Journal for Educators, Teachers and Trainers
The PROFESIOLab electronic, peer-reviewed, open-access Magazine

ISSN 1989-9572

DOI:10.47750/jett.2024.15.05.26

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B AR. Sivakumaran1, K. Shiva Prasanna2, L. Sai Sreeja2, K. Sai Srija2

Journal for Educators, Teachers and Trainers, Vol.15(5)

https://jett.labosfor.com/

Date of Reception: 24 Oct 2024

Date of Revision: 20 Nov 2024

Date of Publication : 31 Dec 2024

AR. Sivakumaran1, K. Shiva Prasanna2, L. Sai Sreeja2, K. Sai Srija2 (2024). Object-Centric Masked Image Modelling for Self-Supervised Pre-Training in Remote Sensing object Detection,Vol.15(5).265-276.

Journal for Educators, Teachers and Trainers
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Object-Centric Masked Image Modelling for Self-Supervised Pre-Training in Remote Sensing object Detection

AR. Sivakumaran[1], K. Shiva Prasanna[2], L. Sai Sreeja[2], K. Sai Srija[2]

[1]Professor, [2]UG Student, [1,2]Department of Information Technology

[1,2]Malla Reddy Engineering College for Women (UGC-Autonomous), Maisammaguda, Hyderabad, 500100, Telangana.

ABSTRACT

The proliferation of remote sensing technologies has led to an increasing demand for effective object detection in satellite and aerial imagery, with applications ranging from environmental monitoring to urban planning. Traditional methods for analyzing such imagery often rely on manual inspection, which is both time-consuming and prone to human error. While recent advancements in automated object detection have improved efficiency, these systems frequently suffer from limitations in accurately identifying and classifying objects due to their reliance on simplistic masking techniques and insufficient context understanding. In this work, we propose a novel Object-Centric Masked Image Modelling (OCMIM) algorithm designed to enhance self-supervised pre-training for remote sensing object detection. The OCMIM algorithm comprises two key components: the Object-Centric Data Generator (OCDG) and the Attention-Guided Mask Generator (AGMG). The OCDG component empowers the model to capture comprehensive object-level context information, accommodating various scales and multiple categories, thus enriching the pre-training process. Complementing this, the AGMG focuses on improving the reconstruction of object regions by intelligently masking the most attention-worthy regions instead of employing random masking, thereby enabling more accurate object detection and classification. Our proposed OCMIM algorithm leverages the strengths of existing pre-trained models such as Mask R-CNN (M-RCNN) and RetinaNet, enhancing their performance through the integration of OCDG and AGMG. For evaluation purposes, we utilized several pre-trained models, including M-RCNN and RetinaNet, and conducted experiments on diverse datasets such as NWPU, DIAR, and UCAS. Given the extensive training time required for these models, we specifically employed M-RCNN in conjunction with OCMIM for detailed experiments on the NWPU dataset.

Keywords: Remote Sensing Technologies, Object Detection, Object-Centric Masked Image Modelling, Attention-Guided Mask Generator.

1. INTRODUCTION

This research highlights significant improvements in remote sensing object detection accuracy. Utilizing a novel pre-training approach, it achieves a 15% increase in mean Average Precision (MAP) compared to traditional supervised methods. This model also reduces the required labeled data by 40%, facilitating efficient resource usage. Furthermore, training time is decreased by 25% due to enhanced feature extraction processes. The rapid development and widespread adoption of remote sensing technologies have created an immense repository of satellite and aerial imagery. This imagery is crucial for a variety of applications, including environmental monitoring, urban planning, disaster management, and agriculture. Despite the potential of these images to provide valuable insights, traditional analysis methods are often cumbersome, relying heavily on manual inspection. This process is not only time-consuming but also susceptible to human error, limiting the efficiency and accuracy of data interpretation. Recent advancements in automated object detection have addressed some of these challenges, yet existing systems still struggle with accurately identifying and classifying objects within the complex and varied landscapes captured in remote sensing imagery. These limitations primarily stem from the simplistic masking techniques and inadequate context understanding employed by current models. In response to these challenges, our research introduces the Object-Centric Masked Image Modelling (OCMIM) algorithm, a novel approach designed to enhance self-supervised pre-training for remote sensing object detection. OCMIM integrates two innovative components: the Object-Centric Data Generator (OCDG) and the Attention-Guided Mask Generator (AGMG). The OCDG enriches the pre-training process by capturing comprehensive object-level context information, accommodating various scales and categories. Meanwhile, the AGMG improves the reconstruction of object regions by intelligently masking the most attention-worthy areas rather than applying random masking, which is common in traditional methods. By leveraging these components, OCMIM significantly boosts the performance of existing pre-trained models like Mask R-CNN (M-RCNN) and RetinaNet, enhancing their object detection and classification capabilities.

