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ICTC 2025

THE 16th INTERNATIONAL CONFERENCE ON
ICT CONVERGENCE

“AI-native ICT Convergence for a sustainable future”

October 14-17, 2025 | Lotte Hotel Jeju, Jeju Island, Korea

Final Program

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This work was supported by the Korean Federation of Science and Technology Societies(KOFST) grant funded by the Korean Government.

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Signal Presence Detection for Spectrum Sensing Using YOLOv8

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Abstract—This paper proposes a spectrum sensing method using a YOLO-based object detection technique to determine the presence of signals in a low probability of intercept (LPI) communication environment. Spectrograms in the time-frequency domain are used as inputs to compare the signal detection performance of the YOLOv5 and YOLOv8 models. The detection performance is evaluated under a 0% false alarm rate condition. Simulation results show that YOLOv8 outperforms YOLOv5 by approximately 1.9 dB at a true positive rate (TPR) of 65%. These results demonstrate the potential applicability of YOLO-based object detection techniques to real-time spectrum sensing.

Index Terms—Deep Learning, YOLO, Spectrum Sensing, Signal Detection, Low Probability of Intercept (LPI)

I. INTRODUCTION

In military operations, the early detection and analysis of enemy communication signals play a critical role in tactical decision-making by providing accurate situational awareness and enabling proactive actions. Low Probability of Intercept (LPI) communication systems used by adversaries are designed to minimize electromagnetic exposure, thereby avoiding detection by radar and signal intelligence systems. These systems are used for covert communications and often utilize techniques such as frequency hopping and low-power transmission to make detection more difficult [1]. As a result, developing technologies for detecting LPI communication signals has become increasingly important. Recently, deep learning-based spectrum detection methods, particularly object detection, have attracted significant research attention [2]. These approaches typically involve converting weak signal patterns in the time-frequency domain into spectrograms, which are then analyzed by AI models to detect the presence of LPI signals.

In this paper, we propose using a YOLO (You Only Look Once)-based object detection model to determine the presence of signals for spectrum sensing. YOLO is a convolutional neural network (CNN)-based one-stage detector that predicts

object locations and classes simultaneously in real time by passing the input image only once through the network. In our study, signals in the time-frequency domain appear as horizontal bar-shaped patterns in the spectrogram, which can be treated as detectable objects. Using YOLO, it becomes possible to identify the presence or absence of signals in the spectrogram. We compare and analyze the signal detection performance of YOLOv5 and YOLOv8 for this task.

II. SPECTRUM SENSING SYSTEM MODEL

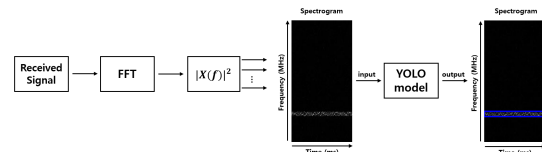


Fig. 1. Block diagram of the YOLO-based spectrum sensing system.

The YOLO-based spectrum sensing method proposed in this paper determines the presence or absence of signals within an observed frequency band by treating it as an object detection problem based on the spectral information of received wideband signals. Figure 1 presents the overall processing flow of the proposed YOLO-based spectrum sensing framework. The received time-domain signal is transformed into the frequency domain using a Fast Fourier Transform (FFT). The FFT results are then accumulated along the time axis and squared to produce a two-dimensional spectrogram in the time-frequency domain. The resulting spectrogram is used as input to the YOLO model, which predicts bounding boxes indicating regions where signals are likely to be present. Based on these predicted bounding boxes, the presence of signals is determined.

III. CRITERIA FOR SIGNAL DETECTION USING PREDICTED BOUNDING BOXES

Figure 2 illustrates the results of signal presence detection using the YOLO model with spectrogram input. A True

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Positive (TP) is defined as a case where the Intersection over Union (IoU) between the ground-truth and predicted bounding boxes exceeds zero. In contrast, if a ground-truth bounding box exists but the model fails to generate a prediction or produces a prediction with zero IoU, the case is classified as a False Negative (FN). When a ground-truth bounding box is not present, but a predicted bounding box is generated, the case is classified as a False Positive (FP). In our work, an FP is regarded as a false alarm. Based on these criteria, each spectrogram is evaluated to determine the presence or absence of a signal.

