

ICUFN 2025

The 16th International Conference on Ubiquitous and Future Networks

July 8 (Tue.) ~ 11 (Fri.), 2025

Iscte - University Institute of Lisbon, Lisbon, Portugal & Virtual Conference

<https://icufn.org>



Final Program

Technically Co-Sponsored by



Organized by



Patrons



Internet of Energy Research Center (Kookmin University)

Center for ICT & Automotive Convergence (Kyungpook National University)

- [P3-8] **Enhancement of C-DRX Efficiency with Traffic Prediction Using Ensemble Learning Models**
Ji-Hee Yu, Yoon Ju Choi, Hyeeyoon Jeong, Jaeun Kim and Hyoung Kyu Song (Sejong University, Rep. of Korea)
- [P3-9] **1XK Differential Space-Time Line Code with Phase-Shift Keying Modulation and Code Hopping for Secure Communications**
Jingon Joung (Chung-Ang University, Rep. of Korea)
- [P3-10] **GNN-Based 5G Localization with Beam Information via Graph Expansion**
Hasom Seo and Hongseok Jung (Hanyang University, Rep. of Korea); Youngsu Cho (Electronics and Telecommunications Research Institute (ETRI), Rep. of Korea); Sunwoo Kim (Hanyang University, Rep. of Korea)
- [P3-11] **Deep Learning-Based Precoding for Partially-Connected Hybrid Beamforming Systems**
Juhyoung Sung (Korea Electronics Technology Institute (KETI), Rep. of Korea); Won-Gi Jeon and Sungyoon Cho (Korea Electronics Technology Institute, Rep. of Korea); Ki Won Kwon (Koera Electronics Technology Institute, Rep. of Korea); Kyung-Won Park (Korea Electronics Technology Institute, Rep. of Korea)
- [P3-12] **Iterative DOA Estimation and MVDR Beamforming for Enhanced SNR in Narrowband Signals**
Hyeongrae Kim, Joomyung Jung and Oh Hyuk Jun (Kwangwoon University, Rep. of Korea)
- [P3-13] **Adaptive Beamforming Technique for Long- Distance, High-Speed Communications of Antarctic Unmanned Exploration Robots**
Woo Yong Lee (Electronics and Telecommunications Research Institute, Rep. of Korea); Keunyoung Kim (ETRI, Rep. of Korea)
- [P3-14] **Coordinated Switching of Forward/Backward Link Signals for Distributed TRP/Reader Based Ambient IoT Systems**
Chanho Yoon, Byung-Jae Kwak and Yongsun Kim (ETRI, Rep. of Korea); Young-Jo Ko (Electronics and Telecommunications Research Institute, Rep. of Korea)
- [P3-15] **Performance Evaluation of Two-Step Random Access with Message Bundling for LEO Satellite Networks**
Taehoon Kim (Hanbat National University, Rep. of Korea); Seong Ho Chae (Tech University of Korea, Rep. of Korea); Inkyu Bang (Hanbat National University, Rep. of Korea)
- [P3-16] **Study on SCMS-Based Certificate and Electronic Signature Validity Verification in C-ITS Environment**
Youngjin Kim (Telecommunications Technology Association, Rep. of Korea)
- [P3-17] **A Mobile System Architecture for Store-and-Forward Operation in Non-Terrestrial Networks**
HyunKyung Yoo (Electronics and Telecommunications Research Institute, Rep. of Korea); Namseok Ko and Mi-ryong Park (ETRI, Rep. of Korea)

