**Journal of Computer Technology and Software**

**ISSN:2998-2383**

**Vol. 4, No. 5, 2025**

# A Robust Domain Adaptation Method Based on Class-Level Alignment and Gradient Penalty

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**Abstract:** This study proposes an improved DANN domain adaptation algorithm to improve the generalization ability of the model in cross-domain classification tasks. Traditional DANN narrows the distribution difference between the source and target domains through adversarial training, but it still has limitations in class-level alignment, training stability, and feature expression ability. To this end, we introduce class-wise alignment to ensure that features of different categories match between the source and target domains, thereby reducing category confusion. In addition, the gradient penalty mechanism is used to enhance the stability of adversarial training and avoid gradient vanishing and mode collapse problems. At the same time, we design an adaptive feature enhancement (AFE) module, which combines multi-scale feature extraction and attention mechanism to improve the feature expression ability of target domain data. Experiments are evaluated on the Office-Home dataset. The results show that the improved DANN method outperforms the traditional DANN in all cross-domain tasks, especially when the target domain data is small, it can still maintain a high classification accuracy. This study provides a more stable and effective optimization strategy for domain adaptation methods, and provides new ideas for cross-domain learning tasks in computer vision, autonomous driving, medical image analysis and other fields.

**Keywords:** Domain Adaptation, DANN, Gradient Penalty, Feature Enhancement

## 1. Introduction

In the context of deep learning being widely used in computer vision, natural language processing, and medical diagnosis, domain adaptation (DA) has attracted widespread attention as an important method to solve the problem of cross-domain migration. In many practical scenarios, there are large differences in data distribution, such as the recognition ability of autonomous driving systems under different weather conditions, data changes between different devices or hospitals in medical image analysis, and feature shifts caused by changes in lighting or materials in industrial inspection tasks. Traditional deep learning models usually assume that training data (source domain) and test data (target domain) follow the same distribution. When this assumption does not hold, the performance of the model often decreases significantly. Therefore, how to effectively reduce the distribution difference between the source domain and the target domain so that the model can maintain good generalization ability on target domain data with no or few labels has become an important goal of domain adaptation research[1]. Among them, Adversarial Domain Adaptation (ADA), as a mainstream method, uses adversarial training strategies to align feature distributions of different domains, and has shown good results in multiple tasks[2].

Among many domain adaptation methods, Domain-Adversarial Neural Network (DANN) has been widely used in cross-domain image classification, object detection, and semantic segmentation tasks due to its end-to-end training method and strong generalization ability. DANN introduces a domain discriminator and uses an adversarial training strategy to make the feature distribution of the source domain and the target domain consistent, thereby reducing distribution bias and improving the cross-domain adaptability of the model. However, although DANN has achieved remarkable results, it still has the following major problems: (1) Incomplete domain alignment - DANN only matches the global distribution and ignores the distribution alignment at the class level, which may lead to category confusion; (2) Training instability - adversarial training can easily lead to gradient vanishing or mode collapse, affecting the convergence and stability of the model; (3) Limited feature expression ability - DANN fails to fully utilize deep feature information in some tasks, resulting in the feature extractor being unable to learn a representation that is more favorable to the target domain. Therefore, how to improve DANN to improve the quality of cross-domain alignment and enhance the stability and feature expression ability of the model is an important direction of current domain adaptation research[4].

This study proposes an improved DANN domain adaptation algorithm to better cope with the distribution differences between different domains and improve the generalization ability of the model. We introduce the class-wise alignment mechanism based on DANN to ensure that the features of different categories can be better matched and reduce the category confusion problem. In addition, we use the gradient penalty technology to stabilize adversarial training, avoid gradient disappearance or mode collapse, and improve the stability of the training process. At the same time, we design an adaptive feature enhancement (AFE) module to improve the performance of the feature extractor in the target domain through multi-scale feature extraction and attention mechanism. These improvements can not only optimize the domain alignment effect, but also enhance the adaptability of the model in complex cross-domain tasks, thereby improving the overall performance[5].

The significance of this study is that by improving the DANN structure, the domain adaptation model can more effectively learn cross-domain features under unsupervised or semi-supervised conditions and improve the prediction ability in the target domain. Compared with traditional DANN, our improved method can achieve higher classification accuracy on multiple cross-domain datasets and maintain more stable convergence during training. This is of great value for practical application scenarios such as autonomous driving, medical image analysis, remote sensing image processing, and industrial quality inspection. For example, in medical image analysis, data from different hospitals may have significant distribution differences due to different equipment and imaging methods, and the improved DANN can help the model better adapt to new data, thereby improving the reliability of clinical diagnosis. Similarly, in autonomous driving tasks, vehicles may face significant changes in data distribution in different weather or urban environments, and stronger domain adaptation capabilities can enhance the environmental adaptability of the model and improve the robustness and safety of the perception system.