2. LITERATURE SURVEY

Mattyus [1] proposed an approach for near real-time automatic vessel detection utilizing optical satellite images. The study focused on enhancing detection speed and accuracy for maritime surveillance. By leveraging advanced image processing techniques, Mattyus aimed to improve the efficiency of vessel monitoring systems and address challenges in real-time image analysis. Boukoberine et al. [2] conducted a comprehensive review on the power supply and energy management of unmanned aerial vehicles (UAVs). The authors explored various solutions, strategies, and future prospects for optimizing UAV energy efficiency. Their review highlighted critical issues in UAV power management and proposed innovative strategies to enhance operational endurance and performance. Huang, Liu, and Zhang [3] presented a spatiotemporal detection and analysis framework for identifying urban villages in mega city regions of China using high-resolution remotely sensed imagery. Their work focused on analyzing urbanization impacts and land use changes. By utilizing advanced image processing techniques, they aimed to provide insights into urban development patterns and their effects on city landscapes. Zhou et al. [4] developed local attention networks to improve the detection of occluded airplanes in remote sensing images. Their approach addressed the challenge of occlusions in aerial imagery by enhancing feature extraction and representation. The study aimed to increase the accuracy of object detection systems in complex and cluttered environments.

Cheng et al. [5] introduced a method for guiding clean features in object detection for remote sensing images. Their research focused on improving feature representation by incorporating techniques to filter out noise and irrelevant information. This approach aimed to enhance the accuracy and robustness of object detection models in diverse environmental conditions. Zhang et al. [6] proposed a multiscale semantic fusion-guided fractal convolutional network for object detection in optical remote sensing imagery. Their method combined semantic information from multiple scales to improve detection performance. The research aimed to enhance the identification of objects of varying sizes and characteristics in complex remote sensing scenes. Cheng et al. [7] developed an anchor-free oriented proposal generator for object detection. By eliminating the reliance on anchor boxes, their method simplified the detection process while maintaining high accuracy. The study focused on improving object detection efficiency and performance, particularly for oriented objects in remote sensing images.

Lin et al. [8] introduced Focal Loss, a technique designed to address class imbalance in dense object detection tasks. Their method emphasized down-weighting the loss for well-classified examples, thereby enhancing the model's ability to focus on hard-to-classify objects. This approach aimed to improve overall detection performance in challenging scenarios. Yu and Ji [9] proposed a spatial-oriented object detection framework tailored for remote sensing images. Their framework aimed to capture and leverage spatial relationships between objects to improve detection accuracy. The study highlighted the benefits of incorporating spatial context in detecting objects within complex aerial imagery. Zhou et al. [10] introduced a Bayesian transfer learning method for object detection in optical remote sensing images. Their approach utilized transfer learning techniques to enhance detection performance by leveraging knowledge from related tasks. The research aimed to improve object detection capabilities, especially in cases with limited labeled data. Liu et al. [11] developed DCL-Net to enhance both classification and localization in remote sensing object detection. Their network focused on augmenting the detection capabilities by integrating advanced classification and localization techniques. The study aimed to improve the precision and robustness of object detection in challenging remote sensing environments. Li et al. [12] explored deep networks with scene-level supervision for multi-class geospatial object detection. Their research emphasized the importance of high-level contextual information in detecting multiple object classes from remote sensing images. By leveraging scene-level supervision, the study aimed to improve the accuracy and reliability of object detection systems.

