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NÂNG CAO HIỆU QUẢ NHẬN DẠNG ĐỐI TƯỢNG TRÊN TẬP DỮ LIỆU QUY MÔ NHỎ THÔNG QUA VIỆC KHAI THÁC ĐẶC TRƯNG HỌC SÂU TIỀN HUẤN LUYỆN

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TỪ KHÓA

Học chuyển giao;
Nhận dạng đối tượng;
VGG16;
Tập dữ liệu tùy chỉnh;
Phát hiện đối tượng nhỏ.

TÓM TẮT

Học chuyển giao đã nổi lên như một phương pháp hiệu quả nhằm nâng cao hiệu suất nhận dạng đối tượng, đặc biệt trong bối cảnh dữ liệu huấn luyện hạn chế. Trong nghiên cứu này, mô hình dựa trên kiến trúc VGG16 được phát triển theo hướng khai thác đặc trưng học sâu tiền huấn luyện nhằm giải quyết bài toán nhận dạng đối tượng trên tập dữ liệu tùy chỉnh gồm 16 loại vật dụng thông thường. Mô hình được tinh chỉnh từ bộ trọng số tiền huấn luyện trên ImageNet và đánh giá qua năm lần huấn luyện độc lập nhằm kiểm chứng độ ổn định của kết quả. Kết quả thực nghiệm cho thấy mô hình đạt độ chính xác trung bình 90,56% với độ lệch chuẩn 2,15%, phản ánh hiệu năng nhận dạng cao, tính ổn định tốt và ưu thế rõ rệt so với phương án huấn luyện từ đầu. Bên cạnh đó, phương pháp đề xuất đạt chỉ số mean Average Precision (mAP) 74,8% tại IoU = 0,5 và 59,3% tại IoU = 0,75, cho thấy khả năng phát hiện đối tượng ổn định ở các ngưỡng đánh giá khác nhau. Đáng chú ý, hiệu suất nhận dạng đối tượng nhỏ được cải thiện (AP_small = 38,2%), khẳng định hiệu quả của học chuyển giao trong việc trích xuất đặc trưng chi tiết. Tuy nhiên, mô hình vẫn gặp khó khăn trong việc phát hiện chính xác các đối tượng cực nhỏ hoặc bị che khuất, cho thấy hạn chế trong biểu diễn đặc trưng ở các tỉ lệ thấp. Nhìn chung, nghiên cứu này khẳng định tính hiệu quả của học chuyển giao trên các tập dữ liệu quy mô học thuật và cung cấp bằng chứng thực nghiệm về khả năng ứng dụng thực tiễn. Trong tương lai, nghiên cứu sẽ tập trung vào tích hợp đặc trưng đa tỉ lệ và khai thác các kiến trúc tiên tiến hơn nhằm nâng cao hiệu suất phát hiện.

IMPROVING OBJECT DETECTION PERFORMANCE ON SMALL-SCALE DATASETS THROUGH PRE-TRAINED DEEP FEATURE EXTRACTION

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ABSTRACT

Transfer learning has emerged as an effective approach for improving object recognition performance, particularly in scenarios with limited training data. In this study, a model based on the VGG16 architecture was developed by exploiting pre-trained deep features to address the object recognition problem on a custom dataset consisting of 16 categories of common objects. The proposed model was fine-tuned using weights pre-trained on the ImageNet dataset and evaluated through five independent training runs to verify the stability of the obtained results. Experimental results demonstrated that the model achieved an average accuracy of 90.56% with a standard deviation of 2.15%, indicating high recognition performance, strong stability, and clear advantages over training-from-scratch approaches. In addition, the proposed method achieved a mean Average Precision (mAP) of 74.8% at IoU = 0.5 and 59.3% at IoU = 0.75, demonstrating robust object detection capability under different evaluation thresholds. Notably, the detection performance for small objects was improved (AP_small = 38.2%), confirming the effectiveness of transfer learning in extracting fine-grained features. However, the model still encountered challenges in accurately detecting extremely small or occluded objects, highlighting limitations in feature representation at low scales. Overall, this study confirms the effectiveness of transfer learning on academic-scale datasets and provides experimental evidence for its practical applicability. Future work will focus on integrating multi-scale feature representations and exploring more advanced architectures to further improve detection performance.

