

Research on Drilling Fluid Flocculation Identification Method Based on Improved Resnet50 Model

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Abstract: Aiming at the problems of low accuracy and high labor cost of traditional methods for identifying the flocculation state of drilling fluid waste, this paper proposes a method for identifying the flocculation state of drilling fluid waste based on the improved ResNet50 model. By building a flocculation acquisition system to obtain image data under different flocculation states and carrying out data enhancement, the original ResNet50 model is used as the base model, based on which the GAM global attention mechanism is introduced to enhance the ability to extract useful information in the flocculation image, and combined with the dimensional dynamic convolution of the ODConv to strengthen the network's generalization ability and adaptability, to achieve intelligent identification of flocculation state of the drilling fluid waste liquid. Experiments are conducted on 6935 flocculated image datasets, and the results show that the H-ResNet50 model designed in this paper achieves classification accuracies of 99.57% and 99.16% on the training and test sets, respectively, which are higher than the classification accuracies of the original ResNet50 model and other common neural network models. Overall, H-ResNet50 can efficiently and correctly identify the flocculation status of drilling fluid waste liquid, which provides the possibility of moving towards intelligent flocculation treatment of drilling fluid waste liquid.

Keywords: Image classification; flocculation identification; deep learning; attention mechanism; multidimensional dynamic convolution.

1. Introduction

Oil occupies an extremely critical energy position in our country and is regarded as the "black blood" of development and the pillar of economic operation. At present, China's petroleum exploitation industry is entering a critical period of technological innovation and strategic transformation, showing a new trend of diversified and high-quality development. Drilling fluid plays a vital role in the oil production phase, it is the lifeline to ensure the smooth drilling process^{1,2}. Drilling fluid is a complex mixture, mainly composed of water or oil-based liquid, and various additives (such as clay, chemical treatment agents, lubricants, etc.)³⁻⁵.

With the advancement of technology, modern drilling fluid technology pays more attention to environmental protection and efficiency, such as using closed-loop systems to recycle drilling fluid to reduce environmental pollution⁶ and the development of new environmentally friendly additives to reduce the ecological impact⁷. The core of the harmless treatment of waste drilling fluid is to minimize the negative impact of drilling activities on the environment and ensure the rational use of resources and the harmonious coexistence of an ecological environment. The solid-liquid separation method is based on the fact that there is a certain solid phase in the waste drilling fluid, and a complex flocculation reaction occurs by adding flocculants to reduce its leachability and prevent the migration and expansion of harmful components. After filtration by the filter press, the cured product can be used as a building material, on the other hand, the filtrate can be used for recycling, which is considered to be a practical and environmentally friendly means of drilling fluid treatment^{8,9}. In this process, the flocculation effect of waste drilling fluid will directly affect the subsequent treatment effect. Therefore, how to efficiently and accurately identify the flocculation effect of waste drilling fluid and adjust the

dosage of flocculant in real-time is the most pending problem.

At present, the flocculation identification of waste drilling fluid mainly relies on manual experience to determine the degree of flocculation, which is highly subjective, prone to misjudgment, and high labor cost. In other flocculation identification, such as water purification flocculation, coal slime water flocculation, and other flocculation fields, there are more methods¹⁰⁻¹⁵. Eshel, G. For particle size distribution analysis by laser diffraction, this method provides a continuous PSD curve, allows detailed data analysis, and can be flexibly applied to classification systems with different floc sizes¹⁶. However, the waste fluid of drilling fluid has high turbidity and poor light transmittance, so this method is not suitable for the identification of waste drilling fluid flocculation. Furukawa, Yoko investigated the effect of organic matter (OM) on the flocculation of colloidal montmorillonite through laboratory experiments and computational flocculation modeling. Based on the Smoluchowski coagulation model and population balance equation (PBE), the model established two key flocculation parameters: adhesion efficiency and decomposition parameters. Interactive optimization of the model results¹⁷. However, the generalization of this method is poor and it lacks the ability of independent learning. With the continuous development of technology, more and more researchers calculate the characteristics of flocs by taking images related to flocculation. Pengfei Ren used an in situ identification system to analyze the particle size, boundary fractal dimension, and eccentricity ratio of the flocs and concluded that excess flocculants would form flocs with more chain and branched structures, limiting further growth of the flocs in the subsequent flocculation¹⁸. Benson T designed a low-cost particle size recognition system, the In Situ Particle Imaging Device (InSiPID), which combines dual CCD cameras and fully automated digital image acquisition and processing

algorithms to efficiently identify particle size¹⁹.

