Journal of Computer Technology and Software

ISSN:2998-2383

Vol. 3, No. 9, 2024

Improving Few-Shot Learning via Dual-Phase Manifold Embedding Optimization

Zihan Zhang[1], Eamon Radcliffe[2]
[1]University of California, Santa Cruz, USA
[2]University of California, Santa Cruz, USA
*Corresponding Author: Zihan Zhang, zihan.z897@ucsc.edu

Abstract: The pursuit of Artificial General Intelligence (AGI) necessitates models capable of rapid adaptation to novel tasks with minimal data, akin to human learning. This paper introduces TSMB (TWO-STAGE MANIFOLD-BASED FEW-SHOT LEARNING), a novel approach to Few-Shot Learning (FSL) that leverages unsupervised learning to harness the geometric distribution of data across tasks. TSMB refines feature representations through a two-stage process: first, by leveraging the topological structure of high-dimensional data to fine-tune general features, and second, by generating virtual samples to integrate semi-supervised learning. This method aims to address the challenges of data scarcity and overfitting, common in FSL. The model comprises a backbone network for feature extraction, a manifold learning module to capture topological results, a manifold support point section to assist learning, and a denoising prototype classifier for decision-making. TSMB demonstrates enhanced generality and performance, offering a promising direction for advancing FSL towards more ethical, sustainable, and effective AI applications.

Keywords: Few-Shot Learning, Manifold Learning, Semi-Supervised Learning, Model Generalization

1. Introduction

In the era of boundless Artificial Intelligence (AI), we are facing a fundamental shift from data-driven to intelligence-driven model learning. In this transition, Few-Shot Learning (FSL) plays a crucial role. Traditional machine learning methods rely on large amounts of labeled data to train models, which limits the widespread application of AI technologies.

The core value of few-shot learning lies in its simulation of human learning mechanisms—how to enable machines to learn and adapt to new environments rapidly with minimal information, just like humans. This ability is essential for achieving true Artificial General Intelligence (AGI), as it allows machines to work effectively in a changing world rather than being limited to specific tasks or domains.

Moreover, few-shot learning plays a key role in driving AI technology towards a more ethical and sustainable direction. By reducing the demand for large-scale datasets, few-shot learning helps lower the energy consumption, environmental impact, and costs of AI systems, while also mitigating potential privacy and ethical issues that may arise during data collection processes. In a world increasingly focused on sustainability and ethical responsibility, this approach provides a more responsible and sustainable path for the future development of AI.

Image classification tasks are among the earliest explored areas in few-shot learning, accumulating the most advanced techniques in this field to date. Simultaneously, classification problems are one of the most fundamental issues. Its successful resolution would also drive developments in other areas of this field. Metric-based few-shot learning models [1], due to their ability to adapt quickly to few-shot tasks, have consistently been the mainstream direction in few-shot learning.

A large body of work has been developed around metric-based models [2], focusing on improving models from the perspectives of more precise class representations and more appropriate metric rules. Optimization-based models [3], capable of fine-tuning data representations using few-shot data, received attention in the early stages but faced certain limitations in research and application due to difficulties in parameter tuning and high computational complexity. From the early exploration of metric-based and optimization-based model approaches to the later introduction of memory modules, meta-learning training [4], attention mechanisms, and transfer learning [5] into models, we have now reached a new stage: how to form task-specific embeddings in situations of data scarcity and high risk of overfitting.

This paper proposes that unsupervised learning should be introduced to fully utilize the geometric distribution or topological structure of data from different few-shot tasks in high-dimensional feature spaces, fine-tuning general feature representations at the task level. Then, by generating virtual samples from support set data to inject supervised information, a semi-supervised learning form is created. Starting from the perspective of representation, this paper attempts to learn specific representations suitable for different few-shot tasks to improve model performance, demonstrating strong generality.

2. Related Work

Few-shot learning (FSL) has emerged as a critical area of research aimed at enabling machine learning models to generalize effectively with minimal labeled data. Traditional approaches in FSL are primarily categorized into metric-based and optimization-based methods. Metric-based models, such as Prototypical Networks and Matching Networks, focus on constructing embedding spaces that minimize intra-class variance while maximizing inter-class separability, allowing for more effective classification in few-shot scenarios [6][7][8]. Optimization-based models, while demonstrating strong adaptability to new tasks, often face computational challenges and require careful parameter tuning [9][10]. Hybrid techniques integrating metric-based and optimization approaches have shown significant improvements in overcoming data scarcity and boosting generalization performance [11][12].