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1. INTRODUCTION

Object detection has become a fundamental task in computer vision, as it simultaneously addresses object classification and spatial localization within images. Unlike conventional image classification, which assigns a single label to an entire image, object detection requires identifying multiple objects along with their spatial positions, typically represented by bounding boxes [1]. This dual requirement significantly increases the complexity of the task while enabling a wide range of real-world applications, including intelligent surveillance systems, autonomous driving, medical diagnostics, industrial inspection, and educational technologies [2-4].

Over the past decade, deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), have achieved state-of-the-art performance in object detection, consistently outperforming traditional handcrafted feature-based methods such as Histogram of Oriented Gradients (HOG) [5] and Scale-Invariant Feature Transform (SIFT) [6]. However, training deep CNN models from scratch remains computationally expensive and requires large-scale annotated datasets, which are often unavailable in resource-constrained research environments.

To address this challenge, transfer learning has emerged as an effective and widely adopted strategy, enabling the reuse of knowledge from models pre-trained on large datasets such as ImageNet [7]. By fine-tuning these pre-trained models for specific tasks, transfer learning not only accelerates convergence but also improves generalization performance and reduces the risk of overfitting, especially when working with limited data.

Among various CNN architectures, VGG16 is one of the most influential due to its simple yet powerful design and strong feature extraction capability [8-9]. Although more recent architectures such as ResNet [10] and EfficientNet [11] provide improved parameter efficiency and deeper representations, VGG16 remains widely adopted in transfer learning scenarios because of its stability and ease of implementation. Nevertheless, its repeated pooling operations can lead to reduced spatial resolution, which negatively affects localization accuracy, particularly for small object detection (SOD) [12].

While previous studies have primarily focused on large-scale benchmarks such as common objects in context (COCO) or pascal visual object classes (VOC), there is still limited research investigating the effectiveness of classical CNNs architectures under transfer learning in small-scale, practical datasets commonly found in academic environments. This research gap motivates the present study, which applies VGG16 with transfer learning to a custom dataset derived from real-world scenarios.

The main contributions of this paper are summarized as follows:

(1) Implementation of a VGG16-based transfer learning framework for object detection on a custom dataset.

(2) Comprehensive empirical comparison between training from scratch and fine-tuning pre-trained weights.

(3) In-depth analysis of model strengths and limitations, particularly in detecting small objects.

(4) Recommendations for future improvements through multi-scale feature fusion and transformer-based architectures.

2. RELATED WORKS

Early object detection approaches were primarily based on handcrafted features, such as HOG [5] and SIFT [6], combined with conventional classifiers. While these methods provided foundational progress, they exhibited limited robustness to variations in illumination, scale, and occlusion, thereby restricting their effectiveness in complex real-world environments.

The advent of deep learning, particularly CNNs, marked a paradigm shift by enabling end-to-end feature learning and substantially improving detection performance. Two-stage detectors, including R-CNN, Fast R-CNN, and Faster R-CNN, achieved high accuracy through a sequential pipeline of region proposal and classification, but suffered from high computational cost and slower inference speed. In contrast, one-stage detectors such as YOLO [13], SSD [14], and EfficientDet [11] were developed to achieve real-time performance, offering faster processing at the expense of reduced accuracy, especially when handling small or densely distributed objects.

More recently, transformer-based architectures have introduced a new direction in object detection by modeling global contextual relationships through attention mechanisms. Methods such as detection transformer [14] and Deformable detection transformer [15] demonstrate improved capability in capturing long-range dependencies and complex spatial interactions, thereby enhancing detection performance in challenging scenarios. However, these approaches often require large-scale datasets and extensive computational resources for effective training, which may limit their applicability in resource-constrained settings.

