Foundation Model Insights and a Multi-Model Approach for Superior Fine-Grained One-shot Subset Selection

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Abstract

One-shot subset selection serves as an effective tool to reduce deep learning training costs by identifying an informative data subset based on the information extracted by an information extractor (IE). Traditional IEs, typically pre-trained on the target dataset, are inherently dataset-dependent. Foundation models (FMs) offer a promising alternative, potentially mitigating this limitation. This work investigates two key questions: (1) Can FM-based subset selection outperform traditional IE-based methods across diverse datasets? (2) Do all FMs perform equally well as IEs for subset selection? Extensive experiments uncovered surprising insights: FMs consistently outperform traditional IEs on fine-grained datasets, whereas their advantage diminishes on coarse-grained datasets with noisy labels. Motivated by these finding, we propose RAM-APL (RAnking Mean-Accuracy of Pseudo-class Labels), a method tailored for fine-grained image datasets. RAM-APL leverages multiple FMs to enhance subset selection by exploiting their complementary strengths. Our approach achieves state-of-the-art performance on fine-grained datasets, including Oxford-IIIT Pet, Food-101, and Caltech-UCSD Birds-200-2011.

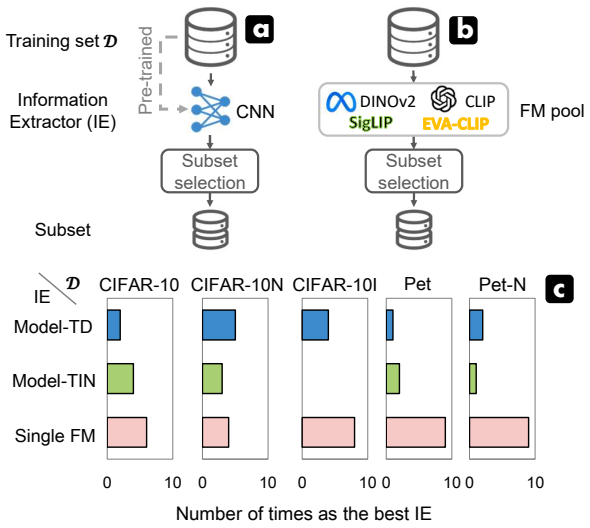

Figure 1. **Comparison of pipelines for one-shot subset selection.** (a) Traditional pipeline (He et al., 2024): Relies on a model pre-trained on the full training set of the target task to extract data information, but this introduces dataset dependency and additional pre-training time. (b) Pipeline with a single foundation model (Xie et al., 2023): Replaces the small pre-trained model with a single FM, potentially mitigating dataset dependency. As shown in (c), on fine-grained datasets, using a single FM as an IE is significantly and consistently superior to using traditional IE, and improves the performance of subset selection at different sampling rates.

1. Introduction

Subset selection, also known as coreset selection (Zheng et al., 2023; Wan et al., 2024b), has become an effective approach to improve model training efficiency by identifying a small, representative subset of training data without significantly compromising model performance. This task is particularly important in scenarios involving large-scale datasets (Wan et al., 2024a; Wang et al., 2025; Jia et al., 2025), where full dataset training is computationally prohibitive. Subset selection methods can be broadly categorized into one-shot (Xia et al., 2024; Yang et al., 2024) and adaptive approaches (Karanam et al., 2022; Killamsetty et al., 2022). In this work, we focus on one-shot subset selection, which identifies subsets in a single pass, offering computational advantages over adaptive methods that require iterative selection during model training.

Traditional one-shot subset selection methods typically rely on a pre-trained model as an information extractor (IE) to derive data characteristics such as features, gradients, or

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uncertainty scores. These characteristics are then used to identify the most representative subset. While numerous strategies—such as feature-based (Agarwal et al., 2020; Sener & Savarese, 2017), uncertainty-based (Coleman et al., 2019; Wu et al., 2024), and gradient matching-based approaches (Mirzasoleiman et al., 2020)—have been proposed, these methods fundamentally depend on pre-trained models obtained by training on the full dataset of the target task, as shown in Figure 1 (a). This inherently introduces significant dataset dependency, which limits their applicability, particularly in large-scale data scenarios. Efforts to reduce this dependency, such as employing lightweight proxy models (Coleman et al., 2019) or minimizing pre-training epochs (Guo et al., 2022), only partially mitigate the computational burden without fundamentally addressing the dataset dependency issue.

Recent advancements in foundation models (FMs), such as pre-trained vision models (Caron et al., 2021; Oquab et al., 2023) and vision-language models (Radford et al., 2021; Zhai et al., 2023; Sun et al., 2023), offer a promising alternative. A natural alternative to subset-based methods is fine-tuning or adapting FMs to the target dataset (Ding et al., 2023). While these approaches leverage pre-trained knowledge, they still require full-dataset access during fine-tuning, which undermines the computational efficiency that subset selection seeks to achieve. Moreover, these methods often face challenges such as overfitting on noisy datasets (Feng et al., 2024) and scalability issues on large datasets. In contrast, subset-based methods decouple the data selection process from task-specific training, enabling efficient learning without full-dataset reliance. With their robust generalization capabilities, FMs can serve as direct alternatives to traditional IEs, enabling dataset-agnostic subset selection pipelines, as illustrated in Figure 1 (b). Unlike traditional pipelines that rely on task-specific pre-training, FM-based pipelines eliminate the need for task-specific pre-training, making them well-suited for large and diverse datasets. Despite their potential, the advantages of FM-based pipelines over traditional methods remain under-explored. While some studies (Xie et al., 2023; Killamsetty et al., 2023) have investigated this approach, prior work (Xie et al., 2023) has revealed that simply using FMs for subset selection does not consistently lead to superior performance. This highlights critical open questions: Can FMs truly replace task-specific IEs in subset selection? If so, under what conditions?

