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ICTC 2024

THE 15th INTERNATIONAL CONFERENCE ON ICT CONVERGENCE

"AI-empowered Digital Innovation"

October 16-18, 2024 | Ramada Plaza Hotel, Jeju Island, Korea

Final Program

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KICS The Korean Institute of Communications and Information Sciences

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Technical Paper Sessions

[Session L7] Healthcare, Biomedicine, and AI for Medical Applications

Oct. 18, 08:30~10:00

Chair : Prof. Soyi Jung (Ajou University, Korea)

Session L7-1 Federated Learning with U-Net for Brain Tumor Segmentation: Impact of Client Numbers and Data Distribution

Le Thu Thuy (FPT University, Vietnam); Nhat Truong Pham (Sungkyunkwan University, Korea (South)); Nam Phuong Tran (Kyung Hee University, Vietnam); Duc Ngoc Minh Dang (FPT University, Ho Chi Minh, Vietnam)

Session L7-2 A Deep Learning Approach for Dealing with Tabular Data in Crop Classification

Priyanga Muruganantham and Santoso Wibowo (Central Queensland University, Australia); Sriman Grandhi (Central Queensland University Melbourne, Australia); Nahina Islam (Central Queensland University, Australia)

Session L7-3 A Review of Wireless Biotelemetry Channel Models Considering Gender and Tissue Composition

Seun Sangodoyin, Narges Moeini and Xipei Liao (Georgia Institute of Technology, USA); Lilas Dagher (University of California, Los Angeles, USA)

Session L7-4 Channel coding and Interleaving blind recognition using deep learning

Jae Hyeon Lee, Seok Jin Hong, Woong Jong Yun and Eui-Rim Jeong (Hanbat National University, Korea (South))

Session L7-5 Necessity of Increasing Kernel Size to Secure Receptive Fields in CNN for Time Series Analysis

Jinmo Kim and Ji-Woong Choi (DGIST, Korea (South))

[Session A8] ICTC Workshop on Satellites & Radars Radio Technologies (IWSRRT)

Oct. 18, 10:20~11:50

Chair : Prof. Sungtek Kahng (Incheon Nat'l University, Korea)

Session A8-1 Small Satelites, use, as its Key, MetaLens Antennas

Seongbu Seo, Woogon Kim, Jaewon Koh, Sanghyun Yun, Bae Jinwoo and Sungtek Kahng (Incheon National University, Korea (South))

Session A8-2 A 130-147.7 GHz CMOS Low Noise Amplifier for Satellite Communication

Jeong-Taek Lim, Jae-Hyeok Song, Jeong-Taek Son, Min-Seok Baek, Jae Eun Lee, Joon Hyung Kim, Byeong Chan Lee, Jong Seong Park, Ilhun Kim, Eun-Gyu Lee, Sun-Kyu Choi and Choul-Young Kim (Chungnam National University, Korea (South))

Session A8-3 Design of a High-Power Radar Waveguide Beam-Steering Antenna and Compensation for Level Degration

Yoonseon Choi, Jong-Myung Woo and Bang Chul Jung (Chungnam National University, Korea (South))

Session A8-4 Agile Beam Radars seek Key MetaLens Antennas

Sungtek Kahng, Woogon Kim, Hongsik Park and Jaewon Koh (Incheon National University, Korea (South)); Yejune Seo (Inchoen National University, Korea (South)); Yeol In Moon (Nissha Korea, Korea (South) & Korea, Korea (South))

Session A8-5 Low-Profile Monopolor Microstrip Antenna for Inter-Satellite Link of LEO Satellite Swarm

Dong-Hyo Lee and Sang-Cherl Lee (Korea Aerospace Research Institute, Korea (South)); Chung-Min Lee, Jin-Pyo Jang and Seongmin Pyo (Hanbat National University, Korea (South))

Channel coding and Interleaving blind recognition using deep learning

Jae-Hyeon Lee
Department of Artificial intelligence
Hanbat National University
Daejeon, Republic of Korea
leejh980247@gmail.com

Woong-Jong Yun
Department of Artificial intelligence
Hanbat National University
Daejeon, Republic of Korea
dndwhddl@gmail.com

Seok-Jin Hong
Department of Artificial intelligence
Hanbat National University
Daejeon, Republic of Korea
lf2net89@gmail.com

*Eui-Rim Jeong
Department of Artificial intelligence
Hanbat National University
Daejeon, Republic of Korea
erjeong@hanbat.ac.kr