In summary, there are many methods of flocculation identification at present, and each has its advantages and disadvantages. Image recognition technology based on computer vision has further improved the speed and accuracy of recognition, and the emergence of deep learning technology has provided more ideas for flocculation recognition²⁰⁻²³. Based on the ResNet-50 network, the following improvements were made in this paper according to the characteristics of the flocculation image of water-based drilling fluid waste. First, the ODConv convolutional module was introduced while the last set of residual structures was reduced. Secondly, GAM attention modules are inserted between residual blocks to efficiently aggregate flocculation features and improve reconstruction performance. The improved H-ResNet-50 network model realizes a more accurate and efficient identification of the flocculation state of the three kinds of drilling fluid waste, which provides a basis for the accurate addition of subsequent flocculants.

2. Construction and Pre-processing of Flocculation Image Data

2.1. Flocculation Image Capture

The image acquisition equipment includes a beaker, an industrial camera, a camera holder, a transmission network cable, a light source, an overhead motorized stirrer, and a computer, as shown in Figure 1. The industrial camera is a Basler brand camera with model number a2A4504-27g5cBAS, which has a resolution of 20.2 MP and a frame rate of 27 fps and can record the images of the different stages of the flocculation reaction. The camera is connected to the computer via a 100Mbit/s Fast Ethernet interface and operates at a voltage of 12-24V. Based on the indoor experimental situation and the actual application conditions, the distance between the beaker and the camera was determined to be 400mm, at which time the camera took the best picture. The light source is JS-DBL209-265, with a size of 800mm×117mm×38mm, power of 30w, and protection level of IP66, and the rotational speed of the overhead electric stirrer is determined to be 100r/min according to the actual experimental situation, which can not only stir the drilling fluid waste fluid well but also ensure that the flocs will not be dispersed due to the fast rotational speed.

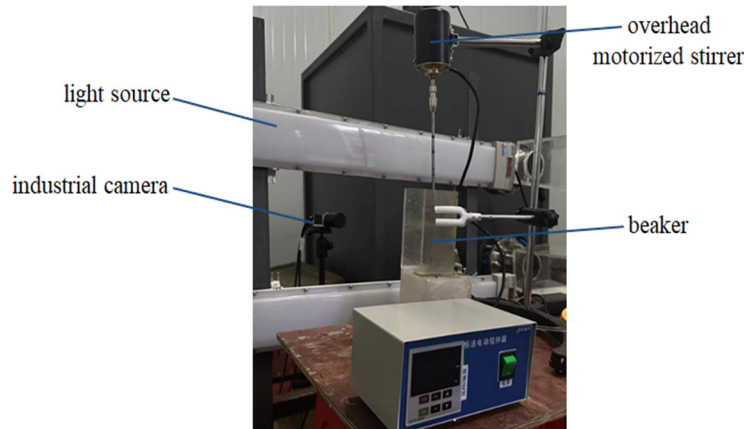


Figure 1. Flocculation image acquisition device

The experimental samples were obtained from the drilling fluid waste from different formations under the QHD33-1 block returned from the drilling site. The drilling fluid waste was stirred well and then 400 ml of the sample was added into a beaker, and the flocculant was extracted with a syringe and slowly injected into the beaker, while the overhead electric stirrer was turned on for stirring. When the flocculation treatment of drilling fluid waste liquids begins, open the image acquisition equipment and photograph the beaker by calling the software development kit accompanying the camera device. After several adjustments to the shooting time to get every 1-second shooting can ensure that the amount of mixed fluid image data is sufficient and there is a certain degree of variability between the individual images, repeat this process until the end of the flocculation process, and all the flocculation images will be captured through the Gigabit network cable transmission to the computer equipment. When the flocculation of the drilling fluid waste is complete, the treated fluid is poured out for subsequent processing or storage.

Inside the image data acquired by this system, there will be

problems such as uneven illumination and external noise, which should be cleaned up first to avoid these invalid data affecting the subsequent experiments. After screening, the system collected a total of 1700 original sample images under different flocculation stages and classified the collected flocculation images into three categories according to the degree of flocculation reaction. The flocculation images of different categories of drilling fluid waste liquids are shown in Figure 2. Level 0 (first stage) images have fewer flocs or particles and the color of the waste liquid is grey. 635 images were taken in this category. The total number of images in this category is 635. 550 images of level 1 (middle stage) were found to have some flocs or particles, and the color of the waste fluid was further deepened. 515 images of level 2 (late stage) were found to have a large number of flocs or particles, and the color of the waste fluid was changed to yellowish-brown, total number of images in this category is 515. Finally, the flocculation images of the three categories of drilling fluid were placed in different folders (representing different category labels) for subsequent flocculation state category classification experiments.

