

Multi-Target Estimation in OFDM Radar using YOLOv8 for Integrated Sensing and Communication

So-Yeon Jeon, Eui-Rim Jeong*

Abstract: In this study, we propose a method for simultaneously estimating the number, velocity, and distance of multiple targets in an Orthogonal Frequency Division Multiplexing (OFDM) radar environment using YOLO (You Only Look Once). The proposed approach employs Doppler-range two-dimensional (2D) signals as the input to the YOLO model, enabling it to learn and predict target characteristics. Since YOLO performs object detection in a single forward pass, it achieves higher computational efficiency compared to conventional CNN-based methods, making it suitable for multi-target estimation tasks. To validate the performance of the proposed method, we conducted simulations under various signal-to-noise ratio (SNR) conditions ranging from -10 dB to 20 dB and considered scenarios with one to five targets. The results show that, with 32 OFDM symbols, the YOLO-based model achieved an average velocity estimation error of 1.34 km/h and an average distance estimation error of 0.71 m. These results represent improvements of 0.56 km/h and 0.89 m, respectively, over conventional CNN-based single-target estimation models, demonstrating the precision of the proposed method. Such performance indicates its potential for effective application in next-generation joint communication and sensing systems.

Keywords: 2D-Periodogram; Distance; Object Detection; OFDM Radar; Velocity; YOLO

1 INTRODUCTION

Recent advancements in radar technology have extended its applications beyond the military domain to a wide range of industries, including autonomous vehicles, drones and UAVs, and medical diagnostics [1, 2]. Radar systems are increasingly integrated into advanced sensors and systems due to their capability to accurately measure the distance, velocity, and direction of remote objects [3]. However, the growing proliferation of wireless communication devices has intensified the issue of frequency spectrum scarcity, posing a challenge for radar systems to improve spectral efficiency [4, 5]. To address this issue, Integrated Sensing and Communication (ISAC) has emerged as a promising paradigm, enabling both communication and radar sensing functionalities to be performed on a single platform [6]. This study proposes an Orthogonal Frequency Division Multiplexing (OFDM)-based radar system that leverages conventional communication signals for sensing purposes, thereby enabling joint communication and radar operations without requiring additional spectrum allocation [7]. This represents a novel approach that maximizes spectral efficiency compared to conventional radar techniques that rely on dedicated radar signals [8, 9].

In an OFDM radar system, signal processing is performed by transforming the time delay and Doppler shift caused by the target into inter-subcarrier frequency changes and inter-symbol phase variations, respectively [10]. With recent advances in deep learning, there has been a surge of interest in enhancing target detection and distance/velocity estimation through nonlinear representation learning. For instance, previous studies employing multi-output CNNs for single-target estimation used 2D-periodograms as input and achieved higher accuracy than traditional CFAR methods [11]. However, such approaches are optimized for single-target scenarios and exhibit degraded performance when applied to multi-target environments, highlighting the need for more flexible solutions. To overcome these structural limitations, this study introduces a new deep learning method

based on YOLOv8 (You Only Look Once), a model optimized for multi-object detection. The proposed method aims to robustly estimate the number, distance, and velocity of multiple targets in complex radar environments. By using 2D-periodograms of OFDM signals as inputs, YOLOv8 effectively learns and predicts target characteristics through its object detection framework. YOLOv8 offers advantages in real-time inference and computational efficiency over other one-stage detectors, making it particularly well-suited for ISAC systems requiring rapid and simultaneous estimation of multiple targets. Simulation results demonstrate that, with an OFDM symbol length of 32, the YOLOv8-based model achieves an average velocity estimation error of 1.34 km/h and an average distance estimation error of 0.71 m under multi-target conditions. In contrast, a conventional CNN-based method optimized for single-target estimation showed higher errors of 1.90 km/h and 1.60 m, respectively. These results confirm the superior performance and stability of the proposed method in multi-target environments. Furthermore, compared to radar systems using dedicated signals [8,9], the proposed approach enables more efficient use of frequency resources while maintaining reliable distance and velocity estimation in complex scenarios. The remainder of this paper is organized as follows. Section 2 describes the OFDM radar system model for integrated sensing and communication. Section 3 details the generation of 2D-periodograms. Section 4 compares the conventional CNN-based method and the proposed YOLOv8-based approach. Section 5 presents simulation-based experimental results, and Section 6 provides a comprehensive analysis and discussion. Finally, Section 7 concludes the study.

