# Digitally Removing Markers for Enhanced Object Detection: Evaluating Marker-Free Datasets for Real-World Applications

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# 1 Scope of the Project

To digitally remove visible markers (e.g., AprilTags) from annotated datasets and evaluate their impact on object detection performance. This research addresses a critical limitation in datasets that rely on markers for ground truth generation, which often restricts their applicability in markerless real-world scenarios.

**The problem in Industry:**

- Datasets annotated using visible markers like AprilTags are widely used for precise localization and ground truth generation in fields such as robotics, augmented reality, and autonomous systems. However, these markers are not present in real-world environments, leading to poor generalization when neural networks trained on such datasets are deployed in markerless scenarios.

- Overfitting to markers during training can make neural networks rely on marker positions as visual cues, which compromises their adaptability to natural scenes.

**Limitations of Current Solutions:**

- Existing solutions typically focus on creating new marker-free datasets However, these approaches are time-consuming, and resource-intensive, and do not leverage the valuable annotated data already available in marker-based datasets.

- Marker removal methods are often either manual or simplistic, lacking the robustness to create realistic marker-free datasets for training.

**Real-World Applications:**

- Autonomous systems and robotics rely heavily on datasets for object detection and pose estimation, where markers like AprilTags are often used in controlled test environments. By removing the dependency on such markers, the research can enable these systems to operate effectively in uncontrolled, real-world settings.

- Other applications include augmented reality systems, where transitioning from marker-based datasets to marker-less detection improves user experiences in diverse environments.

The project aims to address this issue by digitally removing the markers and seamlessly blending the image augmentation. This will be followed by a quantitative evaluation.
**Qualitative Evaluation:** A neural network will be trained on the digitally enhanced dataset and benchmarked against other datasets to assess whether the marker-based dataset provides comparable performance once the markers are removed. This will also determine whether the removal process introduces artifacts from which the neural network inadvertently learns.
This approach will enable efficient reuse of existing marker-based datasets for training object detection models better suited for real-world, markerless applications.

# 2 Optional Objectives

**Domain Adaptation:** To develop domain adaptation techniques that enable the smooth transition of models trained on modified marker-based datasets to fully marker-less datasets.

**Automation of the Marker Removal Pipeline:** To create an automated pipeline for removing markers and generating marker-free datasets with minimal manual intervention.
**Application in Real-World Scenarios:** To validate the trained object detection models in real-world applications, such as autonomous robots or vision systems, to demonstrate the feasibility of marker-free object detection in uncontrolled environments.
**Comparative Study of Marker vs. Marker-Free Models:** To compare the accuracy and generalization capabilities of object detection models trained on the original marker-based datasets versus those trained on the digitally modified datasets.

## 3 Potential obstacles

**Lighting Variations and Marker Visibility:** Managing challenges arising from diverse lighting conditions and shadows that may affect how markers are captured in the dataset, leading to inconsistencies in the marker removal process.
**Perspective Distortions and Angles:** Addressing perspective distortions and varying angles at which markers are captured, may complicate the removal process and create artifacts that affect the quality of the modified datasets.
**Edge Smoothness and Artifact Reduction:** Ensuring smooth transitions in the regions where markers are removed to prevent visual artefacts or unnatural textures that could confuse object detection models.
**Loss of Context in Overlapping Areas:** Handling scenarios where markers overlap with objects of interest, potentially causing a loss of contextual information and affecting object detection accuracy.