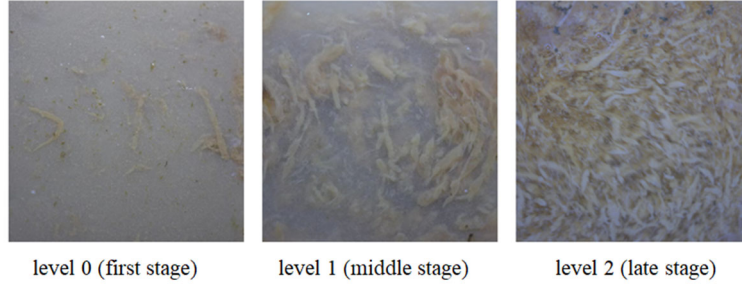


Figure 2. Images of drilling fluid waste liquid under different flocculation states

2.2. Image pre-processing

To ensure that the model can work stably and accurately in a variety of real scenarios, improve the adaptability and generalization ability to flocculation image changes, and reduce the risk of overfitting. In this paper, the original flocculation image dataset used for model training is preprocessed, and the data is enhanced by brightness adjustment, random rotation, and HSV degree enhancement,

as shown in Fig 3. The 1700 original sample images are expanded to 6935, of which the level 0 (pre) images are expanded to 2383, level 1 (mid) images are expanded to 2072, and level 2 (post) images are expanded to 2480. Final. The preprocessed images are divided into training sets and test sets in the ratio of 8:2, and the number of images in each category is shown in Table 1. Finally, data support is provided for subsequent experiments.

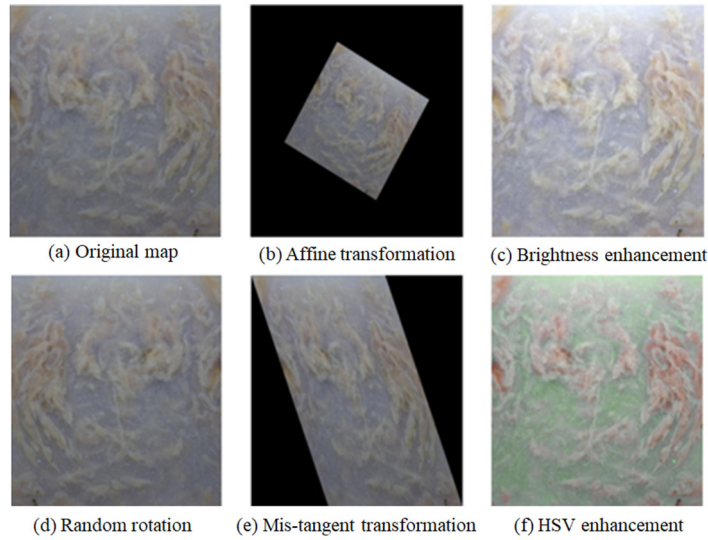


Figure 3. Flocculation image data enhancement

Table 1. Quantity distribution of flocculation image datasets

Flocculation State Class	Training Set	Test Set	Total
Level0(first stage)	1906	477	2383
Level1(middle stage)	1659	413	2072
Level2(late stage)	1984	496	2480
Total	5549	1386	6935

3. Flocculation Image Recognition Model

3.1. ResNet model

ResNet (Residual Neural Network, Residual Neural Network) is a deep learning network model that was proposed in 2015 by Kaiming He et al. researchers from Microsoft Research Asia²⁴. The model was originally designed to address two key problems in deep neural network training: the gradient vanishing/exploding problem and the network degradation problem. The core innovation of ResNet is its unique residual block structure. The two main residual block structures are the Basic Block and the Bottleneck Block. The Basic Block is a simpler structure and is commonly used in

shallow ResNet models such as ResNet18 and ResNet34, while the Bottleneck Block is used in deeper ResNet models such as ResNet50, ResNet101, and ResNet152 to reduce the amount of computation and number of parameters.

Compared to lower-layer networks such as ResNet34, ResNet50 provides more network depth and richer feature expressiveness, which is necessary for recognizing complex details and variations in flocculation images. Compared with the deeper ResNet networks, although the latter may have a slight advantage in some extremely fine tasks, ResNet50, with its less consumption of computational resources and shorter training time, is more suitable for most practical application requirements, especially in scenarios that do not require extreme performance enhancement but focus more on

efficiency and resource management. Therefore, ResNet50 becomes the benchmark network for drilling fluid waste floc image recognition in this paper under its moderate depth, excellent performance, and controllable computational cost.

