CHAPTER 4
DEEP LEARNING FOR REAR COLLISION AVOIDANCE

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4.1 INTRODUCTION

Autonomous driving, cooperative-intelligent transportation systems (C-ITS), artificial intelligence (AI), and the internet of things (IoT) in vehicles are all critical, essential areas of focus for development for today's current car manufacturers, as well as essential areas for improving car safety and making automobiles more competent and more environmentally friendly. Applying technologies such as traffic control systems, intelligent traffic signals, and automobile technology can improve roadways' safety in this context. There is a correlation between vehicles equipped with current active safety technologies and a reduction in severe traffic incidents that could potentially result in death (Adarsha et al., 2021).

According to World Health Organization (WHO), data reveal that lane departure or loss of control causes around 20% of killed and seriously injured (KSI) (World Health Organisation [WHO], 2015). Around 15% of all vehicle accidents involve a collision from the front with a minor overlap, and 25% of all frontal crashes have a slight overlap. In minor overlap collisions, this records around 10% of KSI, whereas vulnerable road user KSI makes for 36%. The usual circumstances are when a possible accident is approaching and how the driver should respond to these situations. These circumstances contribute to the study's motivating influence and the challenges to be solved. When an obstacle suddenly approaches the vehicle, the driver must consider making various judgments and choices, such as "What has appeared?" "Should I steer to avoid a collision?" or "Should I brake?" However, a driver can fail to respond quickly enough to escape the danger when a collision is imminent.

In this case, emergency braking by the autonomous emergency braking (AEB) system can be applied automatically. In addition, the emergency steering by the autonomous emergency steering (AES) system will be applied if it determines that a collision is unavoidable based on the time-to-collision measurement. AEB technology (Yang et al., 2022) is a function that warns drivers of impending collisions and assists them in using the vehicle's full capability. Meanwhile, the AES system is one of the active safety features that help with evasive steering. When a probable collision is detected, unlike AEB, the AES system automatically steers to avoid an accident. In conclusion, it will aid the driver in avoiding a potential accident.

The research will use a vision sensor rather than a radar system because the radar system lacks certain benefits that the vision sensor does feature. The capacity to classify things is one of the benefits that the vision sensor offers that the radar does not have.

Additionally, Vision sensors allow for classifying objects since they capture an image of the desired object, including all its component elements (Forsyth et al., 2012). Furthermore, the vision sensor was chosen for use in this study because it is capable of high-level processing when paired with software. It is one of the reasons why it was selected. Utilizing a vision sensor allows for not only the capability of object segmentation but also the detection of desired objects.

There are currently two distinct methods for calculating visual distance, one based on monocular vision and the other on binocular vision. However, compared to binocular vision, monocular vision for distance estimation provides advantages such as increased speed, simplified operation, and lower cost (Xie et al., 2021). Deep learning-based systems estimate the distance from the monocular vision to attain the same level of accuracy that can be achieved with binocular vision. Consequently, the approach to calculating the distance between vehicles suggested in this research is founded on monocular vision and a method based on deep learning.

In general, to provide an estimate of the distance, two different approaches are used in deep learning. The first method, called depth prediction (Adz-Dzikri et al., 2021), employs a depth map as ground truth. The second method, used to estimate the distance object by determining the item's size (Karthika et al., 2020), uses the object's size as the basis for the calculation. (Adz-Dzikri et al., 2021) use the object's size as the basis for the calculation. They used the single shot detector localization (SSD) method to detect objects, while the depth prediction method was employed to estimate distances. However, depth prediction is not currently feasible for consumer devices due to the amount of computational power and calculation time required, as well as the range limits and associated costs (Khan et al., 2020).

This chapter is structured by introducing relevant work in Section 4.2. Section 4.3 describes the proposed system architecture, while Section 4.4 discusses the experiment's results. Section 4.5 of this chapter provides a summary of the study's findings.

4.2 RELATED WORK

There are two known approaches employing deep learning to estimate distance. The first one uses a depth map as ground truth and is known as depth estimation (Back et al., 2021; Masoumian et al., 2021; Ma et al., 2022), while the second is known as object distance estimation (Arabi et al., 2022; Parmar et al., 2019; Vajgl et al., 2022) and estimates the distance of an item by determining its size. Alternately, deep learning-based depth estimation approaches evaluate the depth of whole scenes but need to estimate the distance between cars precisely. DenseDepth (Adz-Dzikri et al., 2021), DepthNet (Masoumian et al., 2021) and MonoDepth (Back et