Manifold learning has played a growing role in enhancing few-shot learning by modeling the geometric structure of high-dimensional data distributions. The integration of convolutional neural networks (CNNs) with transformer architectures has demonstrated effectiveness in capturing these complex data geometries, thereby improving the adaptability of classifiers to novel tasks [13]. Recent advancements show that leveraging CNN-transformer synergies not only enhances feature representation but also strengthens model performance in predictive modeling across diverse applications [14].

Generative models such as Generative Adversarial Networks (GANs) and variational autoencoders (VAEs) have become essential tools in augmenting datasets and addressing overfitting in few-shot learning tasks. The use of conditional GANs with adaptive weight masking has proven particularly effective in generating realistic virtual samples to enrich the support set, contributing to improved model accuracy and robustness [15]. Generative approaches have also been applied in financial market supervision and medical image analysis to counter data imbalance, demonstrating their versatility across domains [16][17][18]. Furthermore, adversarial learning techniques have been increasingly adopted to enhance model resilience against adversarial attacks, safeguarding the integrity of few-shot classifiers [19].

Semi-supervised learning and transfer learning techniques have also gained traction in addressing the limitations of labeled data in few-shot scenarios. Reinforcement learning-based adaptive user interface generation and meta-learning strategies have been employed to optimize models for personalized applications [20][21]. Transfer learning, coupled with LoRA (Low-Rank Adaptation) fine-tuning, enhances computational efficiency and reduces the resource demands of large-scale models, providing effective solutions for scaling few-shot learning systems [22][23].

Graph neural networks (GNNs) have been widely applied in recommendation systems and stock prediction tasks, underscoring the importance of structured data representations in few-shot learning [24][25]. The hierarchical nature of GNNs facilitates the modeling of complex relationships, further enhancing classification performance in low-data regimes. Dynamic scheduling and Q-learning algorithms have also been leveraged to improve resource optimization and data management, reinforcing the adaptability of machine learning systems across different environments [26][27].

In addition, deep learning frameworks such as VGG19 and fully convolutional networks (FCNs) continue to serve as foundational models for image classification tasks, contributing to the advancement of few-shot learning by providing robust benchmarks [28][29]. Calibration learning techniques, which align model predictions with true data distributions, offer additional mechanisms for mitigating overfitting and improving model generalization under data-limited conditions [30].

Overall, the landscape of few-shot learning continues to evolve through the convergence of manifold learning, semi-supervised techniques, and generative modeling. These advancements contribute to the development of more adaptable and generalizable AI systems capable of addressing the inherent challenges associated with data-scarce environments.

3. Background

3.1 Problem Definition

The conventional N-way K-shot framework proves overly rigid, failing to capture real-world complexities. To address this, we propose a more flexible N-way K-shot task setup that allows for varying amounts of labeled data across categories in the support set. We argue that the configuration of a few-shot learning task's support set is primarily determined by two factors: mean and variance. The mean influences the overall scale of the support set, while the variance reflects the degree of imbalance between classes.

By sampling category sizes from specific statistical distributions, we can precisely control these key parameters. This approach not only accommodates the traditional balanced N-way K-shot setup (viewed as a special case with zero inter-class variance) but also simulates more realistic imbalanced scenarios.

This more challenging framework better mimics real-world conditions and offers a fresh perspective for assessing potential weaknesses in existing few-shot learning models. Additionally, it provides a more comprehensive testing environment for developing and validating novel solutions, thereby fostering further advancements in the field.

4. Method

This chapter first presents the problem definition of few-shot tasks and the task settings for both balanced and imbalanced scenarios in few-shot learning, which are used to evaluate the strengths and weaknesses of models. It then introduces a few-shot learning model, detailing each of its components, such as the feature extractor, manifold learning, manifold support points, and the denoised prototype classifier. The chapter thoroughly describes the training process, formation, and function of each component.

In the following sections of this chapter, each part of the model will be introduced in detail. These parts include the backbone network responsible for feature extraction, the manifold learning module responsible for capturing the topological results of few-shot tasks and fine-tuning the universal feature space, the manifold support points section that assists in manifold learning, and the denoised prototype classifier responsible for making classification decisions.

4.1 Feature Extractor

The classifier relies on the feature vector output by ResNet-12 to make classification decisions.

