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Research Article

Identification of Orthogonal Frequency-Division Multiplexing Modulated Signals with Deep Learning Model

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ABSTRACT

Signal modulation identification plays a crucial role in 5G and beyond systems to obtain a reliable zone by defining certain orthogonal frequency division multiplexing signal patterns for broadcasting in priority areas. However, there is a limited bottleneck traditional methods because of the extracting the features of the signals. In the proposed method, a deep learning-based frequency decomposition solution were used at different signal-to-noise ratio levels with only 10-bit data from six different modulated signals which are BPSK+BPSK, BPSK+8PSK, BPSK+QPSK, QPSK+BPSK, QPSK+8PSK, QPSK+QPSK. The features of the signals were obtained after signal decomposition with the multivariate variational mode decomposition method in low, medium and high frequency stages. The method was validated with an open access orthogonal frequency division multiplexing dataset (DOI:10.21227/xwk3-t431). The proposed model achieved as 94.673% hold out validation accuracy at 0dB in high noisy situation. In the case of 16 dB, where the noise was reduced, a remarkable accuracy of 98.461% was achieved. These experimental results show that the proposed model provides higher accuracy and good consistency. This provides a classification stand on the extraction of signal frequency characteristics and deep learning methods. This result makes it possible to add a new layer of security for the safety communication channel.

Introduction

Baseband signal and band-pass signal models are used in data communication depending on the structure of the 5G communication [1]. In these models, the modulation is performed using a carrier signal in a certain frequency range. The modulated signals obtained after the modulation are coded in the form of pulse code modulation (PCM) [2]. The transmission of the signal throughout the channel is ensured with this coding. Then, the encoded signals are wirelessly broadcasted by the transmitter. Orthogonal frequency division multiplexing (OFDM) is one of the important methods used in the design of advanced 5G wireless communication systems. High spectral efficiency can be achieved while reducing fading and noise in OFDM. In the traditional wireless communication structure, the basic protocol is shared for each user. This sharing is organized according to the cooperation relationship. On the other hand, the rapid development in wireless communication has led to the spread of non-cooperative communication. It is important to be able to define different modulation types of all received signals in a non-cooperative design. The signal modulation identification (SMI) techniques are used in non-cooperative design [3]. When these techniques are used, various eavesdropping risks of wireless users can be identified. This is an important factor to ensure the security and integrity of communication systems.

The secure design of the SMI method is a major technical challenge for determining signal types in non-cooperative OFDM systems. Firstly, it is necessary to define the modulation types in OFDM signals [4]. In this stage, the signal is demodulated. Then, modulation types are predicted by capturing the data in the wireless channel. However, it is possible to detect modulated signals with an artificial intelligence model. This allows us to estimate modulation types even in the case of encrypted data [5].

In the literature, different solutions were presented for estimating the modulation type. Most existing techniques were based on feature extraction and machine learning classification algorithms. Since traditional feature extraction methods rely on statistics, it is difficult to extract the inherent signal characteristics of the different modulation types. This is a major bottleneck problem that needs to be solved. Another problem is that machine learning methods become inadequate when the amount of data in the dataset increases. In essence, the probability of correct classification is not high and it is difficult to implement in practical OFDM systems [6]. In addition, it is important to define OFDM signals in the environment to create a secure zone [7]. The deep learning models (DLM) were used to overcome this bottleneck [8]. In literature, various solutions were proposed to solve these problems. Xie et al. proposed an enhanced identification method with deep neural networks (DNN) [9]. Wang et al. used long short-term memory (LSTM) neural network and deep residual networks (ResNet) to identify the modulation modes of the signal and significantly reduce the training time. The authors stated that signals with high signal to noise ratio (SNR) could be classified [10]. Aslam et al. used genetic programming for classification in signals, which includes four modulation modes, namely binary phase shift keying (BPSK), quadruple phase shift keying (QPSK), 16-frame amplitude modulation (16QAM), and 64-frame amplitude modulation (64QAM) with genetic programming (GP) and k-nearest neighbor (KNN) [11]. Ali & Yangyu proposed principal component analysis (PCA) and KNN classifier to recognize three different modulations, PSK, FSK and QAM. The authors used the data reduced in size with the PCA algorithm. Then, the PSK, FSK and QAM were classified with KNN classifiers. Bouchou et al. proposed a Stacked Sparse Autoencoder (SSAE) based method to recognize modulations including BPSK, QPSK, 8PSK, 16QAM, 64QAM, 16APSK and 32APSK. The authors stated in their experiments that noise increases the classification accuracy [12]. Sony et al., studied the performance implications between "BPSK-BPSK, QPSK-BPSK and QPSK-QPSK" for Non-Orthogonal Multiple Access (NOMA) end users. The authors show that a multi-relay collaborative NOMA system to support 5G, increasing relay nodes increases system diversity [13]. Liu et al. used a model combining convolutional neural networks (CNN) and LSTM to classify modulation signals, namely BPSK, QPSK, 8PSK, QAM16, QAM64, BFSK, CPFSK and PAM4. The authors achieved classification success of 88.5% at high SNR [14]. Zeng et al. classified 11 different modulation signals. The authors used STFT for feature extraction and CNN for classification algorithm [15]. Cui et al. classify the type of modulation in communication, the authors used the LSTM architecture. Phase properties and spatial properties were obtained with LSTM architecture. By design with only a fully connected layer, 11 communication modulation types were classified. Experiments prove that it achieves an accuracy higher than 84.5% even when the SNR is 0 decibel (dB) [16]. Although these proposed methods overcome the problems, analyzing the signal without dividing it into frequencies and classifying the signal without demodulation is still a problem that needs to be solved.

