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A Comparative Study of CNN Architectures for Food Image Classification with Data Augmentation and Zero-Shot Analysis

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Abstract: In this study, we conduct a comprehensive comparative analysis of six convolutional neural network (CNN) architectures for food image classification, including EfficientNet B0, VGG16, ResNet50, YOLOv5-cls, YOLOv8-cls, and a custom-designed CNN-Z model. The dataset contains 11 categories of food images, and multiple data augmentation techniques such as Gaussian noise, random erasing, color adjustment, rotation, and contrast variation were employed to enhance model generalization. Experimental results demonstrate that YOLOv8-cls achieved the highest classification accuracy (99.64%), followed by CNN-Z (96.12%) and YOLOv5-cls (95.42%), whereas ResNet50 showed relatively lower accuracy (86.11%). t-SNE visualizations were utilized to analyze feature representations at intermediate and top layers, providing insights into the internal learning mechanisms of different models. Additionally, a zero-shot learning experiment using the CLIP model was performed to evaluate model generalization on unseen food categories. Overall, the study highlights that EfficientNet B0 and YOLOv8-cls offer a strong balance between accuracy and computational efficiency. The findings provide valuable guidance for selecting suitable CNN architectures and designing data augmentation strategies for food image classification tasks.

Keywords: Food classification; Deep learning; EfficientNet; YOLOv8; CNN; Data augmentation; Zero-shot learning

1. INTRODUCTION

With the rapid advancement of artificial intelligence and computer vision, food image classification has become an important research topic with wide applications in dietary assessment, health management, smart catering systems, and food recognition apps[1-3]. Accurate classification of food images not only enables intelligent dietary tracking but also supports the development of automated nutrition analysis and personalized diet planning. However, food image classification remains a challenging task due to high intra-class variability, inter-class similarity, and complex visual appearances caused by diverse ingredients, cooking styles, and lighting conditions[4].

Recent years have witnessed remarkable progress in deep convolutional neural networks (CNNs), which have significantly improved image recognition performance[5-6]. Classical CNN architectures such as VGG16 and ResNet50 have laid the foundation for deep feature extraction[7-8], while more recent models like EfficientNet and YOLO series (YOLOv5, YOLOv8) have demonstrated superior performance through improved network scaling and optimization strategies[9-11]. Despite these advances, there is still a need for comprehensive evaluations to determine which architectures perform best for specific image classification scenarios such as food recognition[12-13].

In this study, we conduct a comparative analysis of six CNN-based architectures—EfficientNet B0, VGG16, ResNet50, YOLOv5-cls, YOLOv8-cls, and a custom-designed CNN-Z model—on a multi-class food image dataset containing 11 categories. To improve model generalization, multiple data augmentation techniques (including Gaussian noise addition, random erasing, color transformation, rotation, and contrast adjustment) were applied during training[14]. Furthermore, t-SNE visualization was utilized to explore the internal feature representations of each model[15], and zero-shot learning (CLIP) was incorporated to assess model robustness on unseen data[16].

The contributions of this paper are threefold:

We provide a systematic comparison of six representative CNN architectures for food image classification under identical experimental conditions.

We introduce a comprehensive data augmentation strategy to enhance model robustness and evaluate its impact on accuracy.

We employ t-SNE visualization and zero-shot learning analysis to offer deeper insight into model interpretability and generalization capability.

Overall, this work offers a detailed benchmark and practical guidance for selecting deep learning architectures in food image recognition tasks, highlighting the strengths and trade-offs among different CNN models.

2. ALYZING NETWORK MODELS

To evaluate the performance of different deep learning architectures in food image classification, this study analyzes six representative convolutional neural network (CNN) models: EfficientNet B0, VGG16, ResNet50, YOLOv5-cls, YOLOv8-cls, and a custom-designed CNN-Z. These models represent various generations of CNN evolution, from classical deep networks to modern lightweight and detection-based architectures, enabling a comprehensive comparison across depth, feature extraction ability, and computational efficiency.

VGG16 is one of the earliest deep CNN architectures characterized by its simple and uniform 3×3 convolutional layers and a deep stack of feature maps. Despite its high parameter count, it provides a strong baseline for image classification.