2 OFDM RADAR SYSTEM

2.1 System Overview

This section describes the overall architecture and fundamental operating principles of the proposed OFDM radar system. Fig. 1 illustrates the main signal processing

flow of the OFDM radar system for estimating the distance and velocity of targets [11]. On the transmission side, the system follows the same procedure as a conventional OFDM transmitter, where signals are transmitted via antennas. However, a distinguishing feature of this system lies in its ability to process the reflected signals that bounce back from targets and are received by the antenna. These reflected

signals, resulting from the transmitted waveform interacting with objects, contain information such as target distance and velocity. Accordingly, the system estimates these parameters based on the received echoes. In essence, the OFDM system is designed to simultaneously perform communication and radar functions by transmitting signals and analyzing the received reflections within the same operational framework.

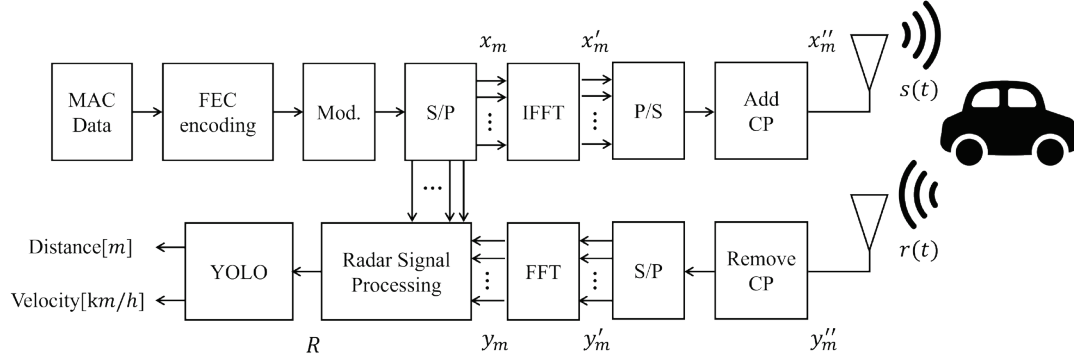


Figure 1 OFDM Radar System

2.2 Methodology

This section describes the signal processing flow and the procedure for generating the 2D-periodogram in the proposed system. On the transmitter side, the system first applies Forward Error Correction (FEC) encoding to the data, then converts it into parallel streams. It performs an inverse fast Fourier transform (IFFT) to convert the signal into the time domain and serializes it. To mitigate inter-symbol interference (ISI), the system adds a cyclic prefix (CP) to each OFDM symbol before transmitting the signal through the antenna. As the signal $s(t)$ propagates, it reflects off targets and arrives at the receiving antenna as $r(t)$. The received signal contains not only the reflected waveform but also channel noise and external interference. Target motion

introduces attenuation, time delay, and Doppler frequency shifts, which distort the signal. On the receiver side, the system removes the cyclic prefix and reshapes the signal into parallel form. It applies a fast Fourier transform (FFT) to obtain the frequency-domain signal. This process repeats for each incoming OFDM symbol to accumulate the signal over time. To estimate distance and velocity, the system compares the received and transmitted signals. It divides each received signal component by the corresponding transmitted component to eliminate modulation effects. Then, it applies a two-dimensional FFT to the accumulated signal to generate a 2D-spectrum. The squared magnitude of this spectrum yields the 2D-periodogram, which the YOLO model uses to estimate the number, velocity, and distance of the targets.

