Semisupervised Few-Shot Remote Sensing Image Classification Based on KNN Distance Entropy

Xuewei Chao and Yang Li

Abstract—**In recent years, remote sensing image processing based on deep learning has been widely applied in many scenes, but the involved deep learning technology requires large-scale labeled data, which has been a practical problem in the remote sensing field. In this study, we proposed a novel data information quality assessment method, called K-nearest neighbor (KNN) distance entropy, to screen the remote sensing images. The evaluation metric was used to assess unlabeled data and assign the pseudolabel, which further constitutes the proposed semisupervised few-shot classification method in this article. The metatask setting was adopted to verify the validity and stability of experimental results. Specifically, the KNN distance entropy metric can be used to distinguish the samples in the core set or boundary set. Experimental results show that the core set samples are more suitable under the few-shot condition, for instance, the metatask average accuracy trained by the core set samples outperforms that by boundary samples by about 18% in the case of 45-ways and 5-shot. The proposed semisupervised few-shot method based on KNN distance entropy achieves significant improvement under different experimental conditions. The visualization of the feature distribution of screened data is shown to provide an intuitive interpretation. This article lays a meaningful foundation for screening and evaluating remote sensing images under few-shot conditions, and inspires the data-efficient few-shot learning based on high-quality data in the remote sensing field.**

Index Terms—**Entropy, feature extraction, image processing, pattern recognition.**

I. Introduction

Recently, remote sensing technology has been developing rapidly with more diverse platforms and forms of data acquisition. The analysis and processing of remote sensing data are important in many fields, such as urban planning, pest monitoring, land use, and vegetation cover [1], [2], [3]. Due to the close combination of the information communication technology and remote sensing, many achievements have been achieved in the fields of geographic information reconstruction, target recognition, and object detection based on remote sensing images [4], [5]. As the key technical support, deep learning is playing an important role in the remote sensing intelligent applications.

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As known, deep learning is a typical data-hungry learning method, which requires amounts of annotated images to deal with computer vision tasks. Although there have been emerging some auxiliary learning methods, such as semisupervised, self-supervised, and unsupervised methods [6], [7], [8], the supervised learning based on labeled data is still the most important implementation form in practical applications. For remote sensing scenes, the data are generally of high resolution, and it is undoubtedly difficult and costly to collect, transmit, and annotate all the samples on a large scale. Thus, it is meaningful to consider data quality assessment to conduct efficient learning based on limited highly informative remote sensing data.

Learning from limited data also refers to few-shot learning, which is a supplement branch to the current deep learning paradigm. The few-shot learning approaches mainly utilize metric learning, transfer learning, and initial parameter optimization to pursue the generalized learning ability of neural networks from limited labeled data [9]. In specific, the metric learning method mainly refers to the similarity calculation between image feature vectors, commonly based on the Euclidean distance, cosine distance, Mahalanobis distance, etc. On this basis, the classification and recognition are completed through nearest-neighbor comparison. The transfer learning method mainly involves at least two domains, and the amount of annotated data in the source domain is sufficient to train and obtain good representation ability. Then, the network is transferred to the new domain for parameters fine-tuning. The initial parameter optimization method is to construct different tasks and find the most suitable network parameters during the task update in the way of metatask. Recently, some few-shot studies and applications have appeared in several fields, such as agriculture [10], [11], [12], industry [13], healthcare [14], and others [15], [16], [17]. In these works, the few-shot data are mostly randomly sampled, ignoring the data quality impact, and just using many repeated experiments to offset this important issue. But the truth is that only a small amount of redundant or low-quality data will never lead to a sensible solution. Thus, from our viewpoint, the prospect of few-shot learning should be located at exploring the information contribution of samples to pursue data-efficient learning.

In terms of image data quality assessment, there are roughly two categories. One is visual perception-oriented image quality assessment, e.g., distortion evaluation; the other is high-level task-oriented image information quality assessment, e.g., recognition and detection. The visual perception-oriented image quality assessment serves human feelings, which is concerned about whether there is noise or transmission distortion, the goal is close to human subjective feelings and score. In specific, there are many different distortion evaluation studies, which are divided into full reference, reduced reference, and no reference [18], [19], [20], [21], [22]. The full reference and reduced reference methods focus on the distortion difference between the reference image and distorted image to calculate the visual quality score of the distorted image, while the no reference methods do not need any reference image. But these studies cannot well solve the practical problems in a remote sensing application, so it is not the focus of this work. For the high-level recognition task-oriented image quality assessment, there are some recent works focused on information contribution and feature visualization of image data, analyzing data redundancy and information difference from the perspective of information entropy [23], [24], [25], [26], [27]. These research works are necessary for the exploration of data-efficient learning methods in the practical applications.

In this article, we focus on the task-oriented remote sensing image quality assessment, aiming to distinguish and screen data in terms of information quality, and reduce the comprehensive cost of remote sensing data acquisition, transmission, and annotation. To the best of our knowledge, this should be the first work to assess the remote sensing image from the perspective of data information quality. According to the few-shot learning paradigm, extensive experiments were carried out to show the influence of image data information quality. The K-nearest neighbor (KNN) distance entropy was used as the evaluation metric to compare the performance of the fixed model. Furthermore, we proposed a semisupervised few-shot learning method based on the KNN distance entropy to realize better experimental results. Finally, the influence of few-shot setting parameters and data scale on the model performance was analyzed. Thus, the key contributions of this study can be summarized as follows.

1) This work focuses on recognition task-oriented remote sensing image quality assessment and proposes to adopt the KNN distance entropy as an evaluation index to screen highly informative data. The experimental results show that the high-quality data under the few-shot condition are core set samples rather than boundary samples. In other words, when the data budget is limited, core set data acquisition and transmission are preferred.
2) We propose a novel semisupervised learning method, which screens highly confident samples with smaller KNN distance entropy from the unlabeled set and automatically assigns them the high-quality pseudolabels. The few-shot experimental results are effectively improved.
3) Many metatask experiments were carried out to compare the average test accuracy and metatask error margin. The effect of few-shot parameters setting, data scale, and semisupervised parameters was also in-depth discussed.

The rest of this article is arranged as follows. Section II introduces the methodology, including the overall framework of this article and the proposed KNN distance entropy workflow. Section III shows the experimental dataset, settings, and results. Section IV discusses this work in terms of several influencing factors. Finally, we conclude the whole article in Section V.

II. Methodology

A. Overall Framework

The overall framework of the proposed semisupervised few-shot remote sensing image classification is shown in Fig. 1. First, according to the few-shot classification paradigm, the initial limited labeled samples with ground-truth labels are selected as N-way and K-shot, which means the data comes from N categories and each category has K samples. In this study, the test set is fixed as N-way and 200-shot, which means there are 200 random test samples in each class. As metatask experiments are carried out, in each experiment the test samples will also be randomly updated. Second, we propose to use the KNN distance entropy as the remote sensing image quality assessment method to judge data information contribution to accurately pick out the pseudo label samples without additional manual labeling. Here, we set the amount of screened data as M times K-shot. Then, the augmented labeled data is updated, including the ground-truth label and pseudolabel data. Finally, the augmented labeled data is forwarded to fine-tune the model and complete the recognition task performance, which will be conducted several times to reduce random experiment error, also called the metatask approach.

B. KNN Distance Entropy

The KNN distance entropy is proposed as a remote sensing data quality assessment method in this article, which evaluates the data information quality in the high-dimensional feature space, shown as in Fig. 2. According to our previous work [23], the original distance entropy calculates the information entropy to assess data information contribution based on the distances between the sample's feature embedding and all the prototypes. In general, there are many ways to calculate the similarity between vectors in high-dimensional space, here; we adopt the Euclidean distance to calculate similarity because of its convenience and versatility. First, a pretrained model on the well-known and large-scale ImageNet dataset is used to map the remote sensing images to the high-dimensional feature embeddings, and the prototypes of each category are computed via calculating the mean value. Then, the distance between each data in the train set and the per prototype is calculated as d_i. Next, all the distances are converted to the proportional distribution $S(d_i)$ based on the Softmax function, shown in (1). The purpose is to normalize the unfixed distances to a proportional distribution, which ranges from 0 to 1 and adds up to 1, so as to facilitate the calculation of the data uncertainty in the next step. Finally, the original distance entropy E_d is calculated as (2). Where, N is the number of categories

$$S(d_i) = \frac{e^{d_i}}{\sum_{j=1}^{\mathrm{N}} e^{d_j}} \tag{1}$$

$$E_d = -\sum_{i=1}^{\mathrm{N}} S(d_i) \cdot \log_2 S(d_i). \tag{2}$$

In this study, we modify the original distance entropy to the KNN distance entropy. The reason is that in most classification

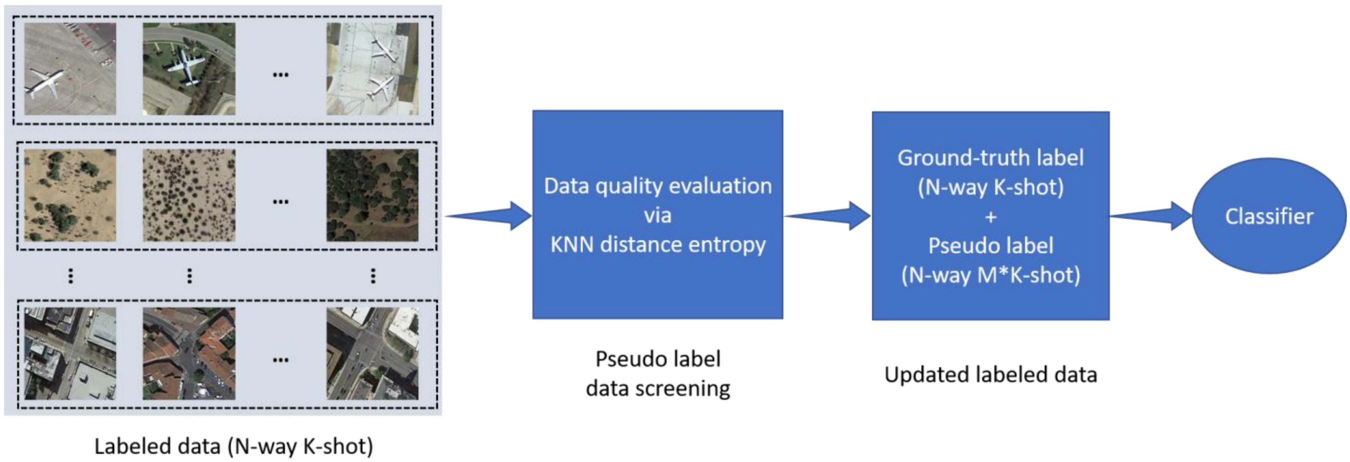

Fig. 1. Overall framework.

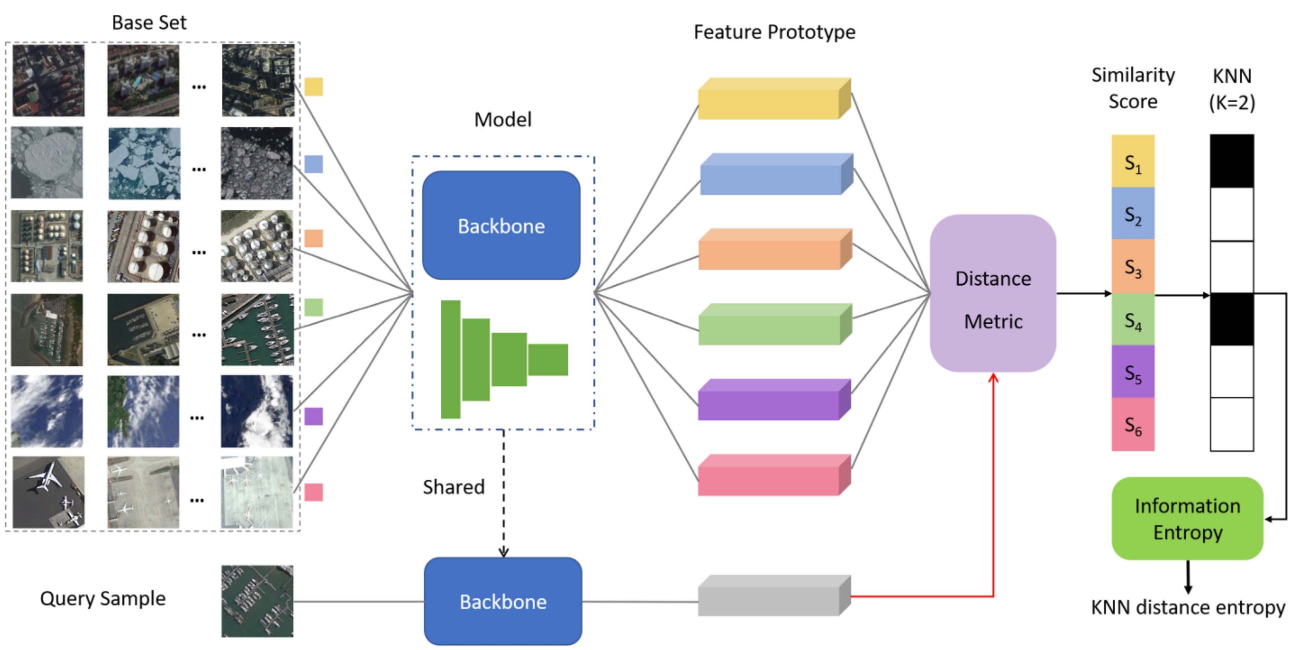

Fig. 2. Workflow of KNN distance entropy.

tasks, a new sample tends to be indistinguishable between only a few classes, not all the classes. This is intuitively easy to understand. So, we introduce the concept of KNN in the evaluation process, i.e., only consider the impact of a few close classes and ignore those obviously not similar, which could efficiently screen the interclass samples close to the decision boundary. In practice, the key modification is to sort the distances between a new sample and the prototypes of all categories from smallest to largest. In the sorted distances, d_1 is the minimum, d_N is the maximum, and the first K samples are used to make the proportional conversion, shown in the following:

$$S^*(d_i) = \frac{e^{d_i}}{\sum_{j=1}^{K} e^{d_j}}. \tag{3}$$

When further calculating the KNN distance entropy value, only the first K proportional distribution is considered, shown in (4). Here, the value of K is set as 2

$$E_d^* = -\sum_{i=1}^{K} S^*(d_i) \cdot \log_2 S^*(d_i). \tag{4}$$

According to the maximum entropy theorem, the KNN distance entropy tends to be the maximum only when a new sample is very difficult to distinguish from the two nearest categories. Otherwise, if a sample is sure to belong to a certain class, its value will be definitely very small. Therefore, the value range of KNN distance entropy is 0–1, which belongs to a standard evaluation value. The abovementioned process describes the evaluation of one query sample and can be used to screen highly informative data for a certain task, but this process needs to be repeated several times until the data budget or targeted performance is reached.

It is worth noting that the KNN distance entropy is a kind of quality evaluation work based on data feature distribution, and its essence is to believe that the fuzzy and uncertain areas are between classes, while clear and confident areas are within classes. So, the novel data comes from the decision boundary.

III. Results and Analysis

A. Experimental Setup

1) Dataset: The experiments were carried out on the public NWPU-RS45 dataset [28], which has 45 classes of remote sensing images with 700 images in each class, used for the classification task. According to the few-shot parameters setting, two kinds of experiments are carried out in this work, one is many classes with few samples, i.e., all 45 categories are used to classify, denoted as 45-ways. The other is a few classes with few samples, i.e., only five or ten categories are randomly selected, denoted as 5-ways or 10-ways.

2) Network and Training Setting: The used network to extract feature embedding is ResNet-18 without a head. The training epochs in each update are 50, the training batch size is 32, the learning rate is default without decay, and the training optimizer is stochastic gradient descent. The best model will be monitored and saved to compare performance. Here, the fixed model is used without various training tricks, because the data information quality is our focus, not the competitive accuracy.

3) Hardware and Software Environment: The experiments are performed based on a computer server with two graphics processing units of NVIDIA TITAN Xp with 12-GB memory. The software environment is Jupyter Notebook, using Python with libraries of TensorFlow (1.12.0), Keras (2.2.4), OpenCV (4.1), and Numpy (1.19.2).

4) Metatask Evaluation: Due to the uncertainty and information differences among different categories, the random selection of categories and samples will bring evaluation risk. The metatask evaluation method is adopted to reduce the random error and enhance the robustness of the results. In specific, in each experimental setting, ten different tasks are repeated. The average metatask results and error margins are counted.

B. Experimental Results on 45 Ways K-Shot

1) *Comparison of Different Screened Samples via KNN Distance Entropy:* In this section, all the categories were considered, with K samples in each category. The purpose of the comparative experiments was to explore the effect of remote sensing image quality in terms of information value on the classification performance when limited labeled data are available. According to the proposed KNN distance entropy method, we evaluated the information quality of the samples in the used dataset. Specifically, in this part, the feature embeddings were extracted from the model pretrained on the public ImageNet, and then the prototypes were calculated, and the information contribution of each image sample on the spatial feature distribution was further evaluated. The number of metatask experiments is ten, and the metatask average test accuracies were shown in Fig. 3, under the experimental setting of 45-ways and K-shot ($K = 5$, 10, 15, and 20). Note that, the shaded areas in Fig. 3 refer to the test error margin, calculated by the mentioned ten repeated metatask experiments.

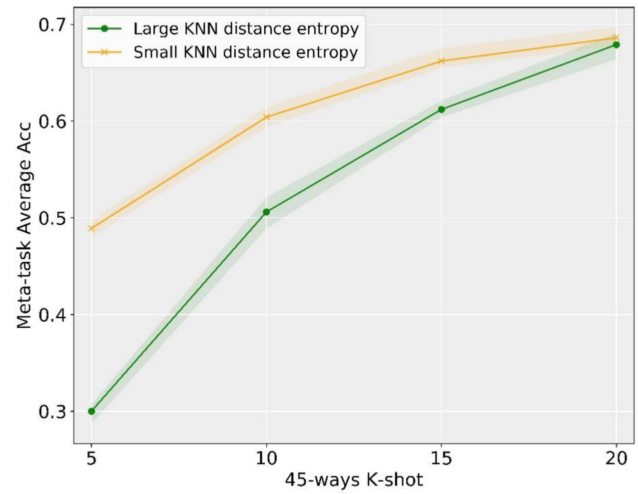

Fig. 3. Metatask average accuracy based on screened data under 45-ways K-shot.

From the abovementioned results, the samples with small KNN distance entropy values have an obvious performance advantages when the available labeled data are limited. According to the calculation principle of the proposed KNN distance entropy, the data with a smaller entropy value corresponds to the common samples near the prototype, which is called the core set in this study. The opposite of that, the samples with larger entropy value are the novelty samples, such as the samples close to the boundary, introducing more uncertainty, called the individualized set. Since the labeled data are very limited under the condition of few-shot learning, it is undoubtedly a better plan to master the core set and the generic knowledge of categories. As the data budget increases, differentiated and personalized samples can be gradually introduced to further improve performance. In summary, for the few-shot classification, the core set samples screened by small KNN distance entropy can outperform those selected by large KNN distance entropy. Furthermore, it is also worth noting that this advantage decreases as the number of samples increases.

2) *Semisupervised Sample Screening via KNN Distance Entropy:* It was proven that KNN distance entropy can distinguish core samples from boundary samples. In this part, we proposed to use KNN distance entropy as the evaluation tool to screen the unlabeled data to enhance the few-shot performance. In specific, all 45 categories were used, K labeled samples were randomly selected from each category, and the remaining samples were scattered and mixed to remove the labels. According to Fig. 2, the labeled K-shot initial data were the base set to fine-tune the feature extractor. All the unlabeled samples were assessed by the KNN distance entropy and then sorted by the entropy value. To quantify the contrast effect, the experimental setup here was to increase the K-shot samples by M times ($M = 1$, 5, and 10), and automatically assigned the screened data pseudolabels judged by the

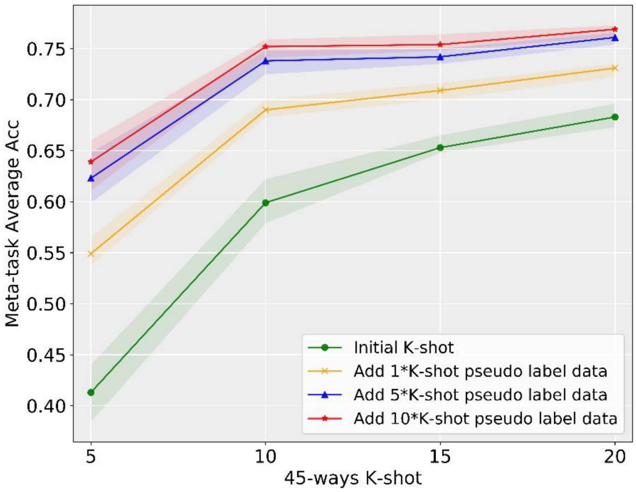

Fig. 4. Random metatask average accuracy under semisupervised 45-ways K-shot.

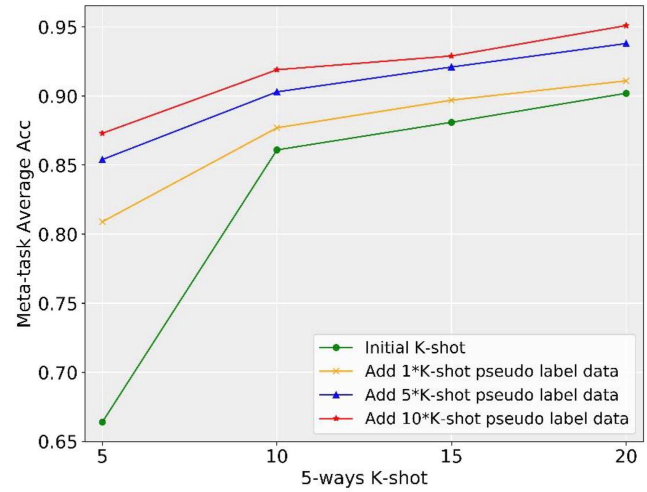

Fig. 5. Random metatask average accuracy under semisupervised 5-ways K-shot.

KNN distance entropy instead of manual labeling. The experimental results were shown in Fig. 4. Similarly, the shaded areas are error bands, calculated by the repeated metatask experiments.

The results show that the addition of pseudolabel samples based on KNN distance entropy is effective under different data scales. But as the size of the added pseudolabel samples increases, the extent of that advantage is shrinking. In each metatask experiment, the K-shot samples are randomly given, and the M times pseudolabel samples are screened to reflect the robustness. This process is repeated ten times.

C. Experimental Results on 5/10 Ways K*-Shot*

1) *Semisupervised Sample Screening for 5 ways K-shot:* Here, we adjusted the scope of the experiment from all categories to randomly selected five categories for each task, to explore the impact of few-shot learning parameters (N-way K-shot), based on which we further carried out the semisupervised comparison experiments driven by the proposed KNN distance entropy. The difference was that the categories and the initial sample selection were all random. And the corresponding experimental results were shown in Fig. 5. The K-shot in this study was fixed as 5, 10, 15, and 20.

By comparing the experimental results in Figs. 4 and 5, it can be found that the trend is basically the same, and the proposed semisupervised method is consistent and effective. The difference is the specific accuracy, which depends on the reduction of the classification task difficulty.

2) *Semisupervised Sample Screening for 10 ways K-shot:* In this section, to further verify the correctness of the KNN distance entropy-driven semisupervised method and explore the effect of few-shot parameter on metatask accuracy, the 10-ways K-shot random experiments were carried out. The average experimental results were shown in Fig. 6. Note that, the results in Figs. 5 and 6 do not have shaded areas, because when the number of categories is reduced, the random selection of categories in each

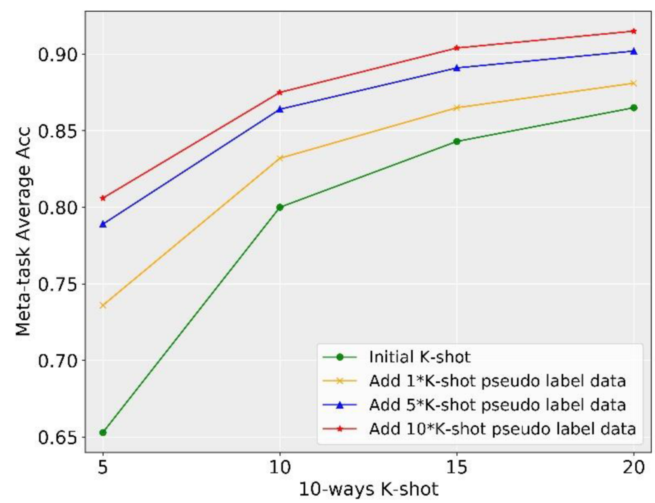

Fig. 6. Random metatask average accuracy under semisupervised 10-ways K-shot.

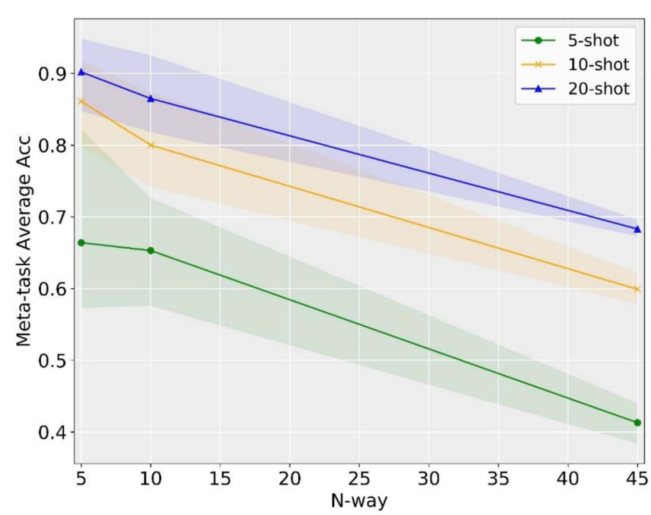

Fig. 7. Influence of few-shot parameters on metatask average accuracy.

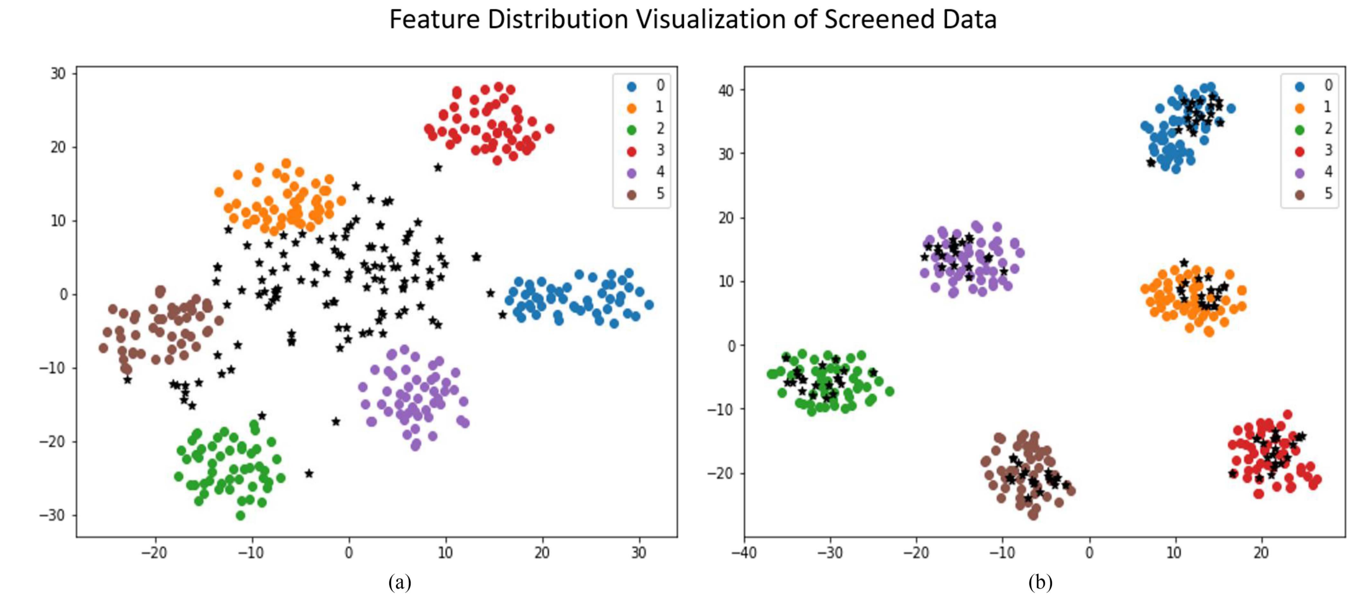

Fig. 8. Feature distribution of screened data by KNN distance entropy. (a) Black stars refer to large KNN distance entropy. (b) Black stars refer to small KNN distance entropy.

metatask experiment leads to large differences in metatask difficulty. Thus, there is high overlap within each other's error bands. To show the results more clearly, we only plot the average results under the case of a few classes. It is seen that the performance improvement trends were consistent with the 5-ways K-shot. The influence of specific experimental parameters is further analyzed in the Discussion section.

IV. Discussion

A. Influence of Few-Shot Parameters: N-Way, K-Shot

The effect of few-shot parameters on the experimental result was discussed. In specific, according to the abovementioned experimental results, the relations of N-way, K-shot, and the metatask average test accuracy were shown in Fig. 7. After repeated experimental verification, there are two basic laws: the larger N-way, the worse the effect, and the larger K-shot, the better the effect. The intuitive explanation is that in few-shot remote sensing image classification, the larger N-way is, the more categories are involved in the classification, so the harder the recognition and discrimination task is. Meanwhile, the larger K-shot is, the more ground-truth label data are available, which is critical for data-driven intelligent models. The more available training data, the more obtained target knowledge. Interestingly, as the N-way increases, the metatask error margin decreases. From our viewpoint, the reason should be that the randomness of the category combination can lead to differences in the difficulty of the task. For instance, it is much harder to tell a lion from a tiger than it is to tell a lion from a house. When the N-way is small, the randomness of this category combination is large, so the error margin tends to be huge, and conversely, this randomness decreases as it tends to all categories.

B. Quality Assessment Differences at Data Scales

In this work, we clarified that the core set samples screened according to the KNN distance entropy were more suitable for few-shot classification. Specifically, the core set samples were bound to the smaller value of KNN distance entropy. Important, to note that this conclusion changes when the size of the available labeled data becomes larger. The related works can be found here [29], [30]. Correspondingly, when a relatively large amount of labeled data is available, the preferred data are the individual data with high uncertainty and information contribution, which can be judged by a large KNN distance entropy value. This phenomenon is somewhat like the human learning style, a wise leaning way is to study gradually, easy before difficult, and general before special. We think this is a good match for the screening strategy based on the KNN distance entropy under different data budgets.

C. Feature Distribution of Screened Data by KNN Distance Entropy

In this work, we proposed to adopt KNN distance entropy to evaluate and screen the unlabeled samples, which were then automatically assigned the pseudolabels to augment the limited labeled data. Generally, it belongs to the semisupervised learning and applications. The core difference of this work is to judge and screen data from the perspective of data information quality and feature embedding distribution, which has better interpretability compared with other works. Specifically, the classical dimensionality reduction algorithm, t-distributed stochastic neighbor embedding (t-SNE), was used to reduce the 512-dimensional image features to two dimensions, which is convenient to visualize the distribution, while preserving the similar relationship between each other. Here, the feature distribution of screened data by KNN distance entropy is visualized in Fig. 8. The visualization results confirm that a small value of the KNN distance entropy can be used to filter out the core set, seen in Fig. 8(b), and their assigned pseudolabels are quite confident compared to those screened by the large KNN distance entropy value in Fig. 8(a). However, on the other hand, the samples screened by large KNN distance entropy fall in the middle and boundary of various categories, which are highly informative samples. This kind of sample will be helpful for continuous performance improvement when the increased data budget is available. Besides, the distribution of color points in Fig. 8(a) and (b) is not the same. The reason is that the used t-SNE dimensionality reduction algorithm is a nonlinear mapping, which requires a batch of data to be mapped at the same time. However, these two figures contain high informative samples and low informative samples respectively, so the mapped distribution cannot be completely consistent, but the interclass and intraclass similarity of colored dots are well preserved.

D. Limitations and Future Work

This article focuses on the issue of image data evaluation and proposes a novel semisupervised learning method via the proposed KNN distance entropy for few-shot remote sensing image classification. The framework and workflow are given, a large number of comparative and repeated experiments has been carried out, and the result analysis and influence of experimental settings are performed. The limitation of this work is that it only considers the basic classification task, and does not involve other more complex image processing tasks, such as detecting and segmentation. Some special cases, such as mislabeling and imbalanced datasets, are also not considered. The limitations mentioned previously will be considered in our future work.

V. Conclusion

This article proposed image information evaluation metric, named KNN distance entropy, and adopted this metric to carry out semisupervised few-shot remote sensing image classification. To reduce the influence of randomized experiments and ensure the robustness of conclusions, this work used the metatask experimental setting and analyzed the metatask average accuracy. The results show that the core set data are more suitable in terms of few-shot learning, due to the limited data budget. The proposed KNN distance entropy-driven semisupervised data screening and addition is proven to be consistently effective under different experimental settings, achieving a significant performance improvement. Furthermore, the influence of few-shot parameters and data scale are discussed, and the feature distribution of screened data is also visualized to better explain the principle and motivation of the proposed method.

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