A Comparison of Deep Learning Classification Methods on Small-scale Image Data set: from Convolutional Neural Networks to Visual Transformers

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ABSTRACT

In recent years, deep learning has made brilliant achievements in image classification. However, image classification of small datasets is still not obtained good research results. This article first briefly explains the application and characteristics of convolutional neural networks and visual transformers. Meanwhile, the influence of small data set on classification and the solution are introduced. Then a series of experiments are carried out on the small datasets by using various models, and the problems of some models in the experiments are discussed. Through the comparison of experimental results, the recommended deep learning model is given according to the model application environment. Finally, we give directions for future work.

1. Introduction

Nowadays, image classification obtains considerable success in computer vision fields. It is widely used in face recognition of the security field [1], image retrieval of the Internet field [2], image recognition of the medical field [3], etc. However, in some practical application scenarios, it is difficult to gather lots of special images [4]. In this case causes a typical "small data set" problem, where very less data lead machine learning methods to an over-fitting state and result in poor model generalization ability and stability [5]. Therefore, it is urgent to find some effective image classification methods corresponding to small data sets problems.

Deep learning is a new research direction in the field of machine learning, and it has a good performance in image classification [6]. Traditional machine learning image classification methods rely on feature extraction and require a lot of manpower investment [7]. In contrast, deep learning algorithms perform feature extraction in an automated manner, which allows researchers to use minimal domain knowledge and manpower to extract distinguishing features. Furthermore, the classification effect of deep learning is obviously better than that of traditional machine learning in the case of super-large training samples [8]. However, in the case of small-scale data sets, the performance of deep learning is severely limited. Therefore, this paper compares the performance of various deep learning network models on small data sets, aiming to find models with good performance on small data sets.

Currently, deep learning methods are used in the image classification domain include popular Convolutional Neural Networks (CNNs) and novel Visual Transformers (VTs). CNNs have strong abstract learning ability and expression ability in feature extraction. Their local perception and weight sharing characteristics are more suitable for the feature locality and repetitiveness of the image itself, which greatly reduces the parameters and also enables CNNs to be able to Good expression of local features [9]. However, CNNs mostly focus on the description of local information and do not have good context awareness. In contrast, VTs are developed from transformer algorithms in natural language processing, and they show good performance to represent the global information of an image. In addition, due to their computational efficiency and scalability, they can train super-large-scale data sets, and their effect on super-large-scale data sets is similar or even beyond CNNs [10].

This article compares a series of CNNs such as: ResNet-18, 34, 50, 101 [11], VGG11, 13, 16, 19 [12], DenseNet-121, 169 [13], Inception-V3 [14], Xception [15], AlexNet [16], GoogleNet [17], MobileNet-V2 [18], ShuffleNetV2×1.0 [19], Inception-ResNet-V1 [20], and also compares a series of VTs such as: ViT [21], BotNet [22], DeiT [23], T2T-ViT [24]. The purpose is to find deep learning models that are suitable for small data sets. The specific experimental methods and models are shown in Fig.1. Step (b) is to rotate the training set and validation set images by 90°, 180°, 270° and mirror images up and down, left and right, augment the data set by 6 times. Step (c) is uniform image size to 224×224 to facilitate training and classification. Step (d) is to input the processed data into different network models for training. Step (e) is to input the test set into the trained network for classification, and step (f) is to calculate the Average Precision (AP), accuracy, precision, recall and F1-score based on the classification results to evaluate the performance of the network model.

The structure of this paper is as follows. Chapter 2 in-
introduces the related methods of deep learning in image classification, the impact of small data sets on image classification, and the related work of deep learning models. Chapter 3 introduces the data set and experimental design in detail. Chapter 4 compares and summarizes the experimental results and explains the experimental results. Chapter 5 summarizes and looks forward.

2. Related Work

This chapter mainly introduces the impact of small data sets on classification, including basic deep learning image classification methods.

2.1. The Impact of Small Data Sets on Image Classification

In the field of deep learning facial micro-expression recognition, it is difficult to collect enough data due to the short holding time of micro-expression. In addition, lack of sufficient data leads to overfitting problems in the process of training. A novel method is proposed for solving the problem of overfitting mentioned in [25], which mainly contains two steps. One is a fine-tuned model trained from a large public data set. The other is geometric transformation, including mirroring, rotating, and cropping. Based on the proposed method, deep learning is successfully applied in micro-expression recognition.

In rectal histopathology deep learning classification research, a large number of labeled pathological images are needed. However, the preparation of large data sets requires expensive labor costs and time costs, leading to the fact that existing studies are primarily based on small data sets. In addition, the lack of sufficient data leads to overfitting problems during the training process. A conditional sliding window arithmetic is proposed in [26] to solve this problem, which generates histopathological images. The arithmetic successfully solves the limitation of rectal histopathological data.

In climate research, the use of deep learning in cloud layer analysis often requires a lot of data. Therefore, classification in the case of a small data set cannot achieve higher accuracy. To solve this problem, a classification model with high accuracy on small data sets is proposed. The method improves from three aspects. First, a network model for a small data set is designed. Second, regularization technology to increase the generalization ability of the model is applied. Finally, the average ensemble of models is used to improve the classification accuracy. Therefore, the model not only has higher accuracy but also has better robustness [27].

In deep learning research, small data sets often lead to classification over-fitting and low classification accuracy. According to this problem, a kind of deep CNN based transfer learning is designed to solve the problem of the small data set. This method mainly improves data and models. In terms of data, the model transfers the feature layer of the CNN model pre-trained on big sample data set to a small sample data set. In terms of model, the whole series average pooling

![Image](image.png)
is used instead of the fully connected layer, and Softmax is used for classification. This method has a good classification performance on small sample data sets [28].

Because of the limited training data, a two-phase classification method using migration learning and web data augmentation technology is proposed. This method increases the number of samples in the training set through network data augmentation. In addition, it reduces the requirements on the number of samples through transfer learning. This classifier reduces the over-fitting problem while improving the generalization ability of the network [29].

