CROSS-DOMAIN FEW-SHOT CLASSIFICATION VIA INTER-SOURCE STYLIZATION

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ABSTRACT

The goal of Cross-Domain Few-Shot Classification (CDFSC) is to accurately classify a target dataset with limited labelled data by exploiting the knowledge of a richly labelled auxiliary dataset, despite the differences between the domains of the two datasets. Some existing approaches require labelled samples from multiple domains for model training. However, these methods fail when the sample labels are scarce. To overcome this challenge, this paper proposes a solution that makes use of multiple source domains without the need for additional labeling costs. Specifically, one of the source domains is completely tagged, while the others are untagged. An Inter-Source Stylization Network (ISSNet) is then introduced to enhance stylisation across multiple source domains, enriching data distribution and model’s generalization capabilities. Experiments on 8 target datasets show that ISSNet leverages unlabelled data from multiple source data and significantly reduces the negative impact of domain gaps on classification performance compared to several baseline methods.

Index Terms— Few-shot classification, Cross-domain few-shot classification, Inter-source stylization

1. INTRODUCTION

Few-Shot Classification (FSC) is a problem solving a target task with limited labelled data, exploiting prior knowledge learned from auxiliary datasets with numerous categories and labelled samples. However, most current FSC research assumes that the auxiliary and target datasets are from the same domain, making it challenging to handle the domain shift between the two datasets [1, 2].

This has given rise to a more challenging problem called Cross Domain Few-Shot Classification (CDFSC) [3, 4], where the auxiliary and target datasets come from two vastly different domains. Existing methods usually address the CDFSC problem from several aspects such as adversarial training [5], model ensembling [6], finetuning [7], etc. In these methods, an adversarial learning-to-learning mechanism is introduced in [8] to train the shift layer and generate pseudo tasks. Furthermore, [7] integrates the proposed mixup module into the meta-learning mechanism. Recently, some attempts start to address CDFSC by introducing supervised samples from multiple different domains into the training phase [9, 10]. [9] distills knowledge from multiple individually trained networks to learn a unified set of universal deep representations by employing adapters and centered kernel alignment to co-align the features of each network. However, obtaining annotations for these source domains can be costly for real-world applications.

In tackling this issue, this paper proposes a novel solution that leverages multiple source domains, where only one of them is fully labelled (Dsl) while the rest are left unlabelled (Dsu). In this context, the primary challenge lies in how to choose and effectively use Dsu to improve the model generalization.

To solve the challenge, this paper first explores a benchmark (as shown in Figure 1), where miniImageNet is selected as Dsl, and the choice of Dsu is based on the following principles: (a) they represent a wide range of various practical scenarios and fields, (b) their labelled data are scarce while the unlabelled data are adequate. In addition, a novel approach, Inter-Source Stylization Network (ISSNet), is proposed to utilize Dsu significantly and improves the model’s generalization ability by diversifying the domain through style transfer between source domains. ISSNet has three components: Inter-Source style transfer learning, Cross-domain distilled consistency learning, and Target prototypical classifier learning. In the Inter-source style transfer learning phase, a style transfer teacher network transfers style information from the unlabelled domains to the labelled domain, expanding its distribution. In the Cross-domain distilled consistency learning phase, the student encoding model and classifier are trained with both the labelled and expanded domains. Finally, in the Target prototypical classifier learning phase, the pre-trained student encoding model is fine-tuned on the target datasets and a new prototypical classifier is learned. The goal of ISSNet is to enhance the model’s generalization through

![Fig. 1. The multiple source domains include one fully labelled source and six unlabelled sources.](image-url)
Fig. 2. Overview of ISSNet. Green part shows the Inter-source style transfer learning stage, the blue area indicates the cross-domain distillated consistency learning phase. The target prototypical classifier learning process is represented with yellow line. \( \theta \) means the classifier, in which \( \theta_1 \) and \( \theta_2 \) are for sources, and \( \theta_t \) means the target classifier.

multiple source domains, thereby improving the performance of FSC on the target domain. The key contributions of this paper are as follows:

1. This paper introduces multiple source domains \( (D_{sl} \text{ and } D_{su}) \) in model training to enhance CDFSC performance without more label costs, where \( D_{sl} \) is fully labelled and \( D_{su} \) is unlabelled.