In this paper, we conduct extensive experiments to investigate the strengths and limitations of using FMs as IEs for subset selection. Detailed experimental statistics and analyses can be found in *Single Model Study* section. Our experiments on subset selection using three kinds of models as IEs on five different types of image datasets, *i.e.,* CIFAR-10 (Krizhevsky et al., 2009), CIFAR-10N-worse (CIFAR-10N) (Wei et al., 2022), CIFAR-10-imbalance (CIFAR-10I) (Cui et al., 2019), Oxford-IIIT Pet (Pet) (Parkhi et al., 2012)) and Oxford-IIIT Pet-N (Pet-N), revealed surprising findings: (1) FMs consistently outperform traditional IEs on both clean and noisy fine-grained datasets; and (2) FMs demonstrate limited advantages for subset selection on coarse-grained datasets with noisy labels.

While FMs are well-suited for fine-grained datasets, the optimal choice of FM as a feature extractor for subset selection remains an open question. Moreover, existing feature-based methods fail to comprehensively analyze feature distributions from both intra- and inter-class perspectives, resulting in suboptimal selection performance. To address these limitations, we introduce a novel subset selection pipeline that leverages multiple FMs with unknown selection performance to enhance fine-grained dataset selection. Our proposed RAM-APL method integrates diverse FMs (*i.e.,* DINOv2 and CLIP) and quantifies data importance through a systematic analysis of feature distributions across both intra- and inter-class levels, achieving state-of-the-art performance on three fine-grained image datasets.

The contributions of our work are three-fold:

- An in-depth study on the strengths and limitations of foundation models compared to traditional information extractors for subset selection reveals that foundation models consistently outperform traditional IEs on fine-grained datasets, whereas their advantage diminishes on coarse-grained datasets with noisy labels.
- A novel subset selection pipeline employing multiple foundation models with unknown selection performance as IEs is proposed for fine-grained image datasets. RAM-APL, an effective subset selection method, is designed based on the novel pipeline.
- Extensive experiments verify the superiority of RAM-APL on three fine-grained image datasets. Specifically on the Caltech-UCSD Birds-200-2011 dataset, RAM-APL achieves an average improvement of 6.4% in prediction accuracy over Random method across all sampling rates.

2. Related Works

Current one-shot subset selection methods typically follow a traditional selection pipeline, which consists of an information extractor, a measurer, and a selector. Various measures have been proposed to leverage the information provided by the extractor to assess data importance, including feature-based (Agarwal et al., 2020; Sener & Savarese, 2017), gradient-based (Kothawade et al., 2022; Killamsetty et al., 2021a), training dynamic-based (Toneva et al., 2018; Swayamdipta et al., 2020; He et al., 2024; Zhang et al., 2024) and other weighting strategies (Zhou et al., 2020;

Coleman et al., 2019; Zheng et al., 2022). Regardless of the above methods, their extractors are usually trained to converge on the full training set of the target task, rendering the pre-trained extractor data-dependent and limiting the applicability of subset selection to new large-scale datasets. For example, TDDS (Zhang et al., 2024) required 90 epochs of extractor training on ImageNet-1K to gather training dynamics, surpassing the 60 epochs needed for training the target model on the coreset. To solve this problem, Coleman *et al.* (Coleman et al., 2019) designed a small proxy model to perform data selection, achieving significantly faster pre-training. Guo *et al.* (Guo et al., 2022) proposed to pre-train a model for a small number of epochs. However, they do not break free from dataset dependency. Recently, some studies (Xie et al., 2023; Killamsetty et al., 2023) have explored using foundation models (FMs) as IEs for data selection, showing promise in addressing dataset dependency. Nevertheless, neither study has conclusively demonstrated that FMs outperform traditionally trained IEs. Specifically, (Xie et al., 2023) found that simply utilizing an FM does not guarantee superior data selection performance, raising questions about the viability of FMs as substitutes for traditional IEs. Our comprehensive investigation reveals that FMs universally dominate traditional IEs on fine-grained datasets (both clean and noisy), while their advantage diminishes on coarse-grained datasets with noisy labels. Furthermore, the contribution of an FM to subset selection varies across datasets. To maximize the potential of FMs for fine-grained subset selection, we propose strategically combining multiple FMs with complementary capabilities.

Since only features can be obtained from each FM, how to effectively use the unaligned features extracted from multiple FMs to measure and select data is the key problem. Existing feature-based subset selection methods can be classified into two main categories: geometry-based methods (Welling, 2009; Sener & Savarese, 2017; Xia et al., 2023) and decision boundary-based methods (Ducoffe & Precioso, 2018; Margatina et al., 2021). For geometry-based methods, studies (Welling, 2009; Sener & Savarese, 2017) selected samples whose distributions are not close to each other in feature space so that subsets do not have redundant information. These subsets usually make the model a good generalization. However, they treat samples whose distributions are not close to each other with equal importance, making subset selection for fine-grained datasets disregard inter-class distribution differences. Decision boundary-based methods select data close to the decision boundary, which is a time-consuming and biased selection process that is not beneficial for model generalization. Taking the best of both types of methods, we propose the subset selection method RAM-APL for fine-grained datasets.

