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A Hybrid Method for Identifying the Feeding Behavior of Tilapia

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ABSTRACT In aquaculture, quantifying the real-time feeding behaviour of fish is essential for making feeding decisions. However, most existing methods for assessing fish appetite are inefficient and subjective. To address these issues, this study proposes an improved tilapia feeding level classification model with ResNet34. First, we introduce the attention module CBAM into the ResNet34 model to adjust the attention of the model according to the importance of different channel features and enhance the effective extraction of important features. We then used migration learning to transfer the knowledge learned from the source data (ImageNet dataset) to the tilapia ingestion image dataset, which allowed us to train the tilapia ingestion behaviour classification model faster while retaining the pre-trained model. Experimental results showed that the improved ResNet34 model in this study achieved an accuracy of 99.72%, an improvement of 7.84 percentage points over the original model. In addition, the model outperformed models such as MobileNetV2, AlexNet, VGG11, ShuffleNet_v2_x0_5 and ResNet18 in terms of accuracy, precision, recall and F1 scores.These results suggest that the proposed method can accurately identify feeding behavior of fish and provide a scientific basis for determining feeding amounts.

INDEX TERMS Tilapia, deep learning, ResNet34, feeding behavior, migration learning, CBAM.

I. INTRODUCTION

Fish is an essential aquaculture component in food security and nutrition [1]. However, with the expansion of

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aquaculture, the fish farming industry is facing some challenges [2]. Traditional fish farming methods have significant space for advancement, particularly in inadequate aquaculture automation and inadequate or excessive feed feeding [3]. In contrast, the lack of automation in aquaculture is reflected by the fact that aquaculturists conduct most of their operations without automated technology. If fish are fed too much, there is a waste of feed, which is not only uneconomical but also detrimental to water quality; if they are fed too little, they are not getting enough to eat, and this poses a threat to their average healthy growth, which in turn reduces the profits earned by aquaculture enterprises or farmers. This paper uses deep learning and other methods to classify and study feeding behavior, which provides better technical support in precision feeding and water quality control [4].

Relying on traditional manual methods to estimate fish feeding needs and set baiting amounts is both time-consuming and laborious, and there is a degree of uncertainty based on the experience of farmers. Computer vision technology's speed, impartiality, and accuracy are ideal for automatic fish identification and classification [5], [6]. Based on machine vision, fish-feeding behavior can be divided into two main categories: 2) Direct assessment methods, which categorize fish-feeding behavior by directly monitoring fish movement. 1) Indirect assessment methods represent fish feeding behavior by residual bait or water quality parameters in culture tanks. Feng et al. investigated the fish feeding intensity indirectly by using bait [7]. Zhou et al. compared dissolved oxygen in the water before and after feeding and predicted real-time feeding intensity based on quantifying the spontaneous collective behavior of fish [8], [9]. Zhou et al. used captured infrared cameras images of fish to analyze the information related to fish feeding and proposed that FIFFB values could better quantify fish feeding behavior by image enhancement, background reduction and target extraction, and elimination of reflective frame images, and also achieved good experimental results [10].

Aquaculture has seen a rise in the use of deep learning models due to their effective feature encoding skills. Deep learning is a data-driven technique miming how neurons work to my depth information from input data and adjust network weights to judge unknown data accurately. Deep learning has become popular in many areas, such as segmentation, as the amount of data that can be collected has grown and computer hardware has become more powerful [11], image style migration [12], image hyper-segmentation reconstruction [13],target detection [14], etc., and has made breakthrough progress. Deep learning has replaced machine learning to quantify the feeding behavior of fish [15]. Fish were used as the study subject and suggested a way to measure the change in fish feeding rate using an enhanced kinetic energy model [16]. Zhao et al. Utilized a hybrid backbone to detect fish in challenging underwater environments [17].Maloy proposed an integrated dual-stream recurrent network (DSRN) based on CNN and LSTM to autonomously record the spatio-temporal swimming behavior of salmon while feeding and non-feeding, but the accuracy rate is only 80% [18].

Most fish behavior recognition algorithms currently rely on convolutional neural networks (CNNs), which have an advantage in capturing local features. However, understanding the overall state of the fish is crucial for recognizing feeding behavior. Therefore, to better handle global features, attention mechanisms can be added to CNNs. Yang et al. proposed a dual-attention network based on EfficientNet-B2 for fine-grained short-term feeding behavior analysis of fish groups, achieving an accuracy rate of 89.56% [19]. Zeng et al. introduced an ASST model based on acoustic signals and attention mechanism to quantify fish feeding behavior, achieving an accuracy rate of 96.16% [20]. Zhang et al. proposed an improved MobileNetV3 network with a Multi-Scale Inverted Fusion (MSIF) channel attention module added for analyzing fish feeding behavior, achieving an accuracy rate of 96.4% [21]. Thus, it is necessary to further analyze the benefits of incorporating attention modules in CNNs to enhance the accuracy of fish feeding behavior classification.

In summary, to overcome the limitations of convolutional neural networks (CNNs) in fish feeding behavior classification and improve classification accuracy, this study focuses on tilapia as the research object and uses an underwater camera to collect tilapia feeding behavior dataset. Attention mechanism was introduced on the basis of the ResNet34 model, and transfer learning was used for optimization. The main contributions of this study are as follows: (1) the use of an underwater camera for dataset collection effectively avoids the interference of water reflection on images, thereby improving the accuracy of data collection; (2) the addition of a CBAM attention module in the model can enhance the extraction ability of effective features, thereby improving the model's performance; (3) transfer learning is used for model optimization, which not only improves the accuracy of the model but also speeds up the model's training.

The rest of this paper is organized as follows: Section II introduces the data collection and experimental methods, Section III discusses the results of different model experiments and validates the proposed model in this paper. Section IV presents the experimental conclusions.

II. MATERIALS AND METHODS

A. EXPERIMENTAL PLATFORM AND DATA COLLECTION

The experiments were performed on a Windows 11 64-bit system environment. The operating system used in the experimental environment is Ubuntu 16.04, the GPU configuration is GeForce GTX 3090 with 32 G.B. of video memory, the CPU configuration is AMD Ryzen 7 6800H with Radeon Graphics, the memory is 16 G.B., and the CUDA version is 11.7. This experiment is based on the PyTorch deep learning framework, and the Python language environment is 3.8.0.

In this paper, feeding behavior data sets were collected in a recirculating water tilapia breeding workshop at the Guangdong Fishery Technology Promotion Station in Nansha District, Guangzhou, China. 8 recirculating breeding ponds with 2.7 m diameter, 1 m height, and 0.8 m depth. In addition, sensors monitored dissolved oxygen, pH value, ammonia nitrogen, and other water environmental factors in the breeding water in real time and maintained within the optimal range. A video data acquisition platform was built, mainly consisting of a circular fish pond made of polypropylene plates, an underwater camera, and a video recorder, as shown in Figure 1. In a real factory farming situation, the collected video images will be seriously affected by the reflective effect on the surface of the water body, so this experiment uses an underwater camera to collect the dataset. The underwater camera is a Hikvision camera, and the camera is installed in the breeding pool through a bracket, The video captured by the underwater camera is then transferred to a computer for storage.

Because this experiment only required data during fish feeding, the recording was focused on the feeding process and the 10 min before and after feeding. Jiasheng feed was chosen twice daily at 9:00 and 17:00 to feed the tilapia to

meet their nutritional needs at various stages. The bait needs to be wetted half an hour before feeding, which can moderately increase tilapia's satiety and stop overfeeding.