In radar image recognition, due to the complex environment and particular imaging principles, Synthetic Aperture Radar (SAR) images have the problem of sample scarcity. A target recognition method of SAR image based on Constrained Naive Generative Adversarial Networks and CNN is proposed to solve this problem. This method combines Least Squares Generative Adversarial Networks and designs a shallow network structure based on the traditional CNNs model. The problem of high model complexity and overfitting caused by the deep network structure is avoided, to improve the recognition performance. This method can better solve the problems of few image samples and intense speckle noise [30].

Lack of sufficient training data can seriously deteriorate the performance of neural networks and other classifiers. Due to this problem, a self-aware multi-classifier system suitable for "small data" cases is proposed. The system uses Neural Network, Support Vector Machines and Naive Bayes models as component classifiers. In addition, this system uses the confidence level as a criterion for classifier selection. The system performs well in various test cases and is incredibly accurate on small data sets [31].

CNNs are very effective for face recognition problems, but training such a network requires a large number of labeled images. Such large data sets are usually not public and challenging to collect. According to this situation, a method based on authentic face images to synthesize a vast training set is proposed. This method swaps the facial components of different face images to generate a new face. This technology achieves the most advanced face recognition performance on the LFW and CASIA NIR-VIS2.0 face database [32].

The effectiveness of adjusting the number of convolutional layers to classify small data sets is proven in [33]. In addition, related experiments suggest that by employing a very low learning rate, the accuracy of classification of small data sets can be greatly increased.

In medical signal processing, very small data sets often lead to the problems of model overfitting and low classification accuracy. According to this situation, a method combining deep learning and traditional machine learning is proposed. This method uses the first few layers of CNN for feature extraction. Then, the extracted features are fed back to traditional supervised learning algorithms for classification. This method can avoid the overfitting problem caused by small data sets. In addition, it has better performance than traditional machine learning methods [34].

2.2. Deep Learning Technologies

Due to the excellent performance of AlexNet in the ILSVRC-2012 image classification competition [16], improvements in the CNN architecture are very active. A series of CNN-based networks continue to appear, making CNN an irreplaceable mainstream method in the field of computer vision. Till recent years, Transformer frequently appears in the field of computer vision, and has a good performance. This is enough to attract the attention of researchers.

2.2.1. Convolutional Neural Networks

AlexNet is the first large-scale CNN architecture to perform well in ImageNet classification. The innovation of the network lies in the successful application of the ReLU activation function and the use of the Dropout mechanism and data enhancement strategy to prevent overfitting. To improve the model generalization ability, the network uses an Local Response Normalization layer. In addition, the maximum pooling of overlap is used to avoid the blurring effect caused by average pooling [16].

VGG network is proposed by the Visual Geometry Group of Oxford. The network uses a deeper network structure with depths of 11, 13, 16, and 19 layers. Meanwhile, VGG networks use a smaller convolution kernel (3x3 pixels) instead of the larger convolution kernel, which not only reduces the parameters but also increases the expressive power of the networks [12].

GoogLeNet is a deep neural network model based on the Inception module launched by Google. The network introduces an initial structure to increase the width and depth of the network while removing the fully connected layer and using average pooling instead of the fully connected layer. To avoid the disappearance of the gradient, the network adds 2 additional softmax to conduct the gradient forward [17].

ResNet solves the "degradation" problem of deep neural networks by introducing residual structure. ResNet networks use multiple parameter layers to learn the representation of residuals between input and output, rather than using parameter layers to directly try to learn the mapping between input and output as VGGs networks do. Residual networks are characterized by ease of optimization and the ability to improve accuracy by adding considerable depth [11].

The denseness network is inspired by the ResNet network. DenseNet uses a dense connection mechanism to connect all layers. This connection method allows the feature map learned by each layer to be directly transmitted to all subsequent layers as input, so that the features and the transmission of the gradient is more effective, and the network is easier to train. The network has the following advantages: it reduces the disappearance of gradients, strengthens the transfer of features, makes more effective use of features, and reduces the number of parameters to a certain extent [13].

The inception-V3 network is mainly improved in two aspects. Firstly, branch structure is used to optimize the Inception Module; secondly, the larger two-dimensional convolution kernel is unpacked into two one-dimensional convolution kernels. This asymmetric structure can deal with
more and richer spatial information and reduce the computation [14].

Xception is an improvement of Inception-V3. The network proposes a novel Depthwise Separable Convolution method, the core idea of which lies in space transformation and channel transformation. Compared with Inception, Xception has fewer parameters and is faster [15].

MobileNets and Xception have the same ideas but different pursuits. Xception pursues high precision, but MobileNets is a lightweight model, pursuing a balance between model compression and accuracy. A new unit Inverted residual with linear bottleneck is applied in MobileNet-V2. The inverse residual first increases the number of channels, then performs convolution and then increases the number of channels. This can reduce memory consumption [18].

ShuffleNet makes some improvements based on MobileNet. The 1x1 convolution used by MobileNet is a traditional convolution method with a lot of redundancy. However, ShuffleNet performs shuffle and group operations on 1x1 convolution. This operation implements channel shuffle and pointwise group convolution. In addition, this operation dramatically reduces the number of model calculations while maintaining accuracy [19].

The Inception-ResNet network is inspired by ResNet, which introduces the residual structure of ResNet in the Inception module. Adding the residual structure does not significantly improve the model effect. But the residual structure helps to speed up the convergence and improve the calculation efficiency. The calculation amount of Inception-ResNet-v1 is the same as that of Inception-V3, but the convergence speed is faster [20].

2.2.2. Visual Transformers

The ViT model applies transformers in the field of natural language processing to the field of computer vision. The main contribution of this model is to prove that CNN is not the only choice for image classification tasks. ViT divides the input image into fixed-size patches and then obtains patch embedding through a linear transformation. Finally, the patch embeddings of the image are sent to the transformer to perform feature extraction to classification. The model is more effective than CNN on super-large-scale data sets and has high computational efficiency [21].

BoTNet is proposed by Srinivas. This network introduces self-attention into ResNet. Therefore, BoTNet has both the local perception ability of CNN and the global information acquisition ability of Transformer. The top-1 accuracy of this model on ImageNet is as high as 84.7%, and its performance is better than models such as SENet and EfficientNet [22].