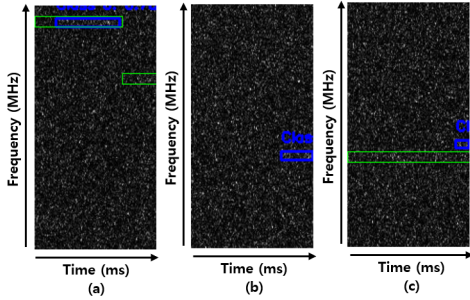


Fig. 2. Signal detection results using the YOLO model: (a) TP, (b) FP, (c) FN.

IV. YOLO MODEL TRAINING SETTINGS

In this study, YOLOv5 and YOLOv8 models are used. For YOLOv5s, the optimizer is AdamW, the learning rate is set to 0.001, and the batch size is 32. For YOLOv8s, the optimizer is also AdamW, the learning rate is 0.001, and the batch size is 64. Both models are trained without pre-trained weights, and early stopping is applied during training.

V. SIMULATION ENVIRONMENT AND RESULTS

The simulation data were generated using MATLAB, and model training and validation were performed in PyTorch. The training and validation datasets were generated with randomly assigned SNR values ranging from -10 to 20 dB, consisting of 50,000 and 10,000 samples, respectively. The test dataset was composed of 10,000 samples at 1 dB intervals within the same SNR range, resulting in a total of 310,000 samples, with Busy and Idle classes evenly balanced at a 50:50 ratio.

Figure 3 shows the comparison of false alarm performance between YOLOv5 and YOLOv8. To ensure a fair comparison, the confidence thresholds of the two models were adjusted, with YOLOv5 set to 0.5 and YOLOv8 set to 0.8. Under these conditions, both models achieve a false alarm rate of 0% across the SNR range from -10 to 20 dB.

Figure 4 illustrates the comparison of true positive performance between YOLOv5 and YOLOv8. At a true positive rate of 65%, YOLOv8 demonstrates approximately 1.9 dB superior performance over YOLOv5. This indicates that YOLOv8 can effectively detect signals even in lower SNR environments.

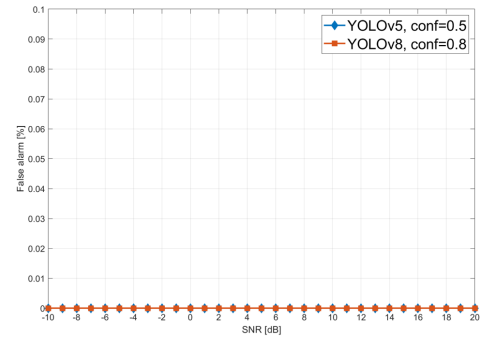


Fig. 3. False alarm performance of YOLOv5 and YOLOv8 across the SNR range.

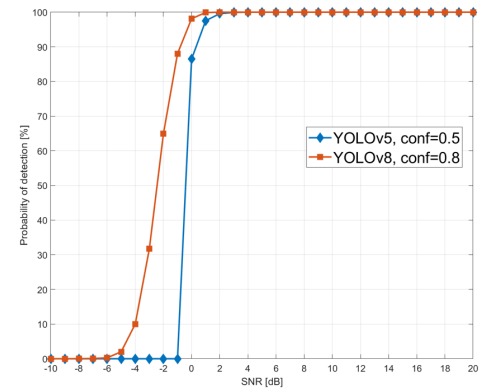


Fig. 4. True positive performance of YOLOv5 and YOLOv8 across the SNR range.

VI. CONCLUSION

In this paper, we proposed a spectrum sensing method based on YOLO for signal detection in low-SNR environments. Signals appeared as horizontally elongated objects in the generated two-dimensional spectrograms and were used as inputs to YOLOv5 and YOLOv8 to determine signal presence. Simulation results show that both models achieve a 0% false alarm rate across the SNR range from -10 to 20 dB, and at a TPR of 65%, YOLOv8 achieves higher performance than YOLOv5 by approximately 1.9 dB. These results demonstrate the effectiveness of the proposed method in detecting signals under low-SNR conditions and suggest its potential for broader applications of YOLO-based detection methods.

ACKNOWLEDGMENT

This research was supported by funding from Korea government((KASA, Korea AeroSpace Administration) (grant number RS-2021-NR05608331)

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