B. DATASET PROCESSING

In this study, the video taken using an underwater camera classified the feeding behavior of tilapia.The image was extracted from the collected video data because the similarity of image features of adjacent frames in the video was extremely high. PotPlayer 64-bit software was used obtained image data using differential frame extraction. The frame rate was 30 fps, and the image was in JPG format. The image data were intercepted under different feeding behavior periods and light intensities. The acquired data had problems, such as single tilapia fish occupying most of the image area and uneven illumination. Then the image data were filtered and labeled. Images were cropped To 1839 × 998 pixels, and regions of interest were extracted to improve the processing speed of the algorithm. In this study, fish-feeding behavior classes were classified into four categories based on fisheries-related research literature [22]; the criteria is shown in Figure 2 and Table 1. Datasets were strictly divided according to the criteria in Table 1 to ensure the high quality of the dataset. Because the data was obtained underwater, picture pre-processing was required because the underwater lighting was inadequate due to the water's light absorption. Pre-processing such as Gaussian noise, Peppery noise, Random noise, scaling cropping and normalization are added in this study to enhance the diversity of the data samples and thus improve the model performance, As shown in Figure 3. After finishing, 16,000 images were obtained, 4,000 images for each category respectively, and randomly divided into training and test

sets according to the ratio of 4:1. The data distribution is shown in Figure 4.

TABLE 1. Classification criteria for tilapia feeding behavior.

Feeding intensity	Tilapia feeding behavior
None	Tilapia do not respond to feed, and the water surface is calm.
weak	A few tilapias react to feed near the breeding pond.
Medium	Tilapia begin to feed in the middle of the pond but have a small range of motion.
Strong	Tilapia feed actively and move in a wide range, causing many water splashes.

C. METHODS

The experimental process, as illustrated in Figure 5, begins with the construction of an experimental platform for data collection. Next, the processed data is fed into different classification network models, including the improved ResNet34 model, and their performance is compared. Based on the comparison, a robust classification model for tilapia feeding behavior is established and optimized. The newly developed image validation approach is then used to assess the model's effectiveness, and if it fails to meet the requirements, the model is retrained. Finally, if the model meets the standards, it produces the desired results.

1) ResNet MODEL

Deep convolutional neural networks have successfully accomplished target detection, image segmentation, and categorization. However, adding more network layers leads to gradient growth, deterioration, and gradient vanishing issues [23]. The ResNet algorithm is a classification and recognition method widely used to solve increasing layers problems. The gradient disappearing encountered in deep neural network training is solved using a residual structure in the ResNet deep neural network framework. ResNet residual structure is shown in Figure 6. Its main principle is to use jump connections internally, i.e., the input and output features of the current residual block are fused to achieve the maximum preservation of the target information in the graph. Where x is the input signal, which is linearly varied through the first layer to obtain F(x), and linearly varied through the second layer to obtain the output signal H(x). As the learning precision of the convolutional neural network approaches maximum during training, the output signal H(x) begins to settle. To ensure that the learning accuracy no longer decreases with the deepening of the training layers, the original x with weights shall become a constant mapping, keeping the output signal H(x) equal to the input signal x, to obtain F(x) = H(x) - x. To make H(x) and x remain equal as the network structure deepens, F(x) must converge to 0. The ResNet training process gradually shifts to learning the residual F(x) converging to 0.

ResNet has different network structures, and in this article.The ResNet34 model consists of 34 layers, including three convolutional layers, five pooling layers and 26 residual blocks. The residual blocks consist of two 3×3 convolutional

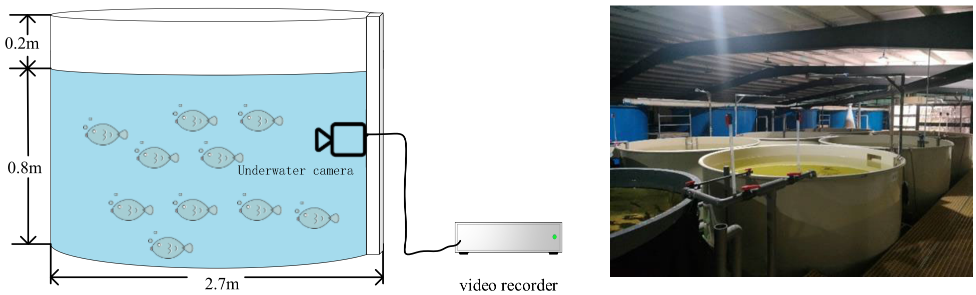

FIGURE 1. **Tilapia video data collection platform.**

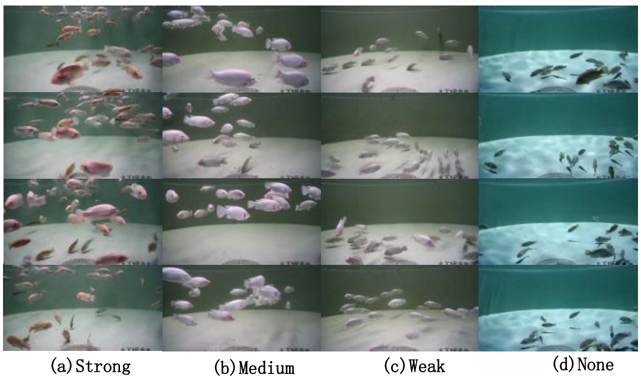

FIGURE 2. **Images of four different feeding levels of tilapia.**

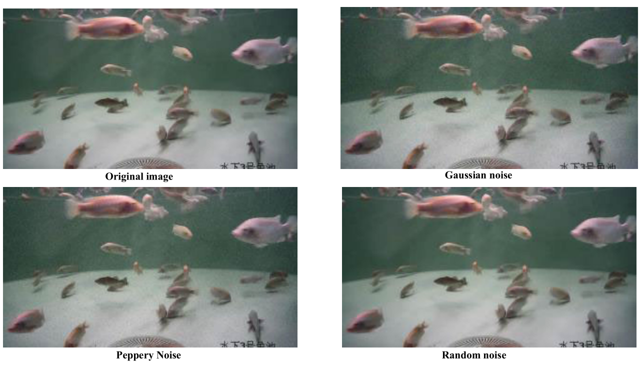

FIGURE 3. **Enhanced image.**

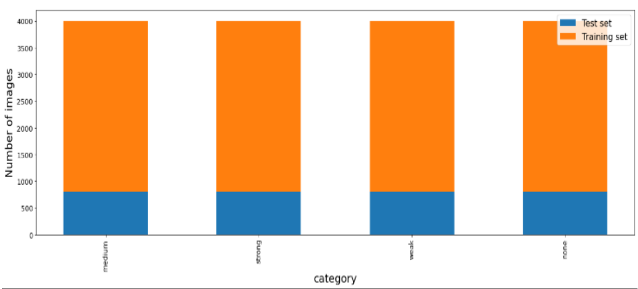

FIGURE 4. **Data set division and sample size.**

layers and a jump connection. The most important feature of this network is its internal composition of homogeneous convolutional units with jump connections to maximize the extraction of target information during convolution. Compared to other traditional convolutional neural networks, ResNet34 has fast training speed, smaller memory footprint, better expression and generalization ability, and can handle more complex tasks [24], [25].

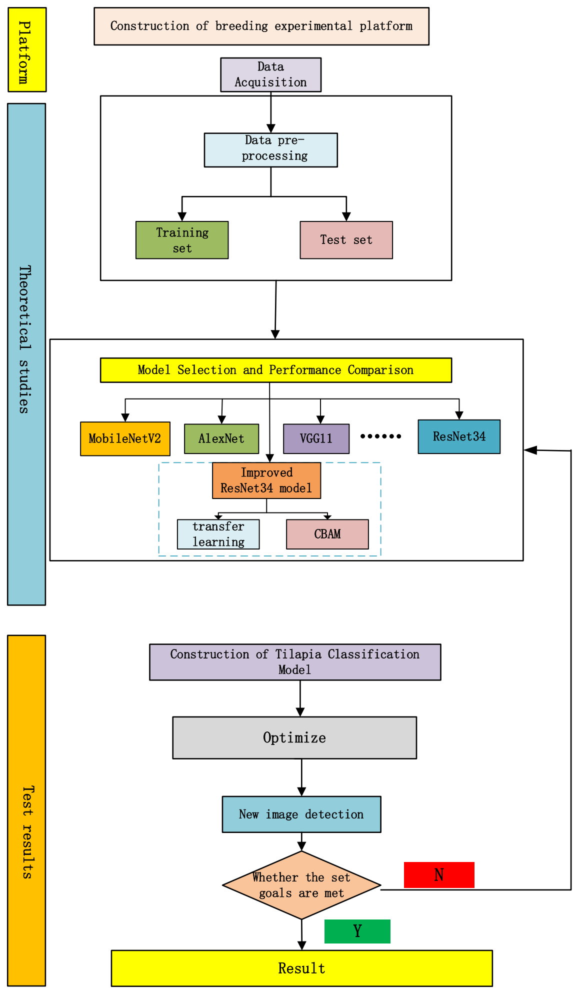

FIGURE 5. **Experiment flow chart.**

2) MIGRATION LEARNING

Transfer learning is a method for accelerating learning on new tasks using already trained neural networks [26], [27]. It can solve new problems on a target dataset faster and more efficiently using pre-trained models trained on large datasets.

