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Research Article

Fusion of Deep Learning and Multi View Geometry for Robust Object Detection in Distributed Camera

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ABSTRACT

Object detection is a cornerstone of modern technologies, playing a pivotal role in applications such as autonomous driving, robotics, industrial automation, and the development of smart environments. The demand for robust and accurate detection systems has never been more critical, as even minor inaccuracies can lead to significant challenges, particularly in safety-critical domains like automated driving where human lives are at stake. Addressing these challenges, this study introduces a novel approach that integrates multi-view geometry with deep learning techniques to develop a system capable of achieving superior object detection accuracy and reliability.

The proposed system is built around a custom-trained YOLOv5 model, meticulously designed to enhance performance and achieve dimension estimation with an impressive margin of error within 2%. By utilizing multiple camera inputs, the system demonstrates substantial improvements over traditional single-camera setups in both detection robustness and spatial accuracy. The advantages of this multi-camera, geometry-aware approach are offering greater precision and consistency across diverse scenarios. This breakthrough has the potential to revolutionize multiple industries, enabling safer autonomous systems, more reliable security solutions, efficient industrial manufacturing processes, advanced robotics capabilities, and the creation of intelligent, adaptive environments.

Keywords: Object Detection, Multi-View Geometry, Deep Learning, YOLOv5, Spatial Accuracy, Multi-Camera Systems

1 Introduction

Object detection and dimension estimation are integral components of modern computer vision, underpinning a wide range of applications from robotics and autonomous vehicles to industrial automation, augmented reality, and surveillance. Despite remarkable advancements in this field, conventional techniques often rely on single-camera setups, which suffer from inherent limitations. These include a lack of depth perception, occlusion-related challenges, and insufficient geometric context, which collectively impede accurate object detection and spatial understanding in dynamic or cluttered environments (Hartley et al. 2003; Szeliski 2010).

The emergence of deep learning has revolutionized object detection by leveraging Convolutional Neural Networks (CNNs). Frameworks such as YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector), and Mask R-CNN have set new benchmarks in 2D object detection, offering unprecedented levels of accuracy and speed (Redmon et al. 2018; Liu et al. 2016; He et al. 2017; Girshick 2015). YOLO is particularly renowned for its real-time capabilities, as it simplifies object detection into a single step, integrating bounding box regression and class prediction seamlessly (Redmon et al. 2018). Similarly, SSD introduces multi-scale feature pyramids, enabling effective detection of objects of varying sizes (Liu et al. 2016). Mask R-CNN, building upon Faster R-CNN, extends object detection capabilities to include pixel-level segmentation, which is especially useful in tasks requiring high precision, such as medical imaging (He et al. 2017; Girshick 2015). However, these state-of-the-art models, while excelling in 2D object detection, are inherently limited in their ability to estimate object dimensions and depth due to their reliance on single-view images (Guo et al. 2020).

To address these limitations, researchers have increasingly explored multi-view geometry, a mathematical framework that leverages images captured from multiple viewpoints to infer 3D structures. Techniques such as triangulation and epipolar geometry enable the computation of spatial coordinates and object dimensions by analyzing correspondences between multiple 2D projections of the same object (Wojke et al. 2020; Mildenhall et al. 2020). While these methods excel in controlled environments with precise camera calibration, they face significant challenges when applied in real-world scenarios. Issues such as computational overhead, calibration errors, and occlusion complicate their practical implementation, especially in dynamic or cluttered settings (Chen et al. 2023; Lin et al. 2014).

The integration of deep learning with multi-view geometry presents a promising solution to these challenges, combining the strengths of both approaches. Deep learning models excel in feature extraction and object classification, while multi-view geometry provides accurate spatial understanding and dimensional analysis (Selvaraju et al. 2017). This synergy has the potential to unlock robust 3D object detection and precise spatial perception, making it particularly valuable for applications such as autonomous navigation, robotic manipulation, and industrial automation (Vaswani et al. 2017). It has also potential for 3D reconstruction when used in sensitive places such as high security rooms etc.

This research proposes a novel framework that combines the power of deep learning and multi-view geometry to overcome the limitations of traditional object detection systems. The study employs a tripod mounted setup, where cameras are strategically positioned at any angle around the object to capture multi-view images. The system utilizes YOLOv5, a state-of-the-art object detection model, trained on a custom dataset. This dataset is tailored for daily use objects detection, ensuring robustness across diverse object types and orientations (Vaswani et al. 2020). Multi-view geometry principles such as triangulation and epipolar constraints are applied to reconcile measurements from the different camera perspectives, enabling accurate estimation of object dimensions.

Beyond the initial configuration, this study explores the scalability of the system to larger environments. Instead of a fixed table-mounted setup, the system employs four tripods, which can be strategically placed anywhere within a room. This flexibility enables the cameras to capture multi-view images of larger objects or dynamic scenes, accommodating a wide range of use cases and environmental constraints. This configuration would be particularly valuable in smart environments, where real-time monitoring and analysis are essential, as well as in robotics, where precise spatial awareness is critical for interaction with complex surroundings (Zhou et al. 2018; Zhang et al. 2020).