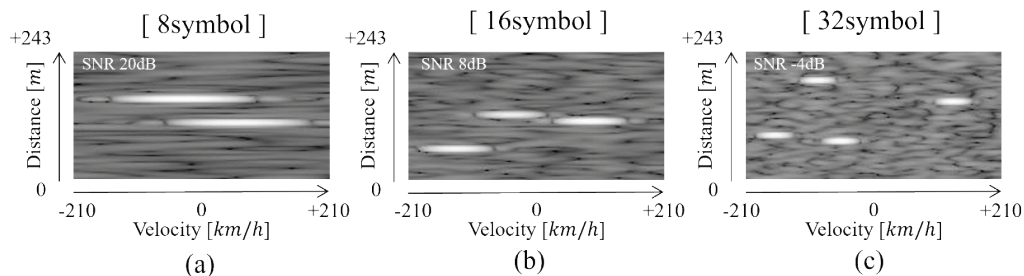


Figure 2 2D-Periodogram (a) 8symbol, (b) 16symbol, (c) 32symbol

3 2D-PERIODOGRAM

The 2D-periodograms used as input to YOLO is represented as a grayscale image, where higher magnitude values appear closer to white and values near zero appear darker or black. Target detection and identification are performed by locating peak values within the 2D-periodogram. The x-coordinate of each peak corresponds to the target's velocity, while the y-coordinate indicates its distance. Fig. 2 presents examples of 2D-periodograms for different numbers of OFDM symbols. Subfigures (a), (b),

and (c) show the results for 8, 16, and 32 OFDM symbols, respectively, with the number of targets set to 2, 3, and 4 accordingly. As illustrated in the figure, increasing the number of OFDM symbols leads to a decrease in the spread of target regions within the 2D-periodogram, enhancing target resolution. The velocity range observable in the 2D-periodogram spans from -210 km/h to $+210$ km/h, while the detectable distance spans from 0 to 243 m. Negative velocities indicate targets moving away from the radar, whereas positive velocities indicate approaching targets. The resolution of the 2D-periodogram is determined by the size

of the 2D-periodograms applied to the signal. In this study, the 2D-FFT size is denoted as $N_{FFT} \times M_{FFT}$, and is set to 2048×256 .

4 TARGET ESTIMATION METHOD

4.1 Conventional Estimation Method

Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in image classification and pattern recognition tasks by effectively learning spatial features through convolutional layers [12]. Leveraging this capability, CNNs can be applied to the 2D-periodogram data to estimate both the number of targets and their respective distance and velocity. However, estimating the number of targets and predicting their distance and velocity are fundamentally different tasks. As such, it is essential to design independent neural network architectures specialized for each task. Specifically, a CNN-based classification model is employed for target number

estimation, while a multi-output CNN regression model is used for distance and velocity prediction. The architecture for the classification model is depicted in Fig. 3, and the regression model for distance and velocity estimation is shown in Fig. 4. Both models share a common backbone structure that consists of five convolutional layers and batch normalization layers to extract key features from the 2D-periodogram. For the classification model, a softmax activation function is applied in the final fully connected layer to probabilistically predict the number of targets, ranging from one to five. In contrast, the multi-output CNN model for distance and velocity estimation directly outputs the estimated values of target distance and speed through its final output layer. Nonetheless, CNN-based multi-output models inherently suffer from a fixed number of output nodes, which presents a significant limitation in dynamic environments where the number of targets varies. Consequently, a separate model must be trained for each possible target count, which restricts practical deployment in scenarios with unknown or varying numbers of targets.