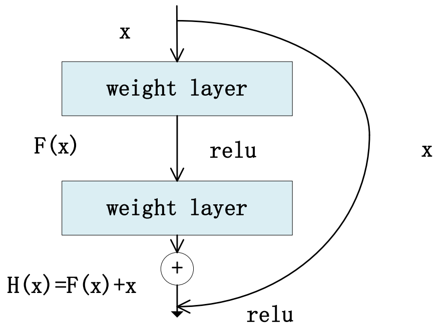

FIGURE 6. Structure of Resnet residuals.

This approach allows for applying knowledge learned in one domain to other domains, allowing the computer to "learn by doing" while saving time in training network models. Therefore, in this study, the concept of transfer learning was employed to fully leverage the extensive knowledge acquired by the ResNet neural network model through training on the ImageNet dataset. This knowledge was effectively applied to address the task of tilapia classification and recognition.

Transfer learning consists of two phases: a pre-training phase and a training phase, as shown in Figure 7. The pre-training phase plays a crucial role in transfer learning, as it allows the model to learn rich feature representations and enhance its generalization ability by leveraging large-scale datasets. In this study, we selected ResNet34, pre-trained on a large-scale image dataset, as the pre-training model to accurately recognize and classify tilapia feeding behavior. During the training phase, we employed a feature detector layer to modify the fully connected layer based on the desired output for different feeding levels of tilapia. To maintain the stability of the learned feature representations from the pre-training phase and avoid losing valuable information, we froze all layers except for the last fully connected layer. By training only the last layer, we could rapidly fine-tune the model to adapt to specific tasks while reducing the need for additional training data. Finally, we trained the model to output four levels of tilapia feeding intensity, including "strong," "moderate," "weak," and "none."

3) ATTENTION MODULE

The attention mechanism focuses on a few essential data elements while ignoring the most irrelevant data [28]. Therefore, the Convolutional Block Attention Module (CBAM) attention method is being explored to enhance feature representation [29]. As shown in Figure 8, The Convolutional Bidirectional Attention Module (CBAM) is a lightweight module consisting of two sub-modules: channel attention and spatial attention [30]. It can be easily inserted into nearly any convolutional neural network with minimal overhead in terms of processing and settings to improve the recognition classification of fish behavior.

The channel attention module of CBAM uses maximum global pooling and global average pooling to extract different tilapia feeding behavior feature information. As shown in Figure 9, for the input features C×H×W, one maximum global pooling and one global average pooling are first performed to obtain two C×1 × 1 channel descriptions [31]. Then, these two feature maps are fed into a 2-layer shared neural network to obtain a new feature map, and the Sigmoid activation function obtains the channel weight coefficients. Finally, the channel weight coefficients are multiplied with the input features to obtain the new features of the scaled tilapia feeding behavior image as the input features of the spatial attention module.

The input of the spatial attention module of CBAM is the output feature of the channel attention module. As shown in Figure 10, the maximum pooling and average pooling of the channel dimension are performed on this feature to obtain two 1×H×W spatial descriptions. These two descriptions are stitched together according to the channels. The spatial weight coefficients are obtained after a 7 × 7 convolution layer and a Sigmoid activation function. Finally, the spatial weight coefficients and the input features are multiplied to obtain the new features of the scaled tilapia feeding behavior image, which has richer local details.

The purpose of this research was to increase the ResNet34 model's precision in estimating the quantity of fish feeding. we embedded the CBAM module into each residual block of the ResNet34 model, as shown in Figure 11. Due to the smaller feature maps of these residual blocks, the CBAM module can better capture the spatial and channel relationships between them with a smaller number of added parameters, resulting in more efficient feature learning. This is particularly important for the smaller feature maps in residual blocks, as the CBAM module can enhance the representation capacity of these feature maps with fewer parameters. Figure 12 illustrates the network structure after using the CBAM module. The network's implementation of the CBAM module enables the model to concentrate more on tilapia's feeding behavior, increasing model precision and resilience. The CBAM module utilises the channel attention and spatial attention mechanisms to adaptively adjust the channel and spatial information of the feature maps and improve the feature representation of the model. The application of this network structure in aquaculture can capture the behavioural characteristics of tilapia more accurately, thus providing a better means of management and monitoring of aquaculture. In addition, this approach is able to extract global features and local details from tilapia feeding behaviour images, thereby enhancing the robustness of the network and capturing key feature information, thereby improving the accuracy of tilapia feeding behaviour classification.

D. LOSS FUNCTION AND EVALUATION INDEX

In this study, the model is constructed using cross-entropy as a loss function for measuring the difference between the predicted category probabilities and the true category labels, providing an explicit target for the model to be optimised

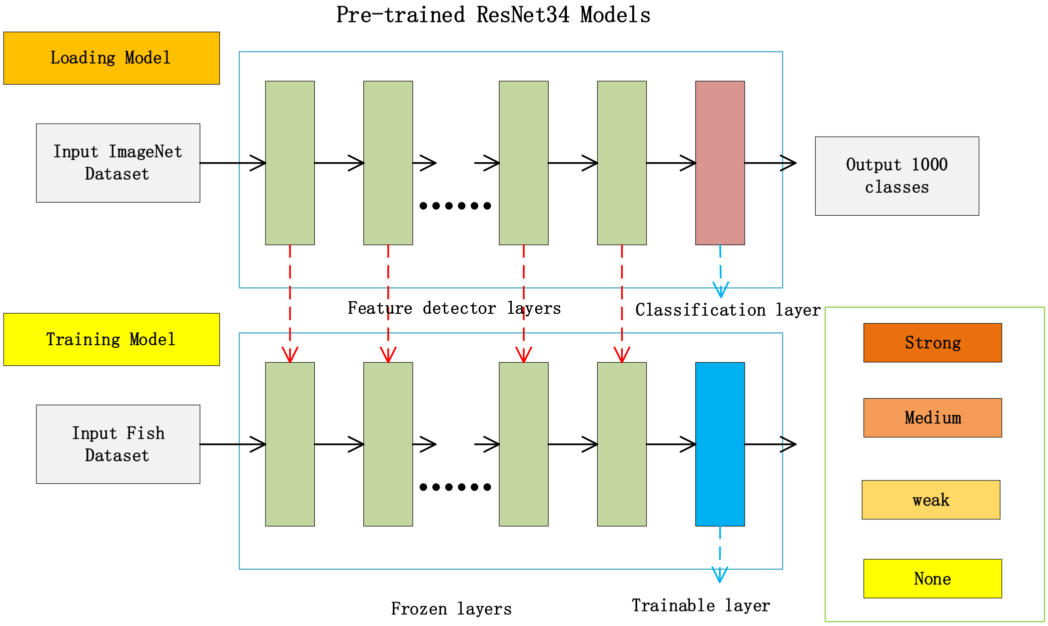

FIGURE 7. ResNet34 migration process.