In this study, a deep learning architecture was designed to classify 6 different modulated signal sequences without the need for demodulation. These modulation types are BPSK+BPSK, BPSK+8PSK, BPSK+QPSK, QPSK+BPSK, QPSK+8PSK, QPSK+QPSK. In this design, the signal was separated into 3 separate components with the multivariate variational mode decomposition (MVMD) method instead of extracting the statistical features of the modulated signals. These are low frequency, mid frequency and high frequency components. The 1 dimensional CNN (1DCNN) block was used before applying the data directly to the Bidirectional Long Short Term Memory (BiLSTM) model. This block provides an effective solution for data transformation, map filtering and kernel sizes. Thus, the model can extract features from observation sequences and map internal features. The modulated OFDM signals are separated into its components and processed with 1DCNN block. Each signal component is applied to the deep learning architecture with the BiLSTM layer as a time series. It is a way to learn spatial and temporal properties simultaneously. Thus, the characteristics of the signal can be extracted. These features are processed with the softmax layer and the signal is placed in 6 separate classes. The main contribution of this design is that it prevents data loss due to statistical analysis. This makes it possible to solve the problem of convergence of classification success. The study was validated using the hold-out method with the open access OFDM dataset (DOI:10.21227/xwk3-t431). The experiments were performed under 0 decibel (dB), 8dB and 16dB SNR effects. In experimental studies, 165000 data were used according to each modulation type and SNR level. 20% of this data is reserved for validation. As a result, the accuracy and the Cohen's kappa metrics were obtained as 98.461% and 98.2% at 16dB, respectively.

Contributions are briefly summarized as follows.

The deep learning-based frequency decomposition method was used to overcome the existing difficulties in classifying orthogonal frequency division multiplexed signals.

The usage of MVMD technique and hybrid deep learning model results in high classification accuracy and Cohen's kappa values at various signal-to-noise ratio levels. This shows the effectiveness of the method. The experimental results demonstrate the consistency of the proposed model and suggest that it could potentially be applied to scenarios such as protecting a Demilitarized Zone (DMZ) through more accurate signal classification, while primarily contributing to signal processing tasks.

This article consists of 4 sections. Section 2 provides the material and method. Experimental results and discussions are given in Section 3. Finally, Section 4 concludes the results and also sheds light on future study.

Material and Methods

Proposed OFDM Detection Architecture

The developed model in this study is presented in Fig. 1. It can identify different modulation types in modulated OFDM signals with end to end recognition. Signals of 6 different modulation types received from OFDM systems are classified with this scheme. Firstly, the 10-bit length signal was divided into 3 different frequency components with MVMD. The decomposition provides that the model schema can learn the spatial and temporal properties of OFDM signals simultaneously. These are low frequency, mid frequency and high frequency components. Then, the signals of these three frequency components are applied to the 1DCNN architecture. At this stage the features of the