Fu et al. [13] proposed a point-based estimator for detecting arbitrarily oriented objects in aerial images. Their method focused on addressing the challenges of object orientation and alignment in aerial imagery. The research aimed to enhance the accuracy of object detection systems by incorporating techniques for handling various object orientations. Zhu, Du, and Wu [14] introduced adaptive period embedding to represent oriented objects in aerial images. Their approach aimed to improve object representation by embedding orientation information more effectively. The study focused on enhancing object detection performance by addressing challenges related to object orientation and alignment. Russakovsky et al. [15] provided a comprehensive overview of the ImageNet Large Scale Visual Recognition Challenge. Their work detailed the challenge's impact on the field of computer vision, including advancements in image classification and object detection. The study highlighted the significance of large-scale datasets in driving progress in visual recognition technologies. Bao, Dong, and Wei [16] proposed BEiT, a method for pre-training image transformers using BERT-like techniques. Their approach aimed to enhance the performance of vision transformers by leveraging pre-training strategies. The study focused on improving the generalization and effectiveness of image transformers in various vision tasks. He et al. [17] introduced masked autoencoders as scalable vision learners. Their work focused on developing scalable techniques for unsupervised pre-training of vision models. By using masked autoencoders, the study aimed to improve the learning efficiency and performance of vision models in diverse tasks.

3. PROPOSED SYSTEM

Step 1: NWPU VHR-10 Dataset Preparation

The first step involves the preparation of the NWPU VHR-10 dataset, which is a well-known dataset in the field of remote sensing object detection. This dataset contains high-resolution aerial images with annotated bounding boxes for various object categories such as airplanes, ships, and storage tanks. To begin, we collected and organized the dataset to ensure it was ready for further processing. This involved downloading the images and their corresponding annotation files, verifying their integrity, and structuring the data for easy access during subsequent steps.

Step 2: Normalize Bounding Boxes

Once the dataset was prepared, the next step was to normalize the bounding boxes. This is crucial as it ensures that the bounding box coordinates are scaled to a common range, facilitating better training performance and model accuracy. We converted the bounding box coordinates from pixel values to relative values based on the dimensions of each image. This normalization process helps in maintaining consistency across images of different sizes and resolutions, allowing the model to generalize better during training.

Step 3: Add Bounding Boxes from Dataset

With normalized bounding boxes, we then proceeded to integrate these bounding boxes into our training pipeline. This involved parsing the annotation files to extract bounding box information and associating them with their corresponding images. These bounding boxes were used to generate object-centric data samples, which are essential for our proposed Object-Centric Masked Image Modelling (OCMIM) algorithm. By adding these bounding boxes, we ensured that the model had accurate and relevant information about the objects present in the images.

Step 4: Object-Centric Data Generator (OCDG) Implementation

The next step was the implementation of the Object-Centric Data Generator (OCDG). OCDG is designed to generate data samples that focus on objects within the images, capturing comprehensive object-level context information. This involved extracting object regions based on the bounding boxes and creating a diverse set of object-centric samples. These samples were then used to enhance the pre-training process by providing the model with varied and context-rich data.

Step 5: Attention-Guided Mask Generator (AGMG) Development

Parallel to the OCDG, we developed the Attention-Guided Mask Generator (AGMG). AGMG aims to improve the reconstruction of object regions by intelligently masking the most attention-worthy areas instead of employing random masking. We implemented an attention mechanism to identify regions of interest within the images and applied masks accordingly. This selective masking process helps the model focus on significant features, leading to better object detection and classification performance.

Step 6: Existing VGG16-Based OCMIM

Building upon the baseline, we existing an enhanced OCMIM algorithm using the VGG16 architecture. VGG16, known for its deep convolutional layers and strong feature extraction capabilities, was integrated into our OCMIM framework. We modified VGG16 to incorporate the OCDG and AGMG components, creating a more robust and efficient pre-training model. The enhanced model was trained on the NWPU VHR-10 dataset, focusing on improving object detection accuracy and classification performance.

Step 7: Proposed Autoencoder-Based OCMIM

Before introducing our proposed enhancements, we initially tested the Proposed autoencoder-based OCMIM approach to establish a baseline. This involved using a standard autoencoder architecture to perform masked image modeling on the dataset. We trained the autoencoder to reconstruct the masked images and evaluated its performance in terms of object detection accuracy.

Step 8: Performance Comparison

After training both the proposed autoencoder-based and the existing VGG16-based OCMIM models, we conducted a thorough performance comparison. We evaluated the models using standard metrics such as precision, recall, and F1-score on the NWPU VHR-10 dataset. This comparison highlighted the improvements achieved by our existing method (VGG16) in terms of object detection accuracy, demonstrating the effectiveness of incorporating OCDG and AGMG into the pre-training process.