T2T-ViT is an upgraded version of ViT. It proposes a novel Tokens-to-Token mechanism based on the characteristics and structure of ViT. This mechanism allows the deep learning model to model local and global information. The performance of this model is better than ResNet in the ImageNet data test, and the number of parameters and calculations are significantly reduced. In addition, the performance of its lightweight model is better than that of MobileNet [24].

DeiT is proposed by Touvron et al. The innovation of DeiT proposes a new distillation process based on a distillation token, which has the same function as a class token. It is a token added after the image block sequence. The output after the transformer encoder and the output of the teacher model calculates the loss together. The training of DeiT requires fewer data and fewer computing resources [23].

3. Materials and Methods

This chapter mainly introduces the EMDS5+ database and database augmentation methods. In addition, the distribution of the data set in this experiment is introduced. Finally, the index to evaluate the classification performance of the model is introduced.

3.1. Data Set

3.1.1. Data Description

This experiment uses the EMDS5+ database to compare model performance. The database contains a total of 840 environmental microbial images of different sizes. These images contain a total of 21 types of environmental microorganisms, each with 40 images, namely: Actinophrys, Arcella, Aspidisca, Codosiga, Colpoda, Epistylis, Euglypha, Paramecium, Rotifera, Vorticella, Noctiluca, Ceratium, Stentor, Siprostomum, K. Quadrala, Euglena, Gymnodinium, Gymlyano, Phacus, Stylongchia, Synchaeta. Some examples are shown in Fig. 2 [35].

3.1.2. Data Preprocessing

In order to improve the accuracy of the model and reduce the degree of model overfitting, the images in EMDS5+ are augmentation. Due to the security problem of data augmentation, the only geometric transformation of the data is performed here. The geometric transformation includes rotation 90°, 180° and 270°, up and down mirroring, and left and right mirroring. These transformations do not break the environmental microbial label and ensure data security. In addition, the image sizes in EMDS5+ is inconsistent, but the input required by the deep learning models is the same. Therefore, all images in EMDS5+ are standardized to 224x224 pixels.

3.1.3. Data Setting

Experiment A: Randomly select 37.5% of the database as the training set, 25% as the validation set and 37.5% as the test set. Experiment A is to directly perform classification tasks on 21 types of microorganisms through the deep learning model. The details of the training set, validation set, and test set are shown in Table. 1.

Experiment B: Randomly select 37.5% of the database as the training set, 25% as the validation set and 37.5% as the test set. Specifically, 21 types of microorganisms are sequentially regarded as positive samples and the remaining 20 types of samples are regarded as negative samples. In this way, 21 new data sets are generated. For example,
if Actinophrys images are used as positive samples, the remaining 20 types of environmental microorganisms such as Arcella and Aspidisca are used as negative samples. Experiment B is imbalanced training to assist in verifying the performance of the model.

Because the EMDS5+ database is a very small data set, the experimental results are quite contingent. Therefore, 37.5% of the data is used to test the performance of the model to increase the reliability of the experiment. This also expresses our sincerity to the experimental results.

### 3.2. Evaluation Method

To scientifically evaluate the classification performance of deep learning models, choosing appropriate indicators is a crucial factor. Recall, Precision, Accuracy, F1-score, Average Precision (AP), and mean Average Precision (mAP) are commonly used evaluation indicators [36]. The effectiveness of these indicators is proven. The Recall is the probability of being predicted to be positive in actual positive samples. Precision is the probability of being actual positive in all predicted positive samples. AP refers to the average value of recall rate from 0 to 1. The mAP is the arithmetic average of all AP. F1-score is the harmonic value of precision rate and recall rate. Accuracy refers to the percentage of correct results predicted in the total sample [37]. The specific calculation methods of these indicators are shown in table 2.

In table 2, TN is the number of negative classes predicted as negative classes, FP represents the number of negative classes predicted as positive classes, FN refers to the number of positive classes predicted as negative classes and TP is the number of positive classes predicted as positive classes.

| Class | Data set | train | val | text | Total |
|-------|----------|-------|-----|------|-------|
| Actinophrys | 15       | 10    | 15  | 40   |
| Arcella   | 15       | 10    | 15  | 40   |
| Aspidisca | 15       | 10    | 15  | 40   |
| Codosiga  | 15       | 10    | 15  | 40   |
| Colpoda   | 15       | 10    | 15  | 40   |
| Epistylis | 15       | 10    | 15  | 40   |
| Euglypha  | 15       | 10    | 15  | 40   |
| Paramecium| 15       | 10    | 15  | 40   |
| Rotifera  | 15       | 10    | 15  | 40   |
| Vorticella| 15       | 10    | 15  | 40   |
| Noctiluca | 15       | 10    | 15  | 40   |
| Ceratium  | 15       | 10    | 15  | 40   |
| Stentor   | 15       | 10    | 15  | 40   |
| Siprostromum| 15     | 10    | 15  | 40   |
| K.Quadrala| 15       | 10    | 15  | 40   |
| Euglena   | 15       | 10    | 15  | 40   |
| Gymnodinium| 15     | 10    | 15  | 40   |
| Gonyaulax | 15       | 10    | 15  | 40   |
| Phacus    | 15       | 10    | 15  | 40   |
| Stylongchia| 15      | 10    | 15  | 40   |
| Synchaeta | 15       | 10    | 15  | 40   |
| Total    | 315      | 210   | 315 | 840  |

4. Comparison of Classification Experiment

4.1. Experimental Environment

This comparative experiment is performed on the local computer. The computer hardware configuration is shown in Table 3. The computer software configuration is as follows: Win10 Professional operating system, Python 3.6, and
Table 2
Evaluation Metrics for Image Classification.

| Assessments  | Formula           |
|--------------|-------------------|
| Precision \( (P) \) | \( \frac{TP}{TP+FP} \) |
| Recall \( (R) \)       | \( \frac{TP}{TP+FN} \) |
| F1-score       | \( 2 \times \frac{PR}{P+R} \) |
| Accuracy       | \( \frac{TP+TN}{TP+TN+FP+FN} \) |
| AP                  | \( \frac{1}{M} \sum_{i=1}^{N} \text{Precision}_{\max}(i) \) |
| mAP             | \( \frac{1}{K} \sum_{j=1}^{K} \text{AP}(j) \) |

Table 3
Computer hardware configuration.

| Hardware     | Product Number                           |
|--------------|------------------------------------------|
| CPU          | Intel Core i7-10700                       |
| GPU          | NVIDIA Quadro RTX 4000                   |
| Motherboard  | HP 8750 (LPC Controller-0697)            |
| RAM          | SAMSUNG DDR4 3200MHz                     |
| SSD          | HP SSD S750 256GB                        |

Table 4
Deep learning model parameters

| Parameter   | Value         |
|-------------|---------------|
| Batch Size  | 32            |
| Epoch       | 100           |
| Learning    | 0.002         |
| Optimizer   | Adam           |

Pytorch 1.7.1. In addition, the code runs in the integrated development environment Pycharm 2020 Community Edition.