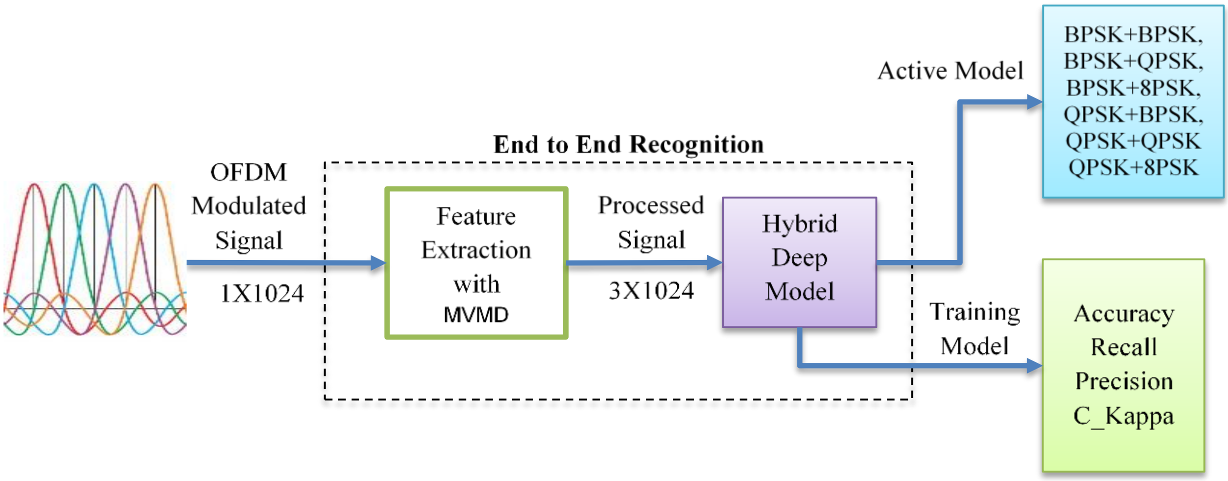


Figure 1. The overall flow chart of the proposed system

modulated signals are extracted from each signal component. Thus, the spatial features were learned by applying a 1024-unit signal to the 1DCNN model (kernel size=3, stride 1, padding on). Then, convoluted signals pass through the batch normalization layer and Rectified Linear Unit (Relu) layers to reduce the output size and avoid overfitting. Along with the 1DCNN network, an LSTM network with 64 LSTM units is used to learn the sequential OFDM signal characteristics. This layer follows with a flattened layer. This layer converts the data into a one-dimensional array for input to the next layer. Finally, the signal is separated into 6 different classes by the softmax layer by transferring these 64 features to the BiLSTM layer.

In the training phase of the deep architecture, the dataset was divided into 80% training and 20% validation. Hold out validation was used to verify the method. Thus, 132000 data were used in training and 33000 data were used in validation. Each sample from a given signal generation instance was allocated exclusively to either the training or validation set, preventing any overlap and ensuring that the validation results accurately reflect the model's generalization performance. This process guarantees that the validation performance accurately reflects the model's generalization capability. The dataset was balanced across six modulation classes. For each SNR level, 55,000 samples were used, with 5,500 samples per class. These samples were randomly selected from different portions of the signal space. Twenty percent of the data was reserved for validation, resulting in 44,000 samples for training and 11,000 samples for validation. The time-frequency representations of the training data are applied to the proposed model and it is examined in the performance evaluation data to find the efficient parameters of the trained deep network. The performance and generalization of the evaluated model are investigated and the classification result is reported in terms of classification accuracy and Cohen kappa value.

Dataset of the study

The OFDM dataset, which was published on the IEEE dataport, was used in the study (DOI:10.21227/xwk3-t431). The dataset contains Software Defined Radio Based OFDM Signal Real Time Modulation Recognition data. The recorded data includes header modulation and payload modulation, respectively, and 6 different modulated signals as BPSK+BPSK, BPSK+8PSK, BPSK+QPSK, QPSK+BPSK, QPSK+8PSK, QPSK+QPSK. In addition, the data with different noise amounts were added to the dataset separately. Therefore, there are 4096 pieces of data produced for each signal type under a certain SNR. Each piece of data has 1024 instances [5, 17].