The Conv Block and Identity Block are two basic building blocks, a direct connection, where the input signal is passed directly to the output without transformation, and a transformation path with several convolutional layers and activation functions. The outputs of the two paths are summed up at the end of the block to form a so-called "residual connection". This design not only ensures the optimization feasibility of the deep network but also makes the network learn the residual information from input to output, which reduces the learning difficulty. In ResNet50, these blocks are flexibly arranged according to the need for network depth. The Identity Block is usually stacked consecutively after the Conv Block to increase the depth of the network without changing the size of the feature map, while the Conv Block is inserted when necessary to adapt to the change of the feature map size or to increase the expressive power of the network. Figure 4 shows the Bottleneck Block module structure.

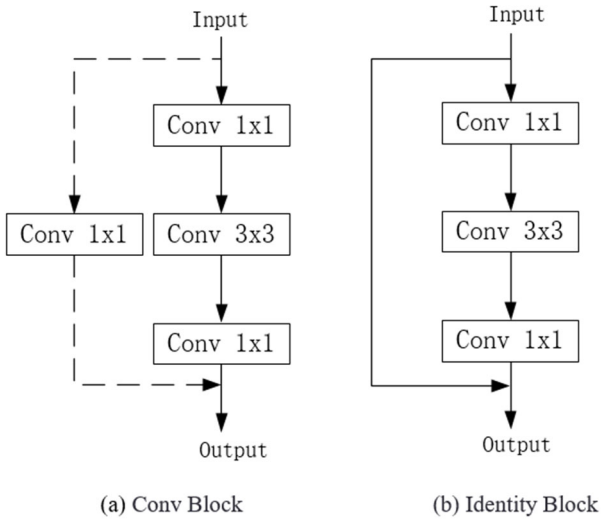


Figure 4. Bottleneck Block module structure

In terms of the overall structure, ResNet50 starts with a 7x7 convolutional layer and a maximum pooling layer to initially extract and narrow down the input image features. Subsequently, the network is divided into four progressively deeper layers (Stages), each consisting of multiple residual blocks; the residual blocks of the initial layers contain downsampling operations, while the remaining layers keep the dimensionality constant mainly through constant blocks. Specifically, ResNet50 employs Bottleneck Block residual blocks, i.e., a series of 1x1, 3x3, and 1x1 convolutional layers within each block, aiming to efficiently integrate and extract features while controlling model complexity. After layers of deepening, the feature maps are converted to fixed-length vectors by global average pooling, then fed into the fully connected layers to complete the classification task, and finally output the probabilities of each category via the softmax function. This unique residual learning framework effectively alleviates the gradient vanishing and degradation problems in deep network training. The classical ResNet50 model network structure is shown in Figure 5.

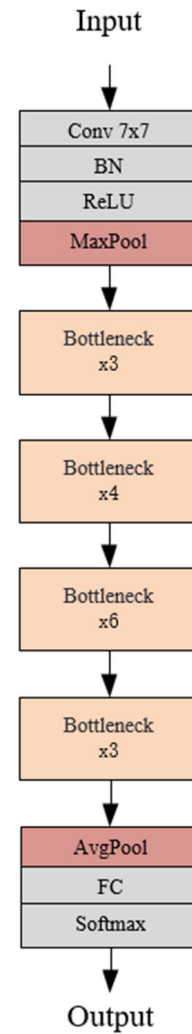


Figure 5. Network structure of classic ResNet50 model

3.2. Improved ResNet model

3.2.1. GAM Global Attention Mechanism

Due to the complexity of drilling fluid waste floc images, the recognition model needs to accurately identify valid information such as flocs or particulate matter from images containing a large amount of interfering information, while the attention mechanism allows the network to automatically focus on the most relevant parts or features of the image, ignoring background noise and other unimportant information. This is particularly important for the recognition of the fine structure and morphology of flocs, which may only account for a small portion of the entire image. Therefore adding an attention mechanism to the floc recognition network can enhance its ability to capture subtle features in drilling fluid waste flocs and improve the accuracy and robustness of the recognition.

In this paper, we chose to add the GAM global attention mechanism to the original ResNet50 model to improve the model's feature extraction capability for drilling fluid waste floc images²⁵. GAM usually contains two key components: channel attention(CA) and spatial attention (SA). Unlike earlier attention mechanisms such as SENet which focuses only on the allocation of attention in the channel dimension²⁶. CBAM combines channel and spatial attention but still has room for improvement²⁷. GAM optimally integrates these two dimensions for more efficient feature representation. Figure 6 shows the structure of the global attention mechanism.