The WRN series network architecture is a further improvement based on ResNet. WRN improves performance by increasing the width of the network rather than the depth. The starting point of this design strategy is to improve model accuracy without excessively increasing network complexity and computational cost. WRN has demonstrated superior performance to the original ResNet in many tasks.

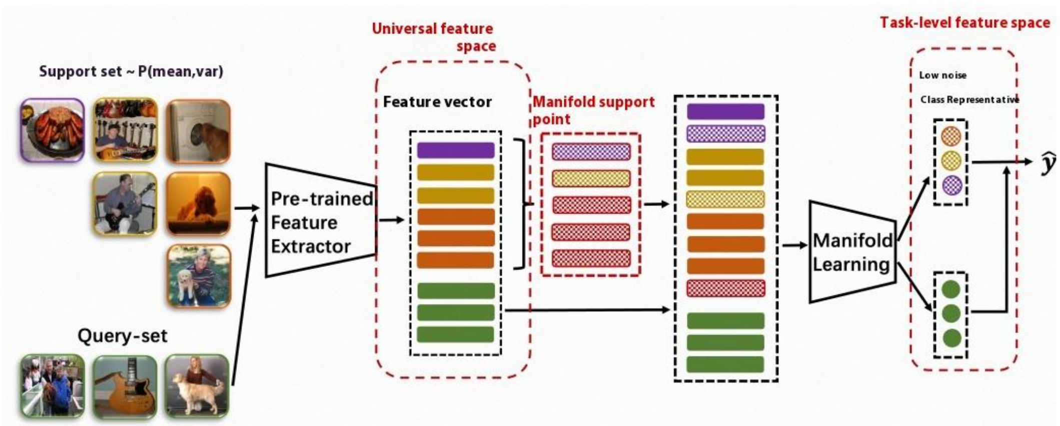

Figure 1. Two-Stage Few-Shot Learning Model (TSMB)

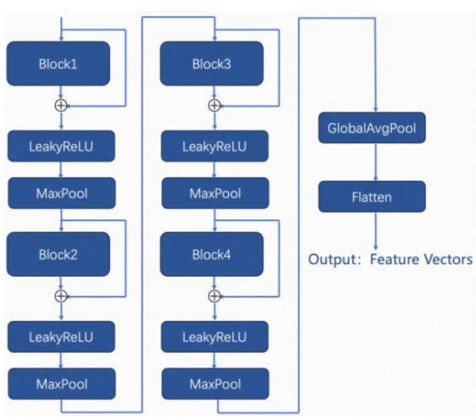

Figure 2. ResNet-12 network architecture

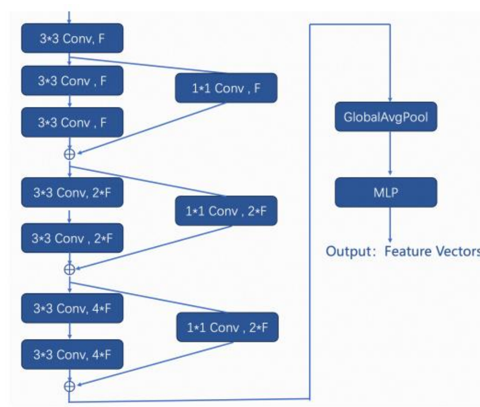

Figure 3. Simplified WRN network architecture

This paper uses feature extractors, specifically backbone network architectures ResNet-12 and WRN-28-10, which are based on early deep learning convolutional neural network architectures but have undergone certain improvements. The block unit includes a convolutional part for feature extraction, a normalization part to accelerate network training, and an activation function part to introduce non-linear transformations. Multiple basic block units are connected in a residual form to constitute the main part of the ResNet network. The architecture of ResNet is shown in Figure 2.

4.2 Full Classification Pre-training

This stage uses conventional end-to-end training to train the convolutional network, with cross-entropy as the loss function. Suppose $(x_i, y_i) \in D_{\text{base}}$, and the total number of categories in D_{base} is C. The loss function is shown in formula (1):

$$L = -\frac{1}{N}\sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}) \tag{1}$$

For sample i, assuming the output of the network's last layer (also called the classification layer or fully connected layer) is z_i, the weight matrix of this layer is W, and the second-to-last layer is represented by f_θ, its output can be called a feature vector or embedding. Then the output of the classification layer can be represented as shown in formula (2):

$$z_i = W f_\theta(x_i) + b \quad (2)$$

Then, $\hat{y}_{i,c}$ can be obtained by formula (3):

$$\hat{y}_{i,c} = \frac{e^{zic}}{\sum_{j=1}^{C} e^{z_{ij}}} \quad (3)$$

Full classification training enables the backbone network to acquire powerful general feature extraction capabilities.