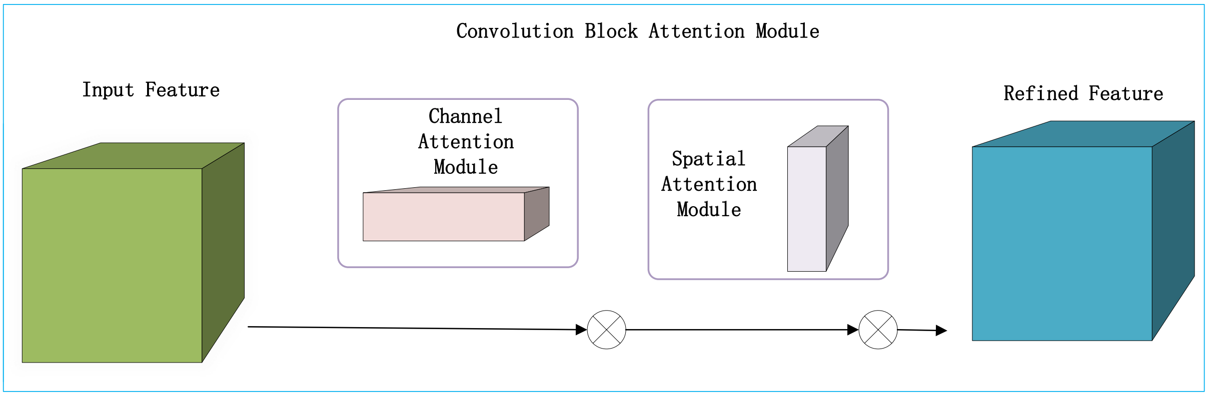

FIGURE 8. CBAM attention mechanism structure diagram.

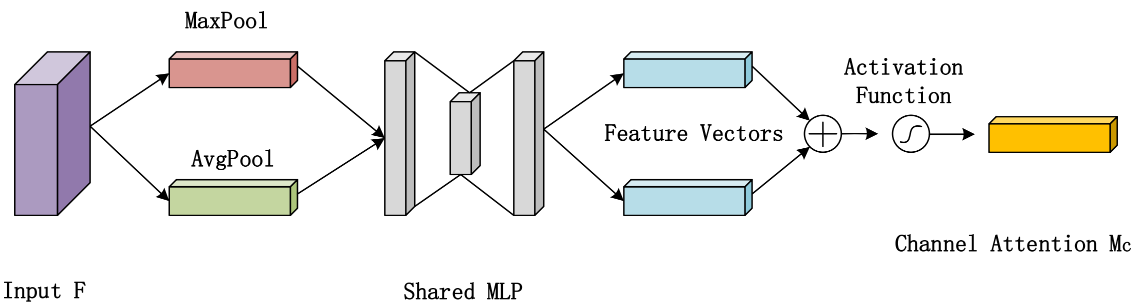

FIGURE 9. CBAM channel attention structure diagram.

during training. In addition, the cross-entropy loss is differentiable, which allows for efficient back-propagation of the error signal and optimisation of the model parameters through gradient descent and its variants [32], [33]. It is calculated as follows.

$$Loss = -\frac{1}{M}\sum_{n=0}^{M-1}\sum\nolimits_{k=0}^{K-1} y_{n,k} lnp_{n,k} \tag{1}$$

Yn,k denotes the nth sample with a true label of k,with a total of M samples with label values of k. pn,k denotes the probability that the nth sample is predicted to be the kth label value. The cross-entropy loss function is convex and can be derived to obtain the global optimum.

The performance of the classification model is evaluated by multiple metrics.This experiment uses precision, memory, accuracy, and F1 score as the assessment indicators.

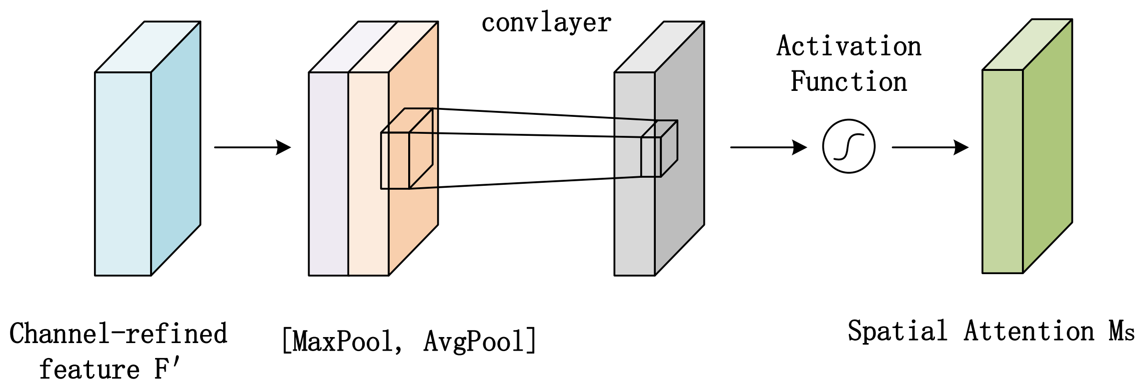

FIGURE 10. CBAM channel attention structure diagram.

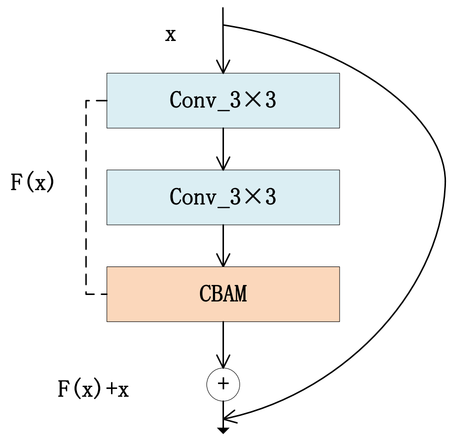

FIGURE 11. Residual Module-CBAM.

Specifically, the overall performance of the model depends of accuracy of the classification of tilapia feeding level. Precision is the proportion of the actual feeding level predicted by the model. It is used to measure the classification accuracy of a model. Recall is used to evaluate the model's ability to classify a specific feeding level, which is the proportion of the feeding level that is correctly classified. F1 score is the harmonic mean of precision and recall, which provides a comprehensive evaluation metric for the task of tilapia feeding level classification, considering both precision and recall. In summary, we use these metrics to comprehensively evaluate the performance of the classification model, and their formulas are shown below.

$$\text{Accuracy} = \frac{AC + AD}{AC + AD + BC + BD} \times 100\% \tag{2}$$

$$Precision = \frac{AC}{AC + BC} \times 100\% \tag{3}$$

$$Recall = \frac{AC}{AC + BD} \times 100\% \tag{4}$$

$$F1 = \frac{2 * precision * recall}{precision + recall} \times 100\% \tag{5}$$

whereas, AC is true positive, BC denotes as False positive, AD as true negative and BD as false negative cases.

E. PARAMETER SETTING

The experiments divided the dataset into a training and a test set in a 4:1 ratio. To represent the 4 different tilapia feeding levels, we modified the fully connected layer of the training model to 4. We trained using the Adam optimization algorithm and set the initial learning rate to 0.001. Thirty-two samples were extracted from the training samples for training each time, i.e., the batch size was set to 32. the total number of training rounds was set to 30, and batch-size samples were taken out of memory each time through the generator. The parameter update of gradient descent is performed once. We use Wandb to record the training data and plot the change curve to monitor the model's performance.

III. RESULTS AND DISCUSSION

A. ITERATIONS EFFECTS ON THE MODEL

By adjusting the number of iterations, one can significantly impact the training accuracy of the model. Increasing the number of iterations enhances the fit of the data, but it also leads to proportional increases in training time. To strike a balance, we conducted experiments comparing the model's Accuracy, Precision, Recall, F1, Loss, and Time metrics across different iterations. The results are presented in Table 2 and Figure 13. With an increasing number of iterations, the model demonstrates gradual improvements in Accuracy, Precision, Recall, Loss, F1, and Time. Precision, Recall, and F1 indicators show steady improvement, accompanied by a decrease in the Loss indicator. However, this progress comes at the expense of increased time consumption. As indicated in Table 2, increasing the number of iterations results in a gradual improvement in Precision, Recall, Accuracy, and F1 metrics, while the Loss metric decreases. Nonetheless, the corresponding time consumption increases.