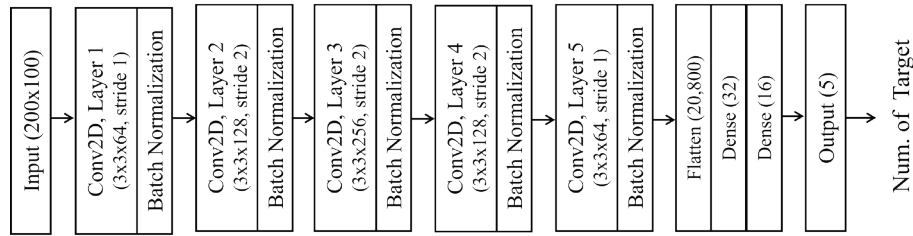


Figure 3 CNN Architecture for Estimating the Number of Targets

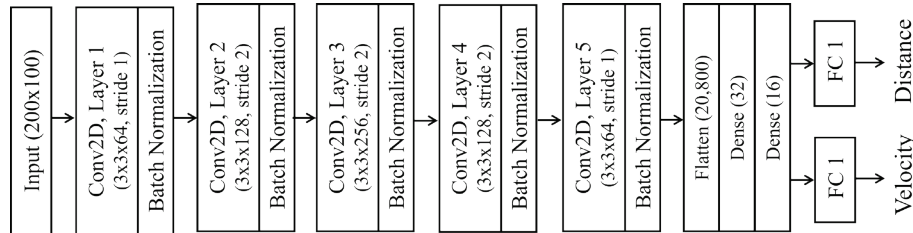


Figure 4 CNN Architecture for Estimating Target Distance and Velocity

4.2 Proposed Estimation Method

The proposed YOLO-based method is designed to directly estimate the distance and velocity of targets using the 2D-periodogram data. YOLO (You Only Look Once) is a CNN-based object detection algorithm that analyzes the entire image in a single forward pass, enabling simultaneous detection of multiple targets along with localization of their corresponding coordinates [13]. This characteristic makes YOLO particularly well-suited for solving the multi-target distance and velocity estimation problem addressed in this study. In conventional CNN-based approaches, the number of targets is first estimated using a classification model. Depending on the predicted count, separate CNN models must then be employed to estimate the distance and velocity for each target. This cascaded structure increases computational complexity and slows down detection. Furthermore, CNNs typically focus on learning local features, which limits their ability to capture global relationships

among multiple targets—posing challenges in scenarios that require understanding inter-target dependencies. In contrast, YOLO divides the input data into a grid structure and detects objects within each grid cell while learning holistic spatial features across the entire input. This enables the model to incorporate global context effectively, even in multi-target environments. Moreover, since YOLO is a one-stage detector, it can estimate the number, location, distance, and velocity of targets in a single inference step. This design provides high computational efficiency and fast detection speed, making it especially suitable for real-time applications that require rapid processing [14, 15].

This study proposes a YOLO-based method for multi-target detection and simultaneous estimation of distance and velocity, with the overall architecture illustrated in Fig. 5. The 2D-periodograms generated through radar signal processing, is resized to a fixed input size of 640×320 and input into the YOLO model to jointly estimate the number, distance, and velocity of targets. The architecture employs the standard YOLOv8s backbone. We construct target

annotations on the 2D-periodogram using the coordinates of spectral peaks, which represent each target's distance and velocity. Each peak serves as the center of a bounding box, with the width and height defined by the surrounding region of the peak. We assign all targets the same class label (class 0), and use the resulting annotations as ground truth for training. We conduct end-to-end training using the full dataset, and Tab. 1 summarizes the key hyperparameters. Given the real-time requirements and computational constraints of radar applications, we adopt the lightweight YOLOv8s model. We optimize the bounding box dimensions based on the number of OFDM symbols and fix the batch size

at 32. We set the learning rate according to the OFDM symbol count: 0.001 for 8 and 16 symbols, and 0.01 for 32 symbols. To prevent overfitting, we apply early stopping, with a patience value of 20 for 8 and 16 symbols, and 10 for 32 symbols. The total number of training epochs is 33, 37, and 22, respectively. We use the Adam optimizer, with an IoU threshold of 0.7 and a confidence threshold set to the default value of 0.25. The loss functions follow the default YOLOv8s configuration: Complete IoU (CIoU) Loss for bounding box regression, Binary Cross Entropy (BCE) Loss for objectness score prediction, and BCE Loss for classification.

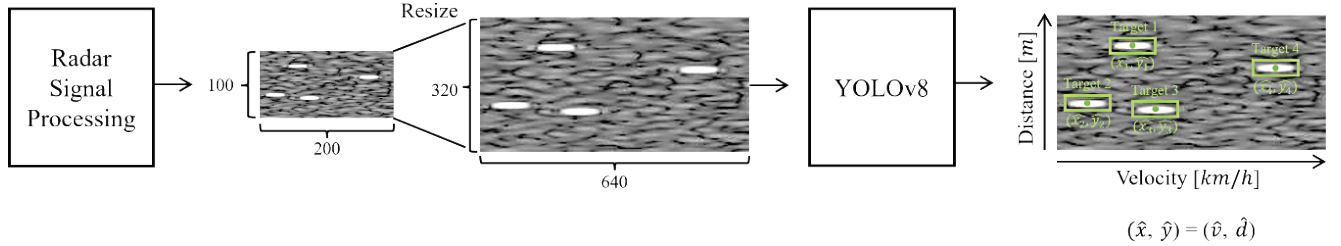


Figure 5 YOLO-Based Multi-Target Velocity & Distance Estimation

Table 1 YOLO Training Hyperparameters

Hyperparameters	Values		
	8symbol	16symbol	32symbol
Model version	YOLOv8s		
Bounding box	40×8	20×8	15×8
Batch size	32	32	32
Learning rate	0.001	0.001	0.01
Patience	20	20	10
Epoch	33	37	22
Optimizer	Adam	Adam	Adam
IOU threshold	0.7		
Confidence threshold	0.25		