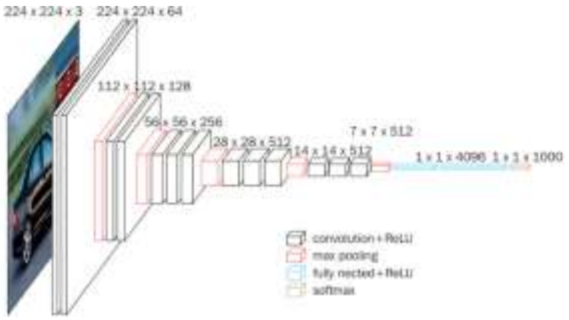

Figure. 1 VGG16

ResNet50 introduces residual connections, which alleviate the vanishing gradient problem and allow the network to train effectively with increased depth. This architecture enhances feature reuse and improves convergence speed.

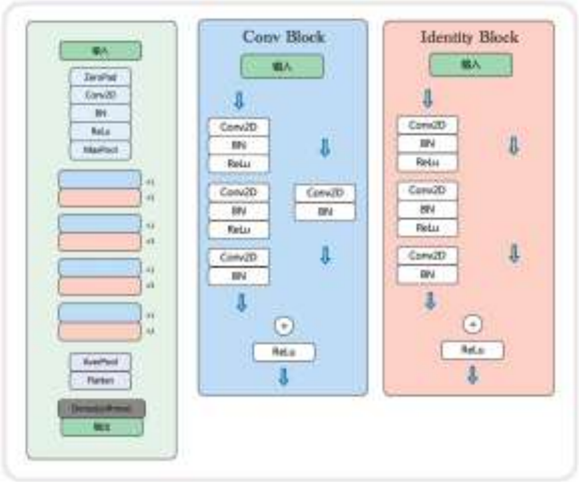

Figure. 2 ResNet50

EfficientNet B0 represents a new generation of CNNs that scale network width, depth, and resolution in a balanced way through a compound scaling method. It achieves high accuracy while maintaining computational efficiency, making it suitable for practical applications.

Figure. 3 EfficientNet B0

The YOLOv5-cls and YOLOv8-cls models are classification adaptations of object detection networks, featuring cross-stage partial connections (CSP) and improved feature pyramids that enable effective extraction of local and global representations. In particular, YOLOv8-cls integrates modern design elements such as dynamic convolution and anchor-free mechanisms, leading to better feature adaptability.