Considering these factors, we select 30 iterations as the optimal choice. Although the training time slightly increases compared to 10 and 20 iterations, the accuracy rate reaches its peak. The loss value is minimized and stabilized, reflecting the model's robustness. Therefore, adjusting the number of iterations allows for optimization of the model's performance. However, it is crucial to strike a balance between

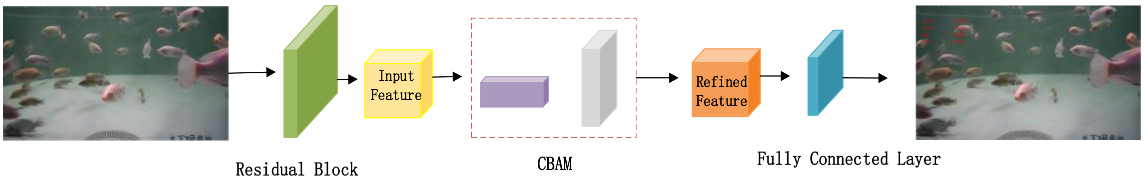

FIGURE 12. Based on ResNet34-CBAM network structure.

TABLE 2. Effect of different iterations of the model.

Number of iterations	Accuracy	Precision	Recall	F1	Loss	Time
10	97.50%	97.60%	97.50%	97.51%	5.29%	1293s
20	99.03%	99.05%	99.03%	99.03%	0.90%	2547s
30	99.72%	99.72%	99.72%	99.72%	0.08%	3071s

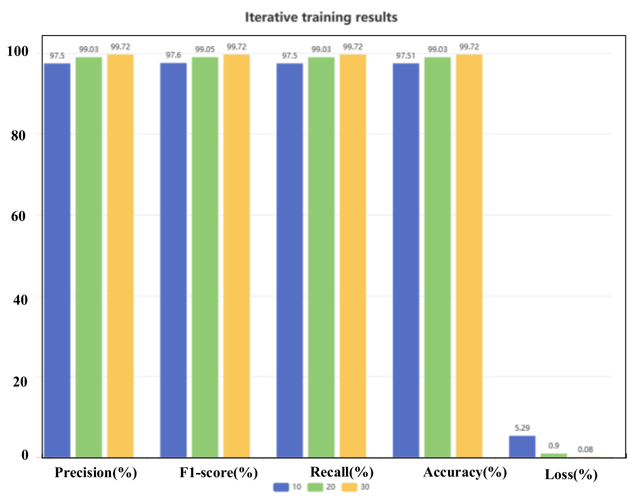

FIGURE 13. Effect of different iterations of training.

training time and model performance when determining the optimal number of iterations. This decision holds significant implications for real production decision-making.

B. ANALYSIS OF EXPERIMENTAL ABLATION RESULTS

In order to verify that we improve the effectiveness of the experiment, we have done two operations. First, a migration learning was conducted on the basis of the RESNET34 model, named ResNet34-T. Based on the above, we add the CA attention module and CBAM attention module in the same position of the ResNet34-T model, and compare the test comparison. As shown in

Table 3, the ResNet34-T model not only increased the accuracy, accuracy, recall rate, and F1 values of 4.84%, 4.67%, 4.84%, and 0.86%, respectively, and the time decreased by 644s. The introduction of migration learning can not only improve the accuracy, but also reduce the training time of the model. The accuracy of the Resnet34-T-CA model was 93.31%, an increase of 1.43%compared to the original model, but the accuracy rate on the basis of migration learning has decreased by 3.41 percentage points. In contrast, the accuracy rate of the model proposed in this article reached 99.72%, which is not only 7.84 percentage points higher than the original model, but also compared to the ResNet34-T model with an unpreparedness module. Accuracy. This shows that the CBAM attention module shows excellent performance in the category of fish feeding, and can categorize different degrees of feeding more accurately.

As shown in Figure 14, the fastest convergence model is the ResNet34-T model, and the final training accuracy is 96.72%. Followed by the ResNet34-T-CBAM model. Although the ResNet34-T-CBAM model is large in the early stage, when the number of iterations tends to stabilize after 20, the model training accuracy is 99.02%, and the final training accuracy is 99.72%. The remaining two models have the same training accuracy, and the final training accuracy is 91.88%and 93.31%. The training results show that this article is based on the ResNet34 improvement network model, both in terms of convergence and model accuracy.

C. DIFFERENT NETWORK MODEL TESTS

Different neural network models are frequently used for computer vision tasks in deep learning. One of the forerunners in deep learning is the AlexNet model [34]. VGGNet improves the model's performance using multiple smaller convolutional kernels [35]. MobileNet, a lightweight network, can run on mobile devices [36], while the number of parameters is reduced by ShuffleNet using shuffle layers [37]. The ResNet model solves the gradient disappearance problem using residual blocks and achieves excellent results in the ImageNet classification challenge [38]. Table 4 and Figure 15 display the experimental results.

TABLE 3. Results of ablation experiments based on ResNet34.

Model	Accuracy	Precision	Recall	F1	Time
ResNet34	91.88 %	92.07%	91.88%	91.90%	2263s
ResNet34-T	96.72%	96.74%	96.72%	92.76%	1619s
ResNet34-T-CA	93.31%	93.52%	93.31%	93.32%	2288s
ResNet34-T-CBAM	99.72%	99.72%	99.72%	99.72%	3071s

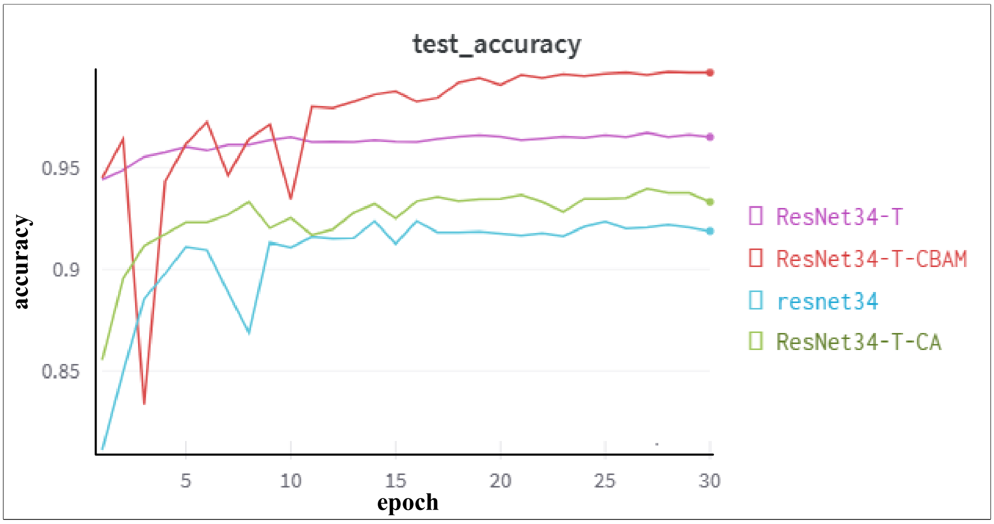

FIGURE 14. Training set accuracy.

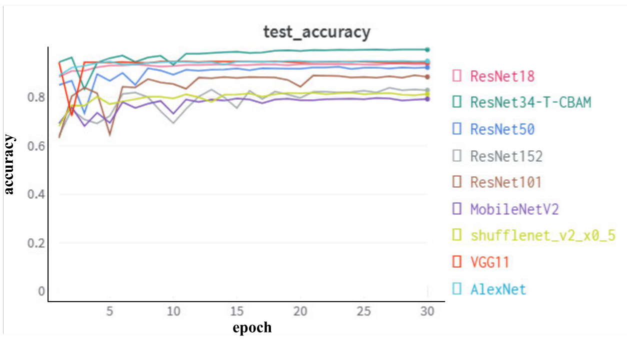

FIGURE 15. Accuracy curves of different model.

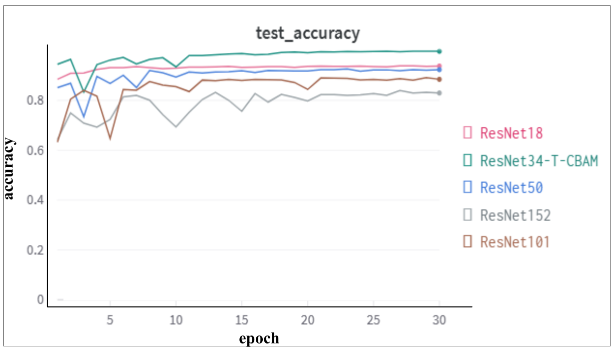

FIGURE 16. ResNet model accuracy curve.