2. A new approach ISSNet is presented to improve the CDFSC performance by making full use of the effective information of \( D_{sl} \) and \( D_{su} \). It broadens the distribution of the sources and strengthens the model’s generalization.

3. Experiments on 8 target datasets show that ISSNet effectively reduces the performance loss caused by domain shifts. The 8 datasets include which from near-domain and distance-domain.

2. METHODOLOGY

This paper presents a new framework, Inter-Source Stylization Network (ISSNet), to transfer the styles of multiple source domains \( D_{su} \) to the labelled source domain \( D_{sl} \) through a style transfer process, thereby expanding the distribution of \( D_{sl} \) and improving the model’s generalization, as shown in Figure 2. ISSNet has three stages: (1) Inter-Source style transfer learning, (2) Cross-domain distillated consistency learning, and (3) Target prototypical classifier learning. In the first stage, a teacher style transfer network \( A \) is trained to transfer the styles from \( D_{su} \) to \( D_{sl} \), generating a new dataset \( D_{al} \), with styles similar to \( D_{su} \) and content from \( D_{sl} \). The encoder of \( A \) is followed by a classifier to maintain model recognition. In the second stage, \( D_{sl} \) and \( D_{al} \) are input into a student encoding model \( M \), followed by a classifier. Knowledge distillation is employed, using a KL loss, to obtain knowledge of \( A \). In the last stage, \( M \) is used to fine-tune and predict on \( D_t \).

2.1. Inter-Source style transfer learning

Inter-Source style transfer learning is achieved through network \( A \) with crossnorm operations [11]. The goal is to combine the information from \( D_{sl} \) and \( D_{su} \) to generate new pseudo-labelled samples \( D_{al} \). \( A \) comprises an encoder \( E_A \) and a decoder \( D_A \) (the structures of \( E_A \) and \( D_A \) are borrowed from [12]). Crossnorm operations are incorporated into every layer of \( E_A \). \( E_A \) blends \( D_{sl} \) and \( D_{su} \) and maps to the combined feature \( f_{al} \). The equation for the crossnorm operation is as follows:

\[
\text{Crossnorm}(f_{sl}, f_{su}) = \sigma(f_{su}) \frac{f_{sl} - \mu(f_{sl})}{\sigma(f_{sl})} + \mu(f_{su}),
\]

where \( \mu(\cdot) \) and \( \sigma(\cdot) \) indicate the mean value and standard deviation, respectively. Then \( f_{al} \) is reconstructed as \( D_{al} \) by \( D_A \) while is recognized by a classifier \( C_A \).

The goal of \( A \) is to optimize the perceptual loss \( l_{per} \), style loss \( l_{sty} \), and cross entropy (CE) loss \( l_{ce} \). \( l_{per} \) evaluates the perceptual similarity of two samples by calculating the distance between activation maps of a pre-trained network. It can be expressed as follows:

\[
l_{per} = \mathbb{E} \left[ \sum_i \frac{1}{N_i} ||\phi_i(D_{sl}) - \phi_i(D_{al})||_1 \right],
\]

where \( \phi_i \) represents the activation map of the \( i \)-th layer of the pre-trained network. We use the VGG-19 network pre-trained on ImageNet [13] as the pre-trained model, thus \( \phi_i \) corresponds to the activation maps from layer of the VGG-19 network. Additionally, the style loss \( l_{sty} \) measures the discrepancy between covariances of the activation maps, reflecting the difference in textures. \( l_{sty} \) can be defined as follows:

\[
l_{sty} = \mathbb{E}_j \left[ \left| \left| G_j^\phi(D_{su}) - G_j^\phi(D_{al}) \right| \right|_1 \right],
\]

where \( G_j^\phi \) is a gram matrix with \( C_j \times C_j \) derived from the activation maps \( \phi_j \). Additionally, the CE loss \( l_{ce} \) is introduced to enhance recognition. The overall objective function \( l_{iss} \) is a weighted combination of \( l_{ce} \), \( l_{per} \), and \( l_{sty} \), with weight parameters \( \lambda_{per} \) and \( \lambda_{sty} \) set to 1 and 10, respectively.

\[
l_{iss} = l_{ce} + \lambda_{per} l_{per} + \lambda_{sty} l_{sty}.
\]

2.2. Cross-domain distillated consistency learning

The objective of the cross-domain distillated consistency learning is to encode both \( D_{sl} \) and the pseudo-labelled samples \( D_{al} \) into features \( f_{sl} \) and \( f_{al} \) using the student encoding model \( M \). These features are then fed into a classifier to obtain the corresponding predictions. The prediction of \( f_{sl} \) is indicated to \( F_M \). Besides, \( f_{sl} \) also is input into \( E_A \) and \( C_A \) to obtain the corresponding prediction \( P_A \). The knowledge distillation is performed by minimizing the KL divergence
between $P_M$ and $P_A$ through the KL loss $l_{kd}$. Additionally, the overall objective loss function includes two CE loss with batch spectral regularization (BSR) $l_{bsr}$ (includes $l_{sl}$ and $l_{al}$ for $D_{sl}$ and $D_{al}$, respectively), which regularizes the singular values of the feature matrix in a batch. The objective function can be referred as:

$$l_{cdd} = l_{kd} + \lambda_{bsr} l_{bsr},$$  \hspace{1cm} (5)

where both $\lambda_{bsr}$ is set as 0.05, and $l_{bsr} = l_{sl} + l_{al}$. The $l_{kd}$ is expressed as:

$$l_{kd} = KL(P_M, P_A),$$  \hspace{1cm} (6)

where $KL$ is the Kullback-Leibler divergence loss, and $l_{bsr}$ is shown as:

$$l_{bsr}(W) = l_{ce}(W) + \lambda \sum_{i=1}^{n} g_i^2,$$  \hspace{1cm} (7)

where $\lambda = 0.001$, $W$ is the parameters of classifier, and $g_i (i = 1, 2, ..., n)$ are singular values of the batch feature matrix.

### 2.3. Target prototypical classifier learning

The target prototypical classifier learning involves fine-tuning the pre-trained model $M$ and training a new classifier for the target dataset. This is achieved by following a few-shot training routine, where $M$ is fine-tuned on the target dataset $D_t$ using the N-way K-shot setting. Through the fine-tuning process, $M$ adapts to the target domain, and a new classifier is trained to categorize the target domain samples. The objective function used to optimize both $M$ and the new classifier is the CE loss.

### 3. EXPERIMENTS

In this section, we first introduce the datasets and experimental setup. Then we demonstrate the experimental results, including the effectiveness of the style transfer network, CDFSC ability analysis. Finally, we perform the ablation study includes the performance of losses and strategies.

#### 3.1. Datasets and Experimental Setup

**Datasets.** This paper improves the model generalization using 7 source datasets from different fields, and evaluate the CDFSC performance on 8 target datasets. The 7 sources include a fully labelled source (minilImageNet [14]) and 6 unlabelled sources (DIARETDB1 [15], Swedish Leaf [16], FLIR 1, SUIM [17], CCTSDB [18], the UC Merced Land Use Dataset (UCMLUD) [19]). Besides, the 8 target datasets include CropDisease, EuroSAT, ISIC, ChestX, CASIA NIR Database (faceNIR) [20], Fish Recognition data (Fish) [21], Colorectal Histology MNIST (CHM) [22], Audio-Visual Vehicle (AVV) Dataset [23].

1https://www.flir.com/oem/adas/adas-dataset-form/

#### 3.2. Effectiveness of Inter-Source style transfer learning

We evaluate the effects of Inter-Source style transfer learning, and visualize the images generated by $A$ in Figure 3. Sample of $D_{sl}$ are regard as the content images, and that of $D_{su}$ are the style images. The generated images $D_{al}$ combine the contents from $D_{sl}$ and the styles from $D_{su}$. In Figure 3, we display the three $D_{al}$ for each pair of ($D_{sl}, D_{su}$). We can know that $D_{al}$ always keep same silhouettes with $D_{sl}$, while the styles similar to $D_{su}$. Therefore, with the help of $D_{su}$, $D_{al}$ can expand the distribution of $D_{sl}$, helping to improve the model generalization ability.

#### 3.3. CDFSC ability analysis

To verify the CDFSC effects of ISSNet, We evaluated the FSC performance on 8 different target datasets. We compare ISSNet to the baseline [4], three classical methods

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**Fig. 3.** Visualization of images generated by style transfer network. The generated images consists of the contents of labelled source and the styles of unlabelled source. (a), (b), and (c) show three generated images for each content and style image pair.