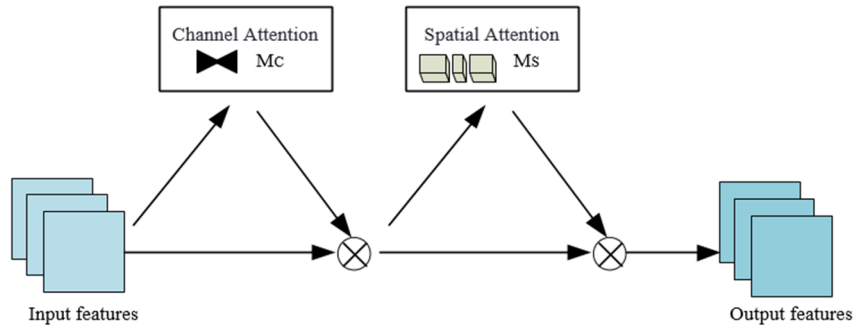


Figure 6. Global attention mechanism structure

(1) Channel Attention Submodule

The channel attention submodule in GAM is designed to automatically assign weights to each channel of the input feature map through a series of operations to highlight useful features and suppress irrelevant information. It uses a three-dimensional arrangement to retain information in three dimensions. It then amplifies the cross-dimensional channel-space dependencies with a two-layer MLP (multilayer perceptron). The number of channels is compressed in layer 1

of the MLP perceptron with a compression ratio of size r to reduce the computational effort in the attention mechanism. Then in layer 2, the MLP perceptron restores the number of channels to the original number of channels, and finally generates the channel weight coefficients using the Sigmoid function, and multiplies the obtained channel weight coefficients with the input feature map to do the weighting process. The structure of the channel attention submodule is shown in Figure 7.

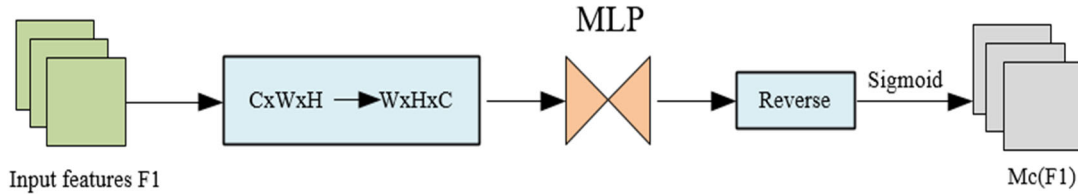


Figure 7. Structure of channel attention submodule

(2) Spatial attention submodule

GAM uses two 7×7 convolutional layers for spatial information fusion to focus the spatial information. At the same time, the module removes the pooling operation to maximize the retention of the useful information of the

feature maps and improve the utilization of the feature maps. In addition, to avoid a significant increase in the number of parameters, grouped convolution with channel blending is used when applied to ResNet50. The structure of the spatial attention submodule is shown in Figure 8.

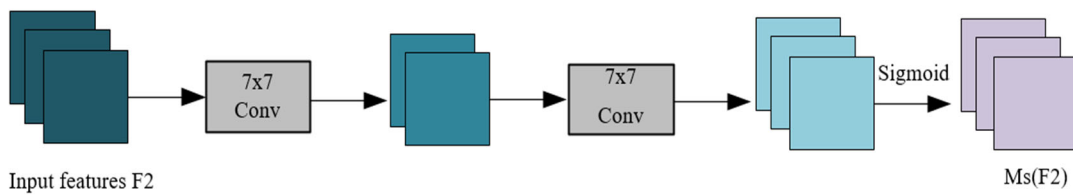


Figure 8. Spatial attention submodule structure

3.2.2. ODConv dimensional dynamic convolution

Dynamic Convolution is a deformation operation in convolution neural networks that adaptively generates convolution kernels at each forward pass based on the input data to better fit the features of the input data²⁸. In the ResNet50 network model, the parameters of the convolution operation are usually fixed and cannot be dynamically adapted to different input data. In contrast, dynamic convolution adaptively adjusts the convolution parameters according to different input data. Some of the waste floes in the drilling fluid waste flocculation image have high feature similarity with the impurities in the drilling fluid, which leads to low recognition accuracy of floes in the original ResNet50 network. The full-dimensional dynamic convolution (ODConv) module can obtain richer flocculation information in the feature extraction process of flocculation images, and improve the

feature extraction ability and sensitivity of the network to small targets, so this paper adds the full-dimensional dynamic convolution (ODConv) module to the original ResNet-50 network to improve the overall classification performance of the network.