Poster Session 4

Room B306, Time 15:30 ~ 17:00

- [P4-1] **Comparative Analysis of CNN Models for SNR Estimation**
Abdullah Al Mahbub (Chosun University, Rep. of Korea); Ijaz Ahmad (Korea University, Rep. of Korea); Seokjoo Shin (Chosun University, Rep. of Korea)
- [P4-2] **Deep Learning-Based Wideband Signal Detection via Time-Frequency Analysis for LPD Communication**
Soyeon Jeon, Jae Hyeon Lee and Eui-Rim Jeong (Hanbat National University, Rep. of Korea)
- [P4-3] **Dynamic 5G Network Slice Management Using Unsupervised Modeling and Explainable AI**
Harun Ur Rashid and Seong Ho Jeong (Hankuk University of Foreign Studies, Rep. of Korea)
- [P4-4] **CNN-Based Spectrum Sensing with Asymmetric Weighting in LPD Communication System**
Jae Hyeon Lee, Soyeon Jeon and Eui-Rim Jeong (Hanbat National University, Rep. of Korea)
- [P4-5] **Optimal Inference Task Length for Minimizing Synchronization Error in Digital Twin Systems**
Subin Choi, Hongjae Jeong, Jonghun Han and Minchae Jung (Sejong University, Rep. of Korea)
- [P4-6] **CDMA-Based Broadband UAC Modem: a Modulation and Demodulation Design Approach**
Taegeon Chung and Kang-Hoon Choi (LIG Nex1, Rep. of Korea); Tae-Ho Im (Hoseo University, Rep. of Korea)
- [P4-7] **Feasibility Analysis of Frequency Sharing Between UAV and AeroMACS Systems**
Ho Kyung Son (ETRI, Rep. of Korea)
- [P4-8] **Non-Orthogonal Multiple Access with Index Modulated Non-Orthogonal Frequency Division Multiplexing**
Md Shahriar Kamal (Kumoh National Institute of Technology, Rep. of Korea); Muhammad Sajid Sarwar (University of British Columbia Okanagan, Rep. of Korea); Soo Young Shin (Kumoh National Institute of Technology, Rep. of Korea)
- [P4-9] **Deep Learning-Based Power Allocation for Cell-Free Massive MIMO Networks with Adaptive Access Point Power Control**
Yoon Ju Choi, Ji-Hee Yu, Hyeeyoon Jeong, Jaeun Kim and Hyoung Kyu Song (Sejong University, Rep. of Korea)
- [P4-10] **Deep Reinforcement Learning-Based Joint Radio Resource Partitioning and Allocation for Cellular V2X Networks**
Heeju Choi, Chungnyeong Lee and Seong Ho Chae (Tech University of Korea, Rep. of Korea)

Deep Learning-Based Wideband Signal Detection via Time-Frequency Analysis for LPD Communication

So-Yeon Jeon
dept. of Artificial Intelligence Hanbat
National University
Sejeong, Republic of Korea
jeonssol1109@gmail.com

Jae-Hyeon Lee
dept. of Artificial Intelligence Hanbat
National University
Sejeong, Republic of Korea
leejh980247@gmail.com

*Eui-Rim Jeong
dept. of Artificial Intelligence Hanbat
National University
Sejeong, Republic of Korea
erjeong@hanbat.ac.kr

Abstract— In this study, we propose a CNN-based spectrum sensing method to detect the presence or absence of signals within a wideband frequency range. The proposed method effectively identifies signal existence by learning various signal patterns through artificial intelligence, without requiring prior knowledge of the signals. The performance of the proposed approach is validated through computer simulations and comparatively evaluated against traditional energy detection methods as well as other deep learning-based models. As a result, the proposed CNN model demonstrates superior detection performance with significantly fewer parameters, highlighting its efficiency in terms of model compactness.

Keywords— *Spectrum Sensing, Spectrogram, Deep Learning, CNN, Wideband.*

I. INTRODUCTION

Modern military operations place great emphasis on information acquisition and analysis capabilities, which have become a critical component of overall operational effectiveness [1]. In particular, the ability to covertly detect and analyze enemy communications plays a key role in securing battlefield dominance. For this reason, advanced military platforms such as stealth fighter jets and unmanned aerial vehicles (UAVs) actively adopt technologies that minimize exposure while conducting various missions, including reconnaissance, surveillance, communication relay, and precision strikes [2]. Among these technologies, Low Probability of Detection (LPD) communication is highly regarded for enabling stable and continuous data transmission without revealing the transmitter's location or operational intent. LPD communication employs techniques such as frequency hopping, spread spectrum, and low-power transmission to conceal the presence of signals, making them difficult to detect using conventional intercept receivers or spectrum analyzers [3], [4]. For example, UAV-to-UAV network communications often adopt wideband frequency hopping (FH) techniques, which rapidly switch frequencies over a broad spectrum within short time intervals. This dynamic frequency behavior poses a significant challenge to real-time interception without the deployment of wideband surveillance systems.

Therefore, to effectively monitor enemy communications in LPD environments, it is essential to develop high-performance interception technologies capable of accurately detecting the presence of signals. In particular, when signals

are received at very low power levels, the surveillance system must be able to reliably determine their presence even before conducting any detailed signal analysis.

