

Text-Guided Open Vocabulary Object Detection using Vision-Language Models

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ABSTRACT

Object detection has become a fundamental task in computer vision, widely used in applications such as surveillance, autonomous systems, and smart technologies. However, most traditional object detection models are limited to recognizing only a fixed set of object categories that they were trained on. This restriction makes them less effective in real-world scenarios, where new and unseen objects frequently appear. To overcome this limitation, Open-Vocabulary Object Detection (OVOD) has emerged as a promising approach that allows models to detect objects based on natural language descriptions rather than predefined labels. In this project, we present a text-guided object detection system that leverages advanced vision-language models, specifically CLIP and OWL-ViT. The proposed system is capable of understanding both visual and textual inputs, enabling it to identify and localize objects dynamically based on user-provided prompts. By mapping images and text into a shared representation space, the system can recognize objects even if they were not part of the training dataset. The architecture integrates image preprocessing, text encoding, feature alignment, and transformer-based detection to ensure accurate and flexible performance. The system is further supported by a user-friendly interface that allows real-time detection and batch processing, making it practical for various real-world applications. Experimental observations show that the model performs effectively in detecting both known and unseen object categories, demonstrating improved flexibility compared to conventional methods. Overall, this work highlights the potential of combining visual understanding with natural language

processing to build more intelligent and adaptable object detection systems.

Keywords: Open Vocabulary Object Detection, Vision-Language Models, CLIP, OWL-ViT, Object Detection, Deep Learning.

1. INTRODUCTION

Object detection is one of the most important and widely studied tasks in the field of computer vision. It involves not only identifying the presence of objects within an image or video frame but also accurately determining their locations using bounding boxes. Over the years, significant progress has been made in this domain with the development of advanced deep learning models such as YOLO (You Only Look Once), SSD (Single Shot Detector), and Faster R-CNN. These models have achieved impressive results in terms of both detection accuracy and real-time performance, making them suitable for applications like surveillance, autonomous driving, and smart systems.

However, despite their success, these conventional object detection models suffer from a fundamental limitation—they operate under a closed-set assumption. This means that they are trained to recognize only a fixed set of object categories defined during the training phase. As a result, if an object that was not part of the training dataset appears in a real-world scenario, the model fails to detect or correctly classify it. In practical environments, where new and diverse objects constantly appear, this limitation significantly restricts the usability and adaptability of traditional detection systems.

To address this challenge, researchers have introduced the concept of Open-Vocabulary Object Detection (OVOD). Unlike traditional

methods, OVOD systems are designed to detect not only known objects but also previously unseen categories by leveraging natural language descriptions. This approach allows users to specify objects using textual prompts, such as “a person holding a phone” or “a red car,” enabling more flexible and dynamic detection capabilities. OVOD represents a shift from rigid, label-based detection to a more semantic and human-like understanding of visual data.

A key factor enabling this advancement is the development of Vision-Language Models (VLMs), which learn a shared representation between images and textual descriptions. These models are trained on large-scale datasets containing image-text pairs, allowing them to understand the relationship between visual features and language. One of the most influential models in this area is CLIP (Contrastive Language-Image Pretraining), which has demonstrated remarkable ability in aligning images with corresponding textual descriptions. By mapping both modalities into a common embedding space, CLIP enables zero-shot learning, where the model can recognize objects it has never explicitly seen during training.

Building upon this idea, OWL-ViT (Open-World Localization Vision Transformer) extends the capabilities of vision-language models to the task of object detection. It combines the strengths of transformer-based architectures with open-vocabulary learning, allowing the system to not only understand text prompts but also accurately localize objects within an image. This makes OWL-ViT particularly powerful for real-world applications where adaptability and generalization are crucial.

In this project, we aim to design and implement a text-guided object detection system that leverages the combined strengths of CLIP and OWL-ViT. The system takes both an image and a user-defined text prompt as input and dynamically detects relevant objects, even if they were not part of the training dataset. By

integrating semantic understanding with precise localization, the proposed approach overcomes the key limitations of traditional object detection methods. Ultimately, this work contributes toward building more intelligent, flexible, and real-world-ready computer vision systems.