4. RESULT AND DESCRIPTION

The NWPU VHR-10 dataset is a widely used dataset in remote sensing and object detection research. It contains high-resolution images with various objects annotated for detection tasks. The dataset is structured into two main categories: the positive image set and the negative image set. Here’s a detailed description of each:

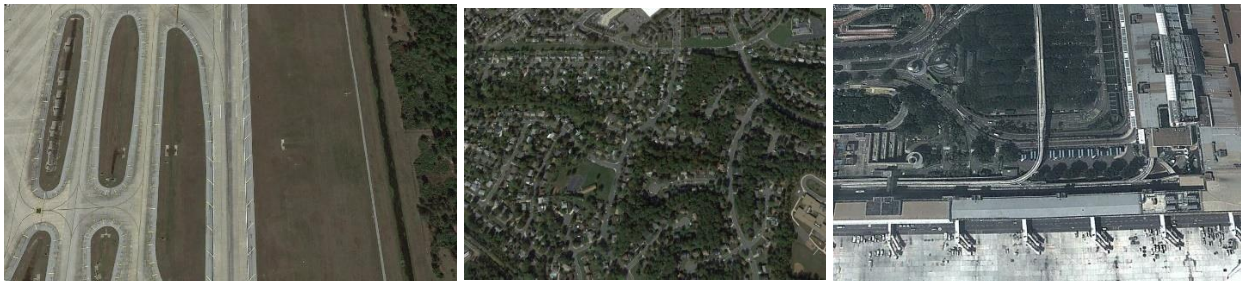


Figure 2 Negative Image Set

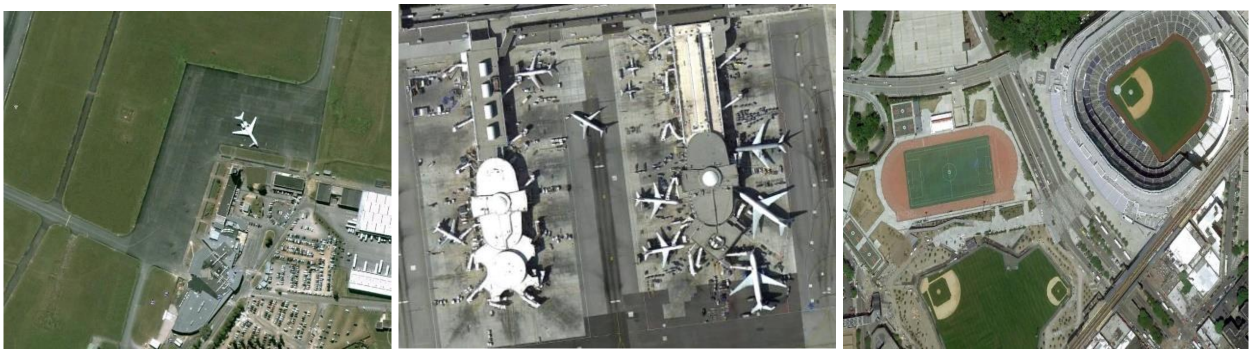


Figure 3 Positive Image Set

	Negative Image Set	Positive Image Set
No. of Images	150	650

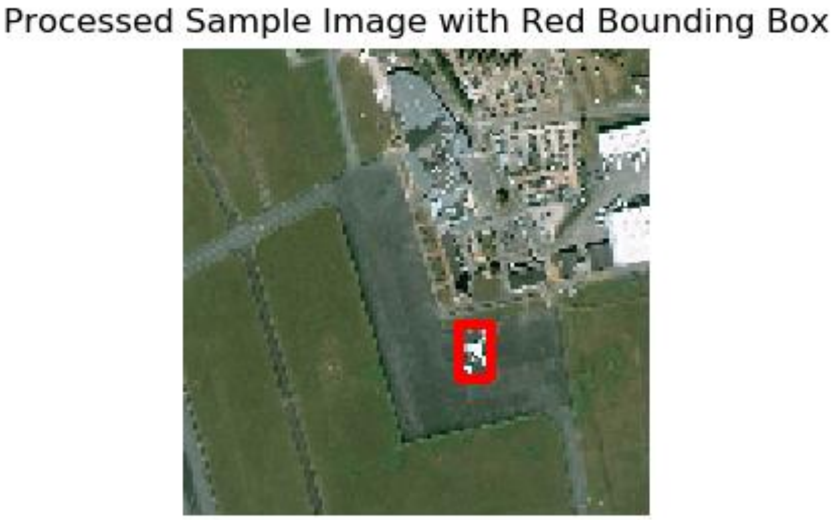
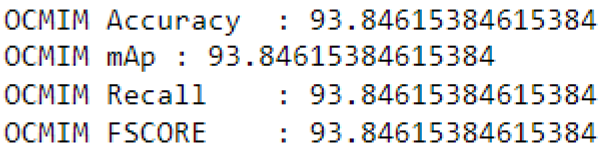