ODConv uses a novel multidimensional attention mechanism at any convolution layer, which can simultaneously learn supplementary attention for the convolution kernel along four dimensions: its space size, the number of input channels, the number of output channels, and the number of convolution cores. These four types of attention are calculated by the corresponding multi-head attention module, and complement each other, further improving the feature extraction ability of CNN. The structure diagram of ODConv is shown in Figure 9. Since each convolution kernel can have its attention distribution, the improved ResNet50

flocculation recognition model can dynamically adjust the attention distribution according to different input flocculation

samples, and this flexibility can improve the generalization ability and adaptability of the network.

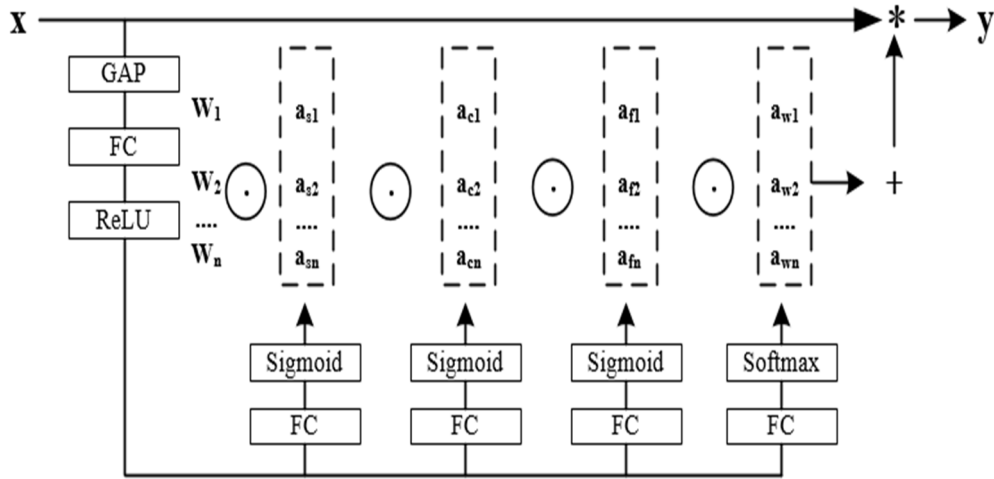


Figure 9. Overall structure of ODConv

3.2.3. Overall structure of the improved model

In this paper, the improved ResNet50 model is named H-ResNet50, and the overall structure of this network is shown in Figure 10. The improved model structure is the same as the main part of the original ResNet50 model structure. The input size of both models is 224x224x3 drilling fluid waste floc images, firstly H-ResNet50 reduces the last layer of Identity Block in the first and second set of residual blocks and introduces ODConv convolutional module in these two parts respectively; this allows it to capture richer contextual cues, and in comparison with the original network model, it provides better accuracy and efficiency tradeoffs and is more focused on adapting to the drilling fluid waste floc images. Then, the GAM global attention mechanism module is introduced at the end of the second and third sets of residual blocks to improve the model's ability to extract features from useful information in the flocculation image, efficiently aggregate flocculation features, and enhance the reconstruction performance. After a series of residual block processing, the size of the output feature map is 7x7x2048, and then input to the fully connected layer after the pool pooling operation, the number of feature channels of the output feature map becomes 3, and the corresponding probability values of the flocculation states of the three classes are output by the Softmax classifier to give the final flocculation identification result of the drilling fluid waste liquid.

In the network structure diagram, Conv represents the convolutional layer in the neural network structure, and "Conv 7x7" indicates that the size of the convolutional kernel is 7x7. ODConv is the newly added full-dimensional dynamic convolutional layer. maxPool represents the maximum pooling layer, GAM represents the global attention mechanism layer, AvgPool represents the average pooling layer, SoftmaX is the fully connected layer, and the whole model contains 4 sets of Bottleneck Blocks, and the number of Bottleneck Blocks are 2, 3, 6, and 3, respectively.

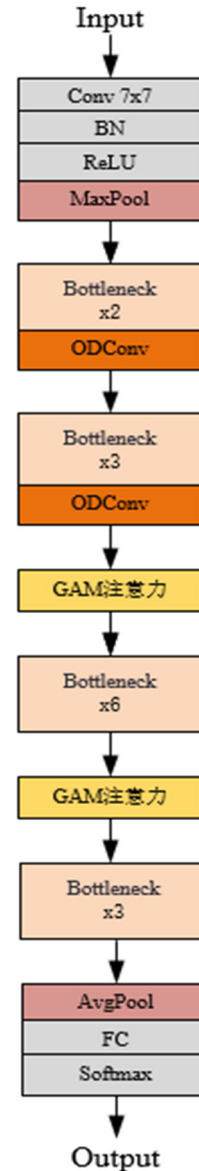


Figure 10. Network structure of H-ResNet50 model

4. Experiment and Result Analysis

4.1. Experimental environment

All the experiments were run in a Windows 11 64-bit system environment and Pytorch deep learning framework based on Python language was chosen. The programming tool was Pycharm Community Edition, Python version 3.11.4, and the hardware conditions were NVIDIA GeForce RTX4060 Laptop GPU graphics card, AMD Ryzen 7 7840H, 3.80 GHz processor, and 16 GB of RAM.

