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Study on Classification of Developmental Stages of Necrophilous Fly Larvae in Hainan Region Based on Transfer Learning and Class-Imbalance Handling

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Abstract: Aiming at the recognition difficulty caused by high morphological similarity between the Early and Middle developmental stages of necrophilous fly larvae and the low proportion of Early-stage samples, this paper constructs a 3-class image dataset containing 2288 images from the Hainan region, and proposes a recognition method based on ResNet50 with transfer learning and class-imbalance handling. The Accuracy and Macro-F1 of the model on the test set reach 95.64% and 93.64%, respectively. Major misclassifications occur mainly between the Early and Middle stages. This work can provide references for the auxiliary analysis of minimum post-mortem interval (PMImin) in forensic entomology in Hainan.

Keywords: Necrophilous fly; Developmental stage; ResNet50; Transfer learning; Focal loss

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1. Introduction

The developmental stages of necrophilous fly larvae serve as critical evidence for inferring the minimum post-mortem interval (PMImin), and the accuracy of their determination directly affects the reliability of post-mortem interval estimation [1–2]. Nevertheless, larvae at the Early and Middle stages bear high morphological similarity. Conventional morphological identification relies on expert experience, which suffers from strong subjectivity and high risk of misjudgment [3]. Furthermore, the developmental rate of necrophilous insects is significantly affected by environmental factors such as temperature [4]. Therefore, it is of practical application value to establish an objective and automatic developmental-stage identification method.

Existing forensic-entomology image research focuses primarily on fly species identification. Deep

learning models have been adopted for recognition of local morphological features such as posterior spiracles, and multi-scale feature reuse has also been utilized to improve the classification performance of insect images [5–7]. However, research on 3-class classification for continuous larval developmental stages remains scarce.

Accordingly, this paper proposes to adopt the ResNet50 model, combined with transfer learning and class-imbalance handling methods, to boost the 3-class classification performance for developmental stages of necrophilous fly larvae, and especially improve the identification effect for the Early and Middle categories [8–10].

2. Research methods

2.1. Dataset and image preprocessing

The dataset contains 2288 images, among which there are 385, 957 and 946 images for the Early, Middle and Late stages respectively (**Figure 1**). The dataset is split at a ratio of 7∶1.5∶1.5 on an individual-basis unit, so as to avoid data leakage caused by similar images across different sets. Random cropping, flipping, rotation, and color jittering are applied for the training set, while deterministic central cropping and normalization are performed for the validation set and test set [11].



Figure 1. Sample illustrations of three developmental stages: Early, Middle, and Late

2.2. Model construction and experimental design

The ImageNet-pre-trained ResNet50 is adopted. Its classification head is replaced with a 3-class fully-connected layer with Dropout (0.3), and full-parameter fine-tuning is implemented [12]. The AdamW optimizer is used for the model with a batch size of 16. Both the learning rate and weight decay are set to . The optimal model is selected according to Macro-F1 on the validation set. Meanwhile, evaluation metrics including Macro-Recall, Macro-F1, and Early Recall are adopted for assessment [10, 13]. Two groups of ablation experiments concerning transfer learning and loss functions are set for the proposed method. The class weights are set as [3.0, 1.0, 1.0], and γ=2.0. Furthermore, multi-model comparison, confusion-matrix analysis, and Grad-CAM are used to analyze model performance [14].

3. Results and discussion

3.1. Model performance analysis

As shown in **Table 1**, the final ResNet50 model achieves an accuracy of 95.64% and a Macro-F1 of 93.64%, outperforming EfficientNet-B0, MobileNetV2, and VGG16 (**Figure 2**). The Recall of the Early class reaches 79.31%, yet the Early class remains the main challenging category.