***Abstract*— This paper proposes two deep learning models for recognizing the types of channel coding and interleaving in a blind scenario, where no information about the transmitted signal is available. For the success of military operations, it is crucial to intercept and analyze enemy communication signals, which requires the ability to blindly recognize the channel coding and interleaving techniques used by the adversary. The signals used in this study are random messages that have passed through channel coding, interleaving, and scrambling. Simulation results show that when the ratio of 0s to 1s in the message is 50:50, the deep neural network (DNN) achieves approximately 62% accuracy in channel coding recognition and 64% accuracy in interleaving recognition, while the convolutional neural network (CNN) achieves 38% and 65% accuracy, respectively. However, when the ratio shifts to 40:60, all recognition models exhibit high accuracy, exceeding 70%. Therefore, the proposed models demonstrate that the recognition performance improves as the difference in the ratio of 0s to 1s in the message increases.**

Keywords*—*Deep Learning, Deep Neural Networks, Convolutional Neural Networks, Channel Coding, Interleaving

I. INTRODUCTION

The success of military operations depends on the ability to intercept enemy communication signals and extract the necessary information. Therefore, it is essential to accurately recognize the communication technologies used by the adversary. In particular, decrypting messages requires the analysis and identification of various communication techniques, such as source coding, channel coding, interleaving, and scrambling. Research on recognizing these technologies has been actively pursued for many years. However, most existing studies are applicable only under limited conditions and lack practicality in the complex and unpredictable environments characteristic of actual military operations. For example, traditional methods often require prior knowledge of the communication environment or are only capable of recognizing specific types of channel coding or interleaving, making them difficult to apply in real-time, dynamic military scenarios. As a result, there is a growing demand for technologies that can more comprehensively recognize a wide range of communication techniques. Recently, studies utilizing deep learning have shown high recognition accuracy in this context. [1,2] Building on this foundation, our study focuses on the recognition of channel coding and interleaving techniques. In this paper, we propose two deep learning models for recognizing the types of channel coding and interleaving in a blind scenario, where no prior information about the transmitted signal is available. The proposed models consider Convolutional Coding, commonly used in the physical layer, Reed-Solomon coding, a type of block coding, as well as scenarios where no channel coding is applied. For interleaving, the models distinguish between block interleaving and cases where no interleaving is applied. Unlike previous studies, which did not account for scenarios without channel coding, this study includes such cases to provide a more comprehensive approach. [3] The input signals for the proposed deep learning models are random messages that have passed through channel coding, interleaving, and scrambling, with the assumption that demodulation has been perfectly completed. Simulation results show that when the ratio of 0s to 1s in the message is 50:50, the deep neural network achieves approximately 62% accuracy in channel coding recognition, while the convolutional neural network achieves 38% accuracy. For interleaving recognition, the accuracies are 64% and 65%, respectively. However, when a bias is introduced, shifting the ratio to 40:60, both channel coding and interleaving recognition rates exceed 70%. Therefore, the proposed models demonstrate that their performance is influenced by the ratio of 0s to 1s in the message, with greater differences in the ratio leading to improved recognition accuracy.

II. SYSTEM MODEL

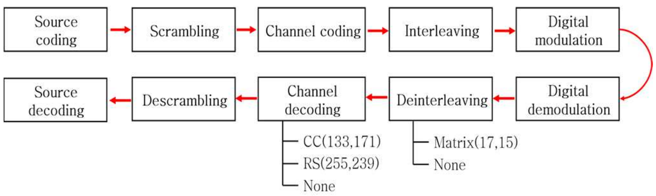

Fig. 1. System Model Block Diagram

Figure 1 presents the block diagram of the overall system model. The message undergoes source coding, where it is compressed into a sequence of 0s and 1s. The message being compressed can take various forms, such as audio, images, or video. The compressed message then passes through a scrambling process, which randomizes the message pattern. Afterward, channel coding is applied, adding parity bits to the message. These added parity bits are used for error correction. The channel-coded message then undergoes interleaving, which shuffles the order of the bits to disperse consecutive errors, followed by the modulation stage. In this study, it is assumed that demodulation is perfectly performed, and the demodulated message is used as input to recognize the types of channel coding and interleaving.