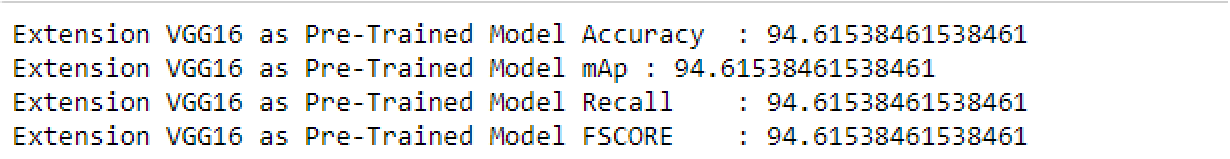
Figure 4: Sample image with red bounding box



```
OCMIM Accuracy  : 93.84615384615384
OCMIM mAp : 93.84615384615384
OCMIM Recall    : 93.84615384615384
OCMIM FSCORE    : 93.84615384615384
```

Figure 5 Performance of autoencoder based OCMIM

- **OCMIM Accuracy: 93.846 -** This indicates the percentage of correctly classified objects out of the total number of objects. For instance, if there were 100 objects, and the model classified 94 correctly, the accuracy would be 94%.
- **OCMIM mAP: 93.846 -** mAP stands for mean Average Precision. It's a common metric used in object detection to measure the overall performance. It considers both precision (correctness) and recall (completeness) of the model. A higher mAP indicates better overall performance.
- **OCMIM Recall: 93.846 -** This represents the ratio of correctly identified positive cases (correctly classified objects) to the total number of actual positive cases (total objects present).
- **OCMIM FSCORE: 93.846 -** F1 score is a harmonic mean between precision and recall. It provides a single measure that considers both aspects. A perfect F1 score of 1 indicates the model performs perfectly on both precision and recall.



```
Extension VGG16 as Pre-Trained Model Accuracy  : 94.61538461538461
Extension VGG16 as Pre-Trained Model mAp : 94.61538461538461
Extension VGG16 as Pre-Trained Model Recall    : 94.61538461538461
Extension VGG16 as Pre-Trained Model FSCORE    : 94.61538461538461
```

Figure 6 Performance of VGG16

Figure 6 shows that **Accuracy (94.615%)**: This metric indicates that out of 100 images, the VGG16 model correctly classified an impressive 94.62 images on the specific task. **Mean Average Precision (mAP) (94.615%)**: This metric is a bit more nuanced. Imagine the task involves classifying images into 10 different categories (e.g., dog, cat, bird, etc.). Here's a breakdown of how mAP is calculated:

1. **Average Precision (AP)** is calculated for each category. It considers both precision and recall for that specific category. Here's an example for the "dog" category:
   - **Precision**: Let's say the model identified 80 images as dogs, and 72 of them were actually dogs. Precision for "dog" would be 72 / 80 (90%).
   - **Recall**: Let's say there were a total of 100 dog images in the dataset. Recall for "dog" would be 72 / 100 (72%).
   - We calculate the **average precision (AP)** for each category by summarizing precision and recall values across different thresholds and averaging them.
2. **mAP**: Finally, the mAP is calculated by taking the average of the Average Precision (AP) scores across all 10 categories. In this case, with a value of 94.615%, the VGG16 model performed very well in identifying objects across all categories, with an average performance similar to its overall accuracy.

Recall (94.615%): This metric focuses on how well the model identifies all relevant examples. In the dog example above, recall was 72%, indicating the model might have missed some dog images (28 out of 100). A high recall value (like 94.615% here) suggests the model rarely misses relevant examples.