3. Preliminary: Subset Selection

In downstream tasks such as image classification and recognition, we consider a large-scale training set $\boldsymbol{\mathcal{D}} = \{I_1, \ldots, I_N\}$ with a dataset size N, where each sample $I_i = (x_i, y_i)$ consists of input data x_i and its corresponding class label $y_i \in \{1, \ldots, C\}$. In scenarios where there's a specified budget p, subset selection is used to identify a subset $\boldsymbol{\mathcal{S}}$ of $\boldsymbol{\mathcal{D}}$ that contains the most informative data for the target downstream task. It is expected that the model $\theta^{\mathcal{S}}$ trained on $\boldsymbol{\mathcal{S}}$ can perform on par with the model $\theta^{\mathcal{D}}$ trained on $\boldsymbol{\mathcal{D}}$. The performance of subset selection is evaluated by the performance of model $\theta^{\mathcal{S}}$ on the test set of the target downstream task. The subset $\boldsymbol{\mathcal{S}} = \{I_1, \ldots, I_M\}$ has a size M, where $M < N$, and the sampling rate for subset selection is defined as $p = M/N$. In the practical study, p is pre-specified, and the subset $\boldsymbol{\mathcal{S}}$ is selected with the expectation of maximizing the target model's accuracy while adhering to the budget constraint.

Subset selection relies on an Information Extractor (IE) to extract information from each sample, which is then used to assess the importance of the sample and select the most informative data. Traditionally, the IE is a model pre-trained on the full training set, which inherently introduces dataset dependency, limiting the applicability of this approach across different datasets. To address this limitation, a more flexible and generalizable approach is necessary, and it is therefore crucial to explore alternatives that reduce or eliminate dataset dependency.

4. Single-Model Study

Foundation Models (FMs) have recently emerged as a promising alternative to traditional information extractors (IEs) for subset selection. However, the advantages of FM-based selection over conventional methods remain largely unexplored. In this section, we investigate whether a single foundation model can effectively replace traditional IEs and address the following two key questions: **Question 1:** In which cases are foundation models most effective, and in which cases are they not? **Question 2:** Do all FMs perform equally? Our extensive experiments reveal several key findings:

- **Observation 1:** FMs demonstrate limited advantages for subset selection on noisy, coarse-grained datasets.
- **Observation 2:** Conversely, FMs significantly and consistently outperform traditional IEs for subset selection on fine-grained datasets (both clean and noisy).
- **Observation 3:** Different FMs perform differently as information extractors for subset selection.

Inspired by Observations 2 and 3, we propose a FM-based

algorithm for superior fine-grained subset selection, which is elaborated in Section 5. In subsequent paragraphs, we provide detailed explanations for these observations.

Experimental Setting. To assess the applicability of foundation models as information extractors (IEs), we conducted subset selection experiments using a single model as the IE across five distinct image datasets: CIFAR-10 (Krizhevsky et al., 2009), CIFAR-10N-worse (CIFAR-10N) (Wei et al., 2022), CIFAR-10-imbalance (CIFAR-10I) (Cui et al., 2019), Oxford-IIIT Pet (Pet) (Parkhi et al., 2012)) and Oxford-IIIT Pet with 20% symmetric label noise (Oxford-IIIT Pet-N, abbreviated as Pet-N). We apply three kinds of models for feature extraction in subset selection respectively. Three kinds of models are: **(1)** models pre-trained on the target training dataset for ten epochs (Guo et al., 2022), referred to as model-TD. Once the target task changes, the model needs to be pre-trained again; **(2)** models pre-trained on TinyImageNet (TIN) (Krizhevsky et al., 2012) for ten epochs, referred to as model-TIN. TinyImageNet is a larger classification dataset, models pre-trained on it possess a stronger representation ability compared to those pre-trained on target datasets. Given this, we think that model-TIN has the potential to serve as an alternative to traditional IEs without retraining when the target task changes; and **(3)** a single foundation model (*i.e.,* DINOv2, CLIP, SigLIP, or EVA-CLIP). To explore the impact of the above three kinds of models as IEs on selection algorithms, we implement four classical algorithms, *i.e.,* MIN, K-center Greedy (KCG) (Sener & Savarese, 2017), Graph Cut (GC) (Iyer et al., 2021) and Moderate_DS (MDS) (Xia et al., 2023) over the extracted features. Besides, we use each selection algorithm to select training samples with various sampling rates (*i.e.,* 10%, 30%, and 50%), and train target models over the selected subsets. Due to the limited page, we provide the detailed experimental setup and results in the *Supplementary Material*.

We analyzed which of the three single models served as the most effective IE across four subset selection methods and three sampling rates. The frequency of each type of single model being the optimal IE under 12 settings on each dataset is presented in Figure 1 (c). Surprisingly, we found that directly using features extracted from the FM for subset selection does not consistently outperform features extracted from traditional pre-trained models.

