# MapFusion: A General Framework for 3D Object Detection with HDMaps

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## Abstract 3D object detection is a key perception component in autonomous driving. Recent approaches primarily rely on Lidar or camera inputs. This paper introduces MapFusion, a framework that enhances 3D object detection by integrating High Definition Maps (HDMaps) into the detection pipeline. The framework includes a FeatureAgg module for feature extraction and fusion from HDMaps, and a MapSeg module for additional segmentation, improving mean Average Precision (mAP) by 1.27 to 2.79 points across various baselines.

## Introduction Autonomous driving technology has advanced significantly, yet integrating robust perception systems remains a challenge, particularly in accurately detecting 3D objects based on 2D images which lose distance information during projection. This paper discusses the limitations of existing approaches and proposes the integration of HDMaps to enhance detection accuracy. The key advantage of HDMaps is their high precision and extensive details about road infrastructure, which are underutilized in current 3D object detection frameworks.

### Problem Statement Traditional sensor-based detection systems, while effective, struggle to differentiate between foreground and background objects under certain conditions due to the lack of texture or detailed environmental information. Integrating HDMaps, which provide high-level environmental context, promises to mitigate these issues and improve the reliability of detected objects in autonomous driving systems.

### Fig. 1: PointPillars Detection with and without MapFusion Fig. 1: (a) illustrates detection inaccuracies in PointPillars due to lack of environmental context with false positives marked by red cycles. (b) demonstrates how integrating MapFusion reduces false positives, with true detections in cyan and ground truth in yellow. The diagram emphasizes the efficacy of the MapFusion framework in enhancing detection reliability.

## Methodology MapFusion involves two primary components: 1. \*\*FeatureAgg Module\*\*: This module extracts and fuses features from HDMaps to enrich the detection system's input data. 2. \*\*MapSeg Module\*\*: An auxiliary segmentation module that utilizes voxel features to predict road maps directly from point clouds under supervision from actual HDMap data.

### System Architecture FeatureAgg module integrates HDMap features with traditional voxel features from point clouds, combining them through a simple concatenation process followed by a convolution operation to refine the features before they are inputted into the detection model.

![Fig. 2](page2\_img1.jpg)

### HDMap Utilization HDMaps offer a detailed representation of the driving environment, including lanes, road signs, and other critical infrastructural elements. These maps are converted into a format compatible with the detection model, which then uses them to improve the accuracy and reliability of object detection results.

## Experimental Setup and Results The effectiveness of MapFusion is tested using three baseline 3D object detection systems: SECOND, PointPillars, and CenterPoint, on the nuScenes dataset. The integration of MapFusion shows considerable improvements in detection accuracy and reliability across all baselines.

### Fig. 3: 2D Feature Extraction Process The 2D feature extractor involves multiple layers of convolutions, which process and refine map data into a form that effectively supplements the raw point cloud data used in traditional 3D object detection systems.

## Conclusion MapFusion represents a significant advance in 3D object detection technology by effectively utilizing HDMaps. Future work will focus on expanding the types of data integrated into the detection system and refining the feature extraction processes to further improve accuracy and reliability. The ultimate goal is to develop a universally applicable framework capable of integrating various forms of environmental data to support robust autonomous driving systems.

## References [1] E. Yurtsever, J. Lambert, A. Carballo, and K. Takeda, "A survey of autonomous driving: Common practices and emerging technologies," IEEE Access, vol. 8, pp. 58,443–58,469, 2020.

[2] E. Arnold, O. Y. Al-Jarrah, M. Dianati, S. Fallah, D. Oxtoby, and A. Mouzakitis, "A survey on 3d object detection methods for autonomous driving applications," IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 10, pp. 3782–3795, 2019.