2. LITERATURE SURVEY

Object detection has seen significant progress over the years, largely due to deep learning techniques. Earlier methods relied on traditional machine learning, which depended heavily on crafted features like edges, textures, and shapes. This approach required a lot of manual work for feature extraction and often struggled in complex real-world situations with changing lighting, scale, and backgrounds. Consequently, these methods had limited accuracy and reliability.

Deep learning changed the game for object detection. Convolutional Neural Networks (CNNs) allowed automatic feature extraction from images, noticeably boosting performance. One of the early breakthroughs was Faster R-CNN, which brought in Region Proposal Networks (RPNs) to pinpoint potential object areas before classification. This method enhanced detection accuracy by concentrating on important parts of the image. However, it needed several processing stages, making it computationally heavy and slower for real-time use.

To tackle the speed issues with two-stage detectors, researchers created single-stage detection models. A model like YOLO (You Only Look Once) conducts object detection in one forward pass, making it very fast and ideal for real-time tasks. YOLO divides the image into grids, predicting bounding boxes and class probabilities simultaneously, which balances speed and accuracy well. EfficientDet introduced a scalable design that improves performance and computational efficiency through compound scaling. Despite these advancements, these models still focus on a fixed set of predefined categories, limiting their adaptability in changing environments.

The development of transformer-based architectures further improved object detection. DETR (Detection Transformer) simplified the detection process by removing the need for region proposals, using a transformer-based encoder-decoder system to directly predict object bounding boxes and classes. Vision Transformer (ViT) showed the benefits of attention mechanisms in understanding global relationships in images, enabling a better grasp of complex scenes. Swin Transformer built on this by introducing hierarchical feature representation, boosting both efficiency and performance. Still, these models generally work under a closed-set assumption, meaning they can only detect objects they were trained on.

To address the challenges of fixed-category detection, researchers created Vision-Language Models (VLMs), which merge visual and textual information. These models train on extensive image-text datasets to learn a shared space where both can be represented. One notable model in this area is CLIP, which uses contrastive learning to align images with their textual descriptions. This capability allows the model to perform zero-shot learning, recognizing and classifying objects not explicitly included in its training data.

Building on this idea, open-vocabulary object detection methods emerged. These techniques use textual prompts to direct the detection process, enabling the system to identify objects based on user-defined descriptions rather than fixed labels. This approach offers high flexibility and adaptability to new or unseen categories. Several models have been suggested to improve this ability. GLIP combines language and image features to enhance object localization, while MDETR integrates textual information into the detection process through transformer architectures. RegionCLIP aims to align specific image regions with their corresponding text descriptions, improving region-level classification accuracy.

Among advanced models, OWL-ViT is notable for open-vocabulary detection. It merges the

strengths of Vision Transformers with vision-language understanding, allowing the detection of objects based on textual queries. Unlike traditional detectors, OWL-ViT does not depend on fixed class labels and can adapt to a broad range of object categories, making it suitable for real-world applications where the potential objects are not predefined.

In summary, the field of object detection has progressed from traditional handcrafted methods to advanced deep learning and transformer-based techniques, culminating in integrated vision-language systems. Open-vocabulary object detection marks a major advancement, allowing models to detect previously unseen objects using natural language descriptions. The proposed system builds on these developments by merging a vision-language model with an object detection framework, achieving flexible, prompt-driven object detection for real-world use.

3. PROPOSED SYSTEM

The proposed system presents an end-to-end text-guided open-vocabulary object detection platform designed to identify and localize objects in images based on user-provided textual descriptions. The system integrates vision-language understanding with deep learning techniques, enabling it to process both image and text inputs simultaneously. By utilizing a pre-trained model, OWL-ViT, the system establishes a connection between visual content and natural language, allowing it to detect objects dynamically based on user queries.

Traditional object detection systems are typically limited to a fixed set of predefined categories, which restricts their applicability in real-world scenarios where new or unseen objects may appear. In contrast, the proposed system adopts an open-vocabulary approach, enabling users to specify any object of interest through a text prompt. This flexibility makes the system more adaptable and scalable, as it does not require retraining for new object categories. The overall architecture is designed as a structured pipeline consisting of input handling,

embedding generation, model inference, and output visualization, ensuring efficient and user-friendly operation.