The high-dimensional feature space formed by the backbone network can help capture diverse information in images. However, the number of classification categories in few-shot tasks is far smaller than in pre-training tasks, and their categories are unrelated. Therefore, the high-dimensional feature space often contains dimensions irrelevant to the current few-shot task. In some cases, irrelevant feature dimensions can become noise, affecting the model's performance. The categories that need to be distinguished between few-shot tasks are also different. Therefore, it is necessary to form task-specific representations adapted to the current task's own situation. The conventional approach is to use fully connected layers to fit the labeled data of new tasks through backpropagation, thereby adapting the model to new tasks and making appropriate classification decisions.

However, few-shot tasks have limited data, and neural networks have strong fitting capabilities, which can easily lead to overfitting. This causes the model to treat noise features as essential features for classification decisions, losing generalization ability.

Therefore, in the model proposed in this paper, manifold learning is introduced. It uses an unsupervised approach to leverage the topological structure of the current task itself to make task-level corrections to the general representation, forming specific embeddings to eliminate some of the negative effects brought by full classification pre-training.

4.3 Meta-Learning Pre-training Phase

During the pre-training stage, meta-learning is introduced to improve the model's ability to quickly adapt to few-shot tasks. This paper extracts few-shot tasks from the D_{base} dataset using the standard N- way K- shot Q- query setup. In the meta-learning stage, the classification layer of the aforementioned convolutional network is removed, leaving the remaining part of the network, which is called the feature extractor or backbone network. The backbone network plus the prototype classifier constitute a new network, namely the few-shot learning model. The few-shot learning model uses the test set data of each task, with a data volume of $Q * N$, to perform end-to-end training on the entire network again, making the model reach a parameter position adapted to few-shot tasks. The loss function calculation is based on prototypes. The prototype calculation is shown in formula (4):

$$P_k = \frac{1}{N_{s,k}} \sum_{x_i \in S_k} f_\phi(x_i) \quad (4)$$

The calculation formula for the loss function is shown in (5):

$$L = -\frac{1}{N*Q} \sum_{i=1}^{N*Q} \sum_{j=1}^{N} y_{i,j} \log(\hat{y}_{i,j}) \quad (5)$$

The calculation of $\hat{y}_{i,c}$ depends on the prototype and metric rule, as shown in formula (6):

$$\hat{y}_{i,c} = \frac{\exp(\tau \cdot d(f\theta(x_i), P_j)}{\sum_{n=1}^{N} \exp(\tau \cdot d(f_\theta(x_i), P_n)} \quad (6)$$

Meta-learning further trains the parameters of the backbone network, making it better adapted to few-shot tasks. In this stage, the determination of scaling parameters also helps the backbone network and metric rules to fit better.

4.4 Denoising Prototype Classifier

In this stage, the learned manifold is utilized to transform the representation of few-shot data in high-dimensional feature space, and the denoised feature vectors (projected feature vectors on the manifold) are used for prototype-based classification. We use the denoised support set data along with the formed virtual data manifold support points to create more reliable denoised prototypes for each category, thus supporting classification decisions, as defined in equation (7):

$$H_c = \frac{1}{|s_c| + 1} \sum_{\tilde{x} \in S_c \cup (M_c)} \tilde{x} \quad (7)$$

The probability that query sample $\boldsymbol{q}$ belongs to category c is shown in equation (8):

$$p(y = c|q_i) = \frac{\exp(\tau \cdot d(\bar{q} \cdot H_c))}{\sum_{n=1}^{N} \exp(\tau \cdot d(\tilde{q}i, Hc'))} \quad (8)$$

where $d(J)$ is the reciprocal of Euclidean distance or cosine distance. τ is a scaling, adaptive parameter, also known as the temperature parameter. τ is determined during the meta-learning phase to facilitate mutual adaptation between the backbone network and the classifier. It can also help maintain a reasonable similarity between query data and prototypes, unconstrained by metric rules. When the metric rule is Euclidean distance, the adaptive parameter can eliminate the influence of the network's output dimension on the similarity range; when the metric rule is cosine similarity, the adaptive parameter can ensure that the similarity between query problems and prototypes is not limited by the cosine function, but rather falls within a reasonable interval to form probability distributions with significant differences.