In the study, this dataset was used for Deep Learning and Software Defined Radio Based OFDM Signal Real-Time Modulation Recognition, which provides additional details and description of the dataset. The dataset, which produces 6 modulated OFDM baseband signals with header modulation and payload modulation, is classified into 6 different classes, as BPSK+BPSK, BPSK+QPSK, BPSK+8PSK, QPSK+BPSK, QPSK+QPSK, QPSK+8PSK, respectively. Experiments were performed by taking the SNR range of each signal 0dB, 8dB and 16dB. The data were obtained balanced among 6 classes. The dataset was balanced across six modulation classes. For each experiment, 165,000 samples per modulation type and SNR level were generated by randomly selecting 55,000 signals from different portions of the signal space and applying three variations to each signal. Of this data, 20% was reserved for validation, resulting in 132,000 samples used for training and 33,000 samples for validation.

OFDM Modulated Signal Processing with Multivariate Variational Mode Decomposition

The MVMD decomposes the signal into different frequency spaces. This enables multidimensional processing of different frequency contents of signals. OFDM modulated signals with different frequency contents are divided into 3 separate frequency components with MVMD. This ensures consistency of signal frequencies containing information at different levels [18]. MVMD splits the one-dimensional signal $u_k(t)$ into a specified

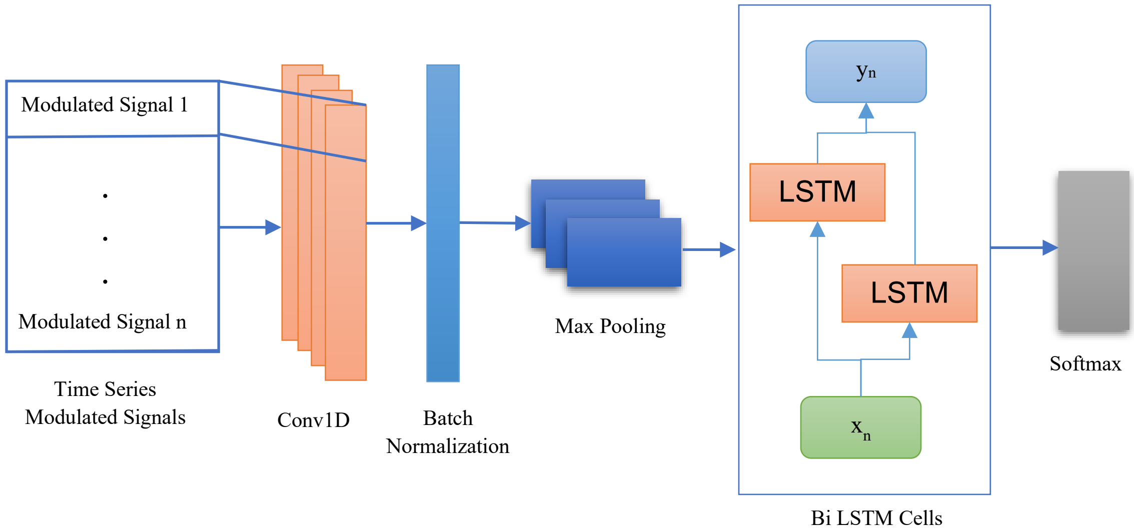


Figure 2. Architecture of proposed deep learning model

number of (k) subcomponents. The result is $x(t) = \sum u_k(t)$. Hilbert-Huang Transform (HHT) is preferred to calculate the $x(t)$. HHT provides a one-sided spectrum. The center frequency is obtained as $u_k(t)$. The center frequency corresponding to the frequency spectrum of each mode is arranged by multiplying the exponential term, in determining the fundamental frequency $w(t)$. The optimization problem of the MVMD is defined in Equation (1), which aims to decompose the input multichannel signal into a set of band-limited intrinsic modes while minimizing their bandwidths. The optimization considers the modulation of each mode around its center frequency [19].

$$minimize\left(\sum_k \sum_c \left\| \partial_t\left[u_{k,c}(t).e^{-jw_k t}\right]\right\|^2\right) \quad (1)$$

In Equation 1, the parameter $u_{k,c}(t)$ is a signal with a single frequency w_k component. The c parameter expresses the signal capacity to be applied in parallel. The number of the decomposed signal modes is determined by k parameter. The exponential term $.e^{-jw_k t}$ shifts the signal to baseband, allowing the bandwidth of each mode to be estimated through the squared L_2 norm of its temporal gradient. This parameter indicates the analytically modulated signal. To solve the constrained optimization problem, a Lagrangian formulation is introduced by incorporating a quadratic penalty term and a Lagrange multiplier to enforce signal reconstruction constraints. The augmented Lagrangian function is expressed in Equation 2.