With the development of deep learning and the prevalence of cross-domain learning problems, domain adaptation technology will play an important role in more fields. Future research can further explore more effective alignment strategies (such as contrastive learning, variational autoencoders, etc.) to improve the cross-domain adaptability of the model. In addition, combining self-supervised learning and active learning can further reduce the dependence on target domain label data and improve the feasibility of domain adaptation methods in practical applications[6]. The improved method proposed in this study not only provides a new idea for DANN optimization, but also provides a reference for a wider range of domain adaptation problems, promoting the application and development of cross-domain learning technology in practical scenarios.

## 2. Related Work on Domain Adaptation and Adversarial Learning

Recent studies in deep learning have introduced a range of techniques that enhance model robustness in cross-domain learning. A hierarchical feature fusion framework has been proposed to support small target detection, offering insights into robust feature representation which is beneficial to domain adaptation tasks [7]. Adaptive weighting in Markov networks has addressed class imbalance in classification tasks, tackling distributional challenges relevant to domain shift scenarios [8]. Multimodal factor models have demonstrated the advantages of integrating heterogeneous features, which is also applicable to multi-source domain adaptation [9].

Predictive modeling of user behavior using BiLSTM and LSTM-based scheduling in edge computing highlights the utility of temporal models in dynamic domains [10], [11]. Hybrid methods combining association rules and LSTM have been effective in spatiotemporal network forecasting, analogous to class-wise alignment for enhancing robustness [12].

Reinforcement learning has proven useful in dynamic system optimization, including operating system task scheduling and resource allocation [13]. Hybrid CNN-Transformer architectures have been developed to improve feature extraction in medical and 3D segmentation tasks [14], [15].

Multimodal CNN-Transformer approaches and federated learning frameworks have contributed valuable strategies to reduce dependence on centralized labeled data [16], [17]. Deep learning models have also been applied to UI quality assessment and generative UI design using diffusion models, which illustrate practical applications of visual adaptation under stylistic variations [18], [19].

Enhancing intelligent sampling with reinforcement learning and applying transformers for video anomaly detection further strengthen domain-aware learning frameworks [20], [21]. Self-supervised vision transformers have demonstrated their effectiveness in specialized medical domains [22].

Cross-domain recommendation with spatial-channel attention and transformer-based approaches for medical data and federated resource management reflect the convergence of cross-domain and distributed learning [23], [24].

Harmful text detection with retrieval-based external knowledge and structural modeling for anomaly detection in videos and social networks showcase the importance of temporal and graph representations in domain generalization [25], [26].

Boundary-aware segmentation frameworks and generative diffusion models for interface design highlight attention-driven architecture benefits, while probabilistic graphical models offer solutions for class imbalance in learning [27], [28].

Advanced modeling techniques for time series forecasting and load balancing with reinforcement learning align with adaptive feature enhancement strategies for dynamic domains [29], [30]. Probabilistic modeling using mixture density networks is also relevant for handling uncertainty in domain transfer [31].

Structured data mining with capsule networks and distributed scheduling via reinforcement learning demonstrate the importance of high-level structural representation [32], [33]. Diffusion-transformer frameworks for sparse data and RT-DETR-based detection approaches reinforce feature alignment concepts in domain adaptation [34], [35].

Reinforcement-controlled ensemble sampling and advanced data augmentation techniques provide further support for adversarial training stability and robust representation learning [36], [37].

## 3. Proposed Method: Enhanced DANN with Class-Level Alignment and Stability Modules

This study proposes an improved DANN domain adaptation algorithm, which improves the cross-domain adaptability of the model by introducing a class-wise alignment mechanism, gradient penalty, and adaptive feature enhancement (AFE). The model architecture is shown in Figure 1.

