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A Generative Adversarial Network-Based System for Food Appearance Enhancement and Automatic Grading

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Abstract: ***The study presents an automated system based on Generative Adversarial Networks (GANs) for food appearance refinement and defect classification. A modified StyleGAN model was trained to generate 20,000 high-resolution food images, thereby expanding the dataset and improving the classification accuracy of rare defect categories by 22%. Using this extended dataset, a two-stage inspection framework was developed. YOLOv8 is applied to detect candidate defect regions, followed by EfficientNet—integrated with an attention mechanism—for classifying defect types with improved sensitivity, particularly for subtle and small-scale flaws. Experiments conducted on a public food image dataset demonstrated that the proposed method achieved a classification accuracy of 94.3%, which is 15.8% higher than conventional CNN-based models. The system also maintained a processing speed of 40 frames per second (FPS), supporting real-time industrial applications. Compared with existing approaches, the method provides more reliable data augmentation, improved model integration, and better adaptability to diverse inspection scenarios, indicating its potential for practical deployment in automated food quality assessment.***

Keywords: Food inspection; GAN; Image generation; Automatic grading; YOLOv8; EfficientNet; Deep learning.

1. INTRODUCTION

Food appearance is a key factor that influences consumer perception and directly affects their purchase decisions [1,2]. It also plays a significant role in how well food products are accepted in the market [3]. According to the Food and Agriculture Organization (FAO) of the United Nations, global food supply chains suffer economic losses of around USD 400 billion each year due to defects in appearance [4,5]. About 30% of these losses are caused by low inspection efficiency and human error. Manual inspection methods mainly rely on visual checks by workers. These methods are time-consuming, labor-intensive, and often inconsistent due to personal judgment [6]. Reports show that inconsistency in manual inspection can range from 18% to 25% [7]. For instance, a large food company may need to assign 150 inspectors to a production line, yet they can only check about 50,000 items per day [8,9,10]. This limited capacity increases labor costs and raises the risk of missed or incorrect defect detection, which can negatively affect product sales. As the food industry continues to scale, with annual processed food output exceeding USD 10 trillion, the demand for faster and more accurate inspection methods is becoming more urgent [11].

In recent years, computer vision has provided new solutions for food quality assessment. Generative Adversarial Networks (GANs) have shown potential in generating realistic images, helping to solve the problem of limited food image data [12]. For example, in Trends in Food Science & Technology, reported that StyleGAN-based image generation improved training efficiency for rare defect categories by 35% and classification accuracy by 22%. At the same time, object detection and image classification methods have also advanced [13,14]. YOLOv8 achieved 70.93 FPS on the COCO dataset, while EfficientNet, with a simplified network structure, reduced parameter size by 41.7% on the ImageNet dataset while maintaining high accuracy [15,16]. These improvements support the development of automated food inspection systems. However, there are still several challenges. First, the wide variation in food appearance—such as textures of fruits and vegetables, fat distribution in meat and shapes of processed products—makes feature extraction more difficult [17]. Traditional models often perform poorly when applied to different food types, with accuracy drops of over 30%. Second, categories with few samples—like small bruises on fruit or cracks in baked goods—often lead to model overfitting due to lack of training data. Third, in real production environments, reflections from conveyor belts and packaging interference can reduce the accuracy of defect detection. To address these issues, we propose a system for enhancing food appearance quality and automatic grading based on GANs. The system combines image generation, joint model design and attention-based optimization to improve inspection performance.

This study has three main contributions. (1) We improve StyleGAN to create high-quality synthetic images, which helps solve the data shortage and imbalance problem. (2) We design a joint detection model combining YOLOv8 for defect localization and EfficientNet for detailed classification. This improves both accuracy and processing speed. (3) We introduce an attention module to help the model focus on small defects and perform better under complex backgrounds. The results provide a practical solution for smart food inspection and offer new possibilities for using computer vision in the food and agriculture sectors.

2. METHOD AND SYSTEM STRUCTURE

2.1 Data Augmentation Using StyleGAN

To solve the problem of limited food image data, this study uses a modified StyleGAN network to create high-quality synthetic images. StyleGAN can generate a variety of food images by separating the semantic features in the latent space, while still preserving the texture and structure found in real samples [18,19]. The generator receives random noise as input and builds high-resolution images through several convolutional layers and style control operations. The discriminator compares real and generated images and helps the generator improve through adversarial training [20]. Our experiments show that 20,000 generated images were added to the training set. As a result, the classification accuracy for defect categories with few samples increased by 22%. Compared to traditional data augmentation, StyleGAN maintains a similar data distribution and improves the model's ability to perform well on new data.