## 4 Starting Position

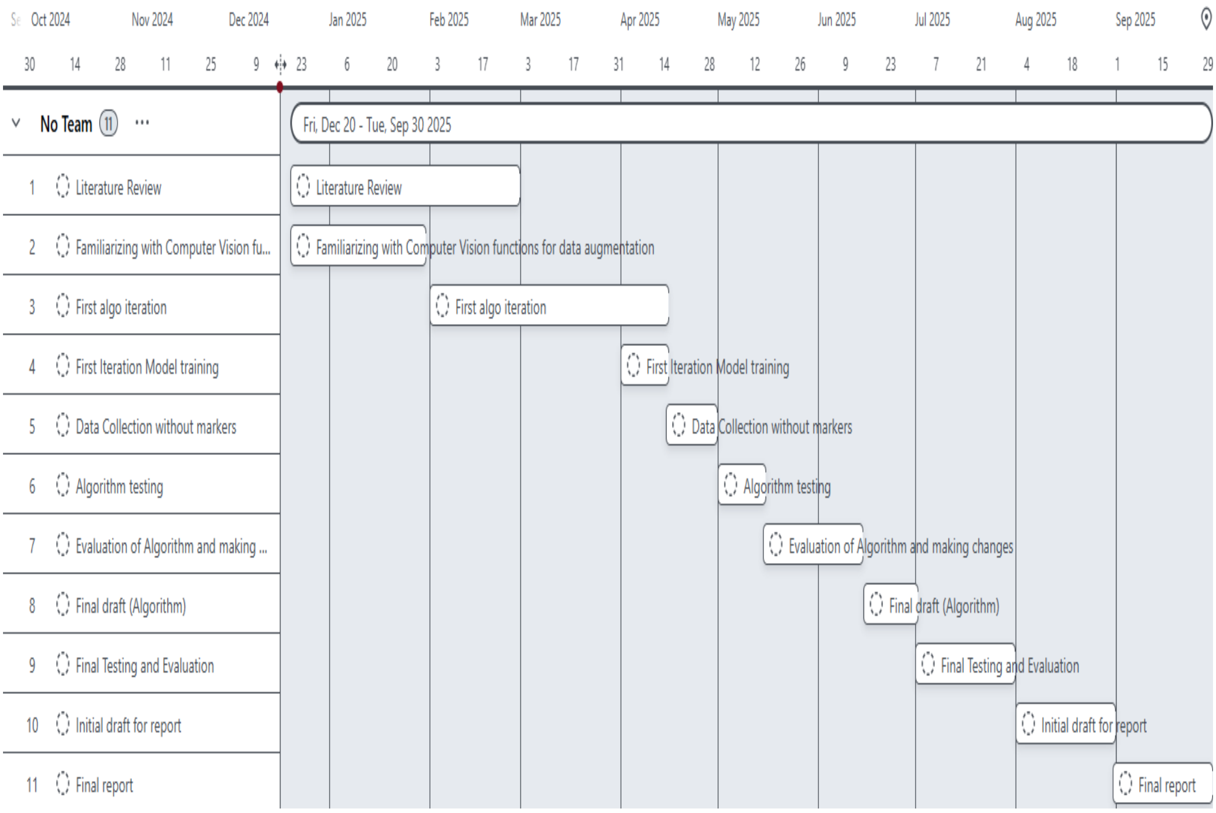
With a background in computer vision, image augmentation, and object detection, I am well-positioned to undertake this project. My academic journey and professional experiences have equipped me with the knowledge and practical skills to handle complex challenges in algorithm development, data processing, and system integration.
I have worked extensively in the automotive industry, developing and implementing algorithms for vehicle control units and battery management systems, and contributing to projects on control strategies. My published research on adaptive SOH estimation using deep learning highlights my capability to combine theoretical knowledge with innovative applications.
These experiences have instilled in me a deep understanding of the level of work, effort, and precision required to achieve meaningful outcomes. This project aligns perfectly with my expertise, allowing me to extend my skills further while making tangible contributions to the field of computer vision and autonomous systems. My starting position reflects my readiness to apply advanced techniques and tools to address the outlined objectives and tackle potential challenges effectively.
I've also attached the link for the GitHub project where I'll be updating my status of the projects and the GitHub repository will be uploaded here.
GitHub Project Link or directly visit the following URL: `https://github.com/users/KaranSankla/projects/4`.

# 5 Source Code

The source code and hardware setup utilized in this project are identical to those employed in the RoboTeach project, which is currently in use at the lab.

Figure 5.1: Setup used for data recording in the RoboTeach project including markers

# 6 Timeplan




The project is scheduled to begin in December 2024 and will run through September 30, 2025, spanning a total of approximately 9 months.

The timeline is divided into multiple phases:

**Initial Phase (Dec 2024 – Feb 2025:)** Literature Review and familiarity with Computer Vision Functions for Data Augmentation will establish a strong foundation for the project.

**Development Phase (Feb 2025 – May 2025):** Key tasks include the First Algorithm Iteration, Model Training, and Data Collection without Markers, forming the core of the project development.

**Testing and Refinement Phase (May 2025 – Jul 2025):** This phase focuses on Algorithm Testing, Evaluation of the Algorithm, and implementing necessary refinements to improve the overall performance.

**Finalization Phase (Jul 2025 – Sep 2025):** The project concludes with the Final Draft (Algorithm), Final Testing and Evaluation, and the preparation of the Initial Draft for the Report followed by the Final Report.

THANK YOU!