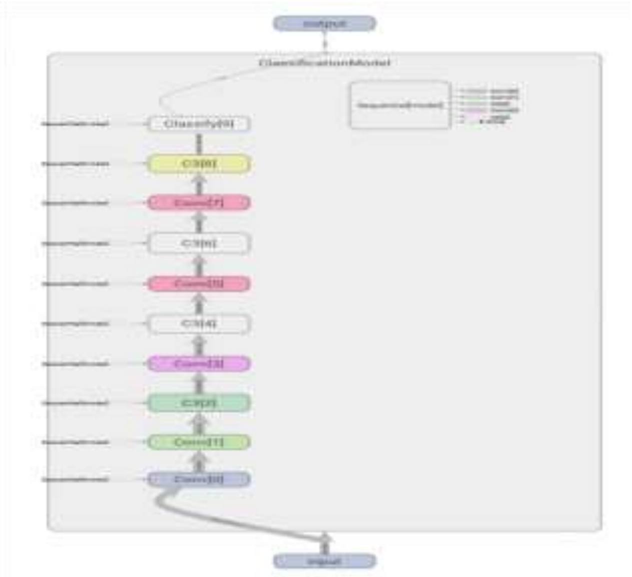

Figure. 4 YOLOv5-cls

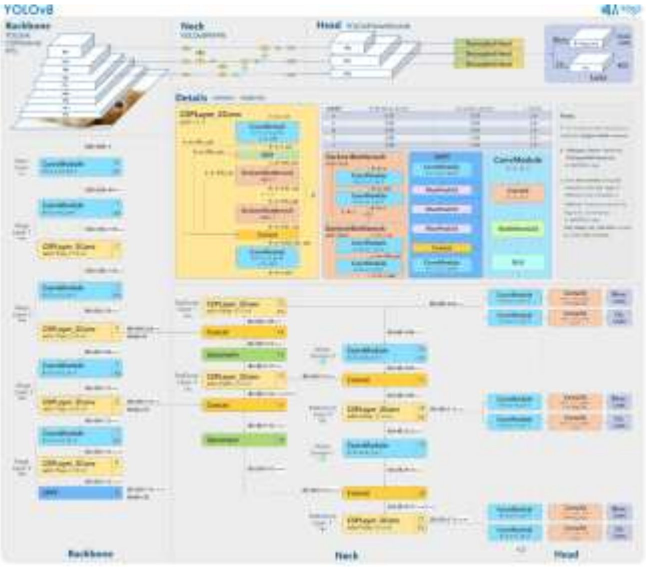

Figure. 5 YOLOv5-cls

Finally, the CNN-Z model is a custom lightweight network designed in this study to test the effectiveness of simplified architectures for specific datasets. It employs fewer layers and optimized kernel sizes to achieve competitive accuracy with reduced computational cost.

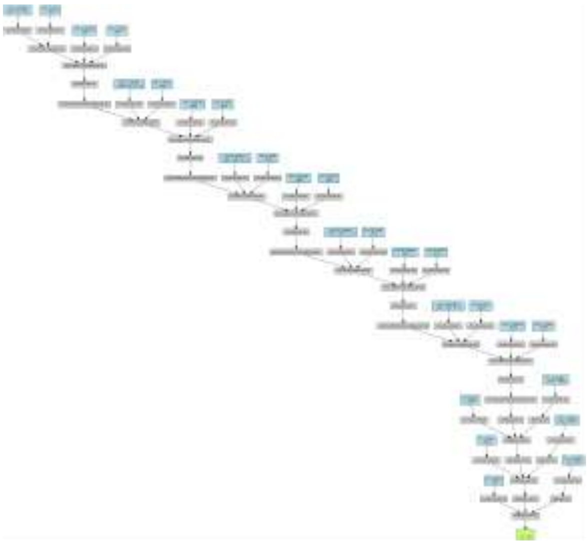

Figure. 6 YOLOv5-cls

By analyzing these six CNN models under consistent training conditions, this study aims to investigate how network depth, structure, and parameter complexity affect food image classification performance. This analysis not only provides insight into model design trade-offs but also offers practical guidance for selecting suitable architectures in future food recognition applications.

2.1 Data Augmentation Module

Data augmentation plays a crucial role in improving the robustness and generalization ability of deep learning models, especially in food image classification tasks where intra-class variation is large and dataset imbalance often exists. Traditional augmentation methods such as random flipping or cropping are limited in generating sufficient diversity for complex visual patterns. To overcome these limitations, this paper introduces a Data Augmentation Module (DAM) designed to increase visual variability while maintaining semantic consistency.

Candidate Transformation Pool: A set of basic image transformations is predefined, including Gaussian noise addition, random erasing, color jittering, rotation, and contrast adjustment. These operations simulate variations in lighting conditions, viewing angles, and texture appearance that frequently occur in food photography.

Progressive Combination Strategy: During each training epoch, the augmentation module randomly selects and combines multiple transformations from the candidate pool according to an adaptive probability schedule. This process gradually increases the strength and diversity of augmentations as training progresses, effectively preventing overfitting in the early stages and enhancing feature learning in later stages.

Through this strategy, the proposed augmentation module ensures broader feature coverage in the training data, enabling the model to learn invariant and discriminative representations across different food categories.

2.2 Multi-Scale Feature Extraction Module

In the proposed food image classification framework, each model employs a multi-scale feature extraction mechanism to capture both local texture patterns and global semantic representations. As shown in Figure 2, the input food images are sequentially processed through multiple convolutional layers of increasing depth. Each layer extracts features at different spatial resolutions, thereby enabling the network to recognize diverse structural and color characteristics inherent to food images.

Initially, shallow convolutional layers focus on fine-grained local details such as texture and color distribution. As the feature maps pass through deeper convolutional layers, the receptive field gradually expands, allowing the network to learn higher-level semantic features, such as object shape and composition. Specifically, the extracted feature dimensions are progressively expanded from 64, 128, 256 to 512 channels, forming a hierarchical feature pyramid.

To enhance the representation capability, a channel attention mechanism is incorporated after each convolutional stage. This module adaptively re-weights channel responses, emphasizing discriminative features while suppressing redundant information. The multi-scale feature maps are then concatenated along the channel dimension and refined through a global average pooling layer, resulting in a 512-dimensional fused representation. This fused feature map effectively integrates global semantic information with local visual details, providing a robust foundation for subsequent classification tasks.