5. Experiment

5.1 Dataset

The MiniImageNet dataset is a widely used benchmark dataset in the fields of Few-Shot Learning (FSL) and Meta-Learning. It is a subset extracted from the larger ILSVRC, specifically designed to test and validate models' ability to learn from very limited data. However, compared to

MiniImageNet, it is much larger in scale, containing approximately 780,000 images. It provides a wider range of categories and more samples to support complex model training. Consequently, it is considered an easier dataset.

5.2 Baselines

To comprehensively compare model performance, in addition to the algorithms introduced in related work, this study incorporates other models for comparison.

The Baseline++ [31] model, unlike earlier models that use the weight vector of the last layer as class representatives, introduces the mean of labeled samples as class representatives. It enhances model performance by modifying the loss function and adjusting training strategies.

MTL improves few-shot models by combining meta-learning and transfer learning.

Relation Networks [32] transform the few-shot learning problem into a relational learning representation, classifying by comparing relationships between support set and query set samples.

LEO [8] generates latent embeddings during the training phase to support rapid task adaptation.

MetaOptNet [33] combines meta-learning frameworks with optimization theory, utilizing convex optimization solvers to quickly adapt to new tasks.

LTP [34] incorporates label smoothing regularization techniques into the loss function, allowing for task-level fine-tuning.

The core idea of P-Transfer [35] is that in few-shot learning tasks, traditional fine-tuning methods may lead to model overfitting on the target task.

5.3 Experiment Results Analysis

The proposed model was tested on both MiniImageNet and TieredImageNet datasets. The results are shown in Tables 1 and 2.

Table 1. Performance on MiniImageNet

Model	BackBone	1-shot	5-shot
Matching Networks	ConvNet-4	42.69	54.20
Prototypical Networks	ConvNet-4	47.73	61.85
Baseline++	ResNet-18	50.83	74.17
TADAM	ResNet-12	57.33	75.17
LTP	ResNet-12	58.25	73.43
MTL	ResNet-12	59.98	73.99
Meta-Baseline	ResNet-12	61.91	77.67
P-Transfer	ResNet-12	62.93	78.77

Table 2. Performance on TieredImageNet

Model	BackBone	1-shot	5-shot
Matching Networks	ConvNet-4	50.64	68.89
Prototypical Networks	ConvNet-4	52.24	71.24
Baseline++	ResNet-18	53.39	69.89
TADAM	ResNet-12	65.00	79.81
LTP	ResNet-12	58.45	73.93
MTL	ResNet-12	64.67	79.93
Meta-Baseline	ResNet-12	67.25	82.07
P-Transfer	ResNet-12	73.04	82.73
TSMB(our)	ResNet-12	0.00	0.00

In the 1-shot task setting the proposed model achieved the best performance on both MiniImageNet and TieredImageNet datasets. In the 5-shot task setting, the model still achieved the best performance on the TieredImageNet dataset, while on the MiniImageNet dataset, it achieved comparable performance to the best model, P-transfer. Although the P-transfer model has a slightly higher accuracy than the proposed model, it has a larger confidence interval. The proposed model excels at handling high-noise few-shot tasks. Evidently, 1-shot is a more challenging few-shot task with greater noise.

To evaluate the model's performance more comprehensively, this study further compared the proposed model with Meta-baseline (the best performing model apart from the proposed one on MiniImageNet and TieredImageNet) on the more fine-grained CUB dataset. The results are shown in Table 3.

Table 3. Compared with Meta-baseline

Setting	Meta-Baseline	TSMB(our)
1-shot	71.85±0.22	79.39±0.24
5-shot	88.51±0.12	89.35±0.13

While maintaining the expected amount of support set data, the support set was transformed from a balanced state to an unbalanced state to test the model's performance under increased support set noise. The Meta-baseline model and the proposed TSMB model were compared under unbalanced conditions, with results shown in Table 4.

Table 4. Compared with Meta-baseline

Datasets	Meta-Baseline	TSMB(our)
MiniImageNet	72.58±0.19	76.68±0.19
TieredImageNet	74.94±0.21	82.42±0.20
CUB	82.84±0.18	87.81±0.16

This sufficiently demonstrates that the proposed model performs well when support set noise increases.