Table 1. Performance comparison among different models

	Accuracy(%)	Macro-Recall (%)	Macro-F1 (%)	Early Recall (%)
ResNet50	95.64	92.41	93.64	79.31
EfficientNet-B0	92.73	87.35	89.00	65.52
MobileNetV2	90.99	86.65	87.16	68.96
VGG16	84.01	70.11	68.67	13.79

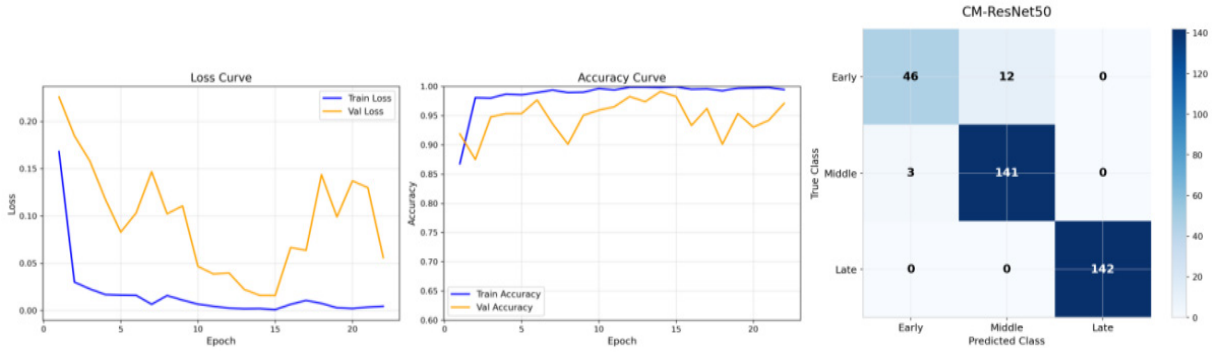

Figure 2. Training curves and confusion matrix of the final ResNet50 model

3.2. Comparison of transfer learning and loss functions

As shown in **Table 2**, after ImageNet pre-training combined with full-parameter fine-tuning, the model Accuracy rises from 63.08% to 95.64%, and Macro-F1 increases from 51.38% to 93.64%. Weighted Cross-Entropy achieves the highest Early Recall (82.76%). Weighted Focal Loss obtains optimal Accuracy and Macro-F1 with the best comprehensive performance; hence, it is adopted as the final solution [15].

Table 2. Experimental results of transfer-learning and loss-function comparison

	Accuracy (%)	Macro-F1 (%)	Early Recall (%)
Random initialization + full-parameter training	63.08	51.38	0.00
Pre-training + classification-head-only training	72.97	63.87	25.86
Pre-training + training layer4 and classification head	90.12	85.32	60.34
Ordinary Cross-Entropy	91.57	87.25	56.90
Weighted Cross-Entropy	93.90	92.67	82.76
Unweighted Focal Loss	91.86	86.86	55.17
Pre-training + full-parameter fine-tuning + weighted Focal Loss	95.64	93.64	79.31

3. Misclassification and Grad-CAM analysis

As illustrated in **Figure 3**, misclassifications mainly take place between Early and Middle stages. Grad-CAM visualization demonstrates that the model focuses chiefly on larval bodies and segment contours without obvious background dependence. It indicates that misjudgments are mainly caused by morphological similarity between adjacent stages and insufficient Early-stage samples, rather than irrelevant background features learned by the model. This result is consistent with the ablation-experiment finding that class-imbalance handling significantly improves Early Recall.

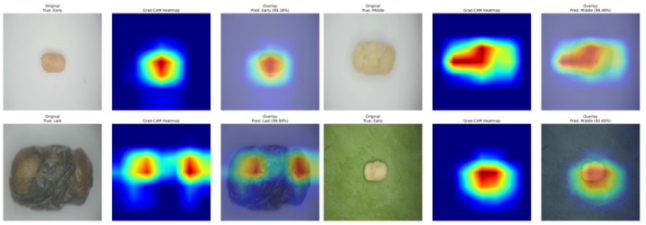

Figure 3. Grad-CAM visualization results of typical samples

4. Conclusion and prospect

Aiming at the problems of high morphological similarity between Early and Middle stages and insufficient Early-stage samples of necrophilous fly larvae, this paper constructs a 3-class dataset for the Hainan region and verifies the effectiveness of ResNet50 combined with transfer learning and weighted Focal Loss. The Accuracy and Macro-F1 reach 95.64% and 93.64%, respectively.

Since samples are collected under a single laboratory environment, the generalization capability across different regions and devices remains to be validated. Moreover, this method only targets developmental-stage classification and cannot replace species identification or complete PMImin inference. In future work, multi-region and multi-device data will be introduced to verify generalization performance, and finer-grained developmental-stage division will be further explored.

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Disclosure statement

The authors declare no conflict of interest.

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