Self-Supervised Techniques for Satellite Imagery: A Novel Approach to Land Cover Classification

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Abstract — This study investigates the use of self-supervised learning (SSL) methods for land cover classification through satellite images, emphasizing clustering algorithms and logistic regression. The research uses an unsupervised method, applying K-Means, Mean Shift, and Gaussian Mixture Model (GMM) clustering techniques for feature extraction from unlabeled data, and then classifies via logistic regression. To assess the effectiveness of these techniques, the Silhouette Score was utilized, with Mean Shift clustering attaining the top score, signifying better cluster cohesion and separation. The findings emphasize the promise of self-supervised methods in addressing the issues posed by restricted labeled datasets for land cover classification, indicating that Mean Shift clustering is the most efficient technique for feature extraction. The results highlight the significance of choosing suitable clustering techniques to enhance classification precision in satellite image assessment, aiding the progress of self-supervised learning in remote sensing fields. This study introduces an innovative and efficient method for land cover classification that does not depend on large amounts of labeled data, showcasing considerable promise for extensive use in environmental monitoring and land-use planning.

Keywords: Self-supervised learning, Satellite Image Classification, Land Cover Classification, Clustering Algorithms, Silhouette Score

I. INTRODUCTION

Land cover classification, environmental monitoring, urban development management, and resource management have all benefited greatly from the use of satellite photography. For this purpose, traditional supervised learning techniques need a lot of labeled data, which can be costly and time-consuming to acquire because of the human annotation procedure. To overcome these problems, self-supervised learning (SSL) has become a viable method that uses unlabeled data to extract meaningful representations, significantly lowering the requirement for labeled datasets while producing impressive results.

A novel method for classifying land cover is investigated in this study, which combines self-supervised learning with clustering and classification techniques such as K-Means, Mean Shift, Gaussian Mixture Model (GMM), and Logistic Regression. The Silhouette Score, a metric that assesses the effectiveness of clustering by looking at the distance between clusters and their internal cohesion, is used to evaluate these methods. High-resolution LISS III satellite photos from Bhuvan-NRSC and an unlabeled tabular dataset from Kaggle.com are used in the study. Combining geographic and tabular data offers unique opportunities and challenges for improving classification systems' scalability and accuracy.

Using self-supervised techniques on satellite pictures, the study aims to link unsupervised representation learning with downstream classification tasks. The proposed framework efficiently extracts and applies features from both datasets by using clustering methods to identify basic data structures and logistic regression for classification. This multi-phase strategy demonstrates the ability of self-supervised learning to improve land cover categorization while decreasing the need for vast volumes of labeled data.

This paper provides a comprehensive evaluation of the proposed method, looking at its benefits, limitations, and practical applications. The experimental results demonstrate the method's efficacy and scalability, offering crucial information for improving satellite image processing using self-supervised methodologies.

II. LITERATURE REVIEW

This work presents a new unsupervised K-means (U-k-means) clustering technique that automatically determines the optimal number of clusters and eliminates the need for initial setups and parameter adjustment. With the use of entropy-based penalty terms and a competitive framework, U-k-means enhance clustering efficacy and exhibit resilience in a range of cluster sizes and shapes. The experimental results demonstrate its superiority over other well-known algorithms, such as R-EM, C-FS, and X-means. The study also highlights the computational effectiveness of U-k-means and analyzes the limitations of conventional K-means, which depend on initial conditions and require pre-specified cluster counts. Additionally, it examines extensions like X-means, which address the problem of unpredictable cluster numbers but still depend on initial configurations, and discusses clustering validity measures including Dunn's index, the Davies-Bouldin index, Silhouette Width, and Gap statistics. By introducing a method that can determine the number of clusters on its own without any initialization, this study marks a breakthrough in unsupervised learning.[1]

The draft examines the most recent developments in self-supervised learning (SSL), specifically concerning the classification of remote sensing scenes. It emphasizes the efficacy of contrastive and non-contrastive techniques, such as MARTA-GANs, SimCLR, and MoCo. By using augmentation procedures and transfer learning, these methods increase classification accuracy by utilizing unlabeled datasets to lessen dependency on expensive annotations. The paper also discusses the unsupervised k-means (U-k-means) algorithm, which automatically determines the optimal number of clusters and optimizes the clustering process by doing away with the requirement for setup and parameter adjustment. By using competitive schemas and entropy-based penalties, U-k-means surpass conventional techniques like X-means and R-EM, guaranteeing efficient clustering over a range of cluster sizes and shapes. In conclusion, the study highlights the increasing importance of SSL and effective clustering algorithms in tackling important issues in the interpretation of remote sensing scenes.[2]

The study offers a succinct overview of image processing methods for categorizing old maps using satellite imagery, with an emphasis on accurately identifying changes in land borders (Asokan et al., 2020). It covers important techniques such as segmentation, classification, feature extraction, and enhancement, outlining their advantages, disadvantages, and problems like poor thresholding and low contrast. It emphasizes how important it is to use computationally intelligent techniques, especially machine learning, to increase the categorization accuracy of complicated satellite photos. The study also highlights applications in environmental monitoring and catastrophe management and stresses the need to carefully evaluate conventional approaches to improve system performance. It does this by providing a systematic analysis of methods, metrics, and findings.[3]