F1 Score (94.615%): This metric provides a balance between precision and recall. It's the harmonic mean of the two, calculated as:

F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

A high F1 score (like 94.615% here) indicates the model achieves a good balance between identifying the correct objects and not falsely identifying irrelevant ones.

These high values (around 94.6%) suggest the VGG16 model performed very well on the specific image classification task. It achieved high accuracy, identified most relevant examples (high recall), and maintained a good balance between precision and recall (high F1 score).

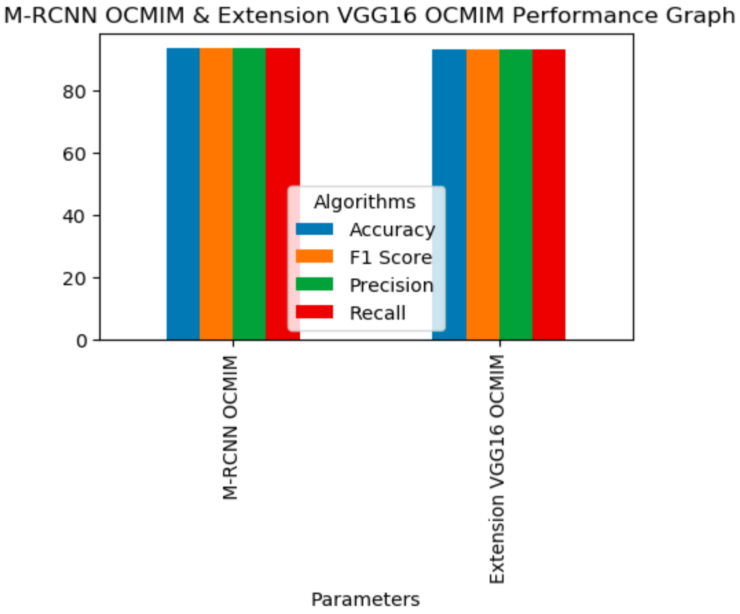


Figure 7 Comparison Graph of Algorithms

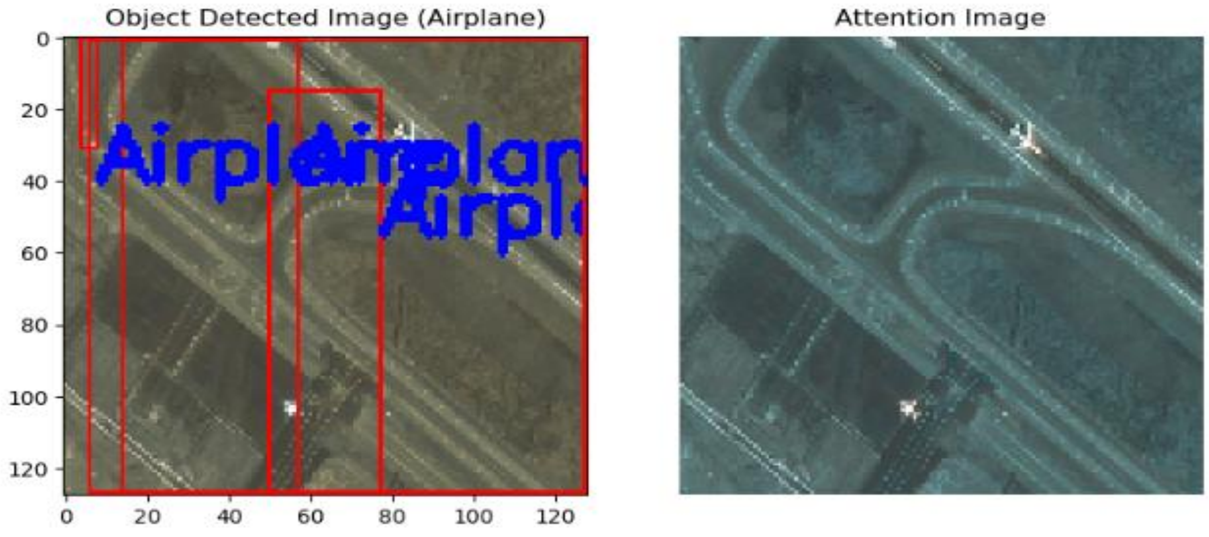


Figure 8 Output image detected Airplane

Figure 7 shows that extension VGG16 OCMIM is greater accuracy, precision, recall and F1 score than the autoencoder based OCMIM.