The efficacy was further validated by comparing various network models. The experimental results show that, in comparison, MobileNetV2 performs the worst, with relatively large fluctuations in the first 10 iterations and stabilization in the later stages. Its accuracy, prediction, recall and F1 value are all the lowest. ShuffleNet_v2_x0_5 is also a lightweight network, but its performance is also poor, with All the metrics being lower than the ResNet34-T-CBAM model. Although these two models have low parameter counts, their overall performance based on comprehensive evaluation metrics is not satisfactory.

Furthermore, despite the similar performance of AlexNet and VGG11 in terms of precision, prediction, F1 score, and recall, the runtime of these models is approximately five times longer than that of the AlexNet model. This can potentially limit their applicability in real-time scenarios. Additionally, by increasing the number of training epochs, the AlexNet model demonstrates better stability compared to VGG11. Notably, both of these models not only perform worse than the model proposed in this paper based on comprehensive evaluation metrics but also have a higher parameter count than the proposed model.

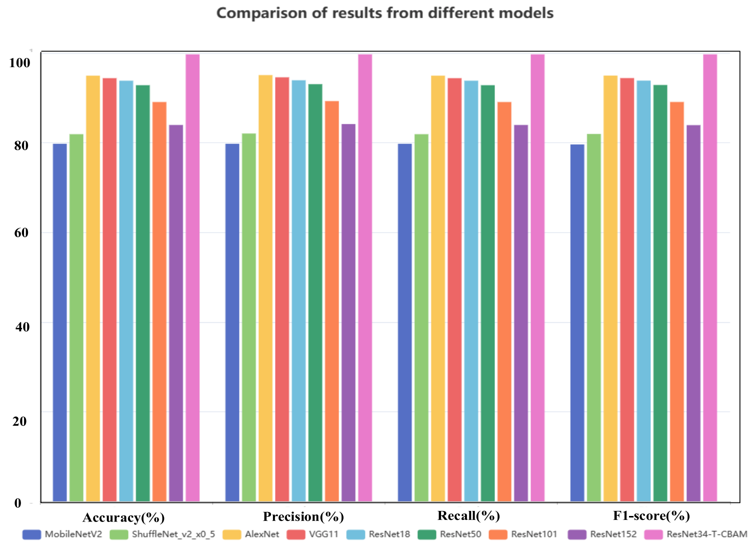

FIGURE 17. Comparison of test results of different models.

TABLE 4. Comparison of experimental results of different image classification algorithms.

Model	Accuracy	Precision	Recall	F1	Time	Parameters
MobileNetV2	79.78%	79.78%	79.78%	79.62%	10217s	3.5M
ShuffleNet_v2_x0_5	81.91%	82.07%	81.91%	81.96%	3147s	1.37M
AlexNet	94.97%	95.09%	94.97%	94.99%	2966s	61.10M
VGG11	94.41%	94.60%	94.41%	94.43%	14075s	132.86M
ResNet18	93.84%	93.94%	93.84%	93.86%	8746s	11.69M
ResNet50	92.84%	93.07%	92.84%	92.89%	2409s	25.56M
ResNet101	89.09%	89.29%	89.09%	89.10%	3305s	44.55M
ResNet152	83.97%	84.17%	83.97%	83.93%	4227s	60.19M
ResNet34-T-CBAM	99.72%	99.72%	99.72%	99.72%	3071s	22.80M

To better investigate the effect of the ResNet model's depth on tilapia's feeding intensity, an experimental comparison was conducted in this paper, including the ResNet18, ResNet50, ResNet101 and ResNet152 models [39]. As shown in Figure 16 the accuracy of the test set decreases instead as the depth of the model increases. This may be due to the problem of overfitting or gradient disappearance of the model due to the large model depth. The accuracy of the ResNet18 model is relatively smooth overall, compared to the ResNet152 model, which fluctuates considerably; the ResNet50 model is similar to the model proposed in this study in terms of accuracy fluctuations but is not as effective as this model; the ResNet101 model has a sudden drop in accuracy at epoch 5 but slowly stabilizes later. Therefore, when applying the ResNet model, the appropriate depth and width of the model should be chosen according to the specific task and data set to avoid the problem of overfitting or underfitting the model.

The ResNet34-T-CBAM model proposed in this paper obtained high recall and F1-score, accuracy and precision in identifying the feeding behavior of tilapia as shown in Figure 17. The AlexNet, VGG11, ResNet18 and ResNet50 models appear less disparate across the different evaluation metrics. The MobileNetV2 model and the ShuffleNet_v2_x0_5 model are more disparate across the different evaluation metrics than the models proposed in this paper.

Figure 18 shows the recognition rates of different models for different categories of tilapia feeding images. Furthermore, The proposed model best recognizes images and can achieve 99.9317% for one of the categories. MobileNetV2,ShuffleNet_v2_x0_5 and ResNet152 models are less effective in recognizing new images with less

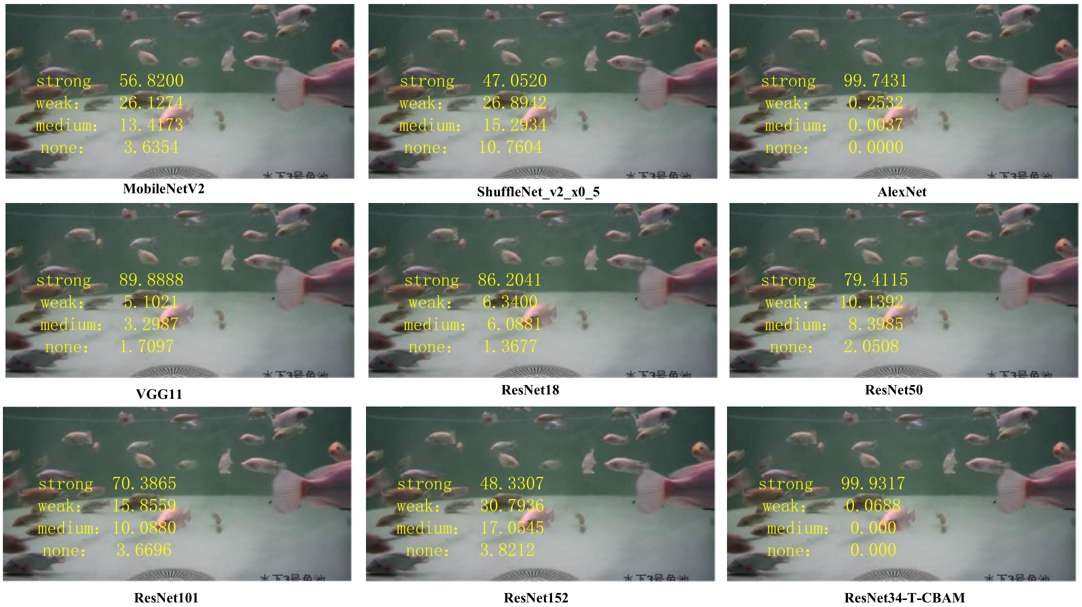

FIGURE 18. Different models predict image effects.

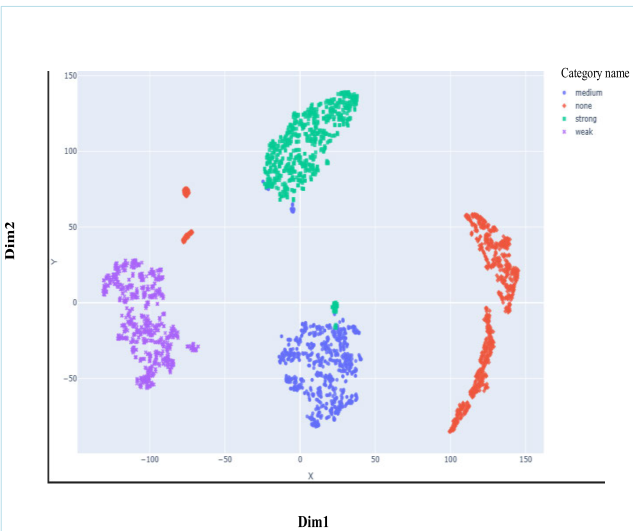

FIGURE 19. t-SNE scatter plot.

than a 60% recognition rate. The AlexNet model is better in recognition. In summary, the model proposed in this paper can classify tilapia feeding level images more accurately.