3.1 System Workflow

The workflow of the proposed system follows a logical sequence of operations that begins with user input and ends with the visualization of detected objects. The process starts when the user provides an image along with a textual description of the object they wish to detect. These inputs are then processed to generate embeddings, which are numerical representations that capture the semantic meaning of both the image and the text.

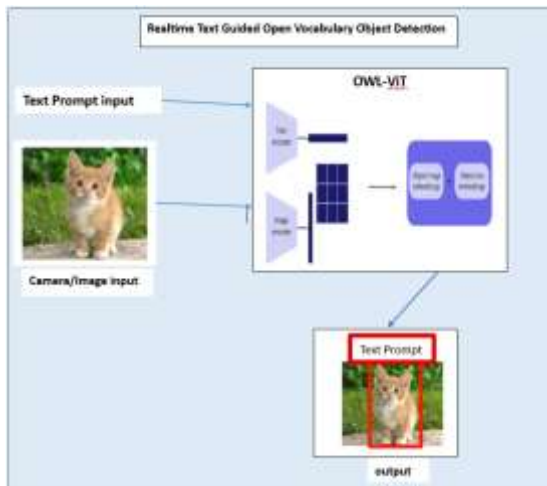


Figure 1. Proposed System Architecture of open vocabulary object detection.

Once the embeddings are generated, they are passed to the OWL-ViT model, which performs the object detection task by identifying regions in the image that correspond to the given textual description. The model produces predictions in the form of bounding boxes and confidence scores, indicating the presence and location of the specified object. These predictions are then processed and visualized in a user-friendly format, allowing users to easily interpret the results.

This workflow ensures a seamless interaction between the user and the system, enabling real-time detection based on dynamic inputs. The modular nature of the architecture also allows for flexibility in extending or modifying

individual components without affecting the overall functionality

The Input Layer is the first stage of the system, responsible for collecting and preparing user-provided data. It handles two main inputs: an image and a text prompt, which together enable text-guided object detection by combining visual information with user intent. The image input provides the visual data for detection and is uploaded through an interface supporting formats such as JPEG and PNG. These images may contain multiple objects, complex backgrounds, and varying conditions like lighting, scale, orientation, and occlusion. After uploading, the image undergoes basic preprocessing to ensure consistency and compatibility, including standardizing the format and preparing it for embedding generation. This ensures reliable and efficient processing even for complex real-world images.

The text prompt specifies the object that the user wants to detect in the image, enabling open-vocabulary detection. Users can input any object name such as “person,” “car,” or “dog,” without being restricted to predefined categories. The text is processed by removing unnecessary spaces and converting it into a structured format suitable for embedding generation. This allows the system to capture the semantic meaning of the user’s query effectively. The flexibility of the text input makes the system adaptable to different scenarios, as it can dynamically interpret user queries rather than relying on fixed labels.

The combination of image and text inputs is essential for the system’s functionality. By processing both together, the system establishes a relationship between the visual content of the image and the meaning of the text prompt. This dual-input approach enables more accurate and context-aware detection. The Input Layer ensures proper alignment of both inputs before passing them to the next stage, which is crucial for generating meaningful representations.

The Processing Layer forms the core of the system, where data transformation and object detection take place. In this stage, both the

image and the text are converted into numerical representations called embeddings. Image embeddings capture visual features such as shapes, textures, and spatial relationships, while text embeddings represent the semantic meaning of the user's query. These embeddings exist in a shared space, allowing the system to compare them and identify regions in the image that match the text. By analyzing this similarity, the system determines which parts of the image correspond to the specified object, enabling open-vocabulary detection based on semantic matching.

The embeddings are then passed to the OWL-ViT model, which performs the detection task by analyzing the similarity between the text embedding and different regions of the image. Based on this analysis, the model predicts bounding boxes that indicate the location of detected objects. Each detection is associated with a confidence score representing the likelihood of a correct match. The inference process is efficient and supports real-time detection, and since the model is pre-trained, it can recognize a wide range of objects without additional training. Finally, the Output and Visualization Layer presents the results by overlaying bounding boxes on the original image and displaying confidence scores, making the output clear and easy to interpret for users.