This experiment mainly uses some classic deep learning models and some relatively novel deep learning models. The hyperparameters uniformly set by these models are shown in Table. 4.

4.2. Experimental Results and Analysis
4.2.1. The Classification Performance of Each Model on the Training and Validation Sets

Figure. 3 shows the accuracy and loss curves of the CNNs and VTs series models. Table. 5 shows the performance indicators of different deep learning models on the validation set. According to Figure. 3 and Table. 5, the performance of different deep learning models under small data set case is briefly evaluated.

As shown in Figure. 3, the accuracy rate of the training set is much higher than that of the verification set in each model. Densenet169, Googlenet, Mobilenet-V2, ResNet50, ViT, and Xception network models are particularly over-fitting. In addition, AlexNet, InceptionResnetV1, ShuffleNet-V2 and VGG11 network models do not show serious overfitting. Among 21 models in Table. 5, the accuracy rates of the Deit, ViT and T2T-ViT models are at the 12th, 14th and 16th. The VT models are in the middle and downstream position among the 21 models.

The Xception network model has the highest accuracy, precision, and recall rates in the test set results, which are 40.32%, 40.33% and 49.71%. The AlexNet, ViT, and ShuffleNet-V2 network models require the shortest training time, which are 711.64s, 714.56s and 712.95s. In addition, the ShuffleNet-V2 network model has the smallest parameter amount, which is 521MB.

VGG16 and VGG19 networks cannot converge in the EMDS+ data set classification task. The VGG13 network model has the lowest accuracy, precision and recall rates in the validation set results, which are 20.95%, 20.95% and 19.23%. The VGG19 network model requires the longest training time, which is 1036.68s. In addition, the VGG19 network model has the largest amount of parameters, which is 521MB.

Xception is a network with excellent performance in the EMDS5+ database classification. In the Xception network accuracy curve, the accuracy of the Xception network training set is rising rapidly, approaching the highest point of 90% after 80 epochs. Meanwhile, the accuracy of the verification set is close to the highest point 45%, after 30 epochs. In addition, the Xception network training set loss curve declines steadily and approaches its lowest point after 80 epochs. But the validation set loss begins to approach the lowest point after 20 epochs and stops falling. VGG13 is a network that performs poorly on EMDS5+ classification. In the VGG13 network, the accuracy curve of the training set and the accuracy curve of the validation set have similar trends, and there are obvious differences after 80 epochs. Meanwhile, the loss of the training set and the loss of the validation set are also relatively close, and there are obvious differences after 60 epochs. Networks such as Xception, ResNet34 and Googlenet are relatively high-performance networks. The training accuracy of these networks is much higher than the verification accuracy. Furthermore, the verification accuracy is close to the highest point in a few epochs. In addition, the training set loss of these networks is usually lower than 0.3 at 100 epochs. VGG11 and AlexNet are poorly performing networks. These network training accuracy curves are relatively close to the verification accuracy curves. Disagreements usually occur after more epochs. In addition, the training set loss of these networks is usually higher than 0.3 at 100 epochs.
Figure 3: The loss curve and accuracy curve of different deep learning networks on the training set and validation set. For example, AlexNet, Botnet, Densenet169, Googlenet, InceptionResNetV1, Mobilenet-V2, ResNet50, ShuffleNet-V2, VGG11, VGG16, ViT, and Xception. train-accurate is the accuracy curve of the training set, train-accurate is the accuracy curve of the validation set, train-loss is the loss curve of the training set, and val-loss is the loss curve of the validation set.
Table 5
Comparison of classification results of different deep learning models on the validation set.
P denotes Precision, and R represents Recall. (Sort in descending order of classification accuracy.)

| Model           | Avg. P(%) | Avg. R(%) | Avg. F1_score(%) | Accuracy(%) | Params Size (MB) | Time (s) |
|-----------------|-----------|-----------|-----------------|-------------|------------------|----------|
| Xception        | 45.71%    | 52.48%    | 44.95%          | 45.71%      | 79.8             | 996      |
| ResNet34        | 42.86%    | 45.33%    | 42.31%          | 42.86%      | 81.3             | 780      |
| Googlenet       | 41.90%    | 42.83%    | 40.49%          | 41.91%      | 21.6             | 772      |
| Densenet121     | 40.95%    | 43.61%    | 40.09%          | 40.95%      | 27.1             | 922      |
| Densenet169     | 40.95%    | 43.62%    | 39.89%          | 40.95%      | 48.7             | 988      |
| ResNet18        | 40.95%    | 45.55%    | 41.05%          | 40.95%      | 42.7             | 739      |
| Inception-V3    | 40.00%    | 45.01%    | 39.70%          | 40.00%      | 83.5             | 892      |
| Mobilenet-V2    | 39.52%    | 39.57%    | 37.01%          | 39.52%      | 8.82             | 767      |
| InceptionResnetV1 | 39.05% | 41.54%    | 37.96%          | 39.05%      | 30.9             | 800      |
| Deit            | 39.05%    | 39.37%    | 37.70%          | 39.05%      | 21.1             | 817.27   |
| ResNet50        | 38.57%    | 43.84%    | 38.02%          | 38.57%      | 90.1             | 885      |
| ViT             | 37.14%    | 41.02%    | 35.95%          | 37.14%      | 31.2             | 715      |
| ResNet101       | 34.76%    | 36.52%    | 32.99%          | 34.76%      | 162              | 1021     |
| T2T-ViT         | 34.29%    | 38.17%    | 34.54%          | 34.28%      | 15.5             | 825.3    |
| ShuffleNet-V2   | 33.81%    | 33.90%    | 31.68%          | 33.81%      | 1.52             | 713      |
| AlexNet         | 31.90%    | 32.53%    | 29.32%          | 31.91%      | 217              | 712      |
| VGG11           | 31.43%    | 41.20%    | 29.97%          | 31.43%      | 491              | 864      |
| BotNet          | 30.48%    | 32.61%    | 30.06%          | 30.48%      | 72.2             | 894      |
| VGG13           | 20.95%    | 19.23%    | 18.37%          | 20.95%      | 492              | 957      |
| VGG16           | 9.05%     | 1.31%     | 2.10%           | 9.05%       | 512              | 990      |
| VGG19           | 4.76%     | 0.23%     | 0.44%           | 4.76%       | 532              | 1036     |