This study aims to develop a spectrum sensing-based interception method capable of identifying the presence or absence of signals across a wide frequency band without prior knowledge. The proposed approach leverages an artificial intelligence model trained on diverse signal patterns in the time-frequency spectrogram domain to determine signal presence in real time. This enables the realization of a high-performance interception system suitable for deployment in LPD communication environments. To this end, we propose a lightweight CNN-based spectrum sensing model and conduct a comprehensive performance evaluation against state-of-the-art deep learning models and conventional energy detection methods. Simulation results demonstrate that the proposed model achieves outstanding detection performance with significantly fewer parameters than existing methods, especially exhibiting high detection accuracy and stable false alarm control in low-SNR environments.

II. PROPOSED SYSTEM MODEL

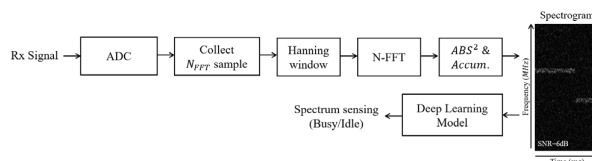


Fig. 1. Proposed Spectrum Sensing System Model

Illustrates the architecture of a deep learning-based interception system designed to detect the presence of frequency-hopping signals within a wideband frequency range. The signal received from adversaries is digitized through a high-speed analog-to-digital converter (ADC) and then sequentially segmented into blocks of N_{FFT} samples for time-segmented frequency analysis. To prevent spectral leakage, a Hanning window is applied to each block prior to performing the Fast Fourier Transform (FFT). The FFT results are accumulated in matrix form. The power spectrum is then calculated by squaring the magnitude of the FFT outputs, and these are integrated along the time axis to visualize a time-frequency representation known as a spectrogram. The resulting spectrogram serves as input to the deep learning model, which solves the task as a binary classification problem, identifying whether a signal is present (busy) or absent (idle).

III. SPECTROGRAM

The spectrogram represents a grayscale image that visually depicts the variation of frequency components over time, as shown in Figure 2. Signal-present regions within the spectrogram appear as bright bands, whereas, under low SNR conditions—as observed in Figures 2(b) and 2(c)—the influence of noise makes it difficult to distinguish signal presence.

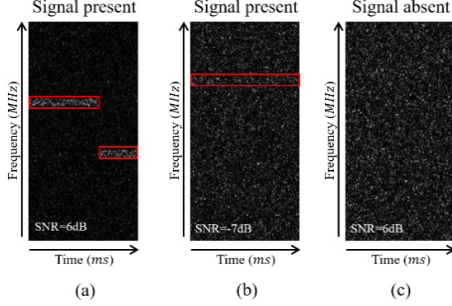


Fig. 2. Spectrogram based on Signal Presence

The vertical axis corresponds to frequency bins determined by the FFT size, and the horizontal axis indicates the number of time blocks based on the observation length. A larger FFT size provides finer frequency resolution within each block, while a longer observation length leads to increased recognition latency. Recognition latency is a critical performance metric in real-time spectrum sensing and is computed as a function of the observation length N_B , the hop size between blocks N_o , the FFT size, and the sampling frequency F_s .

$$T = ((N_B - 1)N_o + N_{FFT})/F_s \quad (1)$$

In this paper, the system was implemented with N_o set to 256, resulting in a recognition latency T of approximately 1092.3 μ s per spectrogram.

IV. TRADITIONAL ENERGY DETECTION

Energy Detection (ED) is a commonly used technique for determining the presence of signals in the spectrum by measuring the energy of the received signal. It is widely adopted due to its ability to operate without requiring prior knowledge of the signal. In ED, the energy statistic T is calculated over a given segment of the received signal $r[n]$ as follows:

$$T = \frac{1}{N} \sum_{n=1}^N |r[n]|^2 \quad (2)$$

Here, N represents the observation window length, indicating the number of samples over which the signal is observed. The computed statistic T is then compared to a predefined threshold λ , and the presence of a signal is determined using the following binary hypothesis test:

$$\begin{cases} H_0: T < \lambda & (\text{Signal absent}) \\ H_1: T \geq \lambda & (\text{Signal present}) \end{cases} \quad (3)$$

The threshold λ is determined based on the statistical properties of the received signal under the assumption of Gaussian noise, and it is typically adjusted to satisfy a target false alarm rate (P_f). The energy detection method offers advantages such as structural simplicity and low computational complexity, making it easy to implement in

various wireless communication environments. However, this method assumes that the noise power is constant, and thus requires accurate prior knowledge of the noise level. If this condition is not met, as is often the case in real-world scenarios, the detection performance may degrade significantly.

