Synthetic-to-Real Transfer Learning for League of Legends Minimap Object Detection (Student Abstract)

Younsung Lee, Yujin Kim, Kyung-Joong Kim*

Dept. of AI Convergence, Gwangju Institute of Science and Technology (GIST), Gwangju, South Korea
{lusung33@gm.gist.ac.kr, ujkim4417@gm.gist.ac.kr, kjkim@gist.ac.kr}

Abstract

Esports is growing rapidly, yet the data available to researchers is limited due to the game company policies. Consequently, vision-based approaches utilizing game screens are gaining attention as a practical alternative. We focus on the League of Legends minimap and address the challenges of champion detection when extracting champion information from the minimap. The challenges in this domain include small objects, rapid movement, and frequent occlusions. We propose a transfer-learning-based object detection pipeline that combines synthetic data with a subset of replay data. Synthetic data enables the rapid generation of diverse scenarios and improves training scalability, while replay data reduces the data distribution gap. This approach achieves 0.588 mean average precision, improving over replay-only by 0.261 and synthetic-only by 0.312, with 6.4 ms latency. Furthermore, we constructed a dataset encompassing all champions, enabling comparative analysis of detection models and supporting reproducible benchmarking for various application studies.

Introduction

Esports has emerged as a rapidly expanding industry, marked by its inclusion as an official discipline in the Asian Games (Committee 2023), international tournaments drawing millions of viewers (Charts 2025). As the industry continues to grow, academic interest in esports has also increased significantly.

Nevertheless, esports research faces a major obstacle: access to game data is often restricted by several reasons, such as publishers' policies (Korotin et al. 2019). In such limited environments, collecting information directly from game screens through computer vision methods provides a scalable and widely applicable alternative (Trivedi et al. 2023). Our work concentrates on League of Legends (LoL), one of the most popular esports games. The game's minimap condenses essential in-game information, and careful analysis of this interface can yield diverse forms of data.

Previous studies (Duay 2023; Kim et al. 2025) have explored the use of object detection models for minimap analyses, but accurate detection in minimap is difficult since minimap elements are small, move quickly, and frequently overlap. These methods often rely on manual labeling or use datasets that include only a subset of champions. It can lead to consuming substantial resources and not proper to fair and comprehensive evaluation.

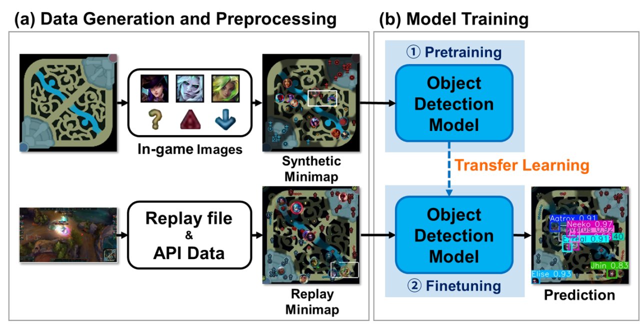

Figure 1: Pipeline overview

To address these issues, we propose a transfer-learning-based object detection pipeline that leverages synthetic minimap data resembling real matches together with a small portion of real replay minimap data. In addition, we construct a replay dataset covering all champions, which enables fair model assessment and provides a reproducible benchmark for subsequent research on champion detection.

Method

The pipeline we propose in Figure 1 focuses on transfer-learning-based object detection in environments where 1) data is limited, 2) backgrounds are static with high visual similarity, and 3) objects are small and frequently overlap. Furthermore, we propose to construct a dataset containing all champions for the training and evaluation process.

Dataset

We constructed two types of datasets to support champion detection on the LoL minimap. Synthetic dataset were generated using publicly accessible Riot Games' Data Dragon resources (Riot Games 2025a), including champion icons, buildings, and objects. Buildings and objects were placed at fixed positions, while champions were randomly positioned to simulate diverse scenarios, with augmentations such as

	N games	*N* images	*N* instances
Train	74	2043	18533
Val	43	1159	10593
Test	73	2048	18615

Table 1: Information for replay dataset

occlusion, blur, and color shifts applied to increase robustness. Additional elements like viewport, fog of war, and ping signs were incorporated to improve visual similarity to real matches.