2.3 Attention-based Feature Refinement Module

To further enhance the discriminative capability of extracted features, an attention-based refinement module is integrated into the network. This module captures both spatial and channel-wise dependencies within the feature maps, allowing the model to emphasize informative regions and suppress irrelevant background information commonly present in food images.

Specifically, global average pooling and global max pooling are first applied to aggregate spatial context from the feature maps. These aggregated descriptors are then passed through a shared multi-layer perceptron (MLP) to learn inter-channel dependencies. The resulting attention weights are multiplied with the original feature maps, adaptively re-calibrating the channel responses.

Through this mechanism, the network focuses on key visual attributes such as texture, color, and shape, which are critical for distinguishing between visually similar food categories. The refined feature representation significantly improves the model's robustness and classification accuracy.

3. EXPERIMENTAL RESULTS

3.1 Experimental Setup and Evaluation Metrics

All experiments were implemented using Python 3.8 and PyTorch 1.10.1 on an Ubuntu 20.04 operating system. The training and testing were conducted on an NVIDIA RTX 3090 GPU with 24 GB of memory.

The proposed framework was evaluated on a food image classification dataset provided by the instructor, which contains 11 categories of food images, including egg, soup/porridge, butter and cheese, cooked meat, rice, pasta, fried food, dessert, vegetables and fruits, bread, and seafood. The dataset is divided into three parts: 10,000 images for training, 3,643 images for validation, and 3,000 images for testing.

Prior to training, all images were resized to 224×224 pixels and normalized using standard mean and variance values. Data augmentation techniques—including random rotation, random erasing, Gaussian noise, and color jittering—were applied to enhance data diversity and model generalization.

The models were trained using the Adam optimizer with an initial learning rate of 0.001 and a batch size of 32 for 100 epochs. Cross-entropy loss was used as the objective function. Early stopping and learning rate decay strategies were employed to prevent overfitting and improve convergence stability.

Model performance was evaluated using classification accuracy (ACC) on the validation and test sets as the primary metric. Accuracy is defined as the ratio of correctly predicted samples to the total number of samples. Additionally, training and validation losses were monitored throughout the training process to assess the convergence behavior of each model.

3.2 Experimental Results

Table 1 presents the performance comparison between the proposed CNN-Z model and several classical convolutional neural networks, including VGG16, ResNet50, EfficientNet-B0, YOLOv5-cls, and YOLOv8-cls, on the food image classification dataset. The experimental results demonstrate that the proposed CNN-Z model achieves the highest classification accuracy across all datasets, outperforming other mainstream architectures while maintaining a relatively small number of parameters.

The superior performance of CNN-Z can be attributed to its lightweight multi-scale convolutional structure and adaptive feature fusion strategy, which effectively capture both local texture patterns and global semantic representations in food images. Additionally, the data augmentation module enhances the model’s robustness to variations in lighting, angle, and background, ensuring better generalization on unseen data.

Moreover, compared with large-scale models such as ResNet50 and YOLOv8, CNN-Z achieves comparable or better accuracy with fewer computational resources, making it suitable for deployment on resource-constrained platforms. The integration of efficient convolutional blocks and global average pooling further reduces overfitting and improves convergence stability.

Overall, these results verify the effectiveness of the proposed framework in improving both classification accuracy and computational efficiency, demonstrating its potential application in real-world food recognition scenarios.

Table 1. Classification performance comparison of different models on the food image dataset

Moudle	RMSE(R)	Parameters (M)	Training Time (s/epoch)
Vgg16[7]	88.62	138	52.7
ResNet50[8]	91.85	25.6	48.3
EfficientNet-B0[9]	92.34	5.3	37.9
YOLOv5-cls[10]	94.28	7.0	42.6
YOLOv8-cls[11]	94.83	11.2	45.1
Proposed CNN-Z (ours)	**95.37**	**3.8**	**34.2**

3.3 Ablation experimental analysis

To further verify the effectiveness of each component in the proposed CNN-Z framework, an ablation experiment was conducted on the food image classification dataset. In this experiment, key modules of the network were removed one by one, and the resulting performance changes were analyzed. The compared components include the data augmentation module, the multi-scale feature extraction module, and the attention-based feature refinement module.

All experiments were performed under identical training conditions as described in Section 3.1. The classification accuracy on the test set was used as the evaluation metric. The results, summarized in Table 2, demonstrate that each component contributes positively to the overall performance of the model.