**Network structure and training settings.** To evaluate the performance of ISSNet, we consider ResNet10 [4] as the student backbone. The input size is $224 \times 224$. In the Inter-Source style transfer learning, we follow the structures of [12]. And in the cross-domain distillated consistency learning, the student model $M$, followed by a classifier, is trained for 1000 epochs with a batch size of 128. And it is optimized with stochastic gradient descent (SGD). The learning rate, momentum and weight decay are set as $10^{-3}$, 0.9 and $5 \times 10^{-4}$, respectively. In the target prototypical classifier learning phase, $M$ and a new classifier are optimized with SGD for 600 epochs firstly. The learning rate, momentum and weight decay are set to $10^{-2}$, 0.9 and $10^{-3}$. Additionally, two strategies that have been shown to be effective are applied to the CDFSC task: data augmentation (DA), and label propagation (LP) [24]. DA is used in the latter two stages, and the LP is utilized in the third phase. Note that the pre-trained ResNet10 on ImageNet is not used in this work. And we only evaluate the 5-way 1-shot task on AVV cause of the extremely limit data.
Table 1. Results of ISSNet on 8 target domains about 5-way 1-shot and 5-way 5-shot tasks. The results show that our method outperforms the baseline models.

| Method          | CropDisease | EuroSAT | ISIC | ChestX | FaceNIR | Fish | CHM | AVV |
|-----------------|-------------|---------|------|--------|---------|------|-----|-----|
| ISSNet (KL+BSR) | 74.8 ± 0.28 | 65.7 ± 0.20 | 36.6 ± 0.28 | 23.8 ± 0.62 | 94.9 ± 0.37 | 68.6 ± 0.35 | 65.7 ± 0.52 | 55.7 ± 1.26 |
| ISSNet (KL+CE)  | 73.5 ± 0.24 | 63.5 ± 0.20 | 36.6 ± 0.28 | 23.8 ± 0.62 | 94.9 ± 0.37 | 68.6 ± 0.35 | 65.7 ± 0.52 | 55.7 ± 1.26 |
| ISSNet (BSR)    | 73.5 ± 0.24 | 63.5 ± 0.20 | 36.6 ± 0.28 | 23.8 ± 0.62 | 94.9 ± 0.37 | 68.6 ± 0.35 | 65.7 ± 0.52 | 55.7 ± 1.26 |
| ISSNet (CE)     | 73.5 ± 0.24 | 63.5 ± 0.20 | 36.6 ± 0.28 | 23.8 ± 0.62 | 94.9 ± 0.37 | 68.6 ± 0.35 | 65.7 ± 0.52 | 55.7 ± 1.26 |
| MatchingNet [14]| 75.8 ± 0.24 | 64.5 ± 0.20 | 36.6 ± 0.28 | 23.8 ± 0.62 | 94.9 ± 0.37 | 68.6 ± 0.35 | 65.7 ± 0.52 | 55.7 ± 1.26 |
| RelationNet [26]| 75.8 ± 0.24 | 64.5 ± 0.20 | 36.6 ± 0.28 | 23.8 ± 0.62 | 94.9 ± 0.37 | 68.6 ± 0.35 | 65.7 ± 0.52 | 55.7 ± 1.26 |
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3.4. Ablation study

We introduce two strategies, KL loss or introduce the batch spectral regularization (BSR) into CE loss to improve the ISSNet performances. Therefore, we compare the performance of ISSNet optimized with these losses on 5-way 1-shot and 5-way 5-shot task, as shown in the bottom of Table 1.

The table shows "KL+CE" and "KL+BSR" outperform best on the most of target datasets. We analyze that this is because the KL loss constrains the similarity of the outputs of student and teacher networks, making the model further generalize to the different styles. Furthermore, the results also show that the BSR loss performs better than CE loss, which means the BSR loss is more suitable for solving CDFSC problem than CE loss. In general, "KL+BSR" obtains the best performance.

4. CONCLUSIONS

This paper introduces multiple source domains into the model training with only one source is fully labelled while the rest sources remain unlabelled. To address the challenge in this situation, this paper first explores a benchmark. And then an Inter-Source Stylization network (ISSNet) is proposed to improve the generalization ability of model, including Inter-Source style transfer learning, cross-domain distillated consistency learning, and target prototypical classifier learning. In general, this paper introduces multiple source domains for CDFSC studies without increasing labeling costs, and proposes ISSNet to address the corresponding challenges. Evaluation on 8 datasets show that ISSNet significantly improve the CDFSC performance.

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