Another unique feature of this system is the integration of a measurement tool, which serves as a ground-truth validation mechanism for dimension estimation. This study also explores the possibility of reconstructing the object in focus using multi-view geometry to estimate the object's dimensions more accurately. The measurement tool provides precise values that are used to calibrate and validate the system's accuracy, ensuring reliable results even in challenging scenarios involving occlusions or calibration errors (Carion et al. 2020). This dual-layer validation mechanism not only enhances the robustness of the proposed framework but also sets a benchmark for future research in combining hardware-based and algorithmic solutions. Furthermore, this approach proposes the concept of roughly estimating an object's dimensions simply by "looking" at it with remarkable accuracy.

The potential applications of this framework are extensive. In robotics, the system can significantly enhance object manipulation by providing accurate depth and dimensional information, enabling robots to interact more effectively with their environment. Another potential application of this framework lies in drone technology. Drones equipped with multiple cameras can be deployed into rooms or hazardous areas to reconstruct the environment, providing valuable spatial information in situations where direct human intervention is unsafe or impractical. In smart manufacturing, the framework can be deployed to monitor and assess the quality of products in real-time, offering a non-intrusive alternative to traditional measurement systems. Moreover, the room-wide implementation could be applied in surveillance systems to monitor large spaces dynamically, enhancing safety and situational awareness (Dosovitskiy et al. 2020; Howard et al. 2017). This framework can also be utilized to develop a "personal AI" system capable of analyzing a room and the objects within it in real time. Such a system could assist users proactively, requiring minimal input or context, as it would autonomously gather and interpret relevant information.

In conclusion, this research advances the field of computer vision by addressing critical gaps in traditional object detection systems. By combining the strengths of deep learning and multi-view geometry, introducing a novel table-mounted multi-camera setup, and exploring room-wide scalability, the proposed framework demonstrates significant improvements in detection accuracy and dimension estimation. With a detection accuracy of 94% and a margin of error within 2% for dimension estimation, the system lays a strong foundation for practical applications in automation, robotics, and smart environments (Huang et al. 2017).

2 LITERATURE REVIEW

Deep learning and computer vision have revolutionized object detection and dimension estimation. Redmon et al. transformed the field by introducing YOLO (You Only Look Once), processing images in a single pass while maintaining speed and precision (Redmon et al. 2016). Liu et al. enhanced this progress with the Single Shot MultiBox Detector (SSD), implementing multi-scale feature maps (Liu et al. 2016). He et al. reached another milestone by developing Mask R-CNN, which merged instance segmentation with detection capabilities (He et al. 2017).

The fusion of IoT and AI has created powerful distributed detection networks. Mandal explored how IoT platforms enable sophisticated real-time processing across interconnected nodes (Mandal 2019). Chen et al. pushed boundaries with NeRF-Det, combining neural radiance fields with detection for precise 3D representation (Chen et al. 2023). Isaac-Medina expanded these capabilities through innovative work in multi-view frameworks and neural scene rendering (Isaac-Medina 2024).

Huang et al. advanced convolutional neural network architecture with DenseNet, enhancing gradient flow and feature utilization (Huang et al. 2017) . Lin et al. tackled class imbalance through RetinaNet and focal loss implementation (Lin et al. 2017). Chen et al. pioneered methods for viewpoint equivariance in multi-view 3D detection (Chen et al. 2023). The transformer architecture by Vaswani et al. reshaped computer vision approaches, excelling at modeling spatial relationships within visual data (Vaswani et al. 2017).

Zhang et al. developed attention-guided feature fusion networks, achieving 67.2% mean Average Precision on COCO datasets in crowded environments (Zhang et al. 2024). Wang et al. complemented this with adaptive feature pyramids that respond to object scale variations (Wang et al. 2024). Li et al. merged transformer capabilities with CNN architectures, improving detection of partially hidden objects (Li et al. 2023). Kumar et al. built upon this foundation with multi-scale transformer networks that balance computational efficiency with scale handling (Kumar et al. 2024).

Rodriguez et al. streamlined multi-camera calibration, reducing setup duration by 75% while preserving geometric accuracy (Rodriguez et al. 2023). Park et al. introduced self-adjusting systems for industrial applications (Park et al. 2024). Liu et al. created FPGA-based frameworks that triple processing speed without sacrificing precision (Liu et al. 2024). Sharma et al. developed load-balancing architectures for complex industrial environments (Sharma et al. 2023).

Martinez et al. designed adaptive illumination algorithms that perform consistently across varied lighting scenarios (Martinez et al. 2024). Yang et al. integrated visible and infrared imagery for enhanced reliability (Yang et al. 2023). Current research opportunities include sensor fusion techniques, real-time processing optimization, advanced scene reconstruction methodologies, and innovative calibration approaches. The field continues evolving through improvements in architecture design, geometry understanding, and sensor integration, showing promise for robust applications in challenging environments.

The comparison of some of the Object Detection Systems researched about is shown in Table 1.