4. RESULTS DESCRIPTION

Figure 2 illustrates the web-based user interface of the proposed Open-Vocabulary Object Detection System, designed to provide an intuitive and interactive environment for detecting objects using natural language prompts. The interface follows a clean and modern layout, divided into two main sections: the control panel and the visualization panel.

On the left side, the *Detection Settings* panel allows users to configure the detection process. It includes an input field labeled “Enter object to detect”, where users can specify the desired object category using natural language (e.g., “a car”, “a dog”). This enables flexible and open-vocabulary detection without restricting the system to predefined classes. Below this, a

confidence threshold slider is provided, allowing users to adjust the sensitivity of the detection model. By modifying this threshold, users can control the balance between detection accuracy and the number of predicted objects, making the system adaptable to different scenarios.



Figure 2. Web interface for proposed Open-Vocabulary Object Detection system

On the main panel, the interface prominently displays the title “*Open-Vocabulary Object Detection*”, along with a short description explaining its functionality—detecting objects using natural language prompts. The central feature of this panel is the *image upload section*, where users can upload input images in formats such as JPG, PNG, or JPEG. The upload component is designed to be user-friendly, supporting drag-and-drop functionality as well as manual file selection.

The interface also includes a “Run Detection” button, which triggers the object detection pipeline once the image and prompt are provided. Upon execution, the system processes the input and displays results in the same panel, ensuring a seamless user experience.

Overall, the interface demonstrates an effective integration of usability and functionality, enabling users to interact with advanced vision-language models in a simple and accessible manner. It highlights the system's capability to perform real-time, prompt-driven object detection while maintaining a clear and organized workflow.



Figure 3. Detection result using text prompt “a car”.

After designing the user interface, the next step in the system workflow is to perform object detection based on the user’s input. Once the image is uploaded and the desired object is specified through a text prompt, the system processes both inputs and prepares them for detection. The backend integrates the object detection model and the vision-language model to analyze the image and identify regions that match the given prompt. This stage demonstrates how the system responds dynamically to user queries and performs prompt-driven detection in real time.

Figure 3 shows the system during the detection process, where the user has entered the prompt “a car” and uploaded an image containing a vehicle in an outdoor environment. The interface clearly displays the uploaded image along with the selected detection settings, including the confidence threshold value. When the “Run Detection” button is clicked, the system begins analyzing the image and displays a status message indicating that detection is in progress.

At this stage, the model scans the image and identifies potential object regions using the detection module. These regions are then compared with the textual prompt using the vision-language model, which determines how closely each region matches the given description. The presence of the status message, such as “Detecting ‘a car’ (threshold: 0.11)”, reflects that the system is actively processing the request and applying the user-defined parameters.

This figure highlights the interactive nature of the system, where users can easily modify inputs and observe how the detection process adapts

accordingly. It also demonstrates the system’s ability to handle real-time input and provide immediate feedback, making it suitable for practical applications that require dynamic and flexible object detection.



Figure 4. Output image showing detected object with bounding box and label.

After the detection process is completed, the system generates the final output by combining the results from both the object detection model and the vision-language model. At this stage, the detected regions are labeled based on their similarity with the given text prompt, and the results are visually presented to the user. This step is important as it clearly shows how accurately the system can identify and localize objects in the image.

Figure 4 shows the final output of the system after processing the input image with the given prompt. In this figure, the detected object is highlighted using a bounding box, and the corresponding label (such as “car”) is displayed along with a confidence score. The bounding box accurately surrounds the object, indicating that the detection model has successfully localized it within the image.

The label assigned to the object is not based on predefined classes but is generated by comparing the image region with the user-provided text prompt. This demonstrates the core concept of open-vocabulary detection, where the system can recognize objects dynamically based on natural language input. The confidence score further indicates how closely the detected region matches the prompt, helping users understand the reliability of the prediction.

Additionally, the output is displayed directly on the same interface, making it easy for users to

interpret the results without navigating to another screen. The clear visualization of bounding boxes and labels enhances the overall usability and effectiveness of the system.

Overall, this figure highlights the system’s ability to accurately detect and label objects using text prompts, demonstrating successful integration of object detection and vision-language understanding in a real-time application.