$$\begin{aligned} &\mathrm{L}(\mathrm{u}_{k,c}, \omega_k, \lambda_c) \\ &= \alpha \sum_k \sum_c \left(\partial_t\left[u_{k,c}(t).e^{-jw_k t}\right]\right)^2 \\ &+ \sum_c x_c(t) - \sum_k u_{k,c}(t)^2 + \sum_c \lambda_c, x_c(t) \\ &- \sum_k u_{k,c}/t) \end{aligned} \quad (2)$$

In Equation 2, $x_c(t)$ denotes the observed multichannel signal, α is the equilibrium parameter and λ_c is the Lagrangian constant. In the unconstrained optimization problem, the components of the different bands of the multipliers are obtained with the alternating direction method algorithm. The solution of this optimization problem is obtained iteratively using the Alternating Direction Method of Multipliers (ADMM), which updates the mode functions $u_{k,c}$, the center frequencies ω_k and the Lagrange multipliers λ_c until convergence.

The Deep Learning Model

The deep learning model used in the study is obtained by using 1DCNN and LSTM models together. The flow of the model is presented in Fig. 2. In 1DCNN architecture, the input data is transformed according to the specified dimensions [20]. The representative features of the OFDM modulated signal are obtained with the transformation. The transformed features are applied to the batch normalization layer. This layer increases the speed, performance and stability of the network. The data coming from the batch normalization layer was subjected to max pooling. This layer contributes to the solution of the overfitting problem. Additionally, by reducing the number of parameters to be learned, the computational cost is reduced and basic translation invariance is achieved. Then, the negative data is eliminated with the Relu layer. The BiLSTM model, which is effective in solving sequential classification problems, determines whether the existing memory is stored or updated with new information. Therefore, BiLSTM is capable of modeling long-range dynamic dependencies, thus avoiding the problem of gradient disappearing during training [21]. In the BiLSTM architecture, there is an input gate, forget gate and exit gate. The BiLSTM model is obtained by the two-way operation of these units in the cell. The memory process is managed with a bidirectional structure.

Table 1. The structure of proposed DLM Architecture

Layer (type)	Output Shape
conv1d_1 (Conv1D)	(1,1024)
batch_normalization_1	(1,1024)
activation_1(Activation)	(1,1024)
Max_pool_1	(1,1024)
dense_1(Dense)	(64)
Blstm_1 (BiLSTM)	(64)
dense_2(Dense)	(8)
Softmax	(6)

The empirically decided hyper parameter values of the DLM architecture are given in Table 1. The deep model yielded the best performance metrics with these values.

Experimental Results and Discussion

In this study, a hybrid deep learning architecture was tried to be appropriately combined in the classification of OFDM modulated signals divided into 3 different frequency components with MVMD. This architecture is coded using the Python environment. Validation and training of the model was carried out with 16 GB RAM, a 6 GB NVIDIA 3050 GPU and a 5th generation CPU with i5 core.

Table 2. The parameters for Deep Learning Model.

Parameters	Values
Max Epochs	500
Initial Learn Rate	0.001
Mini Batch Size	256
Learn Rate Drop Period	40
Learn Rate Drop Factor	0.1

In the proposed model, CNN and LSTM architectures were used as hybrids. OFDM modulated signals applied to these architectures were separated into frequency components with the MVDM model. Each component of the signals, which were separated according to 3 different frequency information, was applied to the 1DCNN model separately. In a way, the extracted signals were applied to the bidirectional BiLSTM structure as such. The data used in the data set of the study were modeled as header modulation and payload modulation. Adapted to handle the hold out validation method, 80% training and 20% validation of data belonging to 6 classes: BPSK+BPSK, BPSK+QPSK, BPSK+8PSK, QPSK+BPSK, QPSK+QPSK, QPSK+8PSK. In addition, the SNR amounts in the used data set were also experimented with data with 0dB, 8dB and 16dB noise added, respectively. The robustness of the method was tested with these experiments. In each experiment, OFDM modulated signals in 6 different classes of 165000 lines were used. Of these signals, 132000 without noise (0dB) were used in the training of the model. The hyper-parameters with the lowest loss value were selected empirically for training. The selected parameters are presented in Table 2. The trained model, on the other hand, was validated with a data set of 33000 data in each validation experiment, with signals containing noise of 0dB, 8dB and 16dB, respectively.