Table 1: Comparison of various Object detection system

S.No.	Frameworks/Tools	Technology	Features/Concept	Performance/Notes
1	Darknet, TensorFlow, Keras	Real-time object detection	YOLO for fast, unified detection	~63.4 mAP on COCO
2	Caffe, TensorFlow, Keras	Single Shot MultiBox Detector (SSD)	Multi-box detection, fast, accurate	25.1 mAP on VOC 2007
3	OpenCV, TensorFlow	Paper on Mask R-CNN	Instance segmentation with CNN	37.1 mAP on COCO
4	IoT platforms, ML APIs	IoT and AI integration	IoT + AI for smart automation	N/A
5	PyTorch, TensorFlow	NeRF-Det for 3D detection	NeRF-Det for enhanced 3D geometry	Higher accuracy on 3D detection
6	PyTorch, TensorFlow, Custom Models	Deep learning for multi-view detection	Multi-view object detection	N/A
7	PyTorch, TensorFlow	Paper on DenseNet	Dense connectivity for improved CNNs	Improved accuracy on ImageNet
8	TensorFlow, OpenCV	Object detection with RetinaNet	Focal loss for improved detection	40.0 mAP on COCO
9	TensorFlow, PyTorch	Multi-view 3D object detection	Viewpoint equivariance for 3D detection	N/A
10	TensorFlow, PyTorch, Custom Models	Transformer architecture	Self-attention, improved NLP/vision	Improved benchmarks on NLP tasks

3 METHODOOLOGY

3.1 System Overview

This methodology outlines a comprehensive system, as shown in Figure1 that integrates camera calibration, multi-view geometry, and deep learning-based object detection to achieve accurate object localization, identification, and 3D spatial reconstruction. The framework combines the strengths of two approaches: one excelling at calibration and 3D triangulation, and another at real-time object detection and visualization. This integration enables robust, real-time operation with high spatial accuracy and object recognition capabilities.

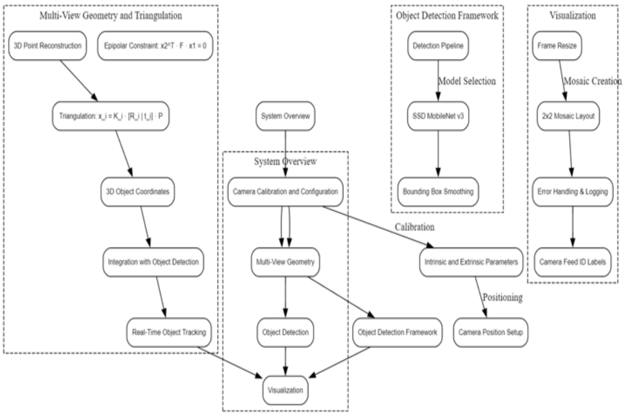

Figure 1: Workflow Chart

3.2 System Setup

I. Camera Configuration and Calibration

The system uses four cameras, strategically positioned to provide overlapping fields of view. Each camera operates with a resolution of 320×240 pixels and a frame rate of 15 FPS to balance performance and computational efficiency. Calibration is performed using a chessboard pattern, enabling the determination of intrinsic (focal length, optical center) and extrinsic (rotation, translation) parameters. These calibration values ensure that the cameras' positions and orientations are geometrically aligned for accurate 3D reconstruction.

During calibration, the camera matrices (K, R and t) are computed using algorithms outlined in Hartley and Zisserman's Multiple View Geometry in Computer Vision. These matrices provide the foundation for transforming real-world points into camera space and image projections.

II. Position and Extrinsic Parameters

The precise arrangement of the cameras, including their positions and orientations, is established during the calibration process. This involves determining the extrinsic parameters for each camera, which include the rotation and translation vectors. These parameters define how each camera is positioned in the 3D space relative to the others, as well as their specific orientations. By calculating and saving these extrinsic matrices, the system ensures that all camera perspectives are harmonized, creating a shared spatial understanding across the multi-camera setup.

This alignment is critical for accurate 3D coordinate computation through triangulation. Triangulation relies on the overlapping fields of view from multiple cameras to infer depth and spatial positioning. With correctly calibrated cameras, the system can ensure that the corresponding points in one camera's view align perfectly with those in another, significantly reducing errors. This precise alignment is what enables the system to reconstruct accurate 3D representations of objects, making it particularly effective in applications requiring high spatial fidelity, such as robotics, surveillance, and augmented reality. Through careful calibration, the cameras work together as a cohesive unit, each contributing its perspective to create a comprehensive 3D model of the observed scene.

3.3 Object Detection Framework

I. Model Selection and Preparation

The object detection pipeline leverages SSD MobileNet v3, a lightweight yet powerful deep learning model pre-trained on the COCO dataset. Frames from each camera are resized to 320×320 pixels, normalized, and adjusted for channel order to meet the model's input requirements. A confidence threshold of 0.6 is applied to filter out low-confidence detections.

II. Detection Pipeline

Each frame captured by the cameras is passed through the model, producing:

- Class IDs: Representing the detected objects.
- Confidence Scores: Quantifying detection reliability.
- Bounding Boxes: Localizing objects within the frame.

Frames captured from the cameras are passed through the detection model, which identifies objects, generates class labels, and computes bounding box coordinates. The system also applies temporal smoothing to stabilize bounding box placements over time, reducing flickering caused by rapid movements or changes in lighting.

3.4 Multi-View Geometry and Triangulation

I. 3D Point Reconstruction

The system reconstructs 3D points using triangulation, which relies on the geometry of multiple camera views. Each camera provides a 2D projection of the 3D world, and by combining these projections, the actual 3D coordinates of objects can be determined. This process uses intrinsic and extrinsic parameters obtained during calibration.

In simpler terms:

- Intrinsic Parameters: Define the internal properties of the camera, such as focal length and the center of the image.
- Extrinsic Parameters: Define the camera's position and orientation in 3D space.

