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Augmentation-based image object classifier

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GENERAL DESCRIPTION OF WORK

Research Aim and Objectives

Image object classification is a crucial task in computer vision, with wide applications in areas such as intelligent surveillance, autonomous driving, and medical image analysis. Deep learning models, especially convolutional neural networks, have achieved significant performance improvements in image classification tasks. However, these models typically require large-scale labeled data for training.

In many practical applications, obtaining sufficient training data is difficult and costly. Data augmentation techniques are commonly used to increase the diversity of training samples. In recent years, generative models such as CycleGAN have demonstrated good capabilities in generating high-quality images and have been applied to data augmentation tasks.

The aim of this research is to examine how CycleGAN-based data augmentation influences image classification under domain variation. In this approach, CycleGAN is used to generate synthetic images that extend the training dataset and to analyze how data diversity affects the behavior and generalization of classification models.

To achieve this aim, the following objectives are addressed:

1.To review existing image classification methods and data augmentation techniques.

2.To analyze the role of generative models, particularly CycleGAN, in data augmentation.

3.To construct a CycleGAN-based augmentation setting for introducing domain variation.

4.To examine how different augmentation strategies influence classification behavior.

Research Object and Research Methods

This paper focuses on image object classification using generative data augmentation techniques. The main objective is to analyze how data augmentation affects classification behavior under limited training data conditions.

To achieve this, we utilize CycleGAN to generate new synthetic images to expand the training dataset, and then combine these generated images with the original dataset to use a classification model as an evaluation tool for analyzing the effect of different data configurations.

This study adopts a structured analytical approach. First, it reviews relevant literature on classification and augmentation. Second, it applies CycleGAN to

generate cross-domain samples. Finally, it examines how different training data configurations influence model behavior.

Scientific Significance and Practical Value

The combination of generative models and image classification models has become an important research direction in the field of computer vision. Using generative models for data augmentation can effectively increase the diversity of datasets and improve the generalization ability of the model.

This study examines how CycleGAN-based augmentation contributes to data diversity by generating cross-domain samples. Instead of focusing on model optimization, the analysis emphasizes how such variation influences feature learning and model behavior.

The findings may provide insights into the role of distribution-level augmentation in addressing domain variation. This is particularly relevant in scenarios where large-scale labeled data are difficult to obtain, such as medical imaging, industrial inspection, and real-world monitoring systems.

INTRODUCTION

Image object classification is an important task in computer vision. It assigns a label to an image based on the object shown. For example, an image can be classified as a car, a person, or an animal. This task is widely used in many real-world applications, such as autonomous driving, medical imaging, security monitoring, and industrial inspection. Because of its wide range of applications, image classification has become a key research topic in recent years.

In the past, image classification mainly relied on traditional machine learning methods. These methods usually include feature extraction and classification. Handcrafted features such as color, texture, and shape are extracted from images, and classifiers such as Support Vector Machines are used for classification. However, these methods depend heavily on manual feature design and cannot effectively represent complex image patterns.

With the development of deep learning, image classification performance has improved significantly. Convolutional Neural Network can automatically learn features from images and achieve high accuracy in image recognition tasks. It has shown strong performance on large datasets such as ImageNet, and has gradually replaced traditional methods in many applications.

However, deep learning models usually require large amounts of labeled data for training. In many practical cases, collecting and labeling data is expensive and time-consuming. When training data is limited, model performance may decrease.

To address this problem, data augmentation is widely used. Traditional methods such as rotation, flipping, and cropping can increase dataset size, but they cannot generate new image structures, which limits data diversity.

In recent years, Generative Adversarial Networks (GAN) have been used to generate new images for data augmentation. CycleGAN can further perform image translation without paired data, making it suitable for many practical applications.

This study explores a CycleGAN-based data augmentation method to introduce cross-domain diversity into training data, focusing on how the generated samples affect data diversity and feature learning.

MAIN PART

The first chapter presents an overview of image object classification and data augmentation techniques. It reviews the evolution of image classification methods from traditional machine learning approaches to modern deep learning models and analyzes the challenges caused by limited training data and domain shift. The chapter also examines existing augmentation strategies, including conventional geometric transformations and generative approaches, and formulates the research objectives of improving classification robustness through data-centric methods.

The second chapter describes the proposed CycleGAN-based data augmentation framework and the overall experimental methodology. It introduces the Yosemite Summer2Winter dataset and analyzes the characteristics of domain variation between summer and winter scenes. The chapter explains the architecture of CycleGAN, including adversarial loss, cycle consistency loss, and identity loss, and discusses how these components contribute to generating visually realistic and semantically consistent cross-domain samples. The process of augmented dataset construction and the experimental evaluation framework are also presented.