The article evaluates six different machine learning methods (Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy ARTMAP, Spectral Angle Mapper (SAM), and Mahalanobis Distance (MD)) for classifying land-use/land-cover (LULC) using satellite imagery. RF consistently demonstrated higher accuracy with a Kappa coefficient of 0.89, whereas MD scored 0.82. The study emphasizes the need for further testing of these classifiers under various scenarios to improve LULC mapping, particularly in regions experiencing rapid urbanization. RF and ANN are known for their effectiveness, with RF reporting Kappa coefficients as high as 0.93 in previous studies.[4]

This study, "Self-Supervised Learning for Satellite Image Analysis and Land Cover Classification," highlights how well deep transfer learning architectures—specifically, VGG16 and Wide ResNet-50—classify land-use and land-cover (LULC) using the RGB version of the Eurostat dataset, achieving an impressive 99.17% classification accuracy. Techniques like gradient trimming, early halting, and data augmentation were applied to enhance model performance and reduce computation time. In order to improve classification accuracy, particularly in situations where labeled data is limited, the review also examines methods like principal component analysis (PCA), deep belief networks, CNNs, hybrid models, and innovations like the Saliency Dual Attention Residual Network and attention mechanisms. The review concludes with a comparative analysis of various models on the Eurostat dataset.[5]

In order to categorize satellite image time series (SITS), Yuan and Lin (2020) provide a self-supervised pretraining technique that uses a transformer-based model called SITS-BERT to extract spectral-temporal features from enormous volumes of unlabeled data. Experiments on three benchmark datasets show that our model outperforms traditional deep learning models in terms of performance and generalization when refined on smaller labeled datasets. The research review classifies approaches into reconstruction-based, generation-based, and context-based strategies and emphasizes the importance of successful pretext tasks in self-supervised learning. The research draws attention to the fact that, despite their potential effectiveness, context-based methods are rarely used in the analysis of satellite time series.[6]

The investigation looks at the classification of land use and land cover (LULC) using hyperspectral and multispectral data using deep learning techniques. It acknowledges the expanding corpus of work devoted to LULC categorization, which reflects a strong interest in remote sensing. The paper discusses a number of issues in this field, such as the dearth of ground-truth data and the complexity of remote sensing data, especially the harmony between temporal and spatial resolution. The authors provide a thorough framework that clarifies the most recent cutting-edge methods, datasets, and challenges in LULC classification. The study also highlights the importance of feature learning and shows how deep learning techniques can improve classification precision in applications involving remote sensing.[7]

A self-supervised pretraining technique for Swin Transformers is presented by Scheibenreif et al. (2022) with the goal of classifying and segmenting land cover in the context of remote sensing. Their study shows that even with a far smaller number of labeled samples, self-supervised learning (SSL) on large unlabeled datasets yields task-agnostic representations that outperform fully supervised methods. The suggested two-phase method increases efficacy in a range of activities by first performing self-guided training and then moving on to a phase of supervised fine-tuning. The study demonstrates how Transformer models, which have traditionally depended on large collections of labeled data, can effectively adjust to situations with little labeled data through SSL and achieve performance levels that are on par with ConvNet architectures that use fewer labeled samples.[8]

III. METHODOLOGY

The approach for this research is divided into specific phases to enable the efficient use of self-supervised methods for classifying land cover through satellite images. These phases consist of gathering and preprocessing data, extracting features with clustering algorithms, categorizing the data, and assessing the results.

A. Data Acquisition

Two datasets were employed for this research:

- Tabular Dataset: An unlabeled CSV dataset was acquired from Kaggle.com. This dataset includes numerical features that represent a range of environmental or spectral characteristics, which serve as a foundation for self-supervised feature learning.
- Satellite Imagery: High-resolution LISS III satellite images were obtained from the Bhuvan-NRSC platform. These images provide essential spatial and spectral information necessary for land cover classification.

B. Data Preprocessing

- Tabular Dataset: Imputation techniques were applied to address missing values, and features were scaled for consistency.
- Satellite Imagery: The LISS III images underwent preprocessing to eliminate noise through the use of Gaussian filters, and multi-spectral analysis was conducted by stacking the bands. Additionally, the images were segmented into smaller tiles for more efficient processing and analysis.

C. Feature Extraction with Clustering Algorithms

To make the most of the self-supervised approach, clustering algorithms were used to uncover inherent patterns within the data:

- K-Means Clustering: Implemented to divide the data into separate clusters based on similarities found in the feature space.
- Mean Shift Clustering: Employed for adaptive clustering without the need to predefine the number of clusters, allowing for the dynamic recognition of data patterns.
- Gaussian Mixture Model (GMM): Leveraged to represent the data distribution as a combination of several Gaussian components, providing a probabilistic view of clustering.
- These clustering techniques facilitated the extraction of significant representations, aiding in downstream classification tasks.

