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[P3-8] Enhancement of C-DRX Efficiency with Traffic Prediction Using Ensemble Learning Models
Ji-Hee Yu, Yoon Ju Choi, Hyeyoon 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)

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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 (Teleconmmunications 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, Hyeyoon 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)

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CNN-Based Spectrum Sensing with Asymmetric Weighting in LPD Communication System

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***Abstract*— In this paper, we propose CNN (Convolutional Neural Network)-based spectrum sensing method with asymmetric weighting to enhance false alarm performance in LPD (Low Probability of Detection) communication systems. The proposed method utilizes WBCE (Weighted Binary Cross Entropy) as the loss function, in which different weights are assigned to the signal-present and idle classes to reflect their importance better. This approach extends the conventional BCE (Binary Cross Entropy) by emphasizing the idle class, where no signal is present. Through simulation, the performance of the proposed method was evaluated with an FFT (Fast Fourier Transform) size of 256 and an observation length of 128. The results show that the average FAR (False Alarm Rate) of CNN trained with standard BCE was approximately 1.5% across all SNR (Signal to Noise Ratio) levels. In contrast, when applying WBCE with a weighting factor of 3 to the idle class, the FAR significantly decreased to approximately 0.05%, demonstrating the effectiveness of the proposed method.**

Keywords—Low Probability of Detection, Convolutional Neural Network, Weighted Binary Cross Entropy, Spectrum Sensing

I. Introduction

Recent research in military and security-oriented applications has focused on LPD communication systems, which aim to prevent the exposure of communication signal existence to unintended receivers [1]. These systems are designed to make signal detection difficult, thereby avoiding eavesdropping or tracking, and they utilize technologies such as power control, frequency hopping, and spread spectrum. In such environ ments, spectrum sensing plays a crucial role in efficiently utilizing limited frequency resources while precisely recognizing the surrounding signal environment [2].

The primary objective of spectrum sensing is to determine whether a signal exists in a given frequency band. A false alarm, which refers to mistakenly detecting a signal when none exists, can critically impact system performance. In particular, within LPD systems, false alarms may trigger unnecessary avoidance actions or reallocation of communication links, which not only reduce overall communication efficiency but also lead to energy waste and transmission delays. Therefore, techniques that can effectively reduce the FAR are essential for the stable operation of LPD systems.

Signal detection in spectrum sensing can be defined as a binary classification problem, and binary classification models based on artificial intelligence generally use the BCE loss function. BCE computes the loss based on the difference between the model's prediction and the actual label, and since it assigns equal importance to both classes during training, it is simple to implement and provides reliable performance in general classification tasks. However, in environments such as LPD systems, where the FAR is a critical performance metric, this symmetric loss structure can be a limitation. If an Idle class (i.e., signal-absent) is mistakenly classified as a Busy class (i.e., signal-present), it may result in unnecessary avoidance actions or inefficient resource usage, ultimately degrading the overall efficiency of the system.

Accordingly, this study analyzes the performance of signal detection through spectrum sensing using the WBCE loss function, which extends the BCE structure by applying class-specific weights. The simulation results show that while the model using BCE exhibited an average FAR of approximately 1.5% across all SNR levels, the model with WBCE significantly reduced the average FAR to around 0.05%, demonstrating improved false alarm performance.

II. System Model

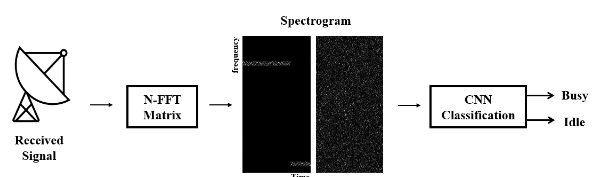

Fig. 1. CNN-based Spectrum sensing block diagram

Figure 1 illustrates the overall process of the proposed CNN-based spectrum sensing method. The process begins with the collection of wideband signals over a defined time interval. The received time-domain signals are converted into the frequency domain by applying the FFT. The resulting frequency-domain data are accumulated over time by stacking the FFT outputs in a matrix format for each time frame. Based on this accumulated data, a spectrogram is generated to visually represent the signal variations in the time-frequency domain.