V. PROPOSED CNN-BASED METHOD

Figure 3 illustrates the overall architecture of the proposed Convolutional Neural Network (CNN)-based spectrum sensing model. Instead of adopting a complex, state-of-the-art deep learning framework, a lightweight CNN structure is employed to enable an efficient model suitable for real-time spectrum sensing. The proposed model consists of a simplified architecture with four convolutional layers and two fully connected layers. Each convolutional layer incorporates ReLU activation, batch normalization, and max pooling. After feature extraction, the fully connected layers—with dropout applied—perform binary classification. A sigmoid activation function is used in the output layer to classify the input as either Busy or Idle. The model is trained using the binary cross-entropy loss function and the Nadam optimizer, with a learning rate of 0.001, a batch size of 64, and 7 training epochs.

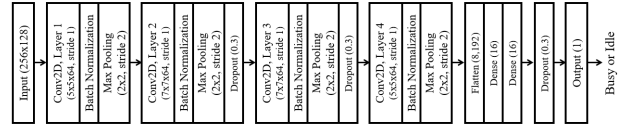


Fig. 3. CNN Architecture for Spectrum Sensing

VI. SIMULATION

A. Simulation Environment

Computer simulations were conducted to compare and validate the proposed model against existing AI models and the conventional energy detection method. The simulation environment is summarized in Table 1, and the experimental setup is based on a wideband signal environment. A total of 50,000 samples were used for training and 10,000 for validation, while 10,000 samples were used for testing at each SNR level. All datasets were evenly divided between samples with signal presence and absence.

TABLE I. SIMULATION PARAMETERS

| Parameters | value |
|---------------------------|------------------------------|
| FFT size | 256 |
| Observation Length | 128 |
| Number of Symbols per hop | 1,000 |
| Bandwidth | 1.25 MHz |
| Sampling rate | 30MHz |
| Modulation Scheme | QPSK |
| Channel Model | AWGN |
| SNR variation range | -10 ~ 20 dB (uniform random) |

Table 2 summarizes the network configurations and parameter sizes of each model. The YOLO model is based on the latest one-stage detection architecture, YOLOv8, and employs the x variant (YOLOv8x), which offers the highest

accuracy and has the largest number of parameters among the models [5]. The ResNet model adopts ResNet34 architecture, which enables deep network training through residual connections, and consists of approximately 20.72 million parameters. The ViT model is composed of 12 Transformer encoder layers ($L \times 12$), and utilizes patch-based input and a self-attention mechanism, resulting in about 10.28 million parameters [6]. In contrast, the proposed CNN model has a compact architecture composed of four 2D convolutional layers using 64 filters of sizes 5×5 and 7×7 , with a total of approximately 0.63 million parameters—at least 16 times fewer than the other models. For fair performance comparison, all models were trained using the WBCE (Weighted Binary Cross Entropy) loss function, and their false alarm rates (P_f) were adjusted to similar levels. This allowed for objective evaluation of detection (P_d) performance differences according to model architecture.

TABLE II. MODEL NETWORK AND PARAMETERS

| | value | | | |
|-----------------|------------|------------|-----------------------|------------------------|
| | YOLO | ResNet | ViT | Proposed CNN |
| Model Network | YOLOv8x | ResNet34 | ViT ($L \times 12$) | 2D Conv 64 64 64 64 |
| Num. of Params. | 68,153,571 | 20,720,449 | 10,281,345 | 638,065 |

B. Simulation Result

Figure 4 presents the spectrum sensing detection (P_d) performance evaluation for each model. All four models showed an increasing trend in detection probability as the SNR increased. CNN, YOLO, and ResNet all achieved 100% detection probability at -2 dB, with CNN outperforming YOLO and ResNet in the low SNR range. Notably, the CNN model demonstrated the most stable performance among the deep learning models under low SNR conditions. The conventional energy detection method (FAR 1% and 2%) reached 100% detection at -1 dB, whereas the CNN model outperformed it by approximately 1.5 dB. Despite having the simplest architecture, CNN achieved the highest performance with only about $1/107$ of YOLO's parameters, $1/33$ of ResNet's, and $1/16$ of ViT's, proving its outstanding efficiency. While YOLO and ResNet showed comparable detection performance to CNN, they required significantly more parameters. In contrast, ViT reached 100% detection at 3 dB, which is about 4 dB lower in performance compared to the energy detection method. This is attributed to the low inductive bias inherent in Transformer-based architectures, which makes it difficult to effectively learn under limited data conditions.