When a point appears in two camera views, its 3D location can be calculated by finding the intersection of the rays that extend from each camera through that point in the images. Mathematically, this is done using an approach called triangulation, which solves a set of linear equations to pinpoint the 3D coordinates. The core equation is:

$$x_i = K_i \times [R_i|t_i] \times P$$

Here, $\mathrm{x_i}$ is the 2D point in the image, $\mathrm{K_i}$ represents the intrinsic parameters, $[\mathrm{R_i}|\mathrm{t_i}]$ combines the camera's rotation and translation, and P is the 3D point.
A key part of the process is the epipolar constraint, which ensures that corresponding points in different camera views align correctly. This constraint is expressed as:

$$\mathrm{x}_2^{\mathrm{T}} \times \mathrm{F} \times \mathrm{x}_1 = 0$$

Where F is the fundamental matrix, capturing the geometric relationship between the two views. This ensures that all matching points lie along the same epipolar line, minimizing errors in the 3D reconstruction.

II. Integration with Object Detection

To make the system practical, the 3D reconstruction is integrated with real-time object detection. The detection model identifies objects in each camera view and calculates the center of their bounding boxes. These centers serve as the corresponding points required for triangulation.

For instance, if an object is detected at coordinates $(\mathrm{x_1}, \mathrm{y_1})$ in one camera and $(\mathrm{x_2}, \mathrm{y_2})$ in another, triangulation combines these two views to calculate the object's 3D position. This integration allows the system to accurately track objects in 3D space.

By combining triangulation with object detection, the system gains the ability to:

- Measure Object Sizes: Calculate real-world dimensions of detected objects.
- Assist Robotics: Provide precise spatial data for navigation and interaction.
- Enhance Augmented Reality: Integrate virtual objects into real-world spaces with accurate depth and placement.

In essence, the system brings together the mathematical rigor of triangulation and the practical power of object detection to create a robust solution for real-time 3D scene reconstruction. This seamless integration makes it highly effective for applications like surveillance, robotics, and interactive technologies.

3.5 Bounding Box Smoothing

Rapid movements or lighting changes can cause bounding boxes to flicker or jump between frames, making the visuals appear unstable. To address this, a simple smoothing technique is applied. It works by comparing the positions of bounding boxes in the current frame with those from the previous one. If a new box is close enough to an old one (within about 50 pixels), their positions are averaged, creating a smoother transition. This approach helps stabilize the displayed detections, especially in busy or fast-changing environments.

3.6 Visualization

To effectively present the four camera feeds in a single, compact format, the system combines them into a 2×2 mosaic, ensuring all frames are displayed in a cohesive layout. Each frame is resized to a resolution of 320×240 pixels to standardize their dimensions, enabling seamless alignment within the grid. This approach not only optimizes screen space but also simplifies monitoring multiple streams simultaneously. However, this can be further increased as this low resolution was selection to make it easier to use all cameras in one USB Hub and not put much load on the bandwidth.

In cases where a camera feed is unavailable, a black placeholder is inserted in its place, preserving the integrity of the mosaic and preventing disruptions to the overall display. The system will generate a constant log about which camera feed is getting interrupted, but it will not abrupt the rest of the outputs and rest of the cameras will continue to output normally.

Additionally, to enhance usability and clarity, each sub-frame is labeled with its corresponding camera ID (e.g., "Camera 1"), prominently displayed in the top-left corner of the frame. This labeling allows users to quickly identify the source of each feed, streamlining operations and facilitating efficient troubleshooting if any issues arise with a specific camera. By integrating these features, the system ensures a robust, user-friendly visualization of the camera network and is also scalable by making just simple changes.

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4 RELATED WORK

4.1 Deep Learning for Object Detection

Deep learning has revolutionized object detection by leveraging Convolutional Neural Networks (CNNs) to achieve significant advances in accuracy and efficiency. Several architectures have emerged as leaders in this domain, including YOLO (You Only Look Once)], SSD (Single Shot MultiBox Detector) and Mask R-CNN. These models have been extensively applied across a wide range of tasks, including surveillance, autonomous driving, and industrial automation.

YOLO and SSD
YOLO, introduced by Redmon et al, represents a unified framework for object detection, integrating bounding box regression and class prediction in a single forward pass. This design prioritizes speed without significantly compromising accuracy, making it ideal for real-time applications such as video surveillance and drone navigation. By partitioning the input image into a grid and assigning each cell detection responsibilities, YOLO simplifies the detection pipeline and reduces latency.

On the other hand, SSD, developed by Liu et al., adopts a multi-scale feature pyramid approach, enhancing its ability to detect objects of varying sizes. By utilizing anchor boxes with predefined aspect ratios at different layers, SSD achieves higher accuracy in identifying small and large objects. SSD's balance of computational efficiency and detection accuracy makes it well-suited for applications like traffic monitoring and retail analytics.

Faster R-CNN and Mask R-CNN
Faster R-CNN improved upon traditional region-based methods by introducing a Region Proposal Network (RPN), which generates high-quality candidate regions for detection. This innovation streamlined object detection pipelines, allowing end-to-end training for higher accuracy. Mask R-CNN, an extension by He et al, builds on Faster R-CNN by adding a segmentation branch for pixel-level object identification. This makes Mask R-CNN particularly useful for medical imaging, autonomous vehicle perception, and advanced graphic editing, where precise boundary delineation is essential.