The generated spectrogram serves as the input to the proposed deep learning model. In this study, a CNN is adopted due to its proven effectiveness in image recognition and processing tasks. CNNs are well suited for handling two-dimensional input data, such as spectrograms, making them a natural fit for this application [3]. The proposed CNN model analyzes the input spectrogram to determine the presence or absence of a signal, performing binary classification into two classes: Busy and Idle. In the spectrogram, the vertical axis corresponds to the FFT size, representing the frequency bins obtained through FFT processing, while the horizontal axis denotes the observation period in the time domain. To ensure consistency and efficient data handling during training, the FFT size and observation length were set to 256 and 128, respectively, throughout the experiments conducted in this study.

III. Asymmetric Weighting in Loss Function and Deep Learning Model Architecture

A. *Asymmetric Weighting in the Loss Function*

The proposed CNN-based spectrum sensing method involves various hyperparameters, among which the loss function is a key factor directly influencing the learning performance of the model. In this study, we apply WBCE, an extension of the commonly used BCE, which allows the adjustment of class-specific importance through weighting [4]. This section presents the definition and characteristics of BCE, along with the rationale for its extension and the application of WBCE. BCE is a widely used loss function for binary classification problems, where the loss is calculated based on the error between the model's prediction and the actual label. It treats both classes with equal importance. The BCE loss function is defined as follows:

$$Loss_{BCE}(\hat{y}, y) = -[y * \log(\hat{y}) + (1-y) * \log(1-\hat{y})]$$

In the loss function, $\hat{y}$ denotes the predicted output of the AI model, while y represents the ground truth label. BCE measures how well the predicted value matches the actual label, and the loss decreases as the prediction becomes more accurate. Due to this property, BCE is commonly used as an important metric for evaluating model performance. During training, monitoring the BCE loss allows for assessing how stably the model maintains its performance over time and how effectively it adapts to changes in the data. However, BCE assigns equal weights to all classes, which may not be suitable in real-world applications where certain types of misclassification are more critical than others. For instance, in LPD communication systems, misclassifying Idle class as Busy can have more serious consequences than the reverse. In such cases, asymmetric loss treatment may not be appropriate.

To address this issue, the proposed method introduces WBCE, which extends BCE by allowing the application of class-specific weights. By assigning different levels of importance to each class, WBCE enables the model to place greater emphasis on more critical predictions, thereby enhancing its ability to accurately classify both Busy and Idle classes. For example, giving a higher weight to the Idle class encourages the model to better learn the patterns associated with signal absence, ultimately contributing to a reduction in the FAR. The next section presents the formulation of WBCE with asymmetric weighting and discusses its effectiveness in improving classification performance.

$$Loss_{WBCE}(\hat{y}, y) = -[w_{Busy} * y * \log(\hat{y}) + w_{Idle} * (1-y) * \log(1-\hat{y})]$$

The above equation represents the computation process of WBCE. Here, w_{Busy} denotes the weight assigned to the Busy class, where a signal is present, and w_{Idle} denotes the weight for the Idle class, where no signal is present. Increasing the value of w_{Busy} results in a higher penalty when a Busy instance is incorrectly classified as Idle, thereby improving the detection performance for the Busy class. Conversely, increasing w_{Idle} imposes a greater penalty on misclassifying Idle instances as Busy, which leads to a reduction in the FAR. By applying class-specific weights through WBCE, it becomes possible to control the trade-off between detection probability and FAR depending on the system's operational priorities.

B. *Network Architecture of the AI Model*

TABLE I. Deep Learning Model Network Structure

Neural Network	64 64 64 64
Epochs	16
Params.	637,553
Loss Function	Weighted Binary Cross-Entropy
Optimizer	Nadam
Activation Function	Conv Layer = 'ReLU' FC Layer = 'Sigmoid'
Batch Size	64
Learning Rate	0.001

This section describes the network architecture of the Deep Learning model used for spectrum sensing. The input to the model is a spectrogram, which captures the time-frequency characteristics of the signal. The proposed model is based on a CNN consisting of four convolutional layers. Each convolutional layer has 64 channels, and Batch Normalization is applied after each layer to improve training stability and convergence speed. The number of training epochs was set to 16, and the total number of trainable parameters in the model is approximately 640,000. To reflect the relative importance of each class, the model employs WBCE as the loss function, incorporating asymmetric weighting. The Nadam optimizer was used for training, with ReLU (Rectified Linear Unit) activation functions applied to the convolutional layers and a Sigmoid activation function used in the output layer. The model was trained with a batch size of 64 and a learning rate of 0.001.