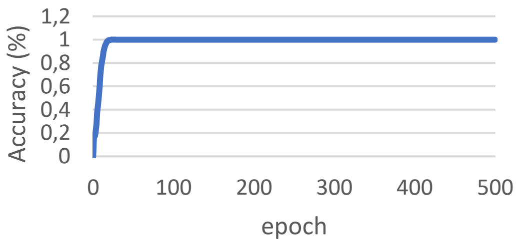
There are 6 different classes in the experimental dataset. Since it is a multi-classification problem, accuracy, recall, precision and Cohen's kappa metrics are used to measure the performance of the model. The expressions true positive (TP), false positive (FP), true negative (TN) and false negative (FN) are used to calculate these metrics. These parameters are obtained from the confusion matrix values. The test label refers to the labeled data and the test prediction refers to the model predictions. The metrics obtained with these parameters are accuracy, recall, precision and Cohen's kappa, respectively. These expressions are obtained by Equations 3, 4, 5 and 6 respectively [22].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

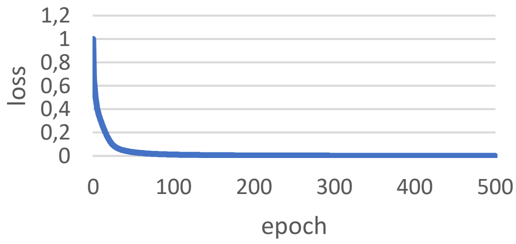
$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$C\_Kappa = \frac{test\ label - test\ prediction}{1 - test\ prediction} \tag{6}$$



(a)



(b)

Figure 3. (a) The accuracy- epoch graph of the training deep learning model (b) The loss- epoch graph of the training deep learning model

Table 3. The Confusion Matrix of the Modulated OFDM Modulation with 0dB SNR

Classifier Results: Header and Payload	Truth Data: BPSK_8PSK	BPSK_BPSK	BPSK_QPSK	QPSK_8PSK	QPSK_BPSK	QPSK_QPSK	Precision (%)
BPSK_8PSK	5259	54	23	0	4	14	98.226
BPSK_BPSK	0	4771	1	0	0	1	99.958
BPSK_QPSK	4	26	5043	0	0	3	99.35
QPSK_8PSK	187	377	355	5492	77	190	82.24
QPSK_BPSK	11	127	16	2	5398	13	96.964
QPSK_QPSK	39	145	62	6	21	5279	95.083
Recall (%)	95.618	86.745	91.691	99.855	98.145	95.982	

The model was trained for 500 epochs in all experiments using the training parameters summarized in Table 2. The loss and accuracy graphics were obtained while through training of the deep learning architecture. These findings presented in Fig. 3a and Fig. 3b. The same configuration was applied for each SNR scenario to ensure consistency in performance evaluation. The training and hold out validation accuracy and loss curves were monitored during the learning process to evaluate the convergence behavior of the proposed model. The results demonstrate that the network achieves stable convergence and maintains consistent performance

between training and validation datasets. This indicates that the proposed architecture is capable of learning discriminative features from OFDM signals without significant overfitting.

An early stopping mechanism was not used in this study. Instead of this progress, a learning rate scheduling strategy was applied to improve training stability and convergence. The initial learning rate was set to 0.001 and decreased by a factor of 0.1 every 40 epochs. This strategy enables the network to progressively refine the learned parameters and achieve stable convergence without premature termination of the training process.

The computational complexity of the proposed architecture was evaluated using floating-point operations (FLOPs). The proposed model included conv1d_1, batch_normalization_1, activation_1, Max_pool_1, dense_1, Blstm_1, dense_2 and Softmax. The computational costs were mostly spent the Conv1D, dense, and BiLSTM layers. The LSTM layer FLOPS were calculated with the sequence length, hidden state size and input dimension. On the other hand, the CNN FLOPS was calculated with kernel size, input channel, number of filters and output length. The estimated computational time for testing a single sample is approximately measured between 0.001 and 0.005 seconds, accounting for typical processing overhead and variations in 100 trials. For a batch of 55,000 test samples, the estimated computational time is approximately measured between 55 and 275 seconds, considering typical processing overhead and system variations in 100 trials.

Furthermore, to validate the effectiveness of the proposed model, a comparative analysis with existing deep learning architectures commonly used in modulation classification was conducted. The comparison results show that the proposed model achieves competitive performance

in terms of classification accuracy and robustness under different SNR conditions.