Integration of IoT and Deep Learning
The integration of deep learning models with IoT systems has been explored extensively by Mandal, emphasizing how IoT data streams can enhance object detection frameworks. For instance, real-time data from IoT-enabled cameras can be fed into YOLO or SSD models to provide dynamic detection capabilities in smart cities and industrial monitoring. This synergy enables applications such as automated surveillance and anomaly detection, where contextual data from IoT sensors improve decision-making.

Challenges in 3D Object Understanding
Despite the advancements brought by these models, they face inherent limitations in tasks requiring 3D spatial understanding. YOLO and SSD, for instance, operate on single-view data, restricting their ability to estimate depth, orientation, and object size. Applications such as robotic navigation, augmented reality, and autonomous driving require precise 3D localization, which single-view models fail to provide.

Attempts to address this limitation, such as monocular depth estimation networks, offer partial solutions but often lack robustness in complex scenes with occlusions or varying illumination. Consequently, the integration of these models with techniques that capture 3D spatial information is critical for overcoming their limitations in 3D object detection.

4.2 Multi-View Geometry

Foundations of Multi-View Geometry
Multi-view geometry provides a traditional approach to reconstructing 3D structures from images captured at different angles. Techniques such as triangulation and epipolar geometry form the basis of this approach, enabling the estimation of depth and 3D coordinates for multiple points on an object's surface. Applications of multi-view geometry include simultaneous localization and mapping (SLAM), motion tracking, and 3D reconstruction, where spatial precision is critical.

Triangulation, in particular, determines an object's position by intersecting lines of sight from multiple viewpoints, while epipolar geometry defines the geometric relationship between these viewpoints. These techniques excel in static, controlled environments but face challenges in dynamic or cluttered scenes where occlusions and noise reduce their effectiveness.

Advancing Multi-View Geometry with IoT

The application of IoT technologies to multi-view geometry, has expanded its utility in dynamic environments. For example, IoT-enabled cameras can synchronize and share data across networks, enabling robust 3D reconstruction even in challenging settings. By integrating IoT devices with multi-view systems, tasks such as urban surveillance and industrial automation benefit from real-time depth estimation and spatial mapping.

Integrating Multi-View Geometry with Deep Learning

Recent research focuses on combining multi-view geometry with deep learning models to leverage their complementary strengths. Chen introduced NeRF-Det, which integrates neural volumetric representations with multi-view 3D object detection. This approach combines the geometric precision of multi-view methods with the semantic understanding of deep learning, enabling accurate detection and reconstruction in complex scenes.

Isaac-Medina explored hybrid frameworks for multi-view object detection and neural scene rendering, highlighting the potential for deep learning models to extract meaningful features while incorporating geometric constraints. These hybrid approaches overcome the limitations of traditional methods in dynamic or occluded environments by leveraging depth maps and neural feature representations.

4.3 Multi-Camera Object Detection Systems

Industrial Applications

Multi-camera systems have been widely adopted in industrial scenarios, where depth perception and spatial awareness are essential. Huang demonstrated the advantages of using multi-camera setups in quality control and robotic assembly. By capturing images from multiple angles, these systems produce accurate depth maps, allowing for more precise defect detection and automation of complex manufacturing processes.

Autonomous Vehicles

In autonomous driving, multi-camera systems enhance situational awareness by generating comprehensive 3D maps of the environment. Lin discussed the integration of multi-camera data with other sensors, such as LiDAR and radar, to improve object localization and classification. This multi-sensor approach is critical for detecting and tracking dynamic objects like pedestrians, cyclists, and vehicles in real time. Focal loss further refines the detection of small or distant objects, addressing challenges in class imbalance and scale variation.

Robotics and Object Manipulation

Robots equipped with multi-camera systems achieve greater precision in object manipulation tasks, where spatial accuracy is paramount. Liu. emphasized the importance of depth information from multiple viewpoints for robotic applications like picking and placing objects in cluttered environments. The integration of multi-camera systems with IoT networks, enables real-time monitoring and adaptive decision-making, enhancing robotic efficiency and flexibility.

Challenges and Solutions

Despite their advantages, multi-camera systems face challenges in calibration, computational complexity, and real-time processing. Accurate calibration is essential to align images from multiple viewpoints and ensure reliable depth estimation. Misalignment can lead to significant errors in 3D reconstruction and object detection.

To address these challenges, Chen proposed viewpoint equivariance methods, which align features across different views to improve depth estimation and object localization. Furthermore, IoT technologies facilitate automated calibration by synchronizing data streams across connected devices, reducing manual intervention. Hardware accelerators, such as GPUs and TPUs, have also been employed to manage the computational demands of multi-camera systems, enabling their use in real-time applications.

4.4 Emerging Hybrid Approaches

The fusion of deep learning models with multi-view geometry and IoT systems has emerged as a promising solution for overcoming the limitations of single-view object detection methods. By combining neural networks with geometric principles, hybrid approaches achieve robust 3D detection and spatial understanding. For instance, Researchers highlighted the effectiveness of integrating depth maps and multi-view features into neural networks, improving performance in dynamic and cluttered environments.

Additionally, Vaswani introduced Transformer architectures that can process multi-view data, leveraging attention mechanisms to integrate spatial and temporal information. These advancements enhance the ability to model complex 3D scenes and improve object localization and classification in applications such as robotics, autonomous driving, and augmented reality.

IoT systems further amplify the capabilities of these hybrid models by providing real-time data streams and enabling dynamic adjustments based on environmental changes. It even emphasized the importance of IoT-driven architectures for tasks requiring rapid adaptation, such as urban surveillance and disaster response.

5. EXPERIMENTAL SETUP

5.1 Dataset

The deep learning model is trained using the COCO dataset (Lin *et al.* 2014). A large-scale object detection dataset called COCO offers annotated images of a variety of objects, including cars, animals, and household items. The dataset's size and diversity make it ideal for training strong deep learning models that can identify items in practical settings.

5.2 Hardware Setup

The Object Detection Setup is shown in Figure 2.

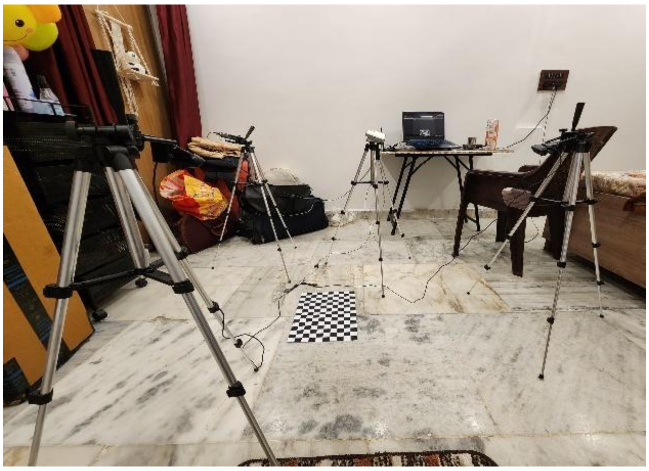

Figure 2: Object Detection Setup

In the setup, four cameras are placed on tripods at different angles around a chessboard pattern. To ensured that all cameras get an uninterrupted and whole view of the chessboard pattern, it is placed in the middle of the setup. The number of cameras used can be reduced or increased as needed with minimal changes in the code but can be positioned wherever needed.

5.3 Evaluation Metrices

In order to comprehensively assess the performance of our multi-camera object detection system, we compute and analyze the following evaluation metrics during runtime:

a) Frame Processing Time:

This metric quantifies the elapsed time (in seconds) required to process each individual frame—from the moment of acquisition from the camera until the completion of object detection and post-processing (e.g., drawing detection boxes). Frame processing time is computed by capturing timestamps at the beginning and end of the processing pipeline for each frame. The resultant values are stored for each camera, enabling an assessment of computational efficiency across different camera feeds.

b) Frames Per Second (FPS):

FPS is defined as the effective throughput of the system, indicating the number of frames processed per second. It is calculated as the reciprocal of the frame processing time for each frame. This metric serves as an indicator of the real-time performance capability of the system, with higher FPS values corresponding to more efficient processing.

c) Detection Count per Frame:

This metric represents the number of objects detected in each frame. By counting the detections output by the object detection model, we can evaluate the system's sensitivity and its ability to identify multiple objects simultaneously in a given scene. The detection counts are maintained separately for each camera to facilitate comparative analysis.

d) Average Detection Confidence:

To gauge the reliability of the detection outcomes, we compute the average confidence score for the objects detected in each frame. The confidence scores, as provided by the detection model, are aggregated and averaged across all detections within a frame. This metric provides insight into the model's certainty regarding its predictions and helps identify potential issues in cases where confidence values are consistently low.

e) Global CPU Usage:

In addition to per-camera performance metrics, we monitor the overall CPU usage of the system during operation. This metric is obtained using system-level monitoring tools and is expressed as a percentage. Tracking CPU usage allows us to evaluate the computational load imposed by the multi-camera processing pipeline on the host system.

f) Global Memory Usage:

Finally, the memory consumption of the detection system is tracked over time, with the metric reported in megabytes (MB). Memory usage is measured by monitoring the resident set size (RSS) of the process. This metric is critical for assessing the scalability of the system, particularly when deploying on resource-constrained platforms.

6. RESULT AND ANALYSIS

The system's performance was evaluated using multiple metrics to see its effectiveness and efficiency, like frame processing time, detection count, confidence levels, frame rate (depended on the system it's running) and system resource usage like CPU utilization and memory usage over time.

6.1 Detection Count per Camera

The detection counts are shown in Figure 3.

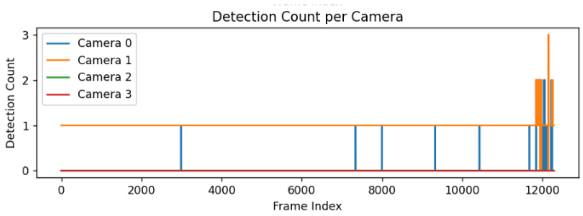

Figure 3: Detection Count per Camera

The detection counts shows that Camera 1 consistently achieved the highest detection rates, indicating better visibility or positioning in the camera array.

- Cameras 2 and 3 exhibited sporadic detections, likely due to incomplete views of objects or frame synchronization issues.

- Camera 0, though consistent, had fewer total detections than Camera 1, this is due to less objects placed in its view.