III. HYPERPARAMETERS AND NETWORK ARCHITECTURE OF THE DEEP LEARNING MODEL

TABLE I. Model Architecture and Hyperparameters for Channel Coding and Interleaving Recognition

Value	Channel Coding		Interleaving	
Neural Network	Proposed DNN	Proposed CNN	Proposed DNN	Proposed CNN
	64 128 128 128 256	64 32 32 16	64 64 128 256	64 32 32 16
Epochs	30	10	25	5
Params.	208,579	550,675	178,690	1,067,282
Loss Function	Categorical Cross-Entropy			
Optimizer	Adam			
Activation function	CNN, DNN Layer -> ReLU FC Layer -> Softmax			
Batch size	128			
Learning Rate	0.001		0.0001	

The proposed deep learning dataset consists of 540,000 samples for training, and 180,000 samples each for validation and testing, divided into 11 sets with a 2% increment in the ratio between 0s and 1s. The quantities for training, validation, and testing datasets result from generating 30,000 and 10,000 samples for each of the 18 combinations of three types of scrambling, three types of channel coding, and two types of interleaving. The neural network architecture and hyperparameters of the deep learning model are detailed in Table 1.

IV. SIMULATION RESULTS

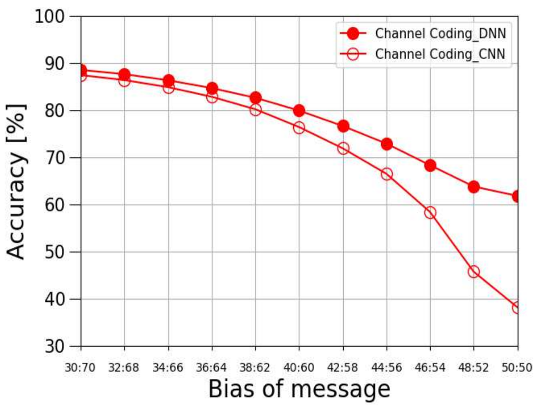

Fig. 2. Channel Coding Recognition Performance by Bias

Figure 2 illustrates the performance of channel coding recognition across different bias levels. For the deep neural network (DNN), the accuracy is approximately 62% when the ratio of 0s to 1s is 50:50. The accuracy increases to 80% at a 40:60 ratio and reaches close to 90% as the ratio shifts to 30:70. In contrast, the convolutional neural network (CNN) achieves about 38% accuracy at a 50:50 ratio, which is lower than that of the DNN. However, its accuracy improves to around 76% at a 40:60 ratio and becomes comparable to the DNN at a 30:70 ratio. Overall, the DNN outperforms the CNN in channel coding recognition performance.

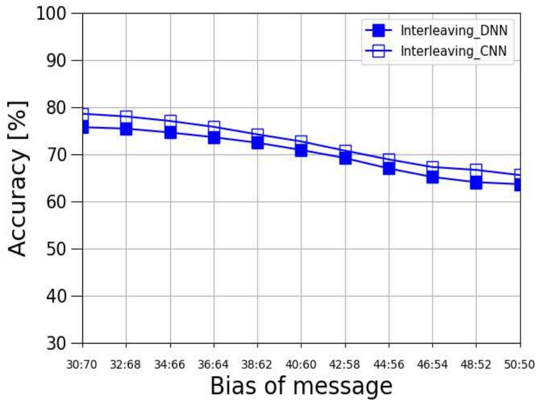

Fig. 3. Interleaving Recognition Performance by Bias

Figure 3 shows the interleaving recognition performance across different bias levels. When the ratio of 0s to 1s is 50:50, the deep neural network (DNN) achieves an accuracy of approximately 64%, while the convolutional neural network (CNN) reaches 66%. As the disparity between the ratio of 0s and 1s increases, the performance improves correspondingly. Overall, CNN outperforms DNN in interleaving recognition.

V. CONCLUTION

In this paper, we proposed two deep learning models for recognizing the types of channel coding and interleaving in a blind scenario, where no information about the transmitted signal is available. When the ratio of 0s to 1s in the message is 50:50, the recognition accuracy for channel coding and interleaving is approximately 62% and 64% for the deep neural network (DNN), and 38% and 66% for the convolutional neural network (CNN), respectively. However, when the ratio is altered to 30:70, the channel coding recognition accuracy approaches 90%, and the interleaving recognition accuracy nearly reaches 80%. These results demonstrate that adjusting the ratio of 0s to 1s can lead to significantly higher recognition accuracy. Future research will explore performance variations by increasing the proportion of 0s as well as 1s.

REFERENCES

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