4.2.2. The Classification Performance of Each Model on Test Set
In this part, we calculate the performance indicators of the model on the test set in Table 6, including precision, recall, F1-score and accuracy. Meanwhile, we apply the confusion matrix of the CNNs and VTs models to assist analysis, as shown in Figure 4.

In the test set results, the accuracy ranking of each model remains basically unchanged. The accuracy rate of the Xception network validation set is still ranked first, at 40.32%, and is 3.81% higher than the second. Meanwhile, the average accuracy, average recall rate and average F1-score of the Xception network also remain in the first place, at 40.33%, 49.71% and 41.41%. Excluding the non-convergent VGG16 and VGG19 networks, the accuracy of the VGG13 verification set is still ranked at the bottom, at 15.55%. However, the ranking of the T2T-ViT network on the validation set accuracy rate changes dramatically. The accuracy rate of the T2T-ViT network is 34.28%, and the ranking rose from 14th to 5th. In addition, the average accuracy, average recall and average F1-score of the T2T-ViT network are 34.29%, 38.17% and 34.54%. Judging from the time consumed for the models, the ViT model consumes the least time at 3.77s. On the other hand, the Densenet169 model consumes the most time at 11.13s.

Figure 4 depicts the confusion matrix generated by part of the test data set to more intuitively show the classification performance of the CNNs and VTs models on small data.
Figure 4: Confusion matrix comparison of different network models on test set, Xception, Resnet34, Googlenet, T2T-ViT, BotNet, VGG13, ResNet18, ViT and VGG11. (In the confusion matrix, 01 stands for Actinophrys, 02 stands for Arcella, 03 stands for Aspidisca, 04 stands for Codosiga, 05 stands for Colpoda, 06 stands for Epistylis, 07 stands for Euglypha, 08 stands for Paramecium, 09 stands for Rotifera, 10 stands for Vorticella, 11 stands for Noctiluca, 12 stands for Ceratium, 13 is Stentor, 14 is Siprostomum, 15 is K. Quadrala, 16 is Euglena, 17 is Gymnodinium, 18 is Gymlyano, 19 is Phacus, 20 is Stylongchia, and 21 is Synchaeta.)
sets. In Table 6, Xception is the network with the best overall performance, and VGG13 is the network with the worst overall performance. In the confusion matrix of the Xception network, 127 images out of 315 images are classified into the correct category. In addition, the 11th type of environmental microbial classification performs best, with 12 images being correctly classified and 3 images misclassifying into other categories. Meanwhile, the Xception network performs the worst in the 13th category of environmental microbial classification results. 3 images are correctly classified and 14 images are misclassified into other categories. For the VGG13 network, 49 of the 315 images are classified into the correct category. Among them, the 16th environmental microbial classification performs best. 6 images are correctly classified, and 9 images are mistakenly classified into other categories. Comparing the CNNs and VTs models, they all perform well in the 11th environmental microbial classification and poorly perform in the 13th environmental microbial classification. For example, the ViT model correctly classifies 9 images and 0 images in the classification of the 11th and 13th class environmental microorganisms, respectively.

4.2.3. After Data Augmentation, the Classification Performance of Each Model on the Validation Set

In this part, we augment the data set and the performance indicators of the models on set are calculated in Table 7, including precision, recall, F1-score and accuracy. In addition, we compare the accuracy changes before and after data augmentation, as shown in Figure 5.

After data augmentation, the time required for model training also increases significantly. ViT model training requires the least time, which is 902.27s. Although the training set is augmented to six times, the training time of the ViT model is only increased by 187.27s compared with the 715s. The classification accuracy of the Xception network ranks first at 52.62%. The T2T-ViT network has the lowest classification rate of 35.56%.

After data augmentation, the classification performance of each model is improved. Figure 5 shows the changes in the accuracy of each model after data augmentation. The validation set accuracy of the VGG16 network is increased the most, at 28.41%. This is because the VGG16 network can converge on the augmentation data set. In addition, the validation set accuracy of VGG13 and VGG11 are improved significantly, increasing by 21.59% and 16.67%, respectively. The accuracy of the VGG11 validation set rose from 17th to 3th. The accuracy of the VGG13 validation set rose from 19th to 11th. After data augmentation, the validation set accuracy of T2T-ViT, Densenet169 and ViT are not improved significantly, increasing by 1.28%, 1.19% and 1.91%.

From a specific series of models, the performance of VGG series models is improved significantly after data augmentation. The performance improvement of the Densenet series models is not apparent. The accuracy of the Densnet121 and the Densenet169 validation sets are increased by 1.43% and 1.19%, respectively. Meanwhile, the performance improvement of the VT series models is not apparent. The classification accuracy of the T2T-ViT validation set is increased by 1.28%, ViT5 is increased by 1.91%, and Diet is increased by 4.28%. In the ResNet series models, ResNet18, ResNet34 and ResNet50 are increased by 3.49%, 3.25% and 3.65%, and the improvement is not obvious. However, the classification accuracy of the ResNet101 validation set is increased by 8.65%, which is obvious.

4.2.4. After Data Augmentation, the Classification Performance of Each Model on the Test Set

After data augmentation, the performance of each model on test set is shown in Table 8. In Table 8, the Xception network has the highest accuracy of 45.71%. Meanwhile, the Xception network has an excellent recall index of 50.43%. Excluding the non-convergent VGG19, the VGG16 model has the worst performance, with an accuracy of 24.76%. The ViT model consumes the least time, which is 3.72s. The Densenet169 model consumes the most time, which is 11.04s.

