC	SPE	SEN
TRADITIONAL METHOD	85.23	85.17	87.12
RS	**88.69**	**87.26**	**87.21**

Table 4: Classification results of two types of amplification methods on TLV2 network (MCIvs.NC).

MODEL	ACC	SPE	SEN
TRADITIONAL METHOD	72.25	74.25	70.19
RS	**75.39**	**77.36**	**73.91**

As can be seen from Tables 3 and 4, the RS algorithm achieved better classification results in Alzheimer's disease classification experiments than the common enhancement method. The RS algorithm can better enhance the network's sensitivity to global lesion features. Therefore, reflected in the results, the amplification method proposed in this article achieved better results. Among them, in the two-classification experiment of MCIvs.NC, the accuracy improvement effect is more obvious. Because the local features of MCI are relatively hidden, it is more necessary to judge the disease through global features, and the model trained by the RS algorithm has better sensitivity to global features, so the accuracy improvement effect is more obvious, which solves the problem of difficult extraction of MCI features to a certain extent.

Evaluation of a network model should not only consider its accuracy, but also the generalization ability, practicality, etc., in which the number of parameters and the amount of computation is an important indicator of the evaluation of the practical performance of a model, the TLV2 network model of this paper was compared with other models in terms of the number of parameters, the amount of computation, and the ability to classify OMSI. In order to ensure the rigour of the experiment, the shallow network of other networks is trained under the ImageNet dataset, and the deep network is retrained under the MRI dataset, and the accuracy on the test set is selected for comparison, and the performance comparison between the TLV2 network model and other models is shown in Table 5.

Table 5: Performance comparison of TLV2 network model and other models.

MODEL	PARAMS	MULS	OMSIVS.NC(%)			MCIVS.NC(%）		
			ACC	SPE	SEN	ACC	SPE	SEN
ALEXNET	61M	0.71	78.56	81.26	78.23	68.25	68.25	69.21
VGG16	138M	15.4	90.12	87.02	91.17	75.36	76.14	77.16
RESNET18	11M	1.82	85.36	86.63	84.26	73.59	73.65	70.25
DENSENET121	8M	2.85	89.23	91.25	87.25	78.26	79.26	75.19
OURS	3M	0.33	90.25	92.87	92.11	79.94	80.66	78.88

Among the two networks, AlexNet and VGG16, VGG16 can be regarded as a strengthened version of the AlexNet model, with twice the depth of the network and more than twice the number of parameters. The number of parameters in AlexNet and VGG16 is large, and the source of the number of parameters is mainly the 3-layer fully-connected layer, in which the first FC layer of VGG16 contains the most parameters. The large number of parameters and computational volume does not indicate excellent network performance. In the Alzheimer's disease classification task and the classification task of ImageNet data in this paper, VGG16 did not achieve a particularly high classification accuracy, which also shows that many parameters of traditional CNN networks do not play an effective role in the operation. The ResNet network takes reference from VGG19, and modifies the parameters based on VGG19 by adding residuals through the short-circuiting mechanism. ResNet18 contains 17 convolutional layers and 1 fully-connected layer. As mentioned in 3.2.1 above, the residual structure reduces and then raises the input dimensions, which reduces the number of network parameters.

At the same time, ResNet18 uses average pooling to reduce the input dimension before the fully connected layer, so the number of parameters of ResNet18 is on the low side. DenseNet121 directly connects the layers of the network to ensure the maximum information transfer between layers, avoiding deepening of the network and gradient gradually becoming smaller. At the same time, since a large number of features are used repeatedly, sufficient features can be obtained by using only a small number of convolutional kernels, saving many parameters. Although there are fewer parameters, the computation of DenseNet121 is still not small because each layer of convolutional operation needs to add in the output feature maps of the previous layer. The model proposed in this paper completes the OMSI recognition work with fewer parameters and computation while ensuring higher classification accuracy.

4. Conclusion

In this paper, we propose a network model based on the lightweight network Mobilenet V2 based on the transfer learning method, which ensures high classification accuracy while completing the recognition task with less number of parameters and computation. To address the problem that deep learning models require a large amount of data for training and patient images are difficult to obtain, this paper proposes the RS algorithm, which masks the local features of the 2DMRI images, augments the dataset, and combines it with the two proposed deep migratory learning classification models, TLV2 and TLV2C, in which TLV2 is the MobileNetV2 that fixes the shallow layer and initializes the deep layer after training on the Image Net dataset.

Network, initialize the deep network and re-train it under MRI dataset. TLV2C redesigns the classifier on the basis of TLV2. The experimental results show that the algorithm proposed in this paper solves the problem of insufficient MRI data, and at the same time is able to identify the signs of musculoskeletal injuries in MRI scans of athletes

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