5 SIMULATION

5.1 Simulation Environment

We generated the training and testing datasets using MATLAB and implemented the CNN and YOLO models with deep learning frameworks such as TensorFlow and PyTorch. Tab. 2 summarizes the OFDM signal parameters used to create the 2D-periodograms in the simulation. In this study, we set the total OFDM symbol duration to 35.74 μ s and used a sampling frequency (F_s) of 122.88 MHz with a 4,096-point FFT. Out of the available subcarriers, we used 1,284, resulting in an effective bandwidth of approximately 40 MHz. The carrier frequency was 28 GHz, and we set the cyclic prefix (CP) length to 296 samples. To investigate model performance, we varied the OFDM signal length across 8, 16, and 32 symbols. The 2D Fourier transform applied to the received signal used a size of 2,048 \times 256. During simulation, we varied the signal-to-noise ratio (SNR) from -10 dB to 20 dB. The training dataset included 50,000 randomly generated samples across the SNR range, with equal representation (10,000 samples each) for target counts from 1 to 5. For testing, we divided the SNR range into 3 dB intervals and generated 2,000 samples per interval and target count, resulting in a total of 110,000 test samples. We randomly assigned the distance and velocity of each target

within predefined bounds. We used the Mean Absolute Error (MAE) to quantitatively evaluate model performance for both distance and velocity estimation.

Table 2 Simulation Environment Parameters

Parameter	Values
OFDM System Duration	35.74 μ s
Sampling frequency	122.88 MHz
IFFT(FFT) size	4096
Bandwidth	40 MHz
Center frequency	28 GHz
Length of CP	296
Num. of OFDM symbol	8, 16, 32
2D FFT size	2048 \times 256
Cropped region size	200 \times 100
Num. of targets	1 ~ 5
SNR range	-10 ~ 20 dB
Num. of Train data	50,000
Num. of Test data	110,000

5.2 Simulation Results

5.2.1 Target Number Estimation Performance

Fig. 6 presents a comparison of the target count estimation accuracy between the CNN and YOLOv8 models under varying SNR conditions and different numbers of OFDM symbols. The simulation results show that both models exhibit improved accuracy as the number of OFDM symbols increases. Similarly, higher SNR conditions lead to improved performance in estimating the number of targets. When comparing the two models, the difference in performance was minimal under high SNR conditions. However, in low SNR environments, YOLOv8 consistently outperformed the CNN-based approach. For example, when the number of OFDM symbols was 8 and the SNR was -10 dB, the CNN model achieved approximately 66% accuracy, whereas YOLOv8 achieved a significantly higher accuracy of 89.16%. Additionally, Tab. 3, which compares the average accuracy across different OFDM symbol counts, confirms

that YOLOv8 consistently outperforms the CNN model for each symbol length. These results indicate that YOLOv8 maintains stable and reliable target count detection performance regardless of the SNR level, demonstrating its robustness in noisy environments.

Table 3 Average Target Number Estimation Accuracy

Model	Accuracy		
	8symbol	16symbol	32symbol
CNN	91.68%	94.28%	96.19%
YOLOv8	93.92%	97.23%	98.08%