6. Conclusion

In this chapter, we first compare the model proposed in this paper with existing high-performing models under the standard balanced task setting for the support set, using the benchmark datasets MiniImageNet and TieredImageNet. TSMB achieves the most outstanding performance.

Subsequently, we introduce the more fine-grained CUB dataset to comprehensively test the model's performance. Following this, we conduct further experiments to evaluate the model's performance under increased support set noise, specifically in the 5-way Any-shot imbalanced task setting.

References

[1] Vinyals O, Blundell C, Lillicrap T, Kavukcuoglu K, Wierstra Da. Matching networks for one shot learning[C]//Proceedings of the International Conference on Neural Information Processing Systems. NIPS, 2016, 29: 3630-3638.

[2] Ye H J, Hu H, Zhan D C, Sha F. Few-shot learning via embedding adaptation with set-to-set functions[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. CVPR, 2020: 8808-8817.

[3] Qi H, Brown M, Lowe D G. Low-shot learning with imprinted weights[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. CVPR, 2018: 5822-5830.

[4] Gharoun H, Momenifar F, Chen F, Gandomi A. Meta-learning approaches for few-shot learning: A survey of recent advances[J]. ACM Computing Surveys, 2023.e

[5] Sun Q, Liu Y, Chua T S, Schiele B. Meta-transfer learning for few-shot learning[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. CVPR, 2019: 403-412.

[6] Y. Wang, Z. Xu, Y. Yao, J. Liu, and J. Lin, "Leveraging Convolutional Neural Network-Transformer Synergy for Predictive Modeling in Risk-Based Applications," arXiv preprint arXiv:2412.18222, 2024.

[7] J. Hu, Z. Liao, J. Gao, Z. Qi, H. Zheng, and C. Wang, "Optimizing Large Language Models with an Enhanced LoRA Fine-Tuning Algorithm for Efficiency and Robustness in NLP Tasks," arXiv preprint arXiv:2412.18729, 2024.

[8] S. Wang, C. Wang, J. Gao, Z. Qi, H. Zheng, and X. Liao, "Feature Alignment-Based Knowledge Distillation for Efficient Compression of Large Language Models," arXiv preprint arXiv:2412.19449, 2024.

[9] W. He, T. Zhou, Y. Xiang, Y. Lin, J. Hu, and R. Bao, "Deep Learning in Image Classification: Evaluating VGG19's Performance on Complex Visual Data," arXiv preprint arXiv:2412.20345, 2024.

[10] X. Li, T. Ruan, Y. Li, Q. Lu, and X. Sun, "A Matrix Logic Approach to Efficient Frequent Itemset Discovery in Large Data Sets," arXiv preprint arXiv:2412.19420, 2024.

[11] R. Zhang, S. Wang, T. Xie, S. Duan, and M. Chen, "Dynamic User Interface Generation for Enhanced Human-Computer Interaction Using Variational Autoencoders," arXiv preprint arXiv:2412.14521, 2024.

[12] Q. Sun, Y. Xue, and Z. Song, "Adaptive User Interface Generation Through Reinforcement Learning: A Data-Driven Approach to Personalization and Optimization," arXiv preprint arXiv:2412.16837, 2024.

[13] Z. Zheng, Y. Xiang, Y. Qi, Y. Lin, and H. Zhang, "Fully Convolutional Neural Networks for High-Precision Medical Image Analysis," Transactions on Computational and Scientific Methods, vol. 4, no. 12, 2024.

[14] M. Jiang, Z. Xu, and Z. Lin, "Dynamic Risk Control and Asset Allocation Using Q-Learning in Financial Markets," Transactions on Computational and Scientific Methods, vol. 4, no. 12, 2024.

[15] G. Huang, Z. Xu, Z. Lin, X. Guo, and M. Jiang, "Artificial Intelligence-Driven Risk Assessment and Control in Financial Derivatives: Exploring Deep Learning and Ensemble Models," Transactions on Computational and Scientific Methods, vol. 4, no. 12, 2024.

[16] J. Hu, R. Bao, Y. Lin, H. Zhang, and Y. Xiang, "Accurate Medical Named Entity Recognition Through Specialized NLP Models," arXiv preprint arXiv:2412.08255, 2024.

[17] P. Li, "Machine Learning Techniques for Pattern Recognition in High-Dimensional Data Mining," arXiv e-prints, arXiv:2412, 2024.