In practical applications, transfer learning has become a critical technique to mitigate data scarcity and computational limitations. Fine-tuning pre-trained networks such as VGG16 [9] and ResNet [10] enables effective knowledge transfer from large-scale datasets, leading to improved accuracy and faster convergence on smaller datasets [7, 15-16]. Despite its relatively lower parameter efficiency compared to modern architectures, VGG16 remains attractive due to its simplicity, interpretability, and stable performance, particularly in academic and resource-limited environments.

Nevertheless, SOD continues to be a persistent challenge. Techniques such as Feature Pyramid Networks (FPN) [17], dilated convolutions [18], and lightweight transformer-based methods [19-20] have been proposed to enhance multi-scale feature representation and improve detection accuracy for small objects. Despite these advancements, recent surveys [8], [16] emphasize that achieving an optimal balance between detection accuracy and computational efficiency remains an unresolved issue, especially in scenarios involving limited data and constrained resources.

Despite the extensive body of work, most existing studies primarily focus on large-scale benchmark datasets such as COCO or Pascal VOC, with limited attention given to small-scale, real-world datasets commonly encountered in academic or applied research contexts. Furthermore, there is a lack of systematic evaluation of how classical CNN architectures, such as VGG16, perform under transfer learning in such constrained settings.

To address this gap, the present study investigates the effectiveness of a VGG16-based transfer learning framework on a custom dataset, providing empirical insights into its performance, limitations, and suitability for small-scale object detection tasks.

3. METHODOLOGY

This study adopts a structured and reproducible experimental pipeline consisting of four main stages: dataset construction, preprocessing, model architecture design, and training strategy. The overall framework is designed to systematically evaluate the effectiveness of transfer learning under limited-data conditions, which are common in academic and real-world applications.

3.1 Dataset Collection and Annotation

To reflect realistic deployment scenarios, a custom dataset was constructed from real-world environments rather than relying on large-scale public benchmarks. The dataset includes 16 categories of common everyday objects, namely tweezers, spoon, shaver, scissors, ruler, pencil sharpener, pencil, pen, nail files, nail clippers, eraser, door lock, cotton swab, chopsticks, brush, and ballpoint pens.

A total of 320 images were collected, with 20 images per category, and each image was manually annotated with bounding boxes. Data acquisition was performed using an iPhone 11 Pro Max, ensuring high-resolution images with realistic lighting and background variations, thereby enhancing ecological validity.

For annotation, the LabelImg tool was employed to generate precise object localization labels. To address the limited dataset size and enhance model generalization, data augmentation techniques were systematically applied, including horizontal flipping, random rotation (±15°), and brightness adjustment. These transformations simulate real-world variability and effectively reduce the risk of overfitting.

The detailed distribution of object categories, corresponding symbols, and the number of collected images is presented in Table 1. Additionally, representative samples from the constructed dataset are illustrated in Figure 1.

Table 1. *List of objects, symbols, and number of collected images*

Object	Symbol	Number of Images
Tweezers	TW	20
Spoon	SP	20
Shaver	SH	20
Scissors	SC	20
Ruler	RL	20
Pencil Sharpener	PS	20
Pencil	PC	20
Pen	PN	20
Nail Files	NF	20
Nail Clippers	NC	20
Eraser	ER	20
Door Lock	DL	20
Cotton Swab	CS	20
Chopsticks	CT	20
Brush	BR	20
Ballpoint Pens	BP	20

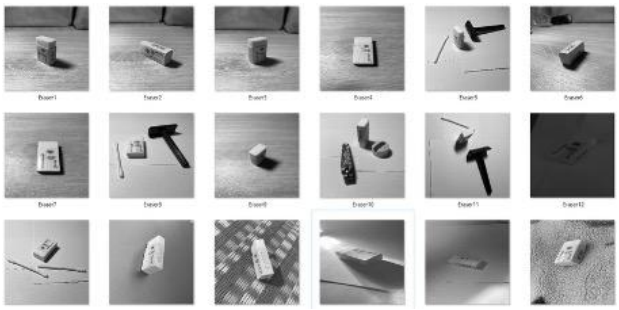

Figure 1. *Some samples are collected in the database*

3.2. Preprocessing

All images were resized to a fixed resolution of 224 × 224 pixels to ensure compatibility with the input requirements of the VGG16 architecture. Pixel intensities were subsequently normalized, and the images were converted into tensor representations compatible with deep learning frameworks.