D. QUANTIFICATION OF FEEDING BEHAVIOR OF FOUR FISH INTENSITY CLASSES

The confusion matrix displays the intensity levels of the predicted results, including "strong," "medium," "weak," and "none." The values on the diagonal represent the model's confidence in correctly identifying the levels of feeding intensity, with higher values indicating more accurate predictions. The dark-colored diagonal elements indicate correctly classified instances with high confidence, while the light-colored off-diagonal elements represent misclassifications or low-confidence classifications.In our experimental study, we compared different confusion matrices to evaluate the classification performance and prediction results of the models, as shown in Figure 20. Models such as MobileNetV2, ShuffleNet_v2_x0_5, ResNet152, and ResNet101 exhibited low-confidence classifications. Specifically, MobileNetV2 and ResNet152 had confidence scores of only 522 and 533, respectively, for the "strong" category. ShuffleNet_v2_x0_5 had a confidence score of only 390 for the "medium" category, which is less than half, while ResNet101 had a confidence score of 664 for the "strong" category. In this study, the ResNet34-T-CBAM model achieved accurate classification for the "none" and "weak" categories, with confidence scores of 800. It also demonstrated high confidence scores for the "medium" and "strong" categories, reaching 798 and 795, respectively. The remaining models had confidence scores around 750 for the feeding intensity categories. Analysis of the confusion matrix indicates that the proposed model in this research performed well in determining the feeding intensity of fish and exhibited high classification accuracy. These results not only validate the effectiveness of our proposed network architecture but also demonstrate the feasibility and significance of our approach in addressing the classification problem of fish feeding intensity in practical applications.

In addition, the t-SNE was used, which maps data into two-or three-dimensional space. It preserves the relative distance relationship between the data. Image processing, text mining, bioinformatics, and many other fields have used this algorithm. In data analysis, using t-SNE can help us better understand and discover the structure and features of the

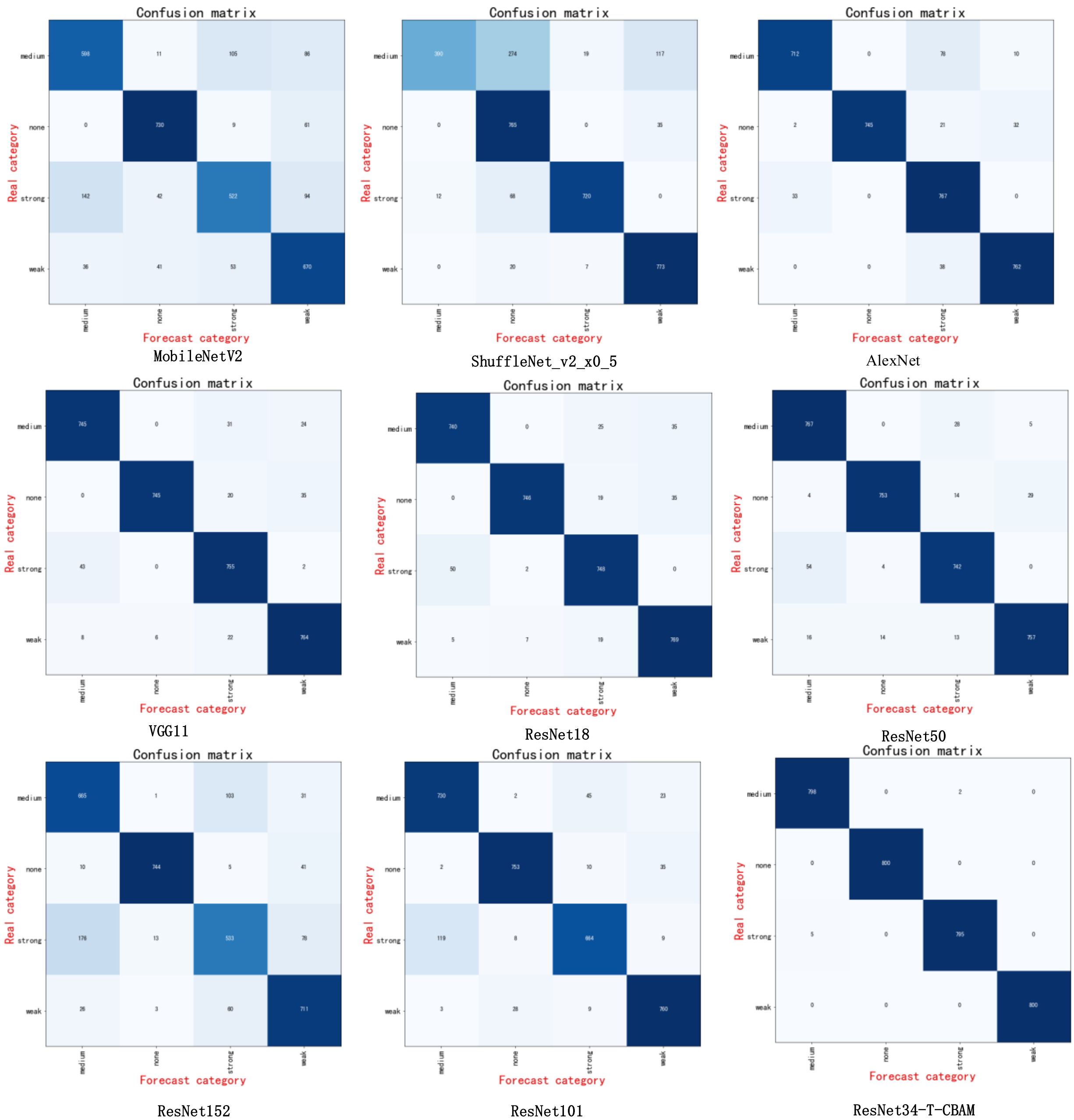

FIGURE 20. Confusion matrix.

data. We use the t-SNE algorithm to map the original data set to a two-dimensional plane and visualize the data points' distribution to show the data's similarities and differences. By observing the relationship between these points, we can more intuitively understand the characteristics and structure of the dataset. In addition, we can use the low-dimensional coordinates generated by t-SNE as new features to be applied in deep learning tasks, such as classification and clustering. t-SNE provides a more intuitive way to understand the nature of the data, thus helping us to better process and analyze complex datasets. As shown in Figure 19, we can observe the semantic feature associations between different tilapia feeding levels. Specifically, we use four different symbols to represent four different feeding levels. Then, we map the semantic features corresponding to different feeding levels to a two-dimensional plane for display. From the figure, we can see that there is some similarity between strong and moderate ingestion degrees. Also, we can find some similarities between some ingestion levels, for example, between no and weak. These results provide an important reference for our in-depth understanding of the relationship between different feeding levels of tilapia.

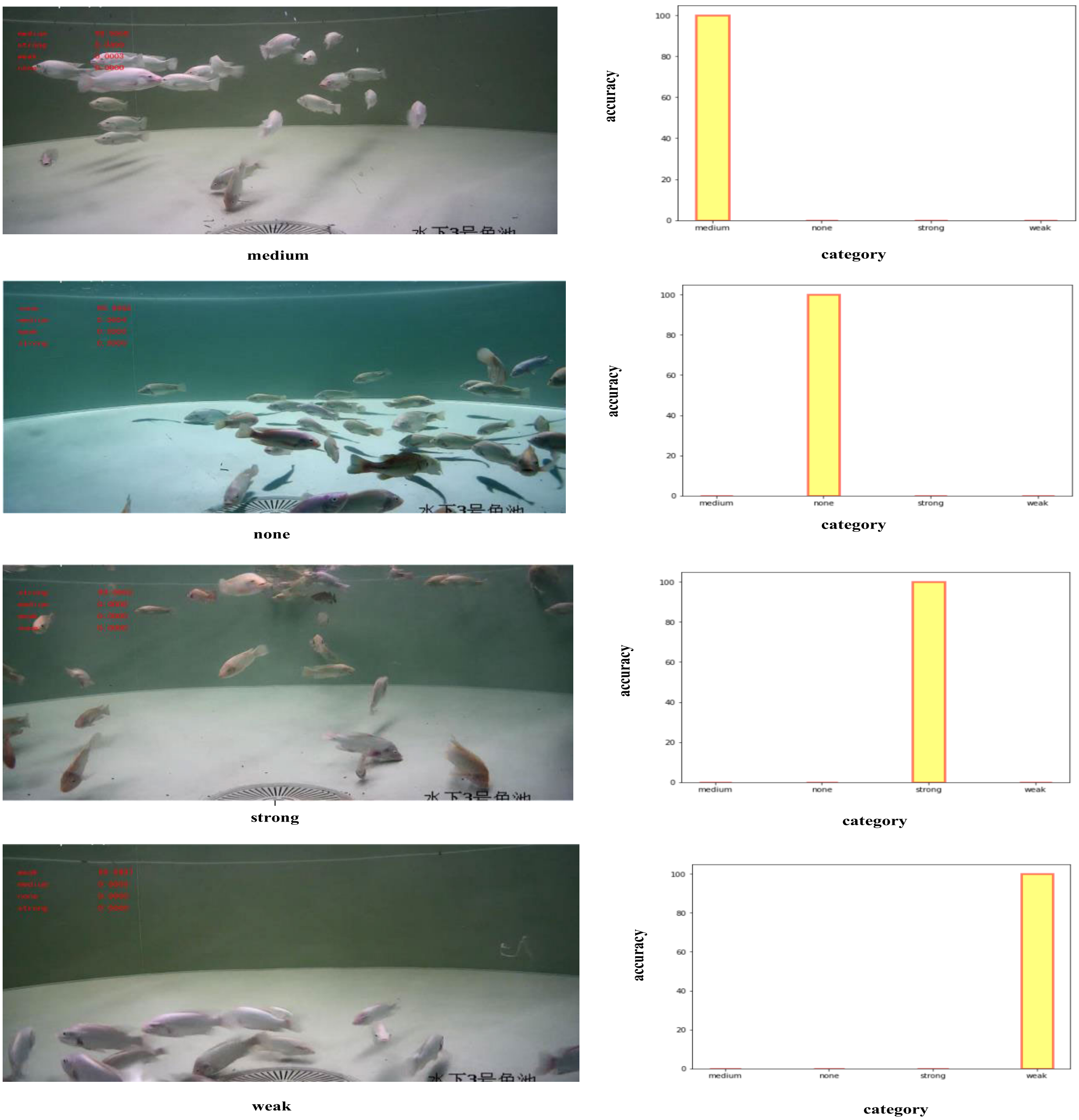

FIGURE 21. Test results and corresponding histograms.

E. MODEL VALIDATION

This study used the trained ResNet34-T-CBAM model to predict new images of tilapia feeding behavior to test the model's effectiveness. The types of quiz images and the corresponding accuracies were displayed on the images through the PIL library to facilitate comparison and analytical studies. For the quiz, four images with different levels of tilapia feeding were selected for testing, and the predicted results and corresponding histograms were presented, as shown in Figure 21. The probabilities of the different feeding level categories are presented in each image. The results show that the probabilities of a medium, none, strong and weak feeding levels on each of the four images are close to 100%, at 99.9558%, 99.9995%, 99.9992% and 99.9997%, respectively. The horizontal and vertical axis represents the category and the confidence level respectively. The results shown in the bar chart clearly show that our model predicts the new images very well. In summary, the high-accuracy fish feeding level recognition model proposed in this study has many practicalapplications. The model can help aqua culturists monitor and evaluate fish feed consumption and growth in real-time, optimizing farm management and saving feed costs.

F. DISCUSSION

1) COMPARE DATA COLLECTION METHODS

Currently, most machine vision-based studies targeting fish feeding behavior have been conducted in the laboratory by simulating realistic culture environments and using overwater cameras to collect data. However, there are limitations in these data because the lighting conditions and culture environment have an impact on them, resulting in an inability to truly reflect the feeding behavior of tilapia in the actual production environment, thus limiting the scope of its application. To address these limitations, this paper uses a method to better collect data by setting up a data collection system underwater in a recirculating culture pond(Figure 1).

2) COMPARE IMAGE CLASSIFICATION METHODS

Currently, image classification is an important research area in computer vision, and there have been many image classification methods widely used. However, these methods usually have problems such as long training time and many parameters, and these problems limit their use in practical applications. In this paper, the above problems are solved using the ResNet34 model, which uses residual learning to reduce the gradient disappearance problem and introduces cross-layer connectivity in the training process to improve the performance of the model. Compared with other image classification methods, the training time of ResNet34 model is relatively short, the number of parameters is relatively small, and a high classification accuracy can be achieved.

3) CONTRIBUTION TO THE CLASSIFICATION OF FISH FEEDING BEHAVIOR

Currently, feeding management in aquaculture still relies on traditional methods such as weather and experience, leading to problems such as uneven feeding, deteriorating water quality and disease outbreaks. To address these problems, next-generation information technologies such as artificial intelligence, Internet of Things and deep learning are applied to the field of accurate feeding in aquaculture, which can reduce labor intensity, improve production efficiency and help upgrade traditional aquaculture to a smart aquaculture model.

In this context, image classification technology is an important component of fish feeding behavior classification. Traditional methods of fish feeding behavior classification rely on manual observation and recording, which have problems such as subjectivity, low efficiency and small data volume. In contrast, fish feeding behavior classification methods based on image classification technology can automatically, quickly and accurately identify and classify fish behavior under different feeding states.

In order to further improve the application of image classification techniques in the field of fish feeding behavior classification, this paper adopts methods such as transfer learning and adding attention modules to better extract the feeding behavior features. The experimental results show that our model is improved in different evaluation metrics with 99.72% accuracy compared with the original model.

IV. CONCLUSION

The research contributions of this study are as follows:

1.Utilizing underwater cameras to capture image sequences of feeding behavior in tilapia, minimizing the impact of lighting disturbances.

2.Introducing transfer learning to reduce model training time.

3.Incorporating the CBAM (Convolutional Block Attention Module) mechanism into the model to enhance effective feature extraction and improve classification performance.

To address the limitations of current methods for assessing fish appetite, such as low accuracy and subjectivity, this study proposes a hybrid model for classifying the degree of feeding behavior in Nile tilapia. Building upon the ResNet34 model, improvements are made by leveraging transfer learning to mitigate the issue of prolonged training time in deep learning. This approach enables the model to acquire universal feature extraction parameters from image classification tasks in the initial training stage, avoiding the need for training from scratch and significantly reducing training time. Additionally, to further enhance network performance, the CBAM attention module is introduced for model refinement. Experimental results demonstrate that the proposed network effectively distinguishes four levels of feeding intensity, namely "strong," "medium," "weak," and "none," achieving a recognition accuracy of 99.72%. The model successfully detects the feeding behavior levels of fish, outperforming other convolutional neural network models. Therefore, this research holds practical significance for aquaculture operators in making optimal feeding decisions and improving farming efficiency, while providing a foundation for precision feeding.

However, this study has certain limitations that warrant further investigation. The methodology was solely tested and evaluated in the context of tilapia farming, and future research should consider conducting tests on different fish species. Furthermore, this study only focused on studying the feeding behavior of Nile tilapia, and future research could incorporate investigations into the accurate delivery of feed quantities, enabling precise feeding for tilapia.

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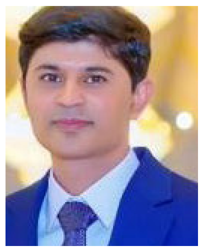

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