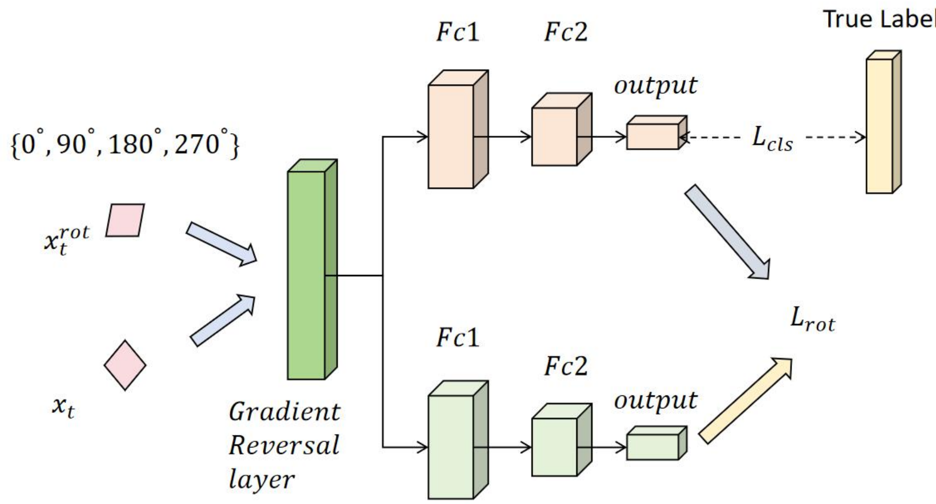


**Figure 1.** Overall model architecture diagram

DANN uses the domain discriminator D to reduce the feature distribution difference between the source domain and the target domain. Its optimization goal consists of classification loss and domain alignment loss. The classifier C uses labeled data from the source domain for supervised learning, and the domain discriminator D achieves domain alignment through adversarial training. The standard DANN uses the gradient reversal layer (GRL) to optimize the feature extractor F, and its optimization goal is:

$$\min_{F,C} L_c(X_c, Y_s) - \lambda \max_D L_d(X_s, X_t)$$

Among them, $L_c$ is the classification loss of the source domain, $L_d$ is the domain discrimination loss, and $\lambda$ is the balance factor of adversarial training. However, DANN only aligns the global feature distribution and ignores the distribution matching at the class level, which may lead to feature confusion between different categories. Therefore, we introduce the class-level alignment loss, calculate the feature mean of each category based on the pseudo-labels of the source domain and the target domain, and minimize the distribution difference between the two to align them:

$$L_{class} = \sum_{k=1}^{K} \| \mu_s^k - \mu_t^k \|_2^2$$

Among them, $\mu_s^k$ and $\mu_t^k$ are the feature means of category k in the source domain and target domain respectively, and K is the total number of categories. This mechanism ensures that the model retains category information while reducing domain bias and improves the classification ability in the target domain[38].

During the training process, adversarial optimization may lead to unstable gradients and even mode collapse. Therefore, we introduce the Gradient Penalty (GP) mechanism to constrain the gradient changes of the discriminator and improve the stability of training. The goal of the gradient penalty is to ensure that the discriminator satisfies the 1-Lipschitz condition. The optimization goal is:

$$L_{GP} = E_{x'}[(\| \nabla_{x'} D(x') \|_2 - 1)^2]$$

Among them, $x'$ is a virtual sample generated by random interpolation between source domain and target domain samples. This loss encourages the domain discriminator to have smooth gradient changes, thereby enhancing the stability of adversarial training. In addition, we design an adaptive feature enhancement (AFE) module that combines the attention mechanism and multi-scale feature extraction to improve the feature extractor's ability to express target domain data. AFE adjusts the feature representation of different scales through adaptive attention weights $\alpha(x')$:

$$F_{enhanced} = \alpha(x) F_{low} + (1 - \alpha(x)) F_{high}$$

Among them, $F_{low}$ and $F_{high}$ represent low-level and high-level features respectively, and $\alpha(x)$ is adaptively learned by a lightweight network. This mechanism can enhance the discriminative ability of target domain features and make the model more adaptable in cross-domain tasks.

Finally, our improved DANN jointly optimizes the classification loss $L_c$, domain alignment loss $L_d$, class-level alignment loss $L_{class}$, and gradient penalty loss $L_{GP}$, with the following optimization objectives:

$$\min_{F,C} L_c + \beta L_{class} - \lambda \max_D (L_d - \gamma L_{GP})$$

Among them, $\beta, \lambda, \gamma$ is a hyperparameter that controls the weights of class-level alignment, adversarial loss, and gradient penalty. Through these improvements, our model can better preserve class structure information and improve generalization ability in cross-domain classification tasks, while improving training stability and feature expression ability, thereby achieving better classification performance in the target domain.