D. Classification with Logistic Regression

The features obtained from clustering were utilized as input for logistic regression. Logistic regression was selected due to its straightforwardness and efficiency in handling both binary and multi-class classification problems. In the classification phase, the derived features were linked to land cover classes, facilitating the recognition of various land types within the datasets.

E. Evaluation Metrics

The cohesion inside clusters and the distance between them were measured using the Silhouette Score, which was used to assess the quality of clustering. The classification's performance was evaluated using standard metrics such as F1-score, recall, accuracy, and precision. The classification metrics verified that the characteristics acquired helped predict different land cover classes, and the Silhouette Score provided useful information about the clusters' dependability for the clustering algorithms.

IV. Results

The findings of this research illustrate the efficacy of various clustering algorithms and their impact on self-supervised feature extraction for land cover classification as shown in Figure 1. Among the clustering techniques, Mean Shift Clustering achieved the highest Silhouette Score of 0.7666, indicating excellent clustering quality with well-formed and cohesive clusters. This emphasizes its capability to adaptively align with the underlying structure of the data without the need for a preset number of clusters, making it particularly effective for this purpose. In contrast, K-Means Clustering recorded a Silhouette Score of 0.5549, signifying moderate clustering quality with fairly distinct cluster separations, but it faced challenges in managing complex or overlapping data patterns. Conversely, the Gaussian Mixture Model (GMM) exhibited the weakest performance among the clustering techniques, showing a Silhouette Score of 0.4122, which suggests difficulties in creating distinct clusters, potentially due to the inherent variability or noise present in the datasets.

When assessing the Logistic Regression classifier, a Silhouette Score of 0.4688 was noted. This signifies that while logistic regression was moderately successful in associating the extracted features with land cover categories, its effectiveness was closely linked to the quality of features provided by the clustering methods. In summary, the results indicate that Mean Shift Clustering yielded the most reliable features for subsequent classification tasks, underscoring the significance of choosing suitable clustering approaches in self-supervised learning frameworks for land cover classification based on satellite imagery.

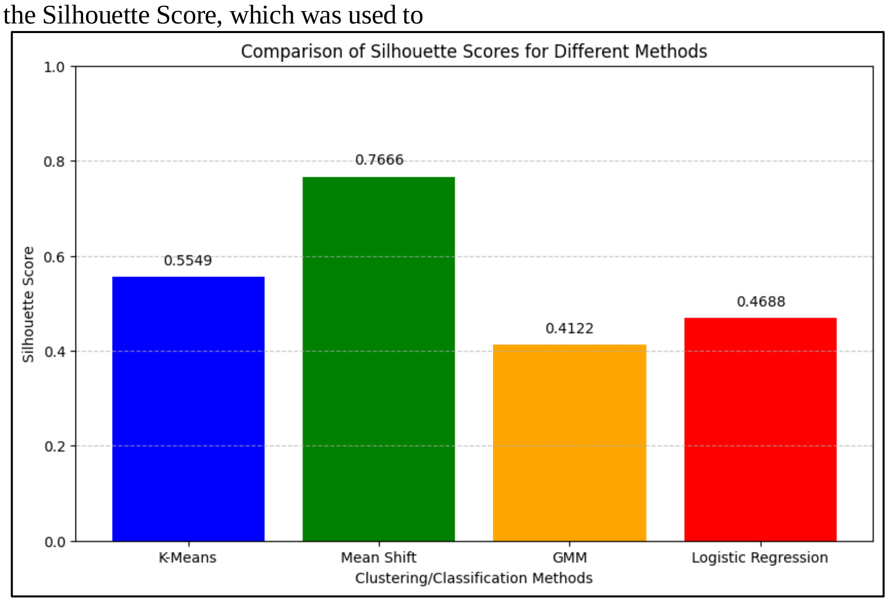

Fig. 1:

V. Conclusion

This study showcased the effectiveness of self-supervised learning methods, especially clustering algorithms and logistic regression, for classifying land cover through satellite images. The research examined different clustering techniques, such as K-Means, Mean Shift, and Gaussian Mixture Model (GMM), and evaluated their effectiveness in deriving significant features from unlabeled data. Of these, Mean Shift Clustering excelled, achieving the highest Silhouette Score and demonstrating better cluster cohesion and separation. This indicates that Mean Shift is very efficient at identifying intricate patterns in the data. In comparison, K-Means Clustering showed average performance, whereas GMM had difficulty in identifying distinct clusters, possibly due to noise or variations in the data. The Logistic Regression classifier utilized on the extracted features demonstrated moderate effectiveness, suggesting that the quality of clustering has a direct impact on classification performance.

In summary, the study emphasizes the success of self-supervised methods in land cover classification, with Mean Shift Clustering yielding the most encouraging outcomes for feature extraction. This study highlights the significance of choosing suitable clustering techniques for feature extraction in satellite image analysis, offering a scalable strategy for land cover classification that doesn’t depend on labeled datasets. Future studies might investigate hybrid models or sophisticated clustering methods to improve the reliability and precision of land cover classification systems.

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