For replay dataset, we collected high-level ranked games from the KR server using the official Riot Games client. Minimap regions were cropped from replay videos, and match logs and timeline data were obtained via Riot Games' API (Riot Games 2025b) to produce ground-truth champion positions. Frames were aligned with timeline data, filtered for missing pairs, and then split into train, validation, and test sets. This design allows the dataset to both mitigate the domain gap with synthetic dataset and fairly evaluate the model.

Model Training

We adopted Ultralytics RT-DETRv2 (Lv et al. 2024; Jocher and Qiu 2025) as the detection model, chosen for its real-time inference capability and robustness to occlusion. Training is conducted in two stages transfer learning: The first step is pretraining using a synthetic dataset, and the second step is finetuning using a replay dataset.

Experiment

Dataset

We generated 200,000 synthetic images and collected 190 replays from 25.7 to 25.15 patch versions, resulting in 5,250 image-label pairs. The dataset includes all 170 champions as of 25.7 patch version, and the games were split at the game level to ensure full champion coverage. Detailed information about the replay dataset is provided in the Table 1. We hope this dataset will serve as a benchmark for further research, and we can make our dataset publicly available upon requests.

Model Training

Pretraining was conducted on the synthetic dataset using AdamW (lr0 = 0.0002, lrf = 0.05, weight decay = 0.0003) on NVIDIA GeForce RTX 4090, and finetuning on the replay dataset employed lower initial learning rates and weight decay (lr0 = 0.00005, weight decay = 0.00005) on NVIDIA GeForce RTX 3070. Due to the high visual similarity in this domain, we applied only a slight HSV augmentation and excluded other augmentations both pretraining and finetuning.

Evaluation

Model performance was evaluated using mean Average Precision (mAP), computed over Intersection over Union (IoU) thresholds from 0.50 to 0.95 with a step size 0.05, denoted as mAP@[.50:.95].

Name	**mAP@[.50:.95]**
Synthetic Dataset Only	0.276
Replay Dataset Only	0.327
Replay Dataset Only (COCO Pretrained)	0.517
Ours (COCO Pretrained)	0.568
Ours (With Augmentation)	0.570
Ours	**0.588**

Table 2: Results of models

Result & Discussion

Based on the results in Table 2, our model achieved **the highest mAP@[.50:.95] at 0.588**, representing an absolute improvement of **+0.261 (+79.6%)** over the model trained solely on the replay dataset and **+0.312 (+113.2%)** over the model trained on the synthetic dataset. Additionally, we performed ablation studies on the COCO dataset pretraining (Lin et al. 2014) and image augmentation. Models initialized with COCO-pretrained weights exhibit lower performance both replay dataset only and our method. In addition, unlike general object detection, we can notice that, applying standard augmentations such as rotation, flipping, scaling, or cropping results in degraded performance. Furthermore, in terms of real-time performance, the end-to-end detection required 6.4 ms per image ($\approx$0.0 ms preprocess, 5.9 ms inference, 0.5 ms postprocess, in NVIDIA GeForce RTX 3070), corresponding to 156 FPS.

These results demonstrate that our approach effectively combines the robustness of synthetic data with the realism of replay data, substantially reducing the domain gap between two domains and improving detection performance. Additionally, standard augmentations reduce discriminability rather than improve generalization, showing that conventional augmentation is detrimental in this domain. Furthermore, features learned from natural images dataset like COCO are poorly suited for icon-style graphics in minimap champion detection, underscoring the necessity of domain-specific synthetic pretraining. Moreover, given that real-time applications typically require 60 FPS ($\approx$16.7 ms), our method leaves approximately 10.3 ms of headroom per frame, confirming that the proposed pipeline can be seamlessly integrated with other real-time modules such as tracking or rendering.

Conclusion

This study demonstrated that a simple method of transfer learning with large-scale synthetic minimap data and limited real replay minimap data can effectively reduce the domain gap in League of Legends champion detection. Our work addresses the challenge of real-time object detection in environments with limited data, high visual similarity, and small, frequently overlapping objects, and we believe that our dataset can serve as a benchmark for future research. Future work includes integrating additional modules, such as tracking and rendering, to enable broader applications.

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