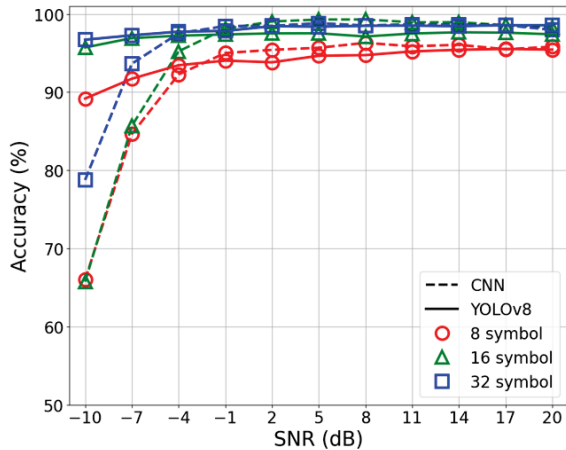


Figure 6 Target Number Estimation Accuracy of CNN and YOLO Models

5.2.2 Velocity and Distance Estimation Performance by Deep Learning Models

Figs. 7(a) and 7(b) illustrate the Mean Absolute Error (MAE) for distance and velocity estimation, respectively, across various SNR levels. Both models demonstrated improved and more stable performance as the SNR increased. However, across the entire SNR range, YOLOv8 consistently achieved lower MAE values than the CNN-based model. For distance estimation, the CNN model yielded an average MAE of 1.60 m, while YOLOv8 achieved a significantly lower average MAE of 0.71 m. In velocity estimation, CNN recorded an average MAE of 1.90 km/h, whereas YOLOv8 achieved 1.34 km/h. These results indicate that YOLOv8 reduced the average estimation error by 0.89 m for distance and 0.56 km/h for velocity compared to the CNN model, confirming its superior accuracy in both tasks.

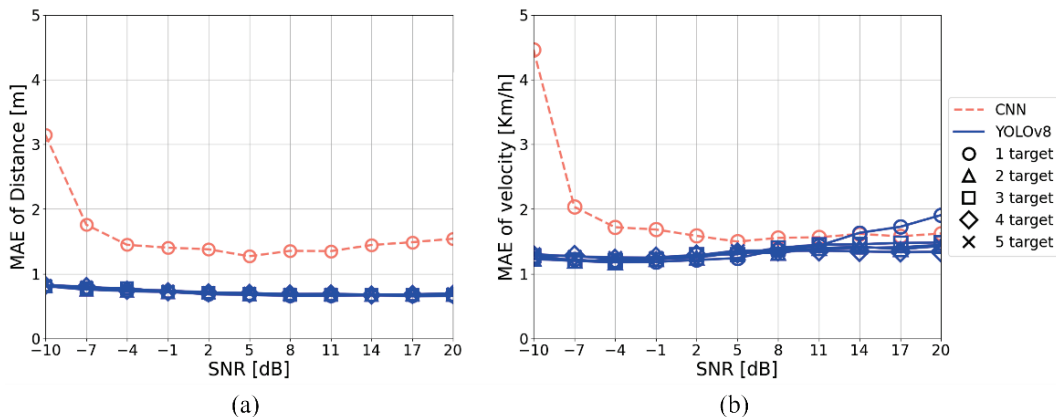


Figure 7 Distance and Velocity Estimation MAE of CNN and YOLO Models: (a) Distance, (b) Velocity

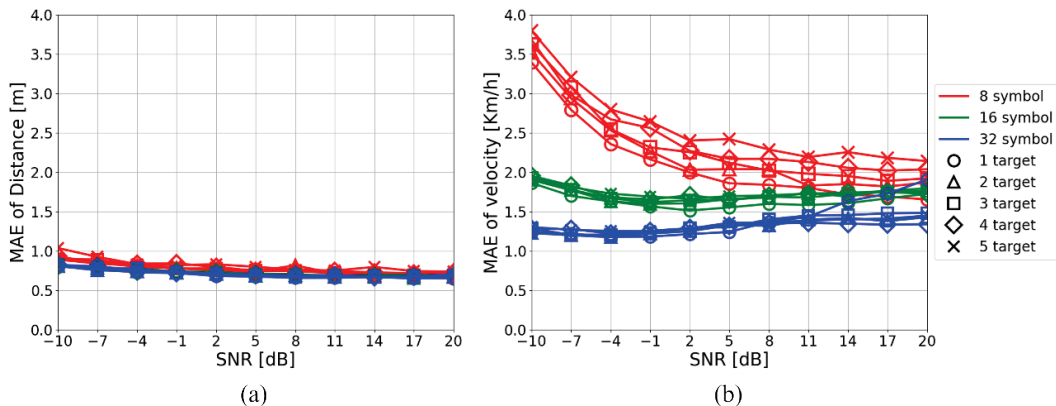


Figure 8 Distance and Velocity Estimation MAE of YOLO Model: (a) Distance, (b) Velocity

5.2.3 The Velocity and Distance Estimation Performance of the Proposed Method

Figs. 8(a) and 8(b) show the variation in Mean Absolute Error (MAE) for velocity and distance estimation,

respectively, as a function of OFDM symbol length under different SNR conditions using the YOLOv8 model. The simulation results indicate that longer OFDM symbol durations and fewer targets generally lead to improved estimation accuracy for both velocity and distance.