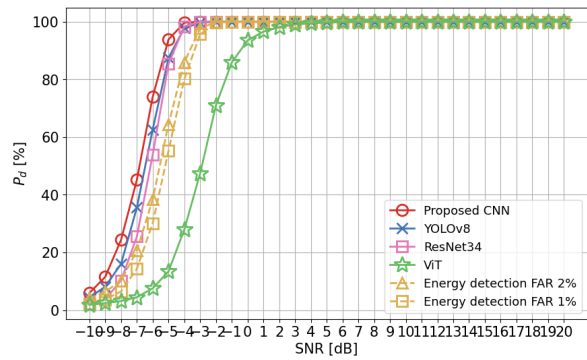


Fig. 4. Comparison of Detection performance

Figure 5 presents the false alarm (P_f) performance evaluation results for the deep learning models in spectrum sensing. All models maintained a consistent false alarm rate regardless of changes in SNR. CNN and YOLO exhibited a false alarm rate of approximately 1.69%, while ResNet and ViT showed about 1.46% and 1.54%, respectively. The conventional energy detection method had fixed false alarm rates of 1% and 2%, depending on the predefined threshold. As the false alarm rates of the deep learning models fall within this range, a fair comparison of detection performance can be conducted under similar false alarm conditions.

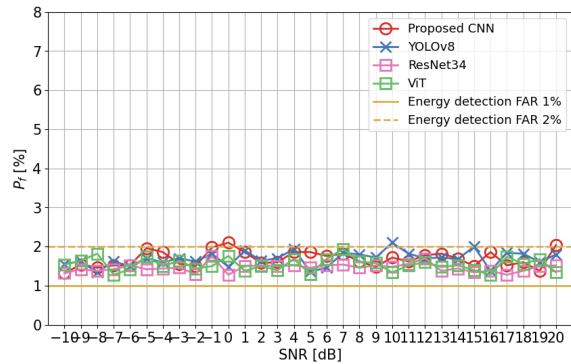


Fig. 5. Comparison of false alarm performance

VII. CONCLUSION

In this study, we proposed a CNN-based spectrum sensing method to detect the presence or absence of signals in a wideband environment and conducted a comparative analysis with state-of-the-art deep learning models, including YOLO, ResNet, and ViT, as well as the conventional energy detection method. Experimental results show that the proposed CNN model achieved a 100% detection rate at -2 dB and outperformed all other deep learning models in detection performance. It also demonstrated approximately 1.5 dB better performance compared to the traditional energy detection approach. Notably, the CNN model achieved the highest performance while maintaining a significantly smaller number of parameters—approximately $1/107$ of YOLO, $1/33$ of ResNet, and $1/16$ of ViT—proving its superiority in model efficiency. The high accuracy and lightweight nature of the proposed CNN model highlight its potential suitability for practical LPD communication monitoring and real-time wireless surveillance systems. Future research will extend the model's capabilities beyond signal presence detection to include time and frequency

localization, enabling the development of more precise spectrum sensing and surveillance systems.

REFERENCES

- [1] R. Kufakunesu, H. Myburgh, and A. De Freitas, "The internet of battle things: a survey on communication challenges and recent solutions," *Discover Internet of Things*, vol. 5, no. 1, p. 3, 2025.
- [2] E. Sepulveda and H. Smith, "Technology challenges of stealth unmanned combat aerial vehicles," *The Aeronautical Journal*, vol. 121, no. 1243, pp. 1261-1295, 2017.
- [3] Z. Li et al., "Intelligent Covert Communication: Recent Advances and Future Research Trends," *Engineering*, 2024.
- [4] J. Magiera, "Detection and direction-of-arrival estimation of weak spread spectrum signals received with antenna array," *Electronics*, vol. 10, no. 21, Art. no. 2566, 2021.
- [5] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: unified, real-time object detection," *Proc. of 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 779-788, 2016.
- [6] A. Dosovitskiy et al., "An image is worth 16x16 words: Transformers for image recognition at scale," *arXiv preprint arXiv:2010.11929*, 2020.