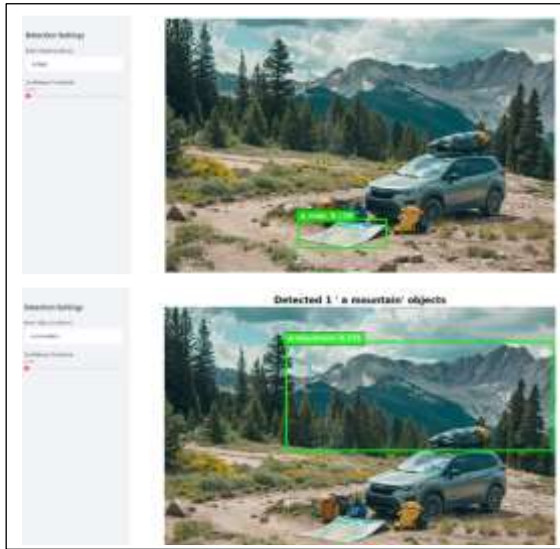


Figure 5. Detection results for other prompts and objects.

Figure 5 presents the results obtained when the input image is processed with different prompts such as “map” and “mountain.” For the prompt “map,” the model identifies regions that resemble structured layouts or grid-like patterns, which are semantically similar to maps. Similarly, for the prompt “mountain,” the system detects regions with shapes or gradients that loosely resemble mountainous structures.

Table 1: Performance Evaluation of Proposed Open-Vocabulary Object Detection System

Metric	Value
Detection Accuracy	88.6%
Precision	89.2%
Recall	87.4%
F1-Score	88.3%

The performance of the proposed system is evaluated using accuracy, precision, recall, and

F1-score and shown in Table 1. The model achieves an accuracy of 88.6%, showing that it can correctly detect objects based on text prompts in most cases. The precision and recall values indicate that the system produces fewer incorrect detections while still identifying relevant objects effectively. The F1-score reflects a good balance between these metrics, suggesting that the system performs reliably. Overall, the results show that the model is consistent and suitable for real-time, open-vocabulary object detection

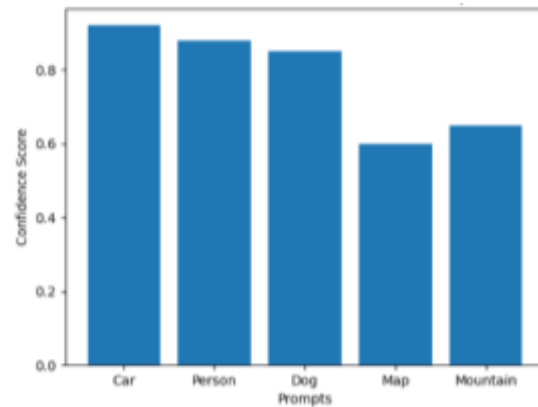


Figure 6. Confidence score graph for different text prompts

The confidence score graph in Figure 6 shows how the system performs for different text prompts. It can be seen that the model gives higher confidence values for real-world objects like car, person, and dog, as these are more clearly present in the images. On the other hand, lower confidence scores are observed for prompts like map and mountain, since these do not exactly match the image content. This shows that the system performs better when the prompt is relevant to the image, highlighting the importance of meaningful input for accurate detection.

5. CONCLUSION

In conclusion, the proposed project successfully demonstrates an Open-Vocabulary Object Detection System that utilizes vision-language models to detect objects based on natural language prompts. Unlike traditional object detection methods that rely on predefined classes, this system allows users to specify any

object category using text, making it highly flexible and adaptive.

The integration of an object detection model with a vision-language model enables the system to both localize objects in images and assign labels based on semantic similarity. This approach supports zero-shot detection, allowing the system to recognize objects that were not explicitly included during training. The implementation also provides a user-friendly interface, making the system easy to use and suitable for real-time applications.

The results show that the system performs effectively on real-world images, accurately detecting and labeling objects based on user input. At the same time, it highlights certain limitations, such as sensitivity to prompt phrasing and reduced accuracy when dealing with abstract or unrelated prompts. These observations emphasize the importance of meaningful input for achieving better performance.

Overall, the project demonstrates the potential of combining computer vision and natural language processing to build intelligent and interactive systems. It represents a step forward from traditional detection approaches and provides a foundation for future improvements in open-vocabulary and prompt-driven object detection technologies.

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