(**Observation**) **FMs demonstrate limited advantages for subset selection on noisy, coarse-grained datasets. In contrast, FMs consistently outperform traditional IEs for subset selection on both clean and noisy fine-grained datasets.** In the case of selecting CIFAR-10N, the FM only emerged as the optimal IE in 4 out of 12 experimental setups. Conversely, the FM performed well on the other four datasets, especially on the Pet and Pet-N. For subset selection on CIFAR-10, the FM was the optimal IE in 6 out of 12 experimental setups, but the best result at each sampling rate was achieved using model-TIN as the IE. In the case of CIFAR-10I, the FM was optimal in 8 out of 12 experimental setups, but at a low sampling rate of 1%, model-TD yielded the best results. Encouragingly, the single FM performed best in 9 out of 12 experimental setups on the Pet and Pet-N datasets and achieved the best results across all sampling rates. Thus, the FM presents a viable alternative to traditionally trained IEs for fine-grained image datasets. The Single-Model Study on more coarse- and fine-grained tasks shows the same conclusions, as summarized in the *Supplementary Material*.

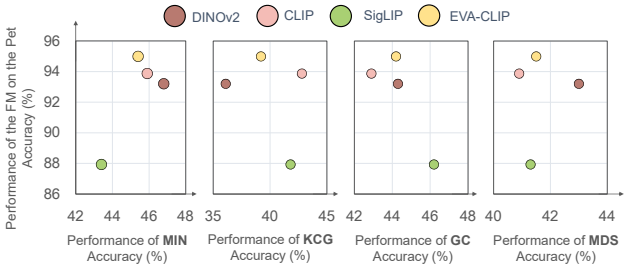


Figure 2. **Relationship between foundation model performance on the target task and subset selection performance using that FM as IE.** Superior target task accuracy does not necessarily lead to better subset selection performance across different foundation models and selection methods.

(**Observation**) **Different FMs perform differently as information extractors for subset selection, and the superior performance of FMs on downstream tasks does not guarantee better subset selection effects**. Various FMs are available, including DINOv2, CLIP, SigLIP, and EVA-CLIP. If the method is to be designed for fine-grained datasets according to the subset selection pipeline (b), an optimal FM needs to be identified first as the IE. An intuitive idea is to identify the optimal FM by testing each on the target task, with the best-performing FM chosen as the IE. However, we observe that superior performance on the downstream task does not guarantee better subset selection. As shown in Figure 2, although EVA-CLIP has strong zero-shot classification on Pet, it is not optimal for any selection method. Furthermore, our experiments indicate that the optimal FM as the IE varies depending on factors such as target datasets, selection methods, and sampling rates. For instance, Figure 2 demonstrates that for selecting 50% of the Pet dataset, DINOv2 performs best as the IE for the MIN method, while CLIP excels for the KCG method. Additional analyses of optimal FMs across sampling rates are presented in the *Supplementary Material*. Therefore, Pipeline (b) requires an additional step to identify the best FM to achieve the most effective performance across different scenarios. This undoubtedly introduces an optimization detour, diverting focus from the primary goals of data measurement and selection.

While FMs are well-suited for fine-grained datasets, the optimal choice of FM as an feature extractor for FM-based subset selection remains an open question. Moreover, existing feature-based methods fail to comprehensively analyze feature distributions from both intra- and inter-class perspectives, resulting in suboptimal selection performance. To address these limitations, we explore a novel subset selection pipeline that directly employs multiple FMs with unknown individual contributions as IEs. Building on our pipeline, we propose the RAM-APL method, achieving state-of-the-art performance on multiple fine-grained datasets.

5. Proposed Method: RAM-APL

We are the first to investigate selection with multiple foundation models. In this section, we mainly propose a baseline method with multiple models as feature extractors. We introduce the problem formulation in Section 5.1. The subset selection method is then explained in detail in Section 5.2, which includes two metrics, namely ranking mean and accuracy of pseudo-class labels.

5.1. Problem Formulation

Multiple foundation models $\boldsymbol{\mathcal{M}_{\mathcal{F}}}$ are used to extract information of training data in our method, where $\boldsymbol{\mathcal{M}_{\mathcal{F}}} = \{M_F^1, \ldots, M_F^m\}$. Foundation models can be directly used as feature extractors, but features of the same samples extracted by different models are not aligned. Therefore, the two key challenges in our method design are effectively fusing features and accurately measuring sample importance based on the fused representations.

5.2. Method

The primary challenge in learning from fine-grained image datasets lies in their large intra-class differences and small inter-class differences. Existing subset selection methods either emphasize intra-class distribution while overlooking inter-class similarities or focus on decision-boundary samples while neglecting samples from other distributions within the class. To address these limitations, we propose RAM-APL, a selection method that quantifies data importance by jointly considering both intra-class and inter-class distributions.

Feature Extraction Given a fine-grained image dataset $\boldsymbol{\mathcal{D}}$, we extract features using multiple FMs M_F^i, where $i \in \{1, \ldots, m\}$. The extracted feature set is denoted as $\boldsymbol{\mathcal{F}} = [\boldsymbol{\mathcal{F}^1}, \ldots, \boldsymbol{\mathcal{F}^m}]$, where $\boldsymbol{\mathcal{F}^i} = [\boldsymbol{F}_1^i, \ldots, \boldsymbol{F}_N^i]$ represents the feature representations of $\boldsymbol{\mathcal{D}}$ obtained from the i^{th} foundation model M_F^i. Each feature vector $\boldsymbol{F}_j^i \in \mathbb{R}^{Ki}$ for a data sample I_j is defined as: $\boldsymbol{F}_j^i = \left[f_j^{i,0}, f_j^{i,1}, \ldots, f_j^{i,K_i-1}\right] \in \mathbb{R}^{K_i}$, where K_i represents the feature dimensionality of the i^{th} model. Since FMs may produce features of varying dimensions, their representations are not necessarily aligned.

RAnking Mean (RAM) RAM maps features extracted by different foundation models from their unaligned feature spaces into a distance ranking space (an aligned space), facilitating the evaluation of data importance based on intra-class distribution.

After acquiring the feature set $\boldsymbol{\mathcal{F}}$, we map the features extracted by each foundation model to a distance-ranking space. Specifically, given the feature set $\boldsymbol{\mathcal{F}^i} = [\boldsymbol{F}_1^i, \ldots, \boldsymbol{F}_N^i]$ from foundation model M_F^i, we define the central feature of class c as the mean feature vector:

$$\tilde{\boldsymbol{F}}_c^i = \frac{1}{|S|} \sum_{j \in S} \boldsymbol{F}_j^i, \tag{1}$$

where S represents the set of indices belonging to class c. The Euclidean distance between a sample $\boldsymbol{F}_j^i$ and its class center $\tilde{\boldsymbol{F}}_c^i$ serves as a measure of representativeness, with smaller distances indicating higher representativeness (Xia et al., 2023):

$$d\left(\boldsymbol{F}_j^i, \tilde{\boldsymbol{F}}_c^i\right) = \|\boldsymbol{F}_j^i - \tilde{\boldsymbol{F}}_c^i\|_2, \tag{2}$$

where $\|\cdot\|_2$ denotes the Euclidean norm. Samples are ranked within each class according to their computed distances, producing ranked values $\boldsymbol{\mathcal{R}}^i = [r_1^i, \ldots, r_{|S|}^i]$ for model M_F^i, where $r_j^i \in \mathbb{Z}^+$ and smaller values indicate closer distances. This process is repeated for all m foundation models, mapping unaligned features into a unified distance-ranking space. The final ranking mean of class c is denoted as:

$$\overline{\boldsymbol{\mathcal{R}}}_{\boldsymbol{c}} = [\overline{r}_1, \ldots, \overline{r}_{|S|}], \tag{3}$$

where $\overline{r}_j = \frac{1}{m*|S|} \sum_{i=1}^{m} r_j^i \in [0, 1]$ represents the normalized ranking mean for sample I_j. A smaller normalized ranking mean indicates greater alignment with class prototypes across foundation models. Visual analyses in the *Supplementary Material* further reveal that samples with lower normalized ranking means tend to exhibit more distinct target objects and simpler backgrounds.

Accuracy of Pseudo-class Labels (APL) APL maps features extracted by various foundation models from their unaligned feature space into a pseudo-class confidence score based on the unified inter-class distance ranking.

After obtaining the feature set $\boldsymbol{\mathcal{F}}$, we assign pseudo-class labels to features extracted from each foundation model separately. Specifically, given the feature set $\boldsymbol{\mathcal{F}^i} = [\boldsymbol{F}_1^i, \ldots, \boldsymbol{F}_N^i]$ from foundation model M_F^i, we first compute the central features of all C classes using Equation (1), collectively denoted as $\tilde{\boldsymbol{F}}^i = [\tilde{\boldsymbol{F}}_0^i, \ldots, \tilde{\boldsymbol{F}}_{(C-1)}^i]$. Next, we

calculate the Euclidean distances between each sample $\boldsymbol{F}_j^i$ and all central features following Equation (2). These distances are represented as: $D(\boldsymbol{F}_j^i) = [d_{j,0}^i, \ldots, d_{j,(C-1)}^i]$, where $d_{j,c}^i$ represents the distance between $\boldsymbol{F}_j^i$ and the central feature $\tilde{\boldsymbol{F}}_c^i$. The pseudo-class label for sample I_j in the feature space of M_F^i is then assigned based on the nearest central feature, computed as:

$$\tilde{y}_j^i = \arg\min\ D(\boldsymbol{F}_j^i). \tag{4}$$

If the assigned pseudo-class label matches the ground-truth label, *i.e.,* $\tilde{y}_j^i = y_j$, then the sample is considered correctly classified in the feature space of M_F^i, and we assign a score of $\varphi_j^i = 1$. Otherwise, we set $\varphi_j^i = 0$.

By repeating this process across all m foundation models, we obtain a set of classification scores for each sample across different feature spaces. The average pseudo-class label accuracy for sample I_j is then computed as:

$$\overline{\varphi}_j = \frac{1}{m}\sum_{i=1}^{m}\varphi_j^i. \tag{5}$$

A lower value of $\overline{\varphi}_j$ indicates that sample I_j is more frequently misclassified across different feature spaces, suggesting a higher degree of similarity to other classes and thus greater difficulty in distinguishing it within the feature distribution. Finally, we represent the overall pseudo-class label accuracy for the entire dataset $\boldsymbol{\mathcal{D}}$ as:

$$\overline{\boldsymbol{\varphi}} = [\overline{\varphi}_1, \ldots, \overline{\varphi}_N]. \tag{6}$$

Subset Selection The importance of data samples in fine-grained learning is quantified through a linear combination of RAnking Mean and the Accuracy of Pseudo-class Labels (RAM-APL), formulated as:

$$Score = W_1 \times \overline{\boldsymbol{\mathcal{R}}} + W_2 \times (1 - \overline{\boldsymbol{\varphi}}). \tag{7}$$

Here, W_1 and W_2 control the contributions of intra-class and inter-class distributions, respectively. Inspired by (Swayamdipta et al., 2020), which highlights that easier samples facilitate optimization, we prioritize high intra-class similarity at lower sampling rates p, gradually incorporating harder samples as p increases. Thus, W_1 and W_2 are dependent on the sampling rate p. The weight functions are defined as:

$$\begin{aligned} W_1 &= \alpha + (1-\alpha) \times \frac{1}{1 + e^{\beta * (\mathrm{p} - 0.5)}} \\ W_2 &= 1 - W_1 \end{aligned} \tag{8}$$

Samples with the smallest scores are selected into $\boldsymbol{\mathcal{S}}$ up to the predefined budget. The hyper-parameters α and β regulate the balance between intra-class and inter-class information across different sampling rates. Experimental results demonstrate that the best selection performance on fine-grained datasets is achieved using $\boldsymbol{\mathcal{M}}_{\boldsymbol{\mathcal{F}}} = \{\text{CLIP, DINOv2}\}$.

6. Experiments

6.1. Experimental Settings

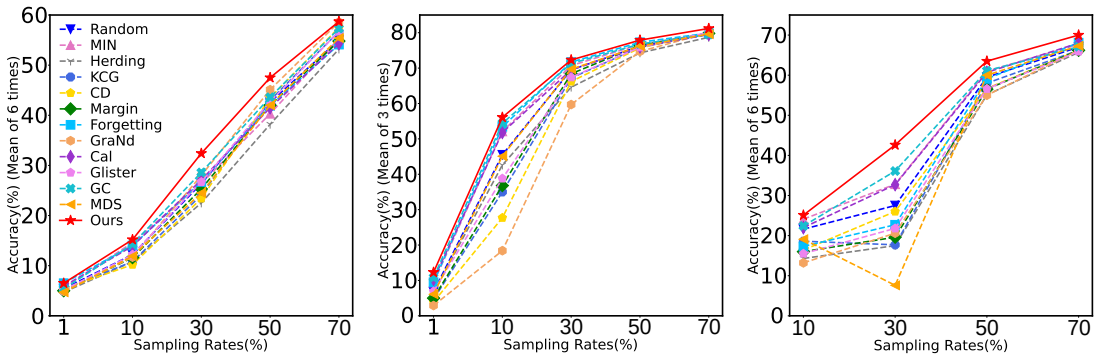
Datasets. We evaluate our method on three classical fine-grained image classification datasets: Oxford-IIIT Pet (Pet) (Parkhi et al., 2012), Food-101 (Bossard et al., 2014), and Caltech-UCSD Birds-200-2011 (CUB-200-2011) (Wah et al., 2011). The Oxford-IIIT Pet comprises 7,349 images of 37 different breeds of cats and dogs. Food-101 has 101 classes, each with 750 training images and 250 test images. CUB-200-2011 consists of 11,788 images of 200 bird subcategories. Detailed dataset statistics are provided in *Supplementary Material*.

Foundation Models as Feature Extractor. We adopt two FMs as feature extractors for fine-grained image datasets, *i.e.,* CLIP-VITl14 (Radford et al., 2021) and DINOv2-VITs14 (Oquab et al., 2023). The visual encoder of CLIP-VITl14 is used to extract image features, while the final layer [CLS] token embedding output of DINOv2-VITs14 serves as the feature representation. We emphasize that these FMs were not fine-tuned on the target datasets and were used solely as feature extractors for subset selection. The impact of varying the number of foundation models on selection performance is discussed in Section 6.4.

Target Model Architecture & Training Parameters. For Pet and Food-101 datasets, we use the 18-layer residual network (ResNet-18) (He et al., 2016) as the model backbone, initializing it randomly for training. For the CUB-200-2011 dataset, we adopt ResNet-50 as the model backbone, initialized with weights pre-trained on ImageNet (Deng et al., 2009). We follow the experimental setup from (Guo et al., 2022). Specifically, we use SGD as the optimizer with batch size 128, initial learning rate 0.1, Cosine decay scheduler, momentum 0.9, weight decay 5×10^{-4}, and 200 training epochs. For data augmentation, we employ a random resized crop to 224×224 resolution, followed by random horizontal flipping on training images. The code of our study is available at: https://github.com/ZhijingWan/RAM-APL.

Evaluation Metric. Prediction accuracy of a well-trained target model on the test set is used as the evaluation metric.