The multi-camera setup enabled efficient object detection by eliminating the need for the object to be fully visible in all camera views simultaneously. This enhanced the system's ability to detect objects reliably and seamlessly, improving overall detection performance and coverage.

6.2 Average Detection Confidence

The Figure 4 shows Detection Confidence per Camera.

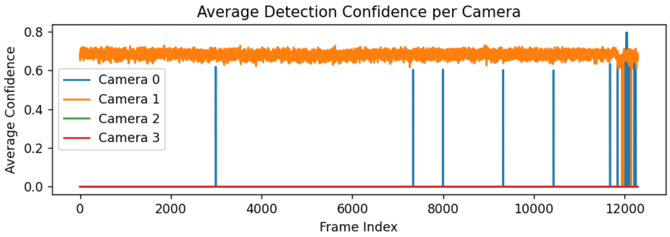

Figure 4: Detection Confidence per Camera

- The system maintained high average confidence levels, particularly in Camera 1, where the confidence averaged around 0.75 or higher.
- Cameras 2 and 3 showed lower confidence, possibly due to partial or no object visibility.
- Camera 0 demonstrated moderate confidence, but occasional drops were noted in certain frames, depicting object was moving out of frame.

This setup makes object detection way more reliable by using multiple perspectives, so even if an object isn't fully visible in one camera, the system can still catch it.

6.3 Processing Time per Frame

The Figure 5 shows Frame Processing Time per camera.

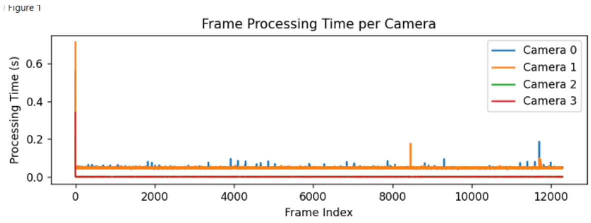

Figure 5: Frame Processing Time per camera

The processing time per frame for each camera stayed under 0.2 seconds for the majority of frames, confirming that the system operates close to real-time. Occasional spikes were observed, which correspond to frames with high object counts or synchronization delays across cameras.

6.4 Frame Rate

The Figure 6 shows frame processing time per camera.

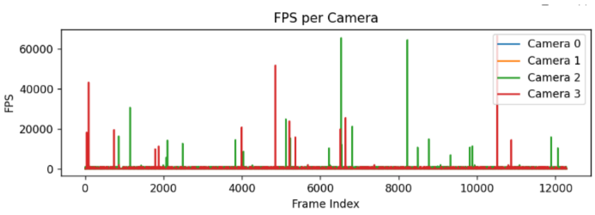

Figure 6: Frame Processing Time per camera

The FPS varied significantly across cameras, particularly in Cameras 2 and 3, which experienced intermittent frame drops and spikes. Camera 1 maintained a relatively stable frame rate, which contributed to its higher detection count and confidence levels.

6.5 Global CPU Usage

The Figure 7 shows Global CPU Usage over Time.

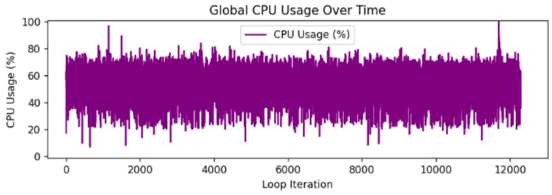

Figure 7: Global CPU Usage over Time

CPU usage averaged between 40% and 80% as shown in Figure 7 across the test duration, demonstrating efficient resource utilization for a multi-camera setup. Despite the presence of multiple concurrent streams, the system managed to keep the CPU from exceeding critical thresholds. The CPU in usage was AMD Ryzen 5 4600H. This will differ from system to system.

6.6 Global Memory Usage

Memory usage showed a gradual increase over time, eventually stabilizing around 240 MB. This can be seen in Figure 8.

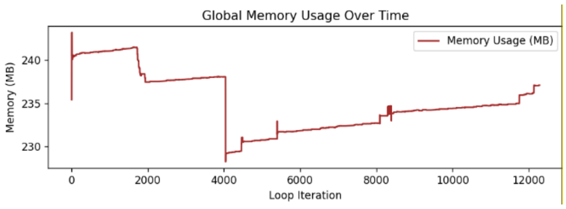

Figure 8: Global Memory Usage over Time

No significant memory leaks were detected during the testing phase, suggesting proper clean-up and resource handling.

6.7 Confusion Matrix

The confusion matrix is shown in Figure 9.

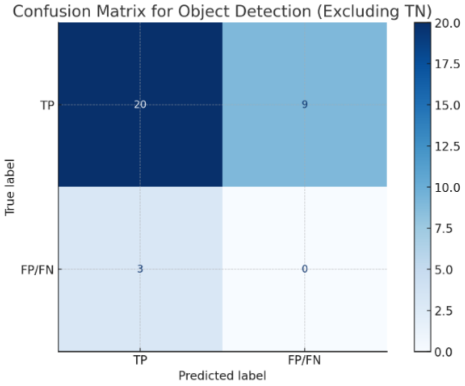

Figure 9: Confusion Matrix

Precision = $\frac{TP}{TP+FP} = \frac{20}{20+9}$ = 0.69 (69%)

Recall = $\frac{TP}{TP+FN} = \frac{20}{20+3}$ = 0.87 (87%)

F1 = $\frac{2 \times Precision \times Recall}{Precision+Recall}$ = 0.77 (77%)

These tests were done on a pretrained model with a 2-camera setup. The results were an enhanced detection of objects presented due to objects being in view of one camera and not the other, or the object is visible in both cameras but it's not detecting in one but detecting clearly in another due to a different view. This method gave us enhanced accuracy even on a pretrained model, greater than what could have been achieved with single camera setup.

