Report

Tactical Recon: Valorant Mentor based on Object Detection Techniques

1. Introduction

In the competitive realm of Valorant, mastering gameplay mechanics and map knowledge is paramount for new players striving to excel. Our project focuses on developing a personalized training solution, the “Tactical Recon" designed to assist novices in learning maps and gameplay mechanics conveniently. By harnessing machine learning and object detection techniques, our platform provides real-time hints and guidance tailored to the player's immediate context. Leveraging advanced algorithms to analyze gameplay footage, the trainer serves as a virtual mentor, offering actionable insights and strategic advice to empower players on their journey to mastery. Through the Tactical Recon: Valorant Mentor, we aim to democratize access to high-quality training resources, accelerating the learning curve for new players and fostering a deeper understanding of Valorant's dynamics and tactics.

2. Methodology

We opted to utilize YOLO v8 as our model of choice for object detection in the Tactical Recon: Valorant Mentor project. YOLO v8 was selected after careful evaluation and comparison with other models due to its capability to provide near real-time detection performance, a critical requirement for our project's objectives. Instead of training the model from scratch, we chose to leverage the efficiency of transfer learning by utilizing a pre-trained instance of YOLO, specifically YOLO nano, and fine-tuning it on our custom dataset.

Given the unavailability of a suitable pre-existing dataset, we undertook the task of creating our own dataset. This process involved extracting frames from multiple gameplay recordings of Valorant and meticulously annotating each image manually using online tools such as Roboflow. The dataset, comprising approximately 2000 images, encompassed 16 distinct classes relevant to Valorant gameplay elements. Prior to training, the dataset was split in the ratio of 70-30 between the training and validation sets to facilitate model evaluation and prevent overfitting.

Subsequently, the annotated data underwent preprocessing for training, primarily involving the scaling of each image's resolution to 640x640 pixels to expedite the training process while maintaining detection accuracy. The model training was conducted for 25 epochs on the Google Colab research platform, leveraging its computational resources. Once trained, the weights of the model were exported for deployment on personal systems, facilitating the demonstration of the Tactical Recon: Valorant Mentor.

3. Challenges Faced

Our project encountered several significant challenges throughout its development. Initially, the unavailability of a suitable dataset posed a major hurdle, necessitating the creation of our own dataset from scratch. This undertaking involved extracting frames from multiple Valorant gameplay recordings and meticulously annotating each image manually, a time-consuming process that required considerable effort.

Following the dataset creation, the next challenge arose in selecting a model that would offer optimal performance for our object detection task. We conducted extensive research and experimentation to identify the most suitable model architecture, weighing factors such as detection accuracy, speed, and compatibility with our dataset.

Additionally, handling class imbalance within the dataset emerged as a significant concern. Certain classes within the dataset were underrepresented, leading to potential biases during model training. We addressed this challenge through techniques such as class weighting and data augmentation to ensure balanced representation across all classes.

Furthermore, the compute-intensive nature of training an object detection model presented logistical challenges. Initially, we struggled to find a system with hardware capable of supporting the computational demands of training. After exploring various options, we ultimately settled on utilizing the Google Colab research platform, which provided the necessary computational resources to train our model efficiently.

4. Learnings

The development of the Tactical Recon: Valorant Mentor project provided invaluable learning experiences across various aspects of machine learning and computer vision. Firstly, we gained insights into the preprocessing steps involved in handling image-based datasets, including resizing, color correction, and rotation. These preprocessing techniques were crucial for enhancing the quality of the dataset and improving model performance.

Additionally, we learned effective strategies for handling class imbalance within image-based databases. Techniques such as class weighting and data augmentation proved instrumental in addressing this challenge, ensuring a balanced representation of classes during model training.

Furthermore, we gained a deeper understanding of how changes in the resolution of images impact training speed and detection accuracy. Experimentation with different image resolutions allowed us to optimize training efficiency while maintaining detection performance.

Moreover, our experience with the YOLO (You Only Look Once) model was particularly enlightening. We delved into the functionality and features of YOLO, exploring its capabilities in object detection tasks and fine-tuning its parameters to suit our project requirements.

Lastly, the project provided a wonderful opportunity to work with the OpenCV library, a powerful tool for computer vision tasks. From extracting frames from videos to visualizing the output of the model by highlighting detected spots within each frame, OpenCV proved indispensable in the development and deployment of the Tactical Recon: Valorant Mentor.