Comparison Methods. Multiple subset selection methods act as baselines for comparison. Specifically, we compare with (1) Random, which uniformly selects samples as the subset; (2) Herding (Welling, 2009); (3) K-Center Greedy (KCG) (Sener & Savarese, 2017); (4) Contextual Diversity (CD) (Agarwal et al., 2020); (5) Margin (Coleman et al., 2019); (6) Forgetting (Toneva et al., 2018); (7) GraNd (Paul et al., 2021); (8) Cal (Margatina et al., 2021); (9) Glister (Killamsetty et al., 2021b); (10) Graph Cut(GC) (Iyer et al., 2021); (11) Moderate_DS (MDS) (Xia et al., 2023); (12) MINimum distance (MIN), which selects samples with the minimum distance from the central feature of its class. Details of baselines are in *Supplementary Material*.



(a) Oxford-IIIT Pet (b) Food-101 (c) CUB-200-2011

Figure 3. **Comparison of our method with baselines on three classical fine-grained image datasets.** Reported values correspond to mean accuracy.

We implemented each selection method based on the one-shot subset selection pipeline using code in the DeepCore library[1]. The information extractors used in baselines (2)-(12) were obtained using the traditional method, *i.e.,* training a model with the same backbone as the target model on the target training set for 10 epochs to ensure a fair comparison.

6.2. Comparison with Baselines

The results comparing the accuracy between the different subset selection methods on each fine-grained dataset are shown in Figure 3. Given each sampling rate, class-balanced sampling is performed. The experiments of each method on Pet were performed five times with different random seeds, while the experiments on Food-101 and CUB-200-2011 were performed three times with different random seeds due to the high computational effort. We adopt $\alpha = 0.2$ and $\beta = 1$ for our method across all datasets.

As shown in Figure 3, our method outperforms all baselines at each sampling rate. We compute the average performance gain of each method over Random across all sampling rates. On Pet, our method achieves a 3.74% average improvement, substantially outperforming the sub-optimal GC method, which shows a 1.52% average improvement. On Food-101, our gain reaches 4.44% compared to GC's 3.04%. On CUB-200-2011, our method shows a 6.40% average improvement versus GC's 2.78%. Detailed performance and additional cross-architecture generalization results are provided in the *Supplementary Material*.

6.3. Ablation Study

Our method mainly consists of two novel designs: two feature measure metrics for multiple foundation models (*i.e.,* "RAM" and "APL"). We evaluate the effectiveness of each design on the Pet dataset. Firstly, the RAM is designed primarily to effectively fuse the features extracted from multiple foundation models in terms of intra-class distribution, enabling the subset selection performance to be not inferior to that of any individual foundation model. As shown in Table 1, when using RAM to fuse the features extracted from CLIP and DINOv2 and selecting the samples with the minimum ranking mean, the performance of "RAM" is better than that of "MIN" with Model-TD or CLIP as the IE at each sampling rate. This validates the effectiveness of the RAM strategy. By combining APL and RAM to assess data importance for subset selection, our method outperforms the "MIN" baseline with DINOv2 as the IE at both 1% and 50% sampling rates. These results highlight the effectiveness of the joint RAM-APL strategy in fine-grained subset selection. Further analysis in the *Supplementary Material* shows that RAM-APL selects more diverse samples, enhancing overall coverage of the feature space.

Table 1. **Ablation study based on Pet.** Model-TD refers to the model pre-trained on Pet for 10 epochs.

Method	IE	Sampling rates		
		1%	50%	70%
MIN	Model-TD	5.6±0.7	40.3±2.6	55.2±2.7
	CLIP	5.6±0.2	45.9±1.8	56.3±0.7
	DINOv2	6.2±0.1	46.8±2.0	**60.5±2.9**
RAM	CLIP+DINOv2	5.9±0.3	47.1±1.4	56.5±2.7
RAM-APL		**6.5±0.4**	**47.5±1.9**	58.7±2.2

6.4. Analysis and Discussion

Parameter analysis. The hyper-parameters α and β are used to set the joint weights W_1 and W_2 according to Formula 8. We study the impact of them in Figure 4, testing five different values for α and β. In particular, we compared the basic weight-setting strategy for fusion, *i.e.,* the equal-

[1]https://github.com/PatrickZH/DeepCore

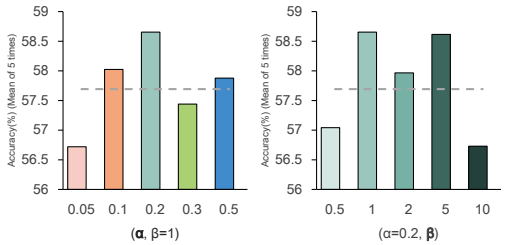


Figure 4. **Parameter analysis when sampling 70% of the Pet.** It shows that our method achieves the best performance when $\alpha = 0.2$ and $\beta = 1$. The grey dotted line indicates the selection method with $Score = \overline{\mathcal{R}} + (1 - \overline{\varphi})$ *i.e.,* the direct assignment $W_1 = W_2 = 1$ without using Formula 7.

weighted fusion strategy, where $W_1 = 1$ and $W_2 = 1$. As illustrated in Figure 4, the best performance was achieved with $\alpha = 0.2$ and $\beta = 1$, outperforming the equal-weighted fusion strategy. When $\alpha = 0.2$ and $\beta = 1$, the fusion weights (W_1, W_2) corresponding to 1%, 10%, 30%, 50%, and 70% sampling rates were (0.696, 0.304), (0.679, 0.321), (0.640, 0.360), (0.600, 0.400), (0.560, 0.44), respectively. As the sampling rate increases, W_2 increases while W_1 remains greater than W_2. This observation suggests that focusing more on inter-class feature distributions as the sampling rate increases helps to select better fine-grained subsets, but it is crucial to ensure that the intra-class assessment scores continue to dominate.

Performance impact of the number of different FMs used for IE. There exists a diverse set of FMs capable of extracting visual features, including DINOv2 (Oquab et al., 2023), CLIP (Radford et al., 2021), SigCLIP (Zhai et al., 2023) and EVA-CLIP (Sun et al., 2023). These models differ in their architectures, training strategies, and training datasets, leading to distinct knowledge and representation capabilities (as demonstrated in the *Supplementary Material*). This raises a natural question: Does incorporating more FMs as IEs enhance our method's performance?

To explore this, we evaluate different combinations of DINOv2-VITs14, CLIP-VITL14, SigLIP-base-patch16-224, and EVA-CLIP-8B[2] on the Pet dataset. As shown in Table 2, using multiple FMs yields better overall performance than any single model. DINOv2+CLIP achieves the best trade-off between efficiency and accuracy, while adding EVA-CLIP yields further overall gains when computational resources permit. These findings support the benefit of multi-model consensus in our framework.

In the main experiments, we adopt DINOv2 and CLIP as our default IE pair, which yields consistent improvements over subset selection baselines across three fine-grained datasets.

[2]We use the SigLIP-base-patch16-224 and EVA-CLIP-8B from HuggingFace (Wolf et al., 2019)

Table 2. **Comparison of the performance of our method using different numbers of foundation models as information extractors.** Here, "D", "C", "S" and "E" represent DINOv2, CLIP, SigLIP, EVA-CLIP, respectively.

IE				Sampling rates				
D	C	S	E	1%	10%	30%	50%	70%
●	○	○	○	5.9±0.3	15.4±1.1	31.6±2.3	47.7±1.1	57.9±4.1
○	●	○	○	5.7±0.4	15.0±0.2	27.9±1.2	43.6±1.9	57.0±0.4
○	○	●	○	6.6±0.3	14.1±1.0	28.8±1.1	43.9±1.7	55.1±2.6
○	○	○	●	5.4±0.3	15.0±0.6	30.2±2.5	44.4±2.3	56.6±1.8
●	●	○	○	6.5±0.4	15.2±1.2	32.4±2.9	47.5±1.9	**58.7±2.2**
●	○	●	○	5.9±0.3	16.2±0.1	31.4±3.2	45.0±1.3	58.6±1.2
●	○	○	●	6.0±0.6	16.0±0.9	**35.8±2.9**	46.5±1.8	54.9±3.5
○	●	●	○	6.4±0.2	15.1±0.4	29.8±1.6	45.9±1.3	56.2±2.7
○	●	○	●	5.9±0.3	15.5±0.7	31.4±1.7	44.2±2.2	55.9±1.8
○	○	●	●	**6.7±0.4**	16.2±0.6	34.7±0.3	45.7±0.8	56.6±2.4
●	●	●	○	6.2±0.8	15.6±0.5	33.2±1.4	**48.3±1.1**	57.6±0.1
●	●	○	●	6.0±0.4	**17.5±1.0**	35.2±1.8	47.9±1.5	55.6±2.1
●	○	●	●	6.1±0.3	16.8±0.6	34.4±2.1	47.0±2.0	55.1±1.6
○	●	●	●	6.1±0.2	16.1±0.3	33.9±1.4	46.8±1.5	55.1±0.5
●	●	●	●	6.5±0.2	16.8±1.1	34.0±2.7	46.3±0.5	56.9±1.1

Table 3. **Comparison of feature fusion strategies.**

Fusion strategy	Sampling rates				
	1%	10%	30%	50%	70%
Concatenate	5.9±0.4	**16.3±0.4**	31.7±1.3	**47.7±3.0**	57.8±1.2
Ours	**6.5±0.4**	15.2±1.2	**32.4±2.9**	47.5±1.9	**58.7±2.2**

Feature fusion strategy. Features extracted from different foundation models often exhibit misalignment due to architectural and training discrepancies. In RAM-APL, a simple fusion baseline is to concatenate features from different foundation models, referred to as "Concatenate." As shown in Table 3, our proposed fusion strategy outperforms simple concatenation, particularly under higher sampling ratios, which are critical in real-world deployment scenarios.

7. Conclusion

This work is the first to explore in-depth foundation models as information extractors (IEs) for one-shot subset selection. Our analysis revealed surprising insights: FMs consistently outperform traditional IEs on fine-grained datasets, whereas their advantage diminishes on coarse-grained datasets with noisy labels. Motivated by these findings, we developed the RAM-APL method, which integrates multiple FMs to enhance subset selection for fine-grained datasets. This pioneering integration paves the way for exploring vast frontiers of subset selection in the era of big data.

Impact Statement

RAM-APL improves data efficiency in machine learning by leveraging multiple foundation models for one-shot subset selection, particularly benefiting fine-grained classification scenarios. By reducing reliance on large, fully labeled datasets, RAM-APL has the potential to lower the barriers to deploying high-performing models in low-resource or underrepresented domains. However, as with all data selection techniques, careful consideration is needed to avoid reinforcing dataset biases or unintentionally omitting critical minority samples. Our method does not involve synthetic data generation or human subjects and poses no direct ethical risks.

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