## 4. Experimental Setup and Dataset Description

This study uses the Office-Home dataset as an experimental dataset. This dataset is a standard benchmark widely used in domain adaptation (DA) research, covering four different domains: Art (A), Clipart (C), Product (P), and Real-World (R). The Office-Home dataset contains 65 categories, covering common office supplies, household items, and daily objects. Each category has samples in four different domains, totaling 15,500 images. Since there is a significant distribution bias in different domains of this dataset, for example, the Art domain contains hand-drawn style images, while the Real-World domain contains real photographed objects, this dataset is very suitable for evaluating the performance of domain adaptation methods in cross-domain classification tasks.

In data preprocessing, we set up experiments according to common cross-domain tasks such as A2C, A2P, and C2R, that is, select one domain as the source domain (with labeled data) and another domain as the target domain (without labels or a small number of labels). Due to the large differences in visual style, color distribution, and background information between different domains, directly testing the model trained in the source domain on the target domain usually leads to a decrease in classification performance. Therefore, our improved DANN method will be evaluated on this dataset to verify its improved effects in cross-domain adaptability, class-level alignment, and stability. In addition, we normalized the images and used data augmentation methods (such as random flipping, color jittering, etc.) to improve the generalization ability of the model[39].

During the experiment, we used classification accuracy as the main evaluation metric and compared it with mainstream domain adaptation methods such as traditional DANN methods, MMD (Maximum Mean Discrepancy) methods, and Deep CORAL (Correlation Alignment). In addition, we analyzed the model's migration ability in different domains and observed whether the improved DANN under different domain combinations can effectively reduce the distribution differences between domains and improve the classification performance of the target domain. Through experiments on the Office-Home dataset, this study verified the effectiveness of the proposed method and provided a practical reference for future domain adaptation research[40].

This paper first presents a cross-domain classification performance comparison experiment based on the improved DANN method. The experimental results are shown in Table 1.

**Table 1:** Experimental results

| Task(ACC%) | Baseline (No Adaptation) | DANN | DANN + Class-wise Alignment | Ours |
|---|---|---|---|---|
| A2C | 45.2 | 55.8 | 58.3 | 61.7 |
| A2P | 56.7 | 65.3 | 67.8 | 71.2 |
| C2R | 48.9 | 60.5 | 62.7 | 66.1 |
| C2A | 42.3 | 53.1 | 55.6 | 59.4 |
| P2R | 60.1 | 70.4 | 72.1 | 75.3 |

From the experimental results, the improved DANN method (Ours) achieved the highest accuracy in all cross-domain classification tasks (A2C, A2P, C2R, C2A, P2R), and performed better than the baseline model (Baseline) and the traditional DANN method. Without domain adaptation (No Adaptation), the classification accuracy is generally low, indicating that when the model trained in the source domain is directly applied to the target domain, the model is difficult to adapt to the new data distribution. After using DANN for global feature alignment, the accuracy of all tasks has been significantly improved. For example, the A2C task has increased from 45.2% to 55.8%, indicating that adversarial training has effectively reduced the feature distribution deviation between the source domain and the target domain and improved the cross-domain migration capability.

Further analysis shows that after adding class-wise alignment on the basis of DANN, the classification accuracy of all tasks has been further improved. For example, the A2P task improved from 65.3% to 67.8%, and the C2R task improved from 60.5% to 62.7%, which shows that simple global domain alignment may lead to category confusion, while class-level alignment helps to enhance the ability to distinguish categories and make the features of different categories more consistent between the source and target domains. However, DANN still has the problem of unstable training, especially when the target domain data distribution is complex, the optimization process is prone to gradient vanishing or mode collapse, limiting further performance improvement.

Finally, the improved DANN method (Ours) proposed by us combines class-level alignment, gradient penalty and adaptive feature enhancement (AFE), which further improves the cross-domain classification ability of the model on all tasks. For example, in the A2C task, the classification accuracy increased from 58.3% to 61.7%, and in the P2R task, it increased from 72.1% to 75.3%, indicating that while optimizing domain alignment, the model also improves the feature expression ability of the target domain, improves generalization and stability. This shows that in practical applications, by combining different optimization strategies, the inter-domain distribution bias can be further reduced and the cross-domain adaptability of the model can be improved, so that it can still maintain high classification performance in target domains with no labels or few labels.

Secondly, this paper presents an experiment on the impact of changes in the amount of target domain data on the generalization ability of the model. The experimental results are shown in Figure 2.