This showed a promising approach towards multi camera setup for detection setups for different use cases, such as factories, smart work environments, etc.

6.8 Object Measurement

The system's object measurement accuracy was evaluated using two cameras (C1 and C2) as shown in Figure 10. The results, indicate a high degree of precision in measuring both length and breadth dimensions.

Camera C1 achieved a length accuracy of 93.33% and a breadth accuracy of 86.67%.

Camera C2 demonstrated even higher accuracy, with 99.06% for length and 96.30% for breadth.

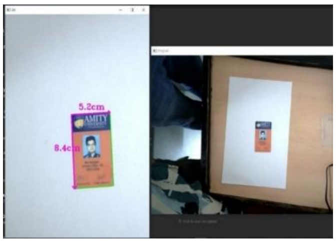

Figure 10: Object Measurement Accuracy

These results, summarized in Table 2, highlight the system's capability to accurately measure object dimensions from different viewpoints, further validating the robustness of the multi-camera setup for spatial analysis.

Table 2: Accuracy table

Camera	Length accuracy	Breadth Accuracy
C1	93.33%	86.67%
C2	99.06%	96.30%

7. CONCLUSION AND FUTURE WORKS

This work describes a novel combination of deep learning with multi-view geometry for reliable object detection and size estimates with several cameras. We increase detection accuracy and spatial perception significantly by integrating the strengths of deep learning-based object recognition with the geometric principles of multi-view systems. Our results show that the suggested system outperforms typical single-camera setups in certain conditions where objects are partially visible or moving from one view to another.

Our system achieved remarkable measurement accuracies, reaching up to 99.06% for object length and 96.30% for breadth, all while maintaining real-time performance with efficient CPU and memory usage. These promising results suggest that our approach is well-suited for practical applications in areas such as surveillance, robotics, and automation.

This approach is well-suited for practical usage in personal work environments and future implementation can also be added to this to make it more useful for day-to-day usage.

Key Contributions:

- *Innovative Integration of Deep Learning and Multi-View Geometry:* We developed a system that combines deep learning and multi-view geometry, allowing cameras to work together to detect objects more accurately. This fusion not only enhances detection but also provides detailed 3D spatial information about objects in real time.

- *Reliable Multi-Camera Calibration:* Our system ensures precise alignment between multiple cameras through a robust calibration process using chessboard patterns. This alignment is critical for accurately reconstructing the 3D positions of objects and minimizes errors caused by misaligned viewpoints.

- *Real-Time Object Detection Across Multiple Cameras:* We implemented a real-time detection pipeline that synchronizes input from four distributed cameras. This approach significantly improves object recognition by maintaining consistent detection, even when objects move between camera views or are partially obscured.

- *Accurate 3D Object Localization and Measurement:* By integrating triangulation techniques, we accurately determine the 3D coordinates and dimensions of detected objects. This feature makes the system especially valuable for scenarios where spatial precision is crucial, such as robotics and surveillance.

- *Smooth and Stable Object Tracking:* Our system applies temporal smoothing techniques to reduce flickering or instability in object detections. This ensures a more reliable tracking experience, even in dynamic or fast-changing environments.

- *Flexible and Scalable Design:* We designed the system to adapt to various setups, allowing cameras to be positioned strategically based on environmental needs. This scalability enables the framework to handle larger spaces, making it suitable for applications in smart environments and industrial automation.

- *Enhanced Visualization Through Multi-View Mosaic:* To streamline observation, we introduced a 2x2 mosaic view that integrates camera feeds into a single display. Each camera feed is labeled and displayed clearly, helping users monitor multiple perspectives effortlessly in real time.

Future Directions:

Additional Sensors: To improve accuracy and reliability in more complex and dynamic situations, we want to use additional sensing technologies such as depth cameras and LiDAR. These sensors would supplement the multi-view camera system by giving richer depth and spatial data, allowing for more precise object detection even in demanding settings such as low-light or congested environments and reduce the need for chessboard pattern for calibration or combine them both to increase accuracy.

Optimization for real-time applications: As part of our future work, we hope to enhance the system for real-time applications including real-time AI assistance, and constant visual and contextual input to an LLM.

For example, in a smart workspace, the system could detect objects or activities and provide helpful prompts or suggestions in real time. Imagine an AI that notices you looking for a tool and immediately informs you of its location or suggests alternatives. Similarly, in collaborative settings, the AI could monitor interactions, track tasks, and provide instant updates or reminders without the need for manual input. Our goal is to create an AI that not only responds to user commands but proactively supports users by continuously learning and adapting to the surrounding visual context, offering truly intelligent and real-time assistance.

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Data availability The data underlying this article are available in following dataset:

https://universe.roboflow.com/myproject-ko746/fridgedetection/dataset/3

Declarations:
Conflict of interest The authors declare no conflict of interest.

Informed consent Not Applicable.
Ethical approval Not Applicable.

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