IV. Simulation Results

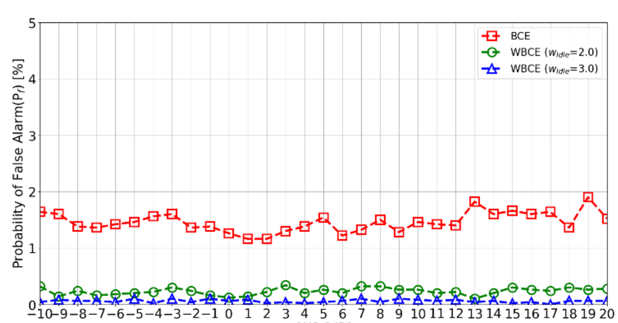

Fig. 2. False Alarm Performance with $\boldsymbol{w_{Idle}}$ Weight Applied

Figure 2 illustrates the changes in false alarm performance when applying the proposed CNN-based spectrum sensing method with the WBCE loss function, which incorporates asymmetric class weighting. For performance comparison, the results using the conventional BCE loss function are also presented. In LPD communication systems, accurately identifying the Idle class is particularly important, as it is directly related to the system's ability to reduce false alarms effectively. Accordingly, in the simulation, the weight for the Busy class was fixed at 1, while the weight for the Idle class was varied to analyze the effect of WBCE on false alarm performance. The simulation was conducted over a SNR range from -10 dB to 20 dB, and the FARs of both BCE-based and WBCE-based models were quantitatively compared under each condition. The results indicate that assigning a weight of 3 to the Idle class yielded the best performance. Specifically, the model using BCE exhibited an average FAR of approximately 1.5% across all SNR levels, whereas the WBCE-based model, with increased emphasis on the Idle class, achieved a significantly lower average FAR of approximately 0.05%. These findings demonstrate that the proposed asymmetric weighting approach substantially improves the accuracy of Idle class prediction, thereby enhancing the overall false alarm performance of the spectrum sensing system.

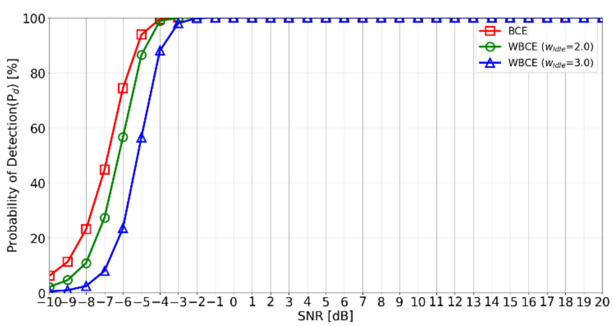

Fig. 3. Detection Performance with w_{Idle} Weight Applied

Figure 3 illustrates the changes in the probability of detection performance when applying the proposed WBCE loss function. As previously discussed, this study primarily aims to reduce the FAR, which is a critical performance metric in LPD communication systems. To achieve this, the weight for the Idle class was set relatively higher. However, such an asymmetric weighting scheme inevitably affects the performance of the Busy class, specifically the detection probability. Simulation results show that the model using the conventional BCE loss function, without any weighting, maintains relatively high detection performance across all SNR levels. In contrast, the WBCE-based model, which increases the Idle class weight to 2 or 3, exhibits a noticeable degradation in detection performance, particularly in low SNR regions. Specifically, when the Idle weight is set to 3, a significant drop in detection performance is observed below an SNR of -5 dB. This is interpreted as the model learning to make more conservative predictions for the Busy class due to the higher penalty assigned to misclassifying the Idle class. These results clearly demonstrate the trade-off between detection probability and FAR when applying asymmetric class weighting through WBCE.

V. CONCLUSION

In this study, the performance of CNN (Convolutional Neural Network)-based spectrum sensing method was analyzed in terms of FAR (False Alarm Rate) and detection probability by applying a loss function with asymmetric weighting, namely WBCE (Weighted Binary Cross Entropy), within the context of LPD (Low Probability of Detection) communication systems. Simulation results demonstrated that assigning a higher weight to the Idle class effectively reduced the FAR, which is particularly suitable for scenarios in LPD systems where accurate detection of signal absence is critical. However, this asymmetric weighting approach introduced a trade-off, as the detection probability tended to decrease in low SNR regions. This outcome suggests that class weight settings should be flexibly adjusted according to the system's operational priorities. The findings of this study are expected to serve as a useful reference for the design of CNN-based spectrum sensing models aimed at enhancing performance in LPD communication systems.

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