5. Results

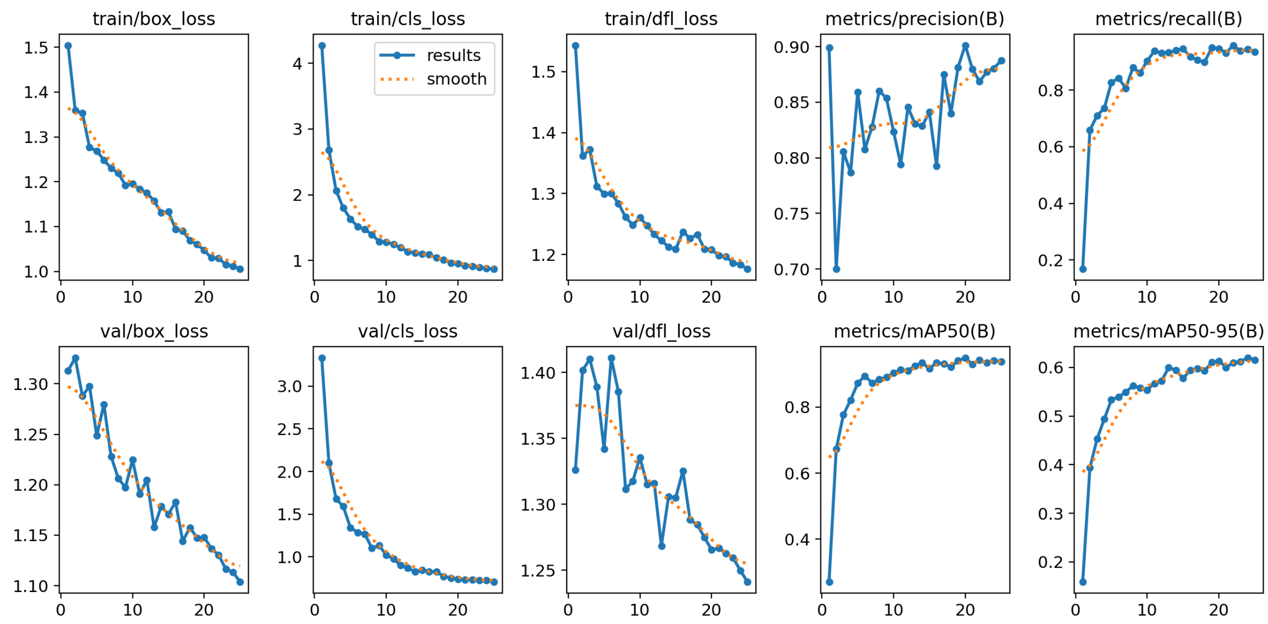

Fig 1 - Training Results

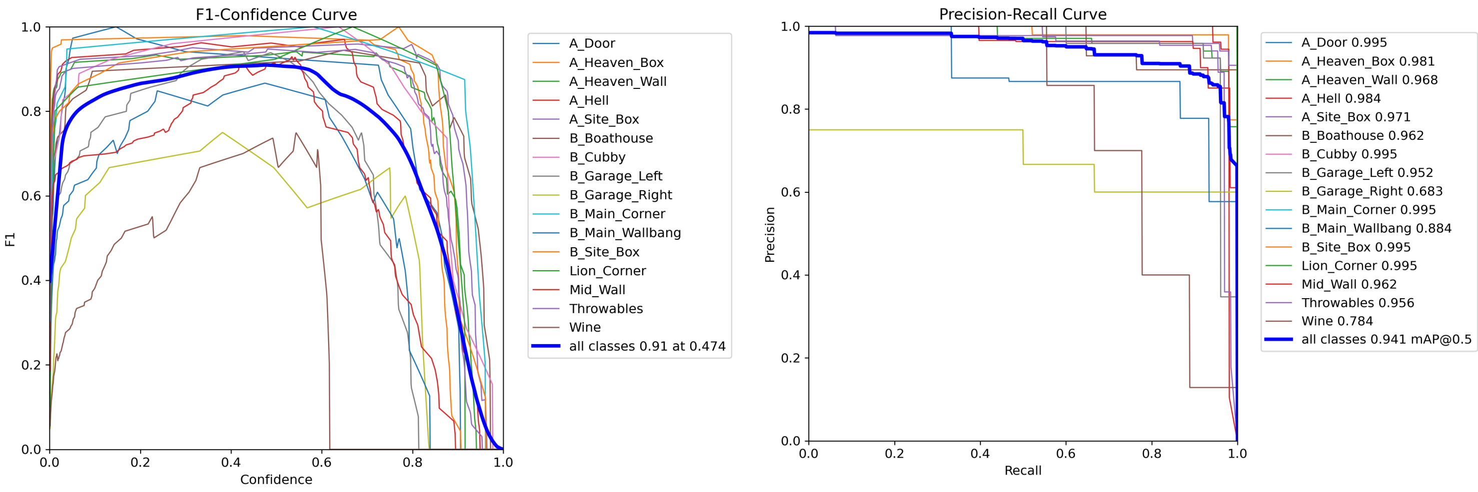

Fig 2 - F1-Confidence Curve and Precision-Recall Curve

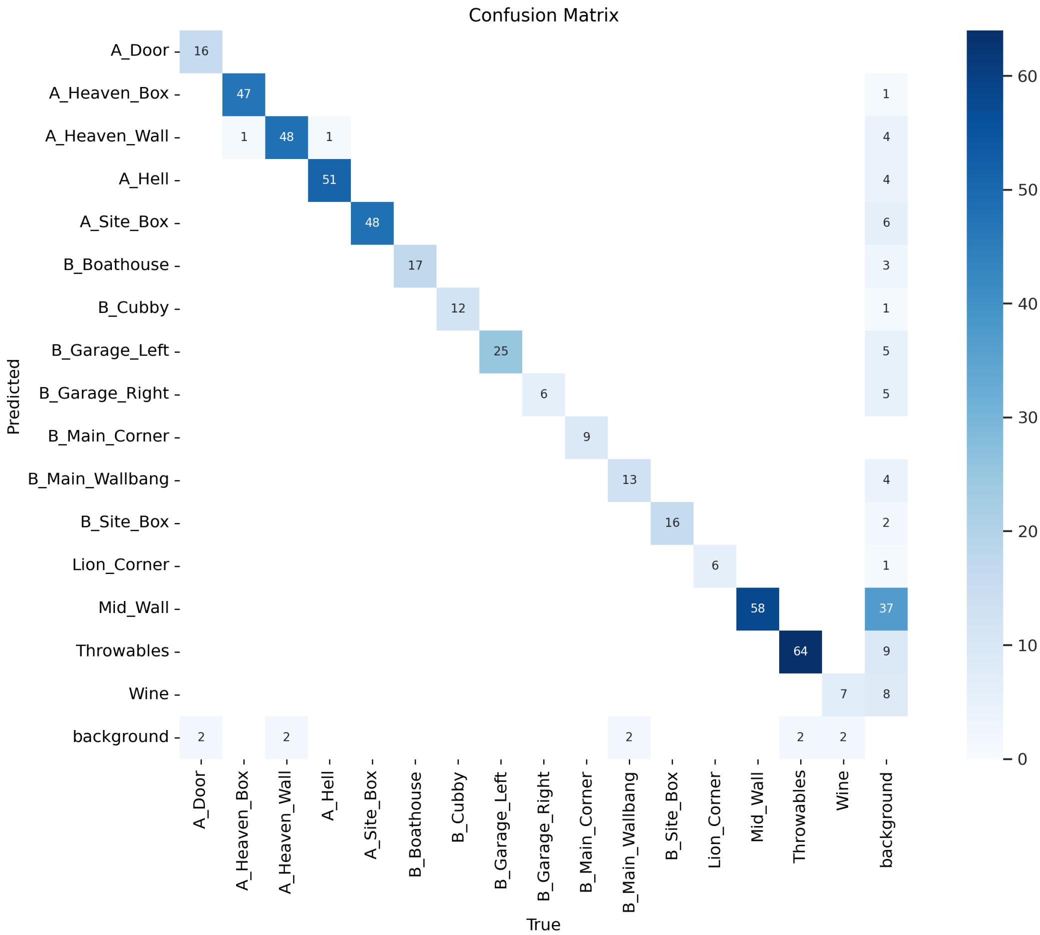

Fig 3 - Confusion Matrix

mAP50 (Overall) = 0.941

mAP50-95 (Overall) = 0.619

Precision (Overall) = 0.881

Recall (Overall) = 0.943

Our model's performance over the training period can be evaluated through various metrics as illustrated in the graphs. The loss graphs exhibit a consistent decrease, indicating an improvement in the model's accuracy in object localization and classification. The precision and recall graphs oscillate initially but show a trend towards stabilization, suggesting that the model's predictive reliability is solidifying as it learns. Lastly, the mean average precision for both the 50% IOU threshold and the cumulative 50-95% IOU thresholds demonstrate a steady increase, signifying a refined ability of the model to accurately detect and classify objects within our dataset. These trends collectively illustrate the successful training and validation of our object detection model, reflecting its potential efficacy in real-world application.

6. Conclusion

The Tactical Recon: Valorant Mentor project has successfully integrated advanced machine learning techniques to enhance gameplay for Valorant players, achieving impressive accuracy in real-time tactical guidance. Through overcoming significant challenges in data preparation and model training, we have not only improved gameplay outcomes but also set a new standard for interactive gaming tools. Looking ahead, we are excited to expand this technology to broader applications, further exploring its potential to transform interactive gaming and training experiences. This project marks a significant step forward in the practical application of AI in enhancing gaming strategies and player engagement.