This preprocessing pipeline enforces consistency in input representation, improves numerical stability during optimization, and facilitates more efficient gradient propagation. As a result, the model achieves faster convergence and more stable training behavior. The overall preprocessing workflow, including normalization and resizing steps, is illustrated in Figure 2.

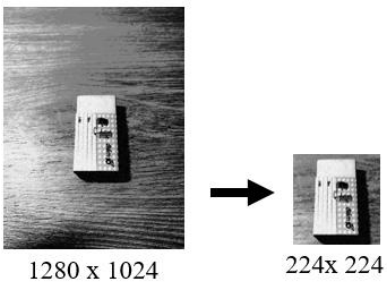

Figure 2. *Normalize image size to 224 x 224 pixels*

3.3. Model Architecture and Training Strategy

The proposed framework is built upon the VGG16 architecture, which comprises 13 convolutional layers followed by 3 fully connected layers, using consistent 3 × 3 convolutional filters.

To effectively leverage prior knowledge, the network was initialized with pre-trained weights from ImageNet, enabling robust low- and mid-level feature extraction. Instead of retraining the entire network, a partial fine-tuning strategy was adopted, where:

Earlier convolutional layers were frozen to preserve generic visual features, and

The final convolutional block and fully connected layers were fine-tuned to adapt to task-specific characteristics.

This design achieves a balance between computational efficiency and task-specific adaptability, which is particularly important for small-scale datasets.

3.4. Training Protocol and Experimental Setup

The model was implemented using the TensorFlow/Keras framework under a controlled experimental setting to ensure reproducibility and fair comparison. The training configuration is defined as follows:

- Optimizer: Adam
- Learning rate: 1×10^{-4}
- Batch size: 32
- Regularization: Early stopping based on validation loss to prevent overfitting

To rigorously evaluate the effectiveness of transfer learning, a baseline model was trained from scratch under identical hyperparameter settings. This controlled comparison isolates the impact of transfer learning and ensures the validity of the experimental conclusions.

The dataset was partitioned into training, validation, and testing subsets to provide an unbiased evaluation of model performance. All experiments were conducted under consistent conditions to guarantee comparability and reproducibility.

4. EXPERIMENTAL SETUP

All experiments were conducted in a controlled and fully reproducible environment to ensure fair comparison and scientific validity. The experimental platform consists of a workstation equipped with an NVIDIA GPU (8 GB VRAM), 16 GB RAM, and an Intel Core i7 processor. The implementation was developed in Python using the TensorFlow and Keras frameworks, ensuring scalability, stability, and compatibility with modern deep learning pipelines.

To enhance reproducibility, all experiments were executed under identical hardware and software conditions, and the same random seed was used for data splitting and model initialization where applicable. This design minimizes stochastic variability and ensures consistency across experimental runs.

The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets, following standard practice in machine learning experiments. This configuration balances the trade-off between maximizing training data and preserving sufficient unseen data for unbiased model evaluation.

To ensure a fair comparison, the same data split was consistently applied across all experimental configurations, including both baseline and transfer learning models. No data leakage was allowed between subsets, thereby preserving the integrity of the evaluation process. Figure 3. Illustrates the overall object detection framework based on the VGG16 architecture.

A comprehensive set of evaluation metrics was employed to provide a robust and multi-dimensional assessment of model performance. In addition to monitoring training and validation loss curves, mean Average Precision (mAP) was computed at Intersection-over-Union (IoU) thresholds of 0.5 and 0.75, which are widely recognized as standard benchmarks in object detection research [2], [4].