The third chapter is devoted to experimental validation and comparative analysis of augmentation strategies. It describes the training process of the CycleGAN model, the generation of synthetic images, and the construction of three experimental configurations: the original dataset, the traditionally augmented dataset, and the CycleGAN-augmented dataset. Qualitative analysis demonstrates that the generated images preserve scene structure while introducing meaningful domain-level variations. Comparative experiments show that CycleGAN-based augmentation increases data diversity and improves robustness and domain generalization compared with conventional augmentation methods.

The fourth chapter presents the implementation and evaluation of the proposed augmentation-based classification framework. A complete experimental pipeline based on CycleGAN was implemented for image generation and classification training. The results confirm the effectiveness of distribution-level augmentation in improving feature learning and classification performance under domain variation. The conducted experiments demonstrate the practical applicability of the proposed data-centric approach and highlight the potential of generative augmentation methods for enhancing image classification systems.

CONCLUSION

This thesis investigates the role of data augmentation in improving image classification performance under domain variation. Rather than focusing on the design of novel classification models, the study adopts a data-centric perspective and examines how different augmentation strategies influence model behavior and generalization ability.

A CycleGAN-based augmentation approach is introduced as a representative method for generating cross-domain variations. The primary objective is to explore how distribution-level augmentation differs from conventional transformation-based methods and how such differences affect the learning process of classification models.

From a methodological perspective, the study is structured around a controlled experimental design. By keeping the classification model fixed and varying the training data configurations, the analysis isolates the effect of data augmentation. This allows a more direct interpretation of how data diversity influences feature learning.

Through the comparative analysis presented in Chapter 3, several observations can be made. It can be observed that the baseline model, which is trained on the original dataset, tends to rely on patterns that are specific to the training domain. This suggests that limited data diversity may lead to reduced robustness when the model encounters unseen visual conditions.

When traditional augmentation methods are applied, the model demonstrates improved robustness to geometric variations. This is likely because such transformations expose the model to different spatial configurations of the same content. However, since these methods do not significantly alter the overall data distribution, their ability to address domain-level variation appears to be limited.

In contrast, the CycleGAN-based augmentation approach introduces variations at the distribution level. It can be observed that the generated samples differ in appearance while preserving structural consistency. This suggests that the model is exposed to a wider range of visual conditions during training.

Such exposure may encourage the model to rely less on domain-specific features and more on structural patterns that remain stable across domains. As a result, the model may achieve improved generalization when applied to images with different visual characteristics.

The qualitative analysis further supports these observations. It can be observed that traditional augmentation produces visually similar samples, whereas CycleGAN-generated images exhibit more substantial variation. At the same time,

the preservation of scene structure indicates that the generated samples remain meaningful for classification tasks.

These findings suggest that augmentation strategies that operate at the distribution level may be more effective in scenarios where domain shift is a significant challenge. This highlights the importance of considering not only the quantity of data but also the type of variation introduced during training.

Despite these observations, several limitations should be acknowledged. First, the study focuses on a single dataset and a specific type of domain variation. As a result, the generality of the findings may be limited.

Second, the experimental evaluation is conducted under a simplified setting. The analysis emphasizes trends and observations rather than precise quantitative comparisons. While this approach allows for clearer interpretation, it may not fully capture the performance differences between methods.

Third, the use of a single generative model limits the scope of the study. Other generative approaches may produce different types of variation, which are not explored in this work.

These limitations suggest several directions for future research. Future work may extend the analysis to additional datasets with different types of domain variation and incorporate more rigorous quantitative evaluation.

It may also be beneficial to examine how data diversity interacts with different model architectures under varying conditions.

Exploring alternative generative models may further improve the understanding of distribution-level augmentation.

This thesis shows that data augmentation plays a critical role in improving model robustness under domain variation. The findings suggest that moving beyond local transformations and considering distribution-level augmentation may provide a more effective approach to enhancing generalization in image classification tasks.

LIST OF OWN PUBLICATIONS

1- Yu, L. / Impact of data augmentation strategies on deep learning-based image classification // New Horizons – 2025: Proceedings of the 12th Belarus–China Youth Innovation Forum.

2- Liu Yu / Analysis of cycle consistent generative adversarial networks for unpaired image translation // International Scientific and Technical Seminar "Information Transmission and Processing Technologies" – 04.2026