4.2. Parameter settings

The flocculation image dataset for this experiment is divided into training and testing sets in the ratio of 8:2, totaling 6935 images, which are used for model training and testing, respectively. The number of flocculated image classes is 3, which is categorized into class 0 (pre), class 1 (mid), and class 2 (post). Therefore, the fully connected layer of all models is modified to 3. The initial learning rate of the Adam optimizer is set to 0.0001, the batch size (Batch size) is set to

16, and the number of iterative training rounds epochs is set to 70 rounds for all models, and the rest of the parameters are set as default.

4.3. Improved ResNet50 ablation experiment results

To verify the effectiveness of the relevant improvements in the H- ResNet50 network constructed in this paper, ablation experiments are conducted on the ResNet50 model with different improvements using the same dataset. To determine the impact of each part of the improvement on the overall performance of the model. In this ablation experiment, the learning rate is 0.0001, the number of iterative training rounds is 70, and the batch size is 16. GAM-ResNet50 denotes the model with only the addition of the GAM global attention mechanism, and OD-ResNet50 denotes the model with only the addition of the ODConv full-dimensional dynamic convolution. The specific results of the ablation experiments are shown in Table 2. Figure 11 shows the accuracy change curve between the original model and H- ResNet50.

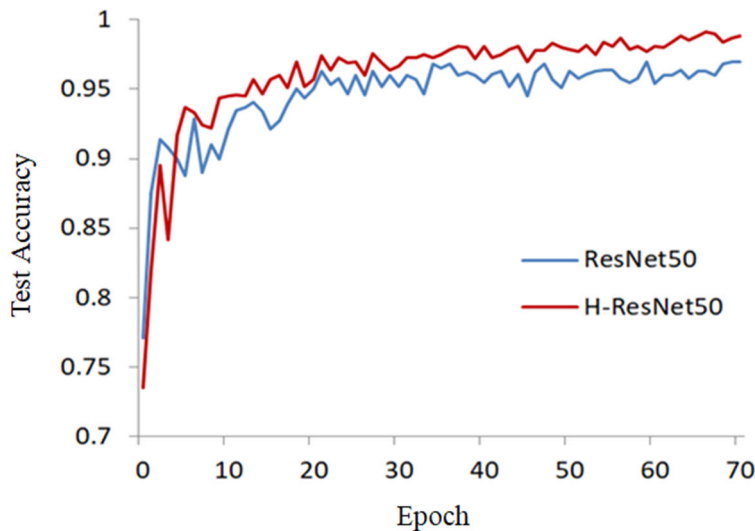


Figure 11. Test accuracy curve of the original network and improved network model

Table 2. Ablation results of the modified ResNet50 model

Model Name	Iteration rounds	Training Accuracy/%	Test Accuracy/%
ResNet50	70	97.96	97.23
GAM-ResNet50	70	98.86	98.65
OD-ResNet50	70	99.15	98.77
H- ResNet50	70	99.57	99.16

The above table shows that the network introducing the GAM global attention mechanism improves the training accuracy by 0.9% and the testing accuracy by 1.42% based on the original network. The network introducing ODConv full-dimensional dynamic convolution improves the training accuracy by 1.19% and the testing accuracy by 1.54% based on the original network. Both parts of the improvement affect the classification accuracy of the original ResNet50 model. Overall, the improved H-ResNet50 model improves the training accuracy and test accuracy by 1.61% and 1.93%, respectively, compared with the original ResNet50 model. The fusion of the two parts of the improved method can optimize the overall performance of the original model to a

greater extent.

4.4. Performance comparison of different network models

To further verify the effectiveness of the H- ResNet50 network, the model designed in this paper is compared with the current network models commonly used in image classification, AlexNet, VGG16, GoogleNet, ResNet34, and ResNet50 are selected for the performance comparison experiments, all the network models are run under the same parameter conditions, and the different network models classification accuracy comparison is shown in Table 3.