The confusion matrix obtained as a result of experimental studies with the data set with an SNR of 0dB is presented in Table 3. Precision and recall values, which are the success metrics of 6 different modulated signals, are also expressed in Table 3 on the basis of each class. While the overall accuracy was calculated as 94.673% for signals with 0 SNR, the Cohen's kappa value was obtained as 93.6%.

The training and validation curves provided in the revised manuscript demonstrate that the model converges effectively within the specified number of epochs and

Table 4. The Confusion Matrix of the Modulated OFDM Modulation with 8dB SNR

Classifier Results: Header and Payload	Truth Data: BPSK_8PSK	BPSK_BPSK	BPSK_QPSK	QPSK_8PSK	QPSK_BPSK	QPSK_QPSK	Precision (%)
BPSK_8PSK	5112	5	22	29	4	7	98.706
BPSK_BPSK	103	5455	68	84	17	33	94.705
BPSK_QPSK	95	17	5293	121	13	15	95.301
QPSK_8PSK	7	2	16	5029	3	5	99.348
QPSK_BPSK	60	4	16	56	5433	9	97.401
QPSK_QPSK	123	17	85	181	30	5431	92.569
Recall (%)	92.945	99.182	96.236	91.436	98.782	98.745	

Table 5. The Confusion Matrix of the Modulated OFDM Modulation with 16dB SNR

		Truth Data						
	Header and Payload	BPSK_8PSK	BPSK_BPSK	BPSK_QPSK	QPSK_8PSK	QPSK_BPSK	QPSK_QPSK	Precision (%)
Classifier Results	BPSK_8PSK	5363	4	3	8	10	10	99.352
	BPSK_BPSK	9	5430	1	5	4	7	99.523
	BPSK_QPSK	26	18	5472	11	29	35	97.872
	QPSK_8PSK	84	40	19	5466	37	85	95.376
	QPSK_BPSK	10	8	4	2	5413	15	99.285
	QPSK_QPSK	8	0	1	8	7	5372	99.553
	Recall (%)	97.509	98.727	99.491	99.382	98.418	97.236	

maintains a consistent performance between the training and validation datasets.

The confusion matrix obtained as a result of experimental studies with the data set with an SNR of 8dB is presented in Table 4. Precision and recall values, which are the success metrics of 6 different modulated signals, are also expressed in Table 4 on the basis of each class. While the overall accuracy was calculated as 96.221% for signals with 0 SNR, the Cohen's kappa value was obtained as 95.5%.

The confusion matrix obtained as a result of experimental studies with the data set with an SNR of 16dB is presented in Table 5. The precision and recall values, which are the success metrics of 6 different modulated signals, are also expressed in Table 5 on the basis of each class. While the overall accuracy was calculated as 98.461% for signals with 0 SNR, the Cohen's kappa value was 98.2%.

The overall performance metrics of the deep learning model in different SNR values are presented in Table 6.

Table 6. Model Performance in different SNR values

Model Performance	Different SNR Values		
	0dB	8dB	16dB
Accuracy (%)	94.673	96.221	98.461
Cohen's kappa (%)	93.600	95.500	98.200

According to the results of the experiments, the proposed model achieved over 90% success in identifying the OFDM signal type under different noise conditions. Especially at the 0dB level, where noise is high, the hold out validation accuracy was achieved as 94.673%. In the case of 16 dB, where the noise was reduced, a remarkable accuracy of 98.461% was achieved. There are various studies in the literature trying to define OFDM signals with image processing. In particular, the analysis of signals converted to images was tried to be achieved with deep learning architectures. In the classification studies performed by obtaining features with the CNN architecture, OFDM was defined from the signals interpreted as 2-dimensional [4, 23, 24, 25]. However, the signals are organized with the 1DCNN architecture, in this study. The processed signals with 1DCNN architecture is an algorithm also included in the literature [26, 27, 28]. Unlike the above studies, OFDM modulated signals are divided into 3 different frequency components with MVMD, in this study. The parameters of the MVMD were carefully selected based on experimental analysis. The number of modes k was set to three to capture the dominant frequency components of the OFDM signals while avoiding over-decomposition, which was verified through preliminary experiments comparing different mode numbers. The balancing parameter α was chosen empirically to achieve an optimal trade-off between data fidelity and smoothness of the decