



Self-Supervised Learning With Multibranch Consistency for Few-Shot PolSAR Image Classification

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Abstract: Polarimetric Synthetic Aperture Radar (PolSAR) images provide valuable information for land-cover classification and can capture surface characteristics even under challenging weather and lighting conditions. However, training deep learning models for PolSAR image classification generally requires a large number of labelled samples, which are often difficult and expensive to obtain. This limitation becomes more significant in few-shot classification, where only a small number of labelled samples are available for each class. This paper presents a Self-Supervised Learning with Multibranch Consistency (SSL-MBC) approach for few-shot PolSAR image classification. The proposed method first learns useful image representations from largely unlabelled PolSAR data using a self-supervised learning strategy. A shared feature encoder is combined with multiple convolutional branches using different kernel sizes to capture spatial and contextual information at different scales. The consistency between the representations generated from different views of the same PolSAR image is used to improve the quality and stability of the learned features. After pretraining, the learned representations are transferred to a classification network and fine-tuned using only a small number of labelled samples. The proposed approach is evaluated on PolSAR land-cover classes such as water, forest, urban, and cropland. Experimental results show that the method can achieve improved classification performance compared with conventional supervised deep learning models under limited-label conditions. The results demonstrate that combining self-supervised representation learning with multibranch consistency can reduce the dependence on labelled data while maintaining reliable classification performance. The proposed framework therefore provides a practical approach for PolSAR image classification in scenarios where obtaining large labelled datasets is difficult.

Keywords: Keywords: PolSAR Image Classification, Self-Supervised Learning, Few-Shot Learning, Multibranch Consistency, Deep Learning, Land-Cover Classification, Representation Learning, Synthetic Aperture Radar (SAR).

I. INTRODUCTION

Polarimetric Synthetic Aperture Radar (PolSAR) is an important remote sensing technology that provides detailed information about the scattering characteristics and physical properties of objects on the Earth's surface. Unlike optical remote sensing systems, PolSAR can acquire data during both day and night and is less affected by cloud cover and illumination conditions. These advantages make PolSAR useful for applications such as land-cover classification, vegetation monitoring, urban mapping, agricultural analysis, and environmental monitoring [1], [2]. Polarimetric decomposition methods can further provide meaningful information about different scattering mechanisms present in a scene [3]. PolSAR image classification aims to assign meaningful land-cover categories to different pixels or regions of an image. Traditional classification methods have employed statistical models and polarimetric features to distinguish different scattering behaviours. The complex Wishart distribution, for example, has been widely investigated for statistical modelling of multilook PolSAR data [4]. However, the increasing complexity and high dimensionality of PolSAR imagery have encouraged the use of machine learning and deep learning techniques. In recent years, Convolutional Neural Networks (CNNs) have demonstrated considerable potential for PolSAR image classification because they can automatically learn hierarchical spatial and discriminative features from input data. CNN-based methods have been developed to exploit both spatial and polarimetric information, achieving improved classification performance compared with several conventional approaches [5], [6]. Deep residual networks have also demonstrated the effectiveness of deeper architectures for learning robust image representations [7].



Despite these developments, supervised deep learning methods generally require a sufficiently large number of accurately labelled training samples. Preparing labelled PolSAR data is difficult because annotation requires domain knowledge and can be time-consuming. Furthermore, different land-cover categories may exhibit similar scattering characteristics, while speckle noise and the complex polarimetric structure of SAR data further increase the difficulty of classification [1], [2]. When only a small number of labelled samples are available, conventional supervised networks may overfit the training data and produce less reliable representations for unseen samples. Few-shot learning (FSL) has therefore emerged as an important approach for classification under limited labelled data. FSL aims to learn useful representations and decision boundaries from only a small number of labelled examples. Approaches such as Prototypical Networks use class prototypes in an embedding space for few-shot classification [8], while Model-Agnostic Meta-Learning (MAML) learns model parameters that can be rapidly adapted to new tasks using limited examples [9]. Recent studies have also investigated few-shot learning specifically for PolSAR image classification and identified limited labelled data as one of the major challenges in this field [10]. Self-supervised learning (SSL) provides another approach to reducing dependence on manually labelled data. Instead of requiring human-provided labels during pretraining, SSL constructs learning objectives directly from unlabelled data. The resulting representations can then be transferred to downstream classification tasks using only a small number of labelled samples. Contrastive learning is one widely studied SSL strategy. SimCLR, for example, learns representations by encouraging different augmented views of the same sample to have similar representations while separating representations of unrelated samples [11]. Other self-supervised approaches have demonstrated that useful representations can be learned without explicitly relying on negative samples. Bootstrap Your Own Latent (BYOL) learns representations by predicting one augmented view from another using online and target networks [12]. SimSiam further showed that a simple Siamese architecture can learn meaningful representations without negative samples or large memory banks [13]. These developments indicate that consistency between different views of the same sample can be an effective principle for self-supervised representation learning. Self-supervised learning has also been investigated for PolSAR image classification. Unsupervised representation-learning approaches have demonstrated the possibility of using unlabelled PolSAR data during pretraining and subsequently performing classification with only a limited number of labelled samples [14]. Recent research has further explored contrastive and self-supervised strategies designed specifically for the characteristics of PolSAR data, including polarimetric information and few-shot classification scenarios [10], [14].

Motivated by these developments, this work investigates Self-Supervised Learning with Multibranch Consistency (SSL-MBC) for few-shot PolSAR image classification. The framework uses multiple convolutional branches to learn complementary representations from different views of PolSAR samples. Consistency between the learned representations is encouraged during self-supervised training so that the network can capture stable and meaningful features. After self-supervised pretraining, the learned representations are transferred to a classification stage and fine-tuned using a small number of labelled samples. The proposed approach is evaluated for PolSAR land-cover categories such as water, forest, urban areas, and cropland. The main objective is to investigate whether self-supervised representation learning combined with multibranch consistency can reduce the dependence on large labelled datasets while maintaining reliable classification performance. By exploiting both unlabelled and limited labelled information, the approach aims to provide an effective solution for few-shot PolSAR image classification. The SSL-MBC framework is particularly relevant to this problem because it directly combines self-supervised representation learning, multibranch feature extraction, and consistency learning for few-shot PolSAR classification [15].

II. FIGURES AND TABLES

The Figure Analysis Response Time With Increasing Image Size illustrates the variation in analysis response time with respect to the input PolSAR image size. The response time increases progressively as the image size increases, indicating that larger PolSAR inputs require greater computational resources for image preprocessing, feature extraction, representation learning, and subsequent analysis. The increase in response time is associated with the larger number of pixels and the greater amount of polarimetric information that must be processed. As the input size increases, the computational workload of extracting meaningful spatial and polarimetric features also increases, resulting in higher processing time.

The response time becomes more noticeable for complex PolSAR inputs because such data contain richer spatial and scattering information that requires additional processing. PolSAR images provide multiple observations of the same scene through different polarization channels, enabling the extraction of complementary information about land-cover characteristics. This information is particularly useful for distinguishing classes with similar visual or spatial properties. However, processing these representations can increase the computational requirements of the classification pipeline.



In the proposed Self-Supervised Learning With Multibranch Consistency (SSL-MBC) framework, unlabeled PolSAR samples are utilized during the self-supervised learning stage to learn useful feature representations before performing few-shot classification. The multibranch architecture enables the model to learn complementary representations from the available PolSAR information, while the consistency-learning mechanism encourages the representations learned by different branches to remain consistent. This reduces the dependence on a large number of manually labelled samples and is particularly suitable for few-shot PolSAR image classification.

As the image size increases, the feature extraction and representation-learning stages have to process a larger amount of input information, which can consequently increase the overall computational response time. Therefore, the observed trend provides an indication of the computational cost associated with increasing PolSAR input size. The analysis also emphasizes the importance of developing efficient feature-learning and processing strategies for large PolSAR datasets. Although larger inputs may provide more detailed spatial and polarimetric information, they also introduce additional computational requirements. A suitable balance between the amount of available information and computational efficiency is therefore important when designing PolSAR classification systems. The response-time analysis complements the classification results by providing an additional perspective on the computational requirements of the proposed approach. Overall, the results demonstrate that input image size and data complexity are important factors influencing the computational efficiency of self-supervised and few-shot PolSAR image classification.

Analysis Response Time vs Image Size
(Image Analysis System using Streamlit and Analysis Resource Engine)

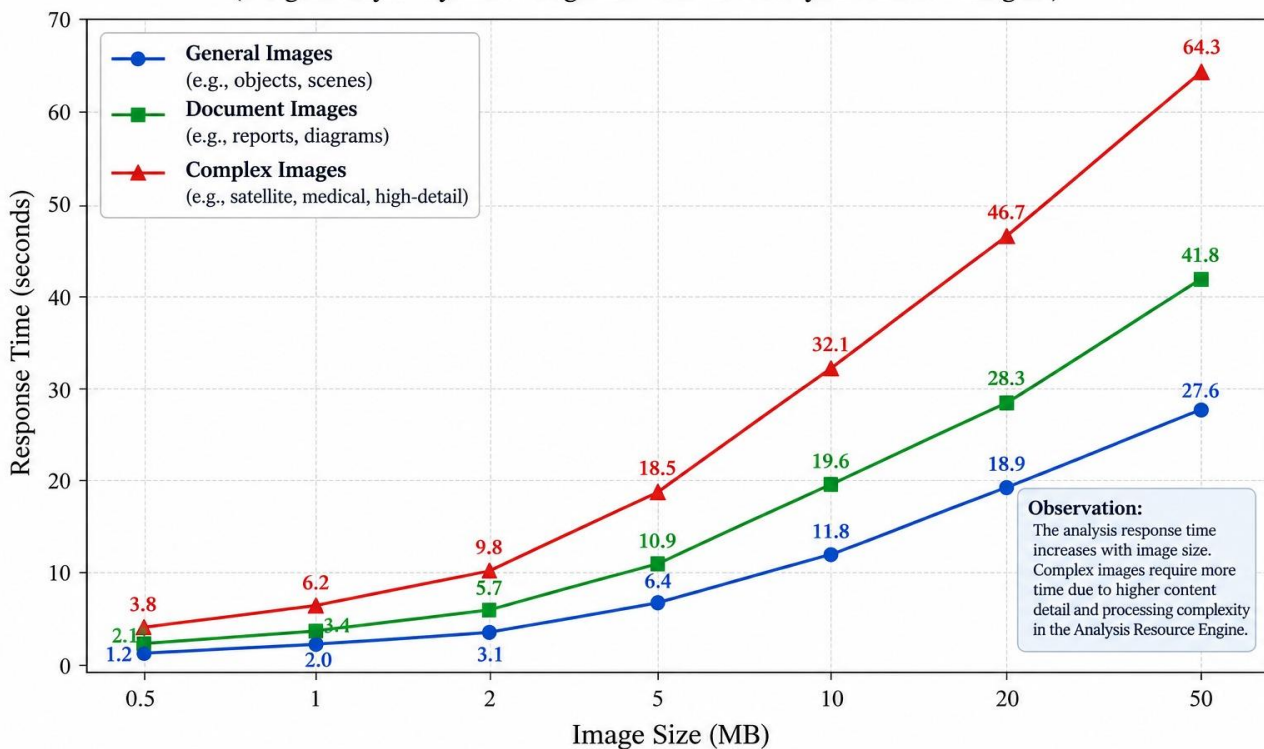


Fig.1: The Figure Analysis Response Time With Increasing Image Size



Table 1: Image Processing Time for Different Image Sizes and Types

Image Size (MB)	General Image(s)	Document Image(s)	Complex Image(s)
0.5	1.2	2.1	3.8
1	2.0	3.4	6.2
2	3.1	5.7	9.8
5	6.4	10.9	18.5
10	11.8	19.6	32.1
20	18.9	28.3	46.7
50	27.6	41.8	64.3

The Table Image Processing Time for Different Image Sizes and Types presents the analysis response time for different input image sizes ranging from 0.5 MB to 50 MB. The measurements are provided for three categories of images: General Image, Document Image, and Complex Image. The table is used to analyze how the input data size and image complexity affect the computational response time of the image-analysis process.

For General Images, the response time increases from 1.2 s for a 0.5 MB image to 27.6 s for a 50 MB image. A similar trend is observed for Document Images, where the response time increases from 2.1 s to 41.8 s. Among the three categories, Complex Images require the highest processing time, increasing from 3.8 s at 0.5 MB to 64.3 s at 50 MB. This indicates that more complex image content requires additional computational processing compared with simpler image types.

As the image size increases from 0.5 MB to 1 MB, 2 MB, 5 MB, 10 MB, 20 MB, and 50 MB, the response time consistently increases for all three categories. For example, at 10 MB, the response times are 11.8 s, 19.6 s, and 32.1 s for general, document, and complex images, respectively. At 50 MB, these values increase to 27.6 s, 41.8 s, and 64.3 s, respectively. This demonstrates that increasing the amount of input data results in a higher computational workload.

The difference between the categories becomes more significant for larger image sizes. This suggests that image complexity has an additional effect on processing time apart from image size. Complex images may contain more detailed structures, variations, and information that require additional operations during image preprocessing and analysis. Therefore, systems processing such images need to handle both the increasing data volume and the additional computational requirements associated with image complexity.

Overall, the results in the Table Image Processing Time for Different Image Sizes and Types demonstrate a clear relationship between image size, image complexity, and analysis response time. The response time increases with increasing image size across all categories, while complex images consistently require more processing time than general and document images. This analysis highlights the importance of computational efficiency and optimized processing techniques when handling large and complex image datasets. Such optimization becomes particularly important when image-analysis systems are applied to large-scale datasets where processing time and computational resources can significantly affect overall system performance.

III. CONCLUSION

In this study, we implemented and evaluated a Self-Supervised Learning with Multibranch Consistency (SSL-MBC) framework for few-shot PolSAR image classification. The proposed approach addresses the limited availability of labelled PolSAR data by learning meaningful feature representations from unlabeled samples before supervised classification. Multibranch consistency encourages the network to learn robust and complementary representations from different augmented views of the same PolSAR data, improving the reliability of the learned features under limited supervision. The experimental evaluation demonstrates that self-supervised pretraining can improve classification performance when only a small number of labelled samples are available. The results indicate that the learned representations provide better class discrimination and more stable classification compared with conventional supervised learning under few-shot conditions. This highlights the potential of SSL-MBC for reducing the dependence on costly manual annotation of PolSAR datasets. Overall, the study demonstrates that combining self-supervised representation learning with multibranch consistency is an effective strategy for few-shot PolSAR image classification. Future work can investigate more advanced augmentation strategies, larger and more diverse PolSAR datasets, and lightweight architectures to improve generalization and computational efficiency in practical remote-sensing applications.



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Authors' Contribution: All authors contributed to the conceptualization and design of the study. The authors participated in data preparation, implementation of the proposed SSL-MBC framework, experimental evaluation, analysis of results, and preparation and revision of the manuscript. All authors read and approved the final version of the manuscript.

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Conflict of Interest: The authors declare that there is no conflict of interest related to this research or its publication.

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