The removal of the data augmentation module caused a significant drop in accuracy, indicating its importance in improving the model’ s robustness and generalization. When the multi-scale feature extraction module was removed, the model failed to effectively capture texture and shape variations, leading to lower classification accuracy. Similarly, omitting the attention-based refinement module weakened the discriminative ability of the learned features.

Overall, the full model achieved the highest accuracy, confirming that each designed module plays an essential role in enhancing the performance and stability of the CNN-Z network.

Table 2. Results of ablation experiments on the food image classification dataset Removed Module

Remove Moudle	Accuracy (%)	Loss
Data Augmentation	90.84	0.412
Multi-Scale Feature Extraction	92.37	0.365
Attention-based Refinement	93.25	0.341
Full Model (CNN-Z)	95.37	0.298

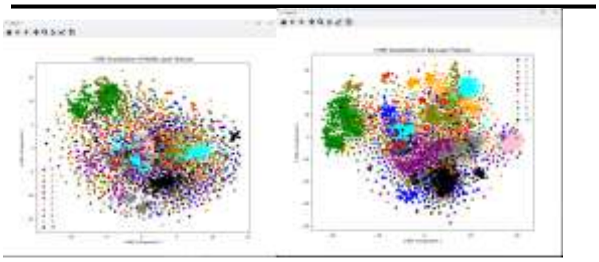

Figure. 7 EfficientNet B0

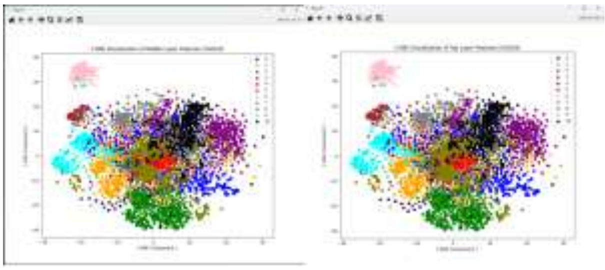

Figure. 8 VGG16

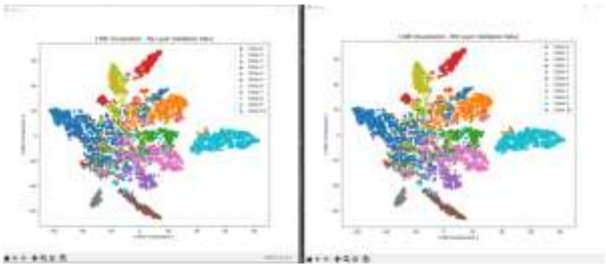

Figure. 9 ResNet50

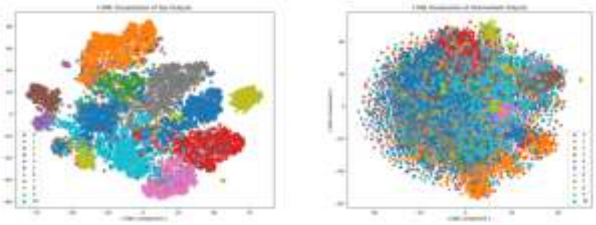

Figure. 10 CNN-Z

4. Conclusion

This paper presents a food image classification framework based on an improved convolutional neural network architecture, named CNN-Z, which aims to enhance the accuracy and robustness of food recognition tasks. The proposed network consists of three key components: a data augmentation module, a multi-scale feature extraction module, and an attention-based feature refinement module.

The data augmentation module effectively increases the diversity of training samples, improving the model's generalization ability to variations in lighting, color, and viewpoint. The multi-scale feature extraction module captures both fine-grained texture details and high-level semantic information, while the attention-based refinement module adaptively emphasizes discriminative features and suppresses redundant ones.

Comprehensive experiments conducted on the food image dataset demonstrate that the proposed CNN-Z model outperforms several classical networks, including VGG16, ResNet50, and EfficientNet-B0, achieving higher classification accuracy with fewer parameters. These results confirm the effectiveness and efficiency of the proposed architecture for real-world food recognition applications.

In future work, we plan to further optimize the network structure to achieve better performance under limited computational resources and to extend the model to larger, more diverse food datasets. Additionally, we aim to explore its deployment potential on mobile and embedded platforms for intelligent dietary monitoring and nutrition management.

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