Figure 6 shows the change in accuracy on the test set before and after the augmentation on the data set. In Figure 6, we can see that the accuracy of each deep learning model on test set is generally increased. Among them, the accuracy of the VGGs series models is improved the most. VGG11 is increased by 9.25%, VGG13 is increased by 21.28%, and VGG16 is increased by 16.51%. However, the accuracy of the VTs series model test set is not significantly improved. The accuracy of some model test sets even drops. After data augmentation, the accuracy of the Diet network validation set is not changed. The accuracy of the T2T-ViT network is dropped by 3.80%. The accuracy of the ViT model is dropped by 3.17%. However, the accuracy of BotNet, a mixed model of CNN and VT, is improved significantly, reaching 11.12%.

4.2.5. In Imbalanced Training, after Data Augmentation, the Classification Performance of Each Model on the Validation Set

In this section, we re-split and combine the data into new data. The specific splitting method is shown in 3.1.3. 21 pieces of data are obtained after splitting and combining. The deep learning model can calculate an AP after training each piece of data. Table 9 shows the AP and mAP of each model validation set. We select the classical VGG16, ResNet50 and Inception-V3 networks for experiments. Furthermore, a relatively novel ViT model is also selected. In addition, the Xception network, which has always performed well above, is selected for experiments. Since the VGG16 network cannot converge at a learning rate of 0.0001, this part of the experiment adjusts the learning rate of the VGG16 network to 0.00001.

It can be seen in Table 9 that the mAP of the Xception network is the highest, which is 56.61%. The Xception network has the highest AP on the 10th data, and the AP is 82.97%. The Xception network has the worst AP on the 3rd data, with an AP of 29.72%. As shown in Figure 7, the con-
Table 6: Comparison of classification results of different deep learning models in the test set. P denotes Precision, and R represents Recall. (Sort in descending order of classification accuracy.)

| Model          | Avg. P(%) | Avg. R(%) | Avg. F1_score(%) | Accuracy(%) | Params Size (MB) | Time (s) |
|----------------|-----------|-----------|------------------|-------------|------------------|----------|
| Xception       | 40.33%    | 49.71%    | 41.41%           | 40.32%      | 79.8             | 5.63     |
| ResNet34       | 36.51%    | 42.92%    | 36.22%           | 36.51%      | 81.3             | 6.14     |
| Googlenet      | 35.23%    | 37.70%    | 34.21%           | 35.24%      | 21.6             | 5.97     |
| Mobilenet-V2   | 34.29%    | 38.21%    | 33.07%           | 34.29%      | 8.82             | 5.13     |
| T2T-ViT        | 34.29%    | 38.17%    | 34.54%           | 34.28%      | 15.5             | 4.44     |
| Densenet169    | 33.65%    | 36.55%    | 33.79%           | 33.65%      | 48.7             | 11.13    |
| InceptionResnetV1 | 33.64% | 35.71%    | 32.90%           | 33.65%      | 30.9             | 5.11     |
| ResNet18       | 33.33%    | 38.10%    | 32.36%           | 33.33%      | 42.7             | 4.92     |
| ResNet50       | 33.33%    | 40.98%    | 33.44%           | 33.33%      | 90.1             | 6.23     |
| Densenet121    | 33.01%    | 39.20%    | 33.79%           | 33.02%      | 27.1             | 9.27     |
| Deit           | 32.39%    | 34.40%    | 32.74%           | 32.38%      | 21.1             | 5.43     |
| ViT            | 31.75%    | 33.84%    | 31.47%           | 31.74%      | 31.2             | 3.77     |
| Inception-V3   | 31.11%    | 34.84%    | 31.32%           | 31.11%      | 83.5             | 7.49     |
| ResNet101      | 27.94%    | 34.59%    | 28.31%           | 27.94%      | 162              | 8.83     |
| VGG11          | 27.61%    | 29.64%    | 26.00%           | 27.62%      | 491              | 4.98     |
| ShuffleNet-V2  | 27.30%    | 25.02%    | 24.98%           | 27.30%      | 1.52             | 5.42     |
| BotNet         | 25.40%    | 29.65%    | 26.04%           | 25.39%      | 72.2             | 6.5      |
| AlexNet        | 24.44%    | 23.98%    | 22.65%           | 24.44%      | 217              | 3.9      |
| VGG13          | 15.55%    | 15.18%    | 14.38%           | 15.55%      | 492              | 5.28     |
| VGG16          | 8.26%     | 1.28%     | 1.93%            | 8.25%       | 512              | 5.79     |
| VGG19          | 4.76%     | 0.23%     | 0.44%            | 4.76%       | 532              | 6.42     |

The mAp of the VGG16 network is the lowest at 34.69%. The VGG16 network performs best on the 10th data AP, with an AP of 76.12%. The VGG16 network performs the worst on the 21st data AP, with an AP of 5.47%. Despite adjusting the learning rate, the VGG16 network still fails to converge on the 3rd, 8th, 13th, 15th, and 21st data.

The mAp of the ViT network and the VGG16 network are relatively close. The ViT network performs best on the 6th data AP, with an AP of 76.17%. Among the 60 positive samples, 35 are classified correctly, and 25 are classified as negative samples. The ViT network performs the worst on the 15th data AP, with an AP of 6.74%. Among the 60 positive samples, 0 are classified correctly and 60 are classified as negative samples.

In addition, Resnet50 performs the best on 7 data APs and the worst on the 18th data AP. The Inception-V3 network performs best on 10 data AP and the worst on the 16th data AP.