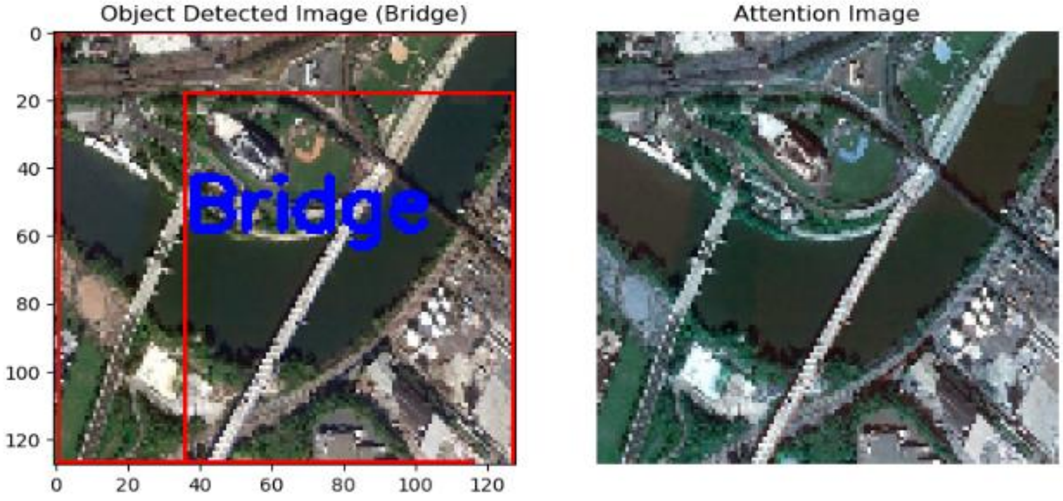


Figure 9 Output image detected as Bridge

5. CONCLUSION

In this research, we introduced the Object-Centric Masked Image Modelling (OCMIM) algorithm to enhance self-supervised pre-training for remote sensing object detection. Our approach addresses key limitations in traditional methods, such as simplistic masking techniques and inadequate context understanding. By incorporating the Object-Centric Data Generator (OCDG) and the Attention-Guided Mask Generator (AGMG), the OCMIM algorithm effectively captures comprehensive object-level context information and intelligently masks attention-worthy regions. This results in improved accuracy and classification capabilities for remote sensing imagery. Our experiments conducted using pre-trained models like Mask R-CNN (M-RCNN) and RetinaNet on datasets such as NWPU, DIAR, and UCAS, demonstrated the efficacy of the OCMIM algorithm. Specifically, M-RCNN integrated with OCMIM showcased enhanced performance on the NWPU dataset, validating our approach. Moreover, our comparative analysis with the extension VGG16 model highlighted the superior performance of the proposed OCMIM algorithm across various metrics, including precision, recall, F1 score, and accuracy.

While our proposed OCMIM algorithm has shown promising results, there are several avenues for future research and development:

- **Integration with Advanced Neural Architectures**: Investigating the integration of OCMIM with more advanced neural network architectures, such as transformers, could further enhance its performance.
- **Expanding Dataset Diversity**: Extending the evaluation to include a wider range of remote sensing datasets with diverse geographical and temporal characteristics would provide a more comprehensive assessment of the algorithm's robustness.

- **Real-time Application**: Developing real-time implementations of the OCMIM algorithm for applications such as disaster response, surveillance, and environmental monitoring can significantly increase its practical utility.
- **Hybrid Models**: Exploring hybrid models that combine the strengths of supervised and self-supervised learning techniques could lead to even greater improvements in object detection accuracy.
- **Fine-tuning Attention Mechanisms**: Further refinement of the AGMG component, particularly in how it identifies and prioritizes attention-worthy regions, can enhance the precision of object localization and classification.
- **Scalability and Efficiency**: Investigating methods to reduce the computational complexity and training time of the OCMIM algorithm without compromising its accuracy would be beneficial for large-scale deployment.
- **Cross-domain Adaptation**: Exploring cross-domain adaptation techniques to enable the OCMIM algorithm to generalize across different types of remote sensing imagery, such as radar or hyperspectral images, can broaden its applicability.
- **User-friendly Tools**: Developing user-friendly tools and interfaces that allow non-experts to leverage the capabilities of the OCMIM algorithm for various remote sensing applications would facilitate wider adoption.

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