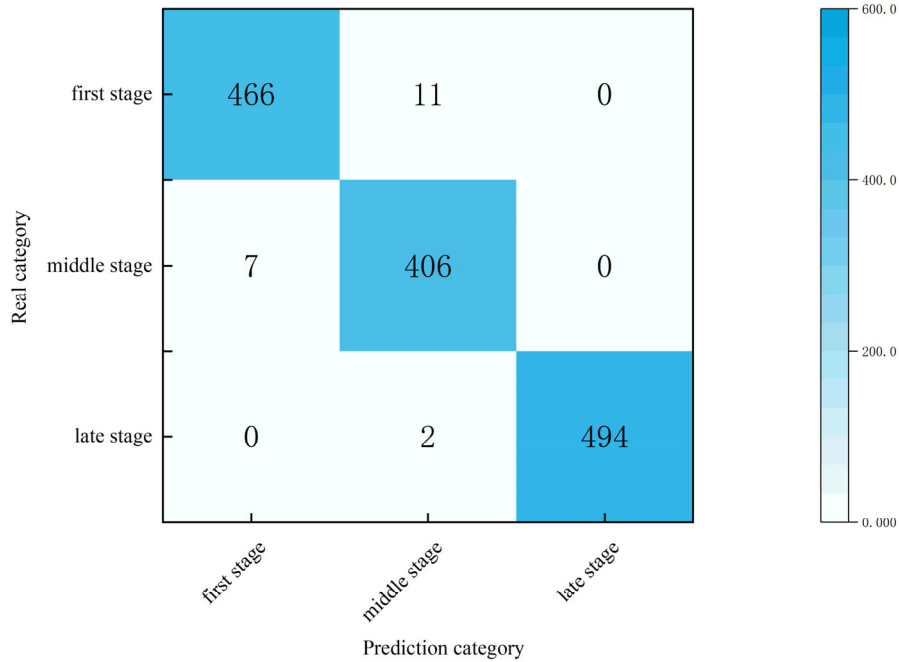
Table 3. Comparison of classification accuracy of different network models

Model Name	Iteration rounds	Test Accuracy/%
AlexNet	70	93.72
VGG16	70	94.85
GoogleNet	70	95.75
ResNet34	70	96.97
ResNet50	70	97.23
H-ResNet50	70	99.16

The above table shows that the classification accuracy of the H-ResNet50 network is 99.16%, which is 5.44%, 4.31%, 3.41%, 2.19%, and 1.93% higher than AlexNet, VGG16, GoogleNet, ResNet34, and ResNet50, respectively, and the H-ResNet50 achieves the optimal accuracy rate in the drilling fluid waste floc classification. The optimal accuracy was achieved in the task, and the classification performance of the algorithm was improved by adding the global attention mechanism and full-dimensional dynamic convolution to the original model, which increased the model's focus on useful information such as flocs, and improved the adaptability of the network.

4.5. Confusion matrix for drilling fluid flocculation identification model

The confusion matrix has a more intuitive display in evaluating the performance of classification models. On the drilling fluid waste fluid flocculation state recognition can show the type of flocculation state that is recognized incorrectly, in this paper, we use the image dataset containing three types of flocculation state to analyze the effect of the H-ResNet50 network model and Figure 12 shows the results of the confusion matrix obtained.

**Figure 12.** Confusion matrix of the test set in the flocculation image data set

As can be seen from Figure 12, the confusion matrix shows the recognition accuracy of each type of flocculation state and the misclassification of each type in the flocculation image test set. It can be found that the early stage of flocculation has the lowest recognition accuracy, and the misclassified images are all misclassified into the middle stage of flocculation. Through analysis, it is found that the images in the early stage of flocculation and the middle stage of flocculation are generally similar, that is, there is little difference between classes. On the other hand, the recognition accuracy of the late flocculation was the highest, and only a very small part of the images were misclassified as the middle flocculation. On the whole, the recognition effect of the H-ResNet50 network is excellent, and it can be applied to the identification of the current flocculation state of drilling fluid waste.

5. Conclusion

In this paper, a drilling fluid waste flocculent state recognition network H-ResNet50 is proposed by improving the original ResNet50 network model, which uses the GAM global attention mechanism to enhance the feature extraction ability of drilling fluid waste flocculent images, while the addition of ODCnv full-dimensional dynamic convolution makes the network more adaptive and generalizable. A series of experiments show that the improved network has the highest classification accuracy of 99.16%, which is significantly higher than the original ResNet50 network model and other common neural network models. It proves the feasibility of using this network in drilling fluid flocculation state identification, which makes up for the shortcomings of the current traditional identification methods such as manual discrimination, and provides more

possibilities for the intelligent identification of drilling fluid flocculation.

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