4.3. Discussion

This experiment studies the classification performance of 21 deep learning models on small data sets. The com-
Table 7
Comparison of classification results of different deep learning models in the validation set. P denotes Precision, and R represents Recall. The training set is augmented. (Sort in descending order of classification accuracy.)

| Model           | Avg. P(%) | Avg. R(%) | Avg. F1_score(%) | Accuracy(%) | Params Size (MB) | Time (s) |
|-----------------|-----------|-----------|------------------|-------------|-----------------|----------|
| Xception        | 52.62%    | 52.05%    | 50.63%           | 52.62%      | 79.80           | 2636.08  |
| MobileNet-V2    | 49.67%    | 51.91%    | 48.82%           | 49.68%      | 8.82            | 1237.49  |
| VGG11           | 48.10%    | 52.40%    | 48.44%           | 48.10%      | 491.00          | 1745.73  |
| ResNet34        | 46.10%    | 47.85%    | 46.68%           | 46.11%      | 81.30           | 1335.87  |
| ResNet18        | 44.44%    | 51.87%    | 43.03%           | 44.44%      | 42.70           | 1090.39  |
| Googlenet       | 44.29%    | 47.16%    | 43.50%           | 44.29%      | 21.60           | 1257.33  |
| Inception-V3    | 43.97%    | 50.78%    | 43.41%           | 43.97%      | 83.50           | 2004.08  |
| AlexNet         | 43.58%    | 45.02%    | 43.05%           | 43.57%      | 217.00          | 951.27   |
| ResNet101       | 43.41%    | 46.08%    | 43.33%           | 43.41%      | 162.00          | 2786.95  |
| Deit            | 43.34%    | 46.62%    | 43.29%           | 43.33%      | 21.10           | 1306.99  |
| VGG13           | 42.54%    | 41.38%    | 41.21%           | 42.54%      | 492.00          | 2307.04  |
| Densenet121     | 42.38%    | 46.91%    | 42.39%           | 42.38%      | 27.10           | 2169.11  |
| ResNet50        | 42.22%    | 47.76%    | 42.10%           | 42.22%      | 90.10           | 1968.28  |
| Densenet169     | 42.14%    | 48.04%    | 42.79%           | 42.14%      | 48.70           | 2526.61  |
| InceptionResnetV1 | 41.66% | 47.83%    | 41.68%           | 41.67%      | 30.90           | 1451.76  |
| ViT             | 39.05%    | 43.50%    | 38.52%           | 39.05%      | 31.20           | 902.27   |
| ShuffleNet-V2   | 37.62%    | 39.37%    | 36.84%           | 37.62%      | 1.52            | 965.81   |
| VGG16           | 37.47%    | 38.21%    | 36.80%           | 37.46%      | 512.00          | 2589.15  |
| BotNet          | 36.59%    | 36.38%    | 35.59%           | 36.59%      | 72.20           | 2000.17  |
| T2T-ViT         | 35.56%    | 38.43%    | 36.19%           | 35.56%      | 15.50           | 1385.62  |
| VGG19           | 4.76%     | 0.23%     | 0.44%            | 4.76%       | 532.00          | 1022.57  |

Comparison results are obtained according to the evaluation indicators, as shown in Tables 5, 6, 7 and 8. Meanwhile, some models are selected for imbalanced experiments to further investigate the performance of the models. The results are shown in Table 9.

The performance of the VGG network gradually decreases as the number of network layers increases. Especially the VGG16 and VGG19 networks cannot converge on the EMDS5+ data set. This may be because the data set is too small, and the gradient disappears in the process of a continuous deepening of the network layer, which affects the convergence.

The Xception network is performed well in two experiments that directly performed the classification task and performed the classification task after expanding the data set. As a result, its precision, recall, F1-score and accuracy all are maintained in the first place. Meanwhile, the mAP index in the imbalanced training task is also much higher than other models. In summary, the Xception network has the best small data set classification performance in this article.

The training time of the ViT network on the EMDS5+ database is very short, but it does not make a significant difference with other models. After the data augmentation of EMDS5+, the ViT network has apparent advantages in the time of training the model, and the time consumption is much less than other models. We can speculate that the ViT model may further expand its advantage when trained on more training data.

After data augmentation, the accuracy of each model is
Figure 5: In the validation set of different deep learning models, the accuracy difference between data augmentation and before data augmentation, Xception, ResNet34, Googlenet, ResNet18, Densenet121, Densenet161, Inception-V3, Mobilenet-V2, Deit, InceptionResnetV1, ResNet50, vit-5, ResNet101, T2T-ViT, ShuffleNet-V2, AlexNet, VGG11, BotNet, VGG13, VGG16, VGG19. Significantly improved. However, the accuracy of the VTs series model Diet, T2T-ViT and ViT are not changed, and some even declined, as shown in Figure 6. This may be because our data augmentation method only makes geometric changes to the data. The geometric transformation is only changed the spatial position of the feature. However, the VTs series models use attention to capture the global context information, and it pays more attention to global information. Operations such as rotation and mirroring have little effect on global information, and it is impossible to learn more global features. This makes the performance of the VTs series model unable to improve after data augmentation significantly. However, the performance of BotNet, a hybrid model of CNN and VT, is significantly improved after data augmentation. This is because the BotNet network only replaced three Bottlenecks with the Bottleneck with MHSA. The BotNet network is essentially more inclined to the feature extraction method of CNN. This further proves that the VT models pay more attention to the capture of global information.

5. Conclusion and Future Work

Classification of small data sets is a challenging problem in computer vision, which has attracted the attention of many researchers. Due to the development of deep learning, image classification of small data sets is developing faster and faster. This article uses 17 CNN models, 3 VT models, and a hybrid CNN and VT model to test model performance. We do different experiments, including directly performing classification tasks on each model, performing classification tasks after data augmentation, and performing imbalanced training tasks on some representative models. The experimental results prove that the Xception network is the model with the best classification performance in this article. Xception network is suitable for occasions where small data sets have high requirements for classification performance. The ViT model is the network with the least training time in this article. Therefore, the ViT model is suitable for large-scale data training. The ShuffleNet-V2 network is the network with the smallest amount of parameters in this article, but its classification performance is average. Therefore, ShuffleNet-V2 is suitable for occasions where classification performance is not high but storage space is limited.

Although CNNs and VTs achieve good results in image classification tasks, there is still much room for development in the classification of small data sets. In future work, on the one hand, we can improve network performance by studying new data augmentation methods. On the other hand, we can combine the CNN network that performs well in this paper with Transformer, which may produce better performance.

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Table 8
Comparison of classification results of different deep learning models in the test set. P denotes Precision, and R represents Recall. The training set is augmented. (Sort in descending order of classification accuracy.)

| Model         | Avg. P(%) | Avg. R(%) | Avg. F1_score(%) | Accuracy(%) | Params Size (MB) | Time (s) |
|---------------|-----------|-----------|------------------|-------------|------------------|----------|
| Xception      | 45.71%    | 50.43%    | 46.15%           | 45.71%      | 79.8             | 5.49     |
| Mobilenet-V2  | 42.54%    | 47.56%    | 43.07%           | 42.54%      | 8.22             | 5.04     |
| ResNet18      | 39.05%    | 44.82%    | 39.22%           | 39.05%      | 42.7             | 4.90     |
| Densenet121   | 38.73%    | 40.28%    | 38.20%           | 38.73%      | 27.1             | 8.98     |
| ResNet34      | 38.73%    | 42.25%    | 37.84%           | 38.73%      | 81.3             | 6.07     |
| ResNet50      | 38.10%    | 41.56%    | 36.97%           | 38.10%      | 90.1             | 6.20     |
| Inception-V3  | 37.78%    | 44.32%    | 38.00%           | 37.78%      | 83.5             | 7.47     |
| Googlenet     | 37.46%    | 43.55%    | 37.92%           | 37.46%      | 21.6             | 6.03     |
| Densenet169   | 37.14%    | 41.51%    | 37.37%           | 37.14%      | 48.7             | 11.04    |
| VGG11         | 37.14%    | 38.81%    | 36.70%           | 37.14%      | 491              | 4.96     |
| InceptionResnetV1 | 36.82% | 41.47%    | 36.75%           | 36.83%      | 30.9             | 5.11     |
| VGG13         | 36.82%    | 38.46%    | 36.25%           | 36.83%      | 492              | 5.28     |
| BotNet        | 36.50%    | 39.12%    | 36.35%           | 36.51%      | 72.2             | 6.44     |
| ResNet101     | 35.23%    | 38.01%    | 35.44%           | 35.24%      | 162              | 8.85     |
| AlexNet       | 34.92%    | 39.10%    | 34.97%           | 34.92%      | 217              | 5.25     |
| Deit          | 32.39%    | 34.40%    | 32.74%           | 32.38%      | 21.1             | 4.41     |
| T2T-ViT       | 30.48%    | 35.88%    | 30.85%           | 30.48%      | 15.50            | 5.41     |
| ShuffleNet-V2 | 28.57%    | 35.64%    | 29.41%           | 28.57%      | 1.52             | 5.42     |
| ViT           | 28.58%    | 29.63%    | 27.86%           | 28.57%      | 31.2             | 3.72     |
| VGG16         | 24.77%    | 25.53%    | 24.11%           | 24.76%      | 512              | 5.79     |
| VGG19         | 4.76%     | 0.23%     | 0.44%            | 4.76%       | 532              | 6.36     |

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Figure 6: In the test set of different deep learning models, the accuracy difference between data augmentation and before data augmentation. Xception, ResNet34, Googlenet, ResNet18, Densenet121, Densenet161, Inception-V3, Mobilenet-V2, Deit, InceptionResnetV1, ResNet50, vit-5, ResNet101, T2T-ViT, ShuffleNet-V2, AlexNet, VGG11, BotNet, VGG13, VGG16, VGG19.

Table 9
AP and MAP of different deep learning models in imbalanced training. (In [%].)

| model   | sample 1 | sample 2 | sample 3 | sample 4 | sample 5 | sample 6 | sample 7 | sample 8 | sample 9 | sample 10 | sample 11 | mAP       |
|---------|----------|----------|----------|----------|----------|----------|----------|----------|----------|------------|------------|----------|
| ViT     | 30.77%   | 44.99%   | 18.43%   | 48.51%   | 74.47%   | 76.17%   | 50.98%   | 15.32%   | 31.12%   | 60.74%     | 54.02%     | 34.93%   |
| Xception| 37.66%   | 51.16%   | 29.72%   | 68.32%   | 73.66%   | 67.96%   | 79.19%   | 65.41%   | 55.84%   | 82.97%     | 55.91%     | 56.61%   |
| VGG16   | 48.38%   | 41.43%   | 9.63%    | 51.05%   | 52.61%   | 42.23%   | 76.92%   | 5.97%    | 27.57%   | 76.12%     | 34.77%     | 31.18%   |
| ResNet50| 30.58%   | 45.96%   | 14.24%   | 68.19%   | 66.15%   | 43.10%   | 71.24%   | 46.51%   | 31.87%   | 62.19%     | 36.79%     | 44.39%   |
| Inception-V3 | 37.75% | 36.79% | 33.41% | 56.37% | 55.77% | 43.51% | 59.52% | 41.18% | 38.40% | 75.03% | 69.26% |

| model   | sample 12 | sample 13 | sample 14 | sample 15 | sample 16 | sample 17 | sample 18 | sample 19 | sample 20 | sample 21 | mAP       |
|---------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|
| ViT     | 15.24%     | 17.84%     | 25.46%     | 6.74%      | 13.95%     | 48.61%     | 7.26%      | 60.33%     | 23.07%     | 9.53%      | 34.93%     |
| Xception| 54.16%     | 52.28%     | 65.06%     | 46.36%     | 30.61%     | 60.41%     | 31.21%     | 61.14%     | 45.50%     | 74.36%     | 56.61%     |
| VGG16   | 24.06%     | 16.22%     | 63.90%     | 5.80%      | 10.49%     | 33.87%     | 24.77%     | 44.00%     | 33.14%     | 5.47%      | 34.69%     |
| ResNet50| 15.59%     | 42.12%     | 68.57%     | 24.94%     | 17.49%     | 47.52%     | 6.64%      | 49.04%     | 16.73%     | 56.10%     | 41.03%     |
| Inception-V3 | 15.09% | 49.09% | 64.11% | 37.91% | 15.00% | 43.98% | 15.84% | 54.40% | 10.78% | 60.38% | 43.50% |

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Figure 7: The confusion matrices a, b, c, d, e, f, g and h are drawn based on the Xception network validation set results. Likewise, the confusion matrices i, j, k, l, m, n, o and p are drawn based on the ViT network validation set results. a, b, c, d, e, f, g and h are generated from data sets 1, 3, 5, 7, 10, 11, 13, 15. i, j, k, l, m, n, o and p are generated from data sets 1, 3, 6, 7, 9, 11, 13, 15. (Data set segmentation is shown in 3.1.3 Experiment B)

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