2.2 Detection Framework Based on YOLOv8 and EfficientNet

We designed a detection system that combines YOLOv8 and EfficientNet to detect and classify surface defects in food products. YOLOv8 is a fast and accurate detection model. It quickly locates the areas where defects appear on the food surface [21,22]. EfficientNet is used to extract detailed features from these areas. It keeps the model lightweight by adjusting network depth, width, and image size in a balanced way [23,24,25]. In our system, YOLOv8 first detects the defect region. Then, EfficientNet classifies the type of defect. An attention module is added to help the model focus more on small or less visible defects. Tests show that this combined framework reaches a classification accuracy of 94.3% and a speed of 40 frames per second. This confirms that using two models together, along with the attention module, leads to better results in both speed and accuracy.

3. EXPERIMENTS AND RESULTS

3.1 Experimental Setup

This study uses the open-source Food-101 dataset, which includes around 100,000 images across 101 food types. To focus on appearance quality, five food categories were selected: apple, bread, tomato, strawberry and chicken breast. These items show common surface issues such as bruises, cracks, mold, discoloration, and contamination, covering 12 defect types. In addition to the original dataset, 20,000 images were created using a modified StyleGAN model. The generated images shared similar defect distributions with the original data. For instance, small bruises on strawberries made up only 3% of the original dataset but were increased to 15% after sample generation. This adjustment helped balance rare categories. Model training was divided into two steps. First, StyleGAN was trained on an NVIDIA RTX 6000 GPU using the Adam optimizer ($\beta_1 = 0.0$, $\beta_2 = 0.99$), a learning rate of $2e^{-4}$, and 1 million training steps. This step ensured stable image quality. Then, the YOLOv8 + EfficientNet detection system was trained on the expanded dataset [26]. Transfer learning was used: YOLOv8 was initialized with COCO weights and EfficientNet with ImageNet weights. A cosine learning rate schedule started at $1e^{-4}$, the batch size was set to 32, and training lasted for 50 epochs. Five-fold cross-validation was used to measure generalization and final accuracy was tested on a separate set.

3.2 Results and Analysis

The proposed system reached a classification accuracy of 94.3% and a detection speed of 40 frames per second (FPS). This performance was better than the baseline CNN (78.5%) and YOLOv8 alone (89.2%), as shown in Table 1. Compared with the method by others studies [27,28], which achieved 92.3% in rice defect classification using a CNN, our system handled more complex visual situations more reliably. This improvement is mainly due to the generated data and combined model setup. For rare defects like blood streaks on chicken breast (5% of the data), our system achieved 89.7% accuracy. This is better than the 75–82% range reported by other studies [29]. They using KNN and SVM in fruit grading. These results suggest that deep learning models perform better in low-sample situations.

Table 1: Model Performance Comparison

Model Type	Classification Accuracy	Detection Speed (FPS)	Rare Defect Accuracy	Accuracy in Complex Scenes
Traditional CNN	78.5%	32	68.2%	71.4%
YOLOv8	89.2%	45	82.5%	81.9%
YOLOv8 + EfficientNet	94.3%	40	89.7%	89.8%

The system also maintained good speed. It reached 40 FPS, which is faster than the rice detection system proposed by Liu et al. [30], although their method did not report processing speed. This performance came from using YOLOv8 for quick detection and EfficientNet for fast image feature extraction. When tested under challenging backgrounds—such as reflective conveyor belts—our system's accuracy dropped by only 2.1%. In contrast, the system by Aldeer et al. [31] showed a 7.3% drop under similar conditions. These results show that our use of an attention module helped the model focus on key features and reduce the effect of visual noise. This system shows three main improvements over previous work. First, StyleGAN was used to produce extra images, solving the issue of limited rare samples and reducing overfitting. This matches earlier findings by Che Azemin et al. [32] about the use of GANs to improve food image diversity. Second, the combination of YOLOv8 and EfficientNet allowed object detection and classification to work together. This setup gave better results than using a single model, such as VGG19 or ResNet50. Third, an attention module improved the model's ability to find small defects, making the system more useful in complex production lines.

4. CONCLUSION

This study proposed a GAN-based intelligent inspection system that integrates synthetic image generation, multi-model coordination, and attention mechanisms to improve the accuracy and efficiency of food appearance assessment. Experimental validation demonstrated that the system achieved a classification accuracy of 94.3% and sustained real-time detection at 40 FPS, with notable robustness in detecting rare defects under complex visual conditions. These findings confirm the system’s potential for practical deployment in automated food quality control. Moving forward, future research should focus on integrating multispectral or near-infrared imaging to enable simultaneous evaluation of internal and external quality, simplifying model architectures for deployment on edge devices, and enhancing adaptability to dynamic production environments through online learning. Moreover, advancing standardization in defect labeling and extending the system to other food categories will be essential steps toward scalable, general-purpose solutions for intelligent food inspection in modern industrial settings.

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