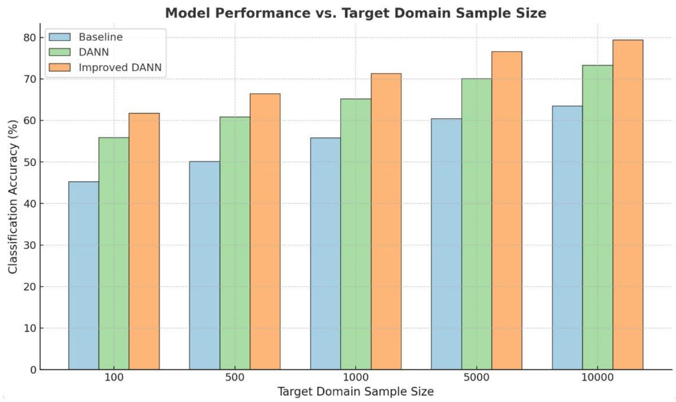


**Figure 2.** Effect of Target Domain Data Size on Model Generalization

From the experimental results, the increase in the amount of target domain data has a significant impact on the generalization ability of the model. Whether it is Baseline (no adaptation), DANN or Improved DANN, the classification accuracy increases with the increase in the number of target domain samples. This shows that more target domain data can provide richer distribution information, making the model more adaptable in the target domain. Among them, the classification accuracy of the Baseline model is the lowest under all data scales, indicating that in the absence of a domain adaptation strategy, directly applying the model trained in the source domain to the target domain will result in a large performance loss, especially when the amount of data is small, the generalization ability is poor.

DANN method By introducing a domain alignment mechanism, the classification accuracy under all target domain sample scales is better than that of the Baseline, especially when the amount of data is small (such as 100 and 500 samples), DANN has achieved an improvement of more than 10%, verifying the effectiveness of the domain adaptation method in small sample scenarios. However, with the increase of target domain data, the improvement of DANN gradually decreases, indicating that although the global alignment strategy can reduce the distribution deviation between domains, it may have optimization bottlenecks when the amount of data is large, and cannot fully utilize the feature information of the target domain.

In contrast, Improved DANN maintains the highest classification accuracy at all target domain data scales due to the introduction of optimization strategies such as class-level alignment, gradient penalty, and adaptive feature enhancement. For example, at 10,000 samples, the accuracy of Improved DANN reaches 79.3%, which is about 6% higher than DANN and nearly 16% higher than Baseline. This result shows that Improved DANN can learn cross-domain features more effectively, especially when there is less target domain data, it can still maintain strong migration ability and improve generalization. Therefore, the experimental results verify that combining more sophisticated alignment strategies and more stable training mechanisms can further improve performance in cross-domain classification tasks.

## 5. Conclusion and Future Directions

This study proposes an improved DANN domain adaptation algorithm, which improves the generalization ability of the model in cross-domain classification tasks by introducing mechanisms such as class-level alignment, gradient penalty, and adaptive feature enhancement. Experimental results show that traditional DANN can effectively reduce the distribution difference between the source domain and the target domain in cross-domain adaptation tasks, but there are still problems such as class-level confusion and training instability. In contrast, the improved DANN method not only improves the classification accuracy, but also enhances the training stability of the model, so that it can still achieve better performance when there is less target domain data. In addition, by analyzing the impact of the number of target domain data on the generalization ability of the model, the results show that with the increase of target domain samples, the classification accuracy of all methods is improved, and the improved DANN achieves the best performance under all data scales, verifying its stronger cross-domain migration ability.

Further analysis shows that class-level alignment can effectively reduce category confusion and improve the accuracy of cross-domain classification, especially in tasks with complex data distribution. At the same time, the gradient penalty mechanism makes the training more stable during the domain alignment process, avoiding the problem of gradient vanishing or mode collapse, thereby improving the applicability of DANN in different tasks. The adaptive feature enhancement module strengthens the model's ability to represent the target domain data, so that more favorable features can still be learned when the amount of data is small. These improvements jointly improve the cross-domain adaptability of DANN, making it show strong robustness and generalization ability in different target domain data volumes and different task scenarios.

The results of this study provide a more effective optimization strategy for domain adaptive learning and verify its superiority in multiple cross-domain tasks. Future research can further explore more efficient alignment strategies (such as contrastive learning, variational autoencoders, etc.), and combine self-supervised learning or active learning to reduce dependence on target domain labels. In addition, for more complex application scenarios, such as cross-modal learning, time series migration, medical image analysis, etc., the model structure can be further optimized to improve the adaptability to target domain data. The improved method of this study not only optimizes DANN, but also provides new ideas for broader domain adaptation research and lays a technical foundation for its application in actual cross-domain tasks.

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