Additionally, as the SNR increases, MAE consistently decreases across all conditions. Notably, the lowest estimation errors were observed when the OFDM symbol length was 32, with an average velocity estimation error of 1.34 km/h and a distance estimation error of 0.71 m. Tab. 4 summarizes the average estimation performance for velocity and distance across different symbol lengths, clearly showing a decreasing trend in MAE as the number of OFDM symbols increases.

Table 4 Average MAE of Velocity and Distance Estimation

MAE	YOLOv8s		
	8symbol	16symbol	32symbol
Velocity (km/h)	2.3403	1.7088	1.3366
Distance (m)	0.7764	0.7162	0.7118

6 DISCUSSION

In summary, the proposed YOLOv8-based multi-target distance and velocity estimation method demonstrated stable performance across various signal-to-noise ratio (SNR) conditions and target counts. While conventional CNN-based models compress features into a single vector or focus on a single class—leading to information loss and reduced accuracy in multi-target environments—YOLOv8 takes advantage of its structural design to simultaneously detect the presence and location of multiple objects in the input signal. This allows the model to flexibly handle varying numbers of targets without requiring a predefined number of outputs. In addition, CNN has a fixed number of output nodes, which means a separate model is needed for each target count. Therefore, in our comparison, the CNN model was trained under the simplest condition—single-target only—while the YOLO model was trained to handle one to five targets. Despite this, YOLO achieved higher accuracy and lower estimation errors, demonstrating that it is an effective model not only for multi-target scenarios but also for single-target conditions. Meanwhile, since this study was conducted using computer-simulated data, it does not fully reflect real-world wireless conditions such as interference, channel distortion, and multipath effects. Moreover, the quantitative analysis of performance degradation in cases where targets have very similar distances and velocities was limited. As future work, we plan to validate the model's robustness using real-world field data. We also intend to explore new methods, such as enforcing minimum distance constraints between targets, to maintain high accuracy even in densely populated target environments. These extensions are expected to further enhance the practicality and reliability of the proposed model.

7 CONCLUSION

This study proposes a novel method for simultaneously estimating the number, distance, and velocity of multiple targets in an OFDM-based radar environment using YOLO (You Only Look Once). The approach aims to address the issue of limited frequency resources caused by dedicated radar signals while also overcoming the structural limitations of conventional two-stage CNN-based estimation methods in multi-target scenarios. Ultimately, the goal is to develop a real-time estimation technique suitable for next-generation

Integrated Sensing and Communication (ISAC) systems. The proposed YOLO-based method adopts a one-stage detection architecture that enables the simultaneous prediction of target count, distance, and velocity. It maintains high computational efficiency and accuracy even under diverse SNR conditions and in the presence of multiple targets. Notably, with an OFDM symbol length of 32, the YOLO model achieved an average velocity estimation error of 1.34 km/h and a distance estimation error of 0.71 m—representing improvements of 0.56 km/h and 0.89 m, respectively, compared to the baseline CNN approach. These results are attributed to YOLOv8's real-time inference capabilities and its strength in multi-object detection, which effectively leverage the distinct target features observable in the 2D-periodogram. Moreover, the proposed method enables accurate distance and velocity estimation without relying on dedicated radar signals, thereby conserving frequency resources and maximizing spectral efficiency—enhancing the practical utility of ISAC technologies. To address the limitations of simulation-based evaluation, future work will validate the model's generalization performance and real-time applicability using real-world wireless data. To this end, an OFDM-based radar system tailored to 5G communication environments will be developed, and experiments will be conducted to assess its robustness and deployment feasibility. In the long term, the proposed method will also be evaluated under emerging 6G network conditions to verify its practicality and scalability across diverse communication scenarios.

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Authors' contacts:

So-Yeon Jeon, Master's Course
Department of Artificial Intelligence,
Hanbat National University,
109 Jiphyeonbuk-ro, Sejong, 30139, Republic of Korea
jeonso1109@gmail.com

Eui-Rim Jeong, Professor
(Corresponding author)
Department of Artificial Intelligence Software,
Hanbat National University,
109 Jiphyeonbuk-ro, Sejong, 30139, Republic of Korea
Mobile Phone: +82-010-4710-1082
erjeong@hanbat.ac.kr