[18] X. Wang, "Dynamic Scheduling Strategies for Resource Optimization in Computing Environments," arXiv preprint arXiv:2412.17301, 2024.

[19] W. Liu, Z. Zhang, X. Li, J. Hu, Y. Luo, and J. Du, "Enhancing Recommendation Systems with GNNs and Addressing Over-Smoothing," arXiv preprint arXiv:2412.03097, 2024.

[20] P. Feng, Y. Li, Y. Qi, X. Guo, and Z. Lin, "Collaborative Optimization in Financial Data Mining Through Deep Learning and ResNeXt," arXiv preprint arXiv:2412.17314, 2024.

[21] M. Jiang, Y. Liang, S. Han, K. Ma, Y. Chen, and Z. Xu, "Leveraging Generative Adversarial Networks for Addressing Data Imbalance in Financial Market Supervision," arXiv preprint arXiv:2412.15222, 2024.

[22] Q. Yu, Z. Xu, and Z. Ke, "Deep Learning for Cross-Border Transaction Anomaly Detection in Anti-Money Laundering Systems," arXiv preprint arXiv:2412.07027, 2024.

[23] J. Hu, Z. Qi, J. Wei, J. Chen, R. Bao, and X. Qiu, "Few-Shot Learning with Adaptive Weight Masking in Conditional GANs," arXiv preprint arXiv:2412.03105, 2024.

[24] J. Yao, Y. Dong, J. Wang, B. Wang, H. Zheng, and H. Qin, "Stock Type Prediction Model Based on Hierarchical Graph Neural Network," arXiv preprint arXiv:2412.06862, 2024.

[25] Y. Wu, M. Sun, H. Zheng, J. Hu, Y. Liang, and Z. Lin, "Integrative Analysis of Financial Market Sentiment Using CNN and GRU for Risk Prediction and Alert Systems," arXiv preprint arXiv:2412.10199, 2024.

[26] Z. Liu, X. Xia, H. Zhang, and Z. Xie, "Analyze the impact of the epidemic on New York taxis by machine learning algorithms and recommendations for optimal prediction algorithms," in Proc. 2021 3rd Int. Conf. Robotics Systems and Automation Engineering, pp. 46-52, May 2021.

[27] J. Song and Z. Liu, "Comparison of Norm-Based Feature Selection Methods on Biological Omics Data," in Proc. 5th Int. Conf. Advances in Image Processing, pp. 109-112, Nov. 2021.

[28] Z. Liu, M. Wu, B. Peng, Y. Liu, Q. Peng, and C. Zou, "Calibration Learning for Few-shot Novel Product Description," in Proc. 46th Int. ACM SIGIR Conf. Research and Development in Information Retrieval, pp. 1864-1868, Jul. 2023.

[29] Y. Yang, "Adversarial Attack Against Images Classification based on Generative Adversarial Networks," arXiv preprint arXiv:2412.16662, 2024.

[30] Y. Yang, C. Tao, and X. Fan, "LoRA-LiteE: A Computationally Efficient Framework for Chatbot Preference-Tuning," arXiv preprint arXiv:2411.09947, 2024.

[31] Weiyu C, Yencheng L, Zsolt K, Yuchiang F W, Jiabin H. A closer look at few-shot classification[C]//Proceedings of the International Conference on Learning Representations. ICLR, 2019.

[32] Sung F, Yang Y, Zhang L, Xiang T, Torr P H, Hospedales T M. Learning to compare: Relation network for few-shot learning[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. CVPR, 2018: 1199-1208.

[33] Rusu A A, Rao D, Sygnowski J, Vinyals O, Pascanu R, Osindero S, Hadsell R. Meta-learning with latent embedding optimization[J]. ArXiv Preprint ArXiv:1807.05960, 2018.

[34] Lee K, Maji S, Ravichandran A, Soatto S. Meta-learning with differentiable convex optimization[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. CVPR, 2019: 10657-10665.

[35] Gao F, Luo X, Yang Z, Zhang Q. Label smoothing and task-adaptive loss function based on prototype network for few-shot learning[J]. Neural Networks, 2022, 156: 39-48.

[36] Shen Z, Liu Z, Qin J, Savvides M, Cheng K T. Partial is better than all: Revisiting fine-tuning strategy for few-shot learning[C]//Proceedings of the AAAI conference on artificial intelligence. AAAI, 2021, 35(11): 9594-9602.