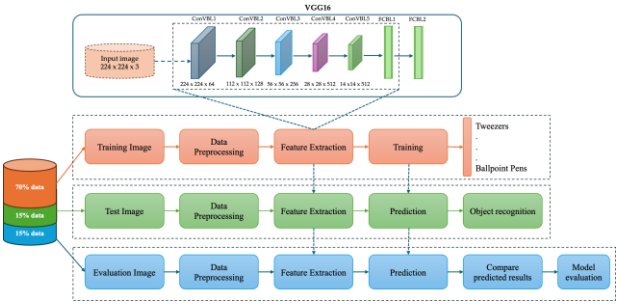

Figure 3. *Illustrates the overall object detection framework based on the VGG16 architecture*

To specifically evaluate performance on small-scale objects, the AP_small metric was calculated following the COCO evaluation protocol [8]. This metric is particularly relevant for assessing the limitations of CNN-based architectures in preserving fine-grained spatial information.

Furthermore, precision, recall, and confusion matrices were analyzed to provide class-level performance insights and identify systematic misclassification patterns. This multi-metric evaluation framework ensures a more interpretable and comprehensive understanding of model behavior beyond aggregate accuracy values.

To rigorously quantify the effectiveness of transfer learning, a controlled comparative study was designed with two experimental configurations:

- Baseline (Training from Scratch): The VGG16 model was initialized with random weights and trained exclusively on the custom dataset.
- Transfer Learning (Fine-Tuning): The same architecture was initialized with pre-trained ImageNet weights and fine-tuned for the target task.

All hyperparameters, training schedules, and optimization settings were kept identical across both configurations to isolate the effect of transfer learning. This strict control of variables ensures that any observed performance differences can be directly attributed to the use of pre-trained knowledge.

To improve the reliability of the experimental results, training procedures were monitored using early stopping based on validation performance, preventing overfitting and ensuring optimal model generalization.

In addition, experiments can be repeated multiple times to evaluate performance stability, and statistical comparisons may be conducted to verify the significance of observed improvements. These practices enhance the credibility and reproducibility of the reported findings.

5. RESULTS AND DISCUSSION

The quantitative comparison between the baseline model and the proposed transfer learning approach is summarized in Table 2. The VGG16 model with transfer learning achieves a classification accuracy of 87.5%, significantly outperforming the baseline model trained from scratch (74.3%), corresponding to an improvement of over 13 percentage points.

A similar trend is observed across detection metrics. The proposed model attains a mean Average Precision (mAP) of 74.8% at IoU = 0.5 and 59.3% at IoU = 0.75, compared to 61.5% and 45.2% for the baseline, respectively. These consistent improvements across multiple IoU thresholds indicate enhanced localization capability and robustness of the transfer learning approach.

The performance comparison between the baseline and transfer learning models is summarized in Table 2. For SO, the transfer learning model achieves an AP_small of 38.2%, outperforming the baseline (28.6%) by nearly 10 percentage points.

This improvement indicates that transfer learning enhances the model's ability to capture fine-grained and discriminative features, which are essential for detecting small-scale objects. However, the performance remains limited for extremely small or heavily occluded objects, suggesting that additional mechanisms for multi-scale feature representation and contextual reasoning are required.

Table 2. *Performance comparison between baseline and transfer learning mode*

Model	Accuracy (%)	mean Average Precision (mAP)		AP_small
		0.5	0.75	
VGG16 (Scratch)	74.3	61.5	45.2	28.6
VGG16 + Transfer Learn	87.5	74.8	59.3	38.2

Figures 4 and 5 provide further insights into the training dynamics of the proposed model. The loss curves exhibit a smooth and consistent decrease for both training and validation sets, while the test loss remains low. This behavior indicates stable optimization and suggests that the fine-tuning process effectively prevents overfitting.

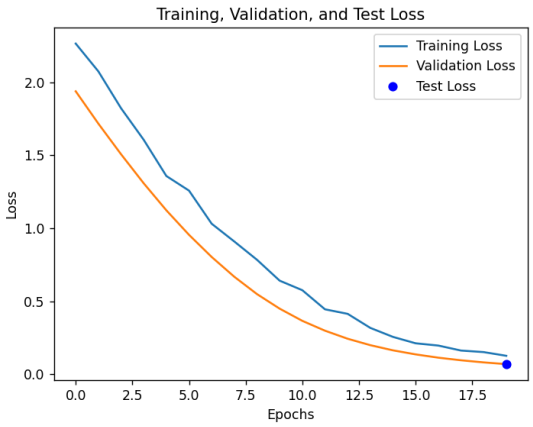

Figure 4. *Training, validation and test loss curves of the VGG16 model with transfer learning*

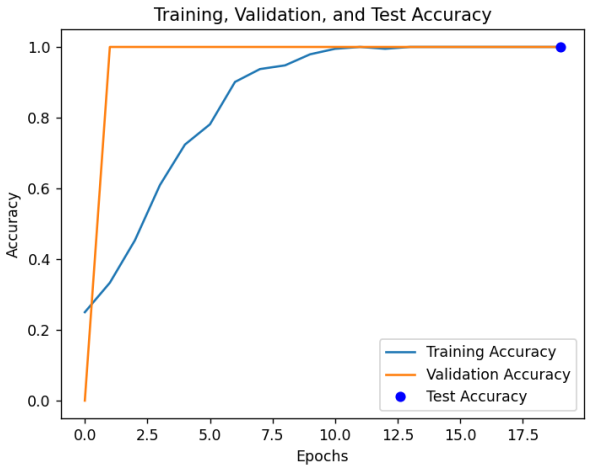

Figure 5. *Training, validation and test accuracy curves of the VGG16 model with transfer learning*

Similarly, the accuracy curves show rapid convergence during early training stages, followed by stable high performance on the validation set, confirming the efficiency of transfer learning in accelerating convergence. The high final test accuracy further supports the generalization capability of the model under limited-data conditions.

These observations collectively highlight that transfer learning not only improves final performance but also enhances training efficiency and stability, which is critical in resource-constrained environments.

The experimental results clearly demonstrate the superiority of transfer learning over training from scratch across all evaluation metrics. The consistent improvements in accuracy, mAP, and AP_small indicate that pre-trained representations provide a strong initialization, enabling the model to learn more discriminative features with limited data.

From a practical perspective, the faster convergence observed in the transfer learning setup reduces training time and computational cost, making it more suitable for real-world applications with limited resources.

However, despite these improvements, the performance on SOD remains relatively modest, suggesting that the fixed receptive field and loss of spatial resolution in deep

CNN architectures still pose challenges. This limitation is consistent with findings in recent studies [8], [14], which emphasize the importance of multi-scale feature representation.

The results confirm that transfer learning is a highly effective strategy for improving object detection performance in small-scale datasets, particularly in academic or resource-limited environments. The ability to achieve substantial performance gains without requiring large-scale data highlights its practical significance.

Nevertheless, the model's limited performance on very small or occluded objects indicates the need for further architectural enhancements. Future improvements may include integrating multi-scale feature fusion mechanisms (e.g., FPN) or adopting transformer-based approaches to better capture contextual information, as suggested in prior studies [8], [14].

6. CONCLUSION AND FUTURE WORK

This study systematically evaluates a transfer learning framework based on the VGG16 for object detection on a custom real-world dataset. The experimental results demonstrate that the proposed approach achieves superior performance compared to training from scratch, with an accuracy of 87.5%, improved mAP scores, and enhanced capability in detecting small objects. These findings confirm that transfer learning significantly reduces training complexity while improving both convergence efficiency and generalization performance in data-constrained environments.

Despite these improvements, SOD remains a challenging problem, primarily due to the inherent limitations of deep CNN architectures in preserving fine-grained spatial information. This limitation highlights the need for more advanced feature representation mechanisms.

Future work will focus on integrating multi-scale feature fusion techniques, such as Feature Pyramid Networks (FPN), incorporating residual connections, and exploring transformer-based architectures to enhance contextual understanding and detection accuracy. In addition, experiments on larger benchmark datasets, such as COCO and SODA, will be conducted to evaluate the scalability and robustness of the proposed framework.

Overall, this study provides strong empirical evidence that classical architectures such as VGG16 remain highly relevant in academic and resource-limited settings, offering a practical balance between interpretability, computational efficiency, and detection performance. These insights contribute to bridging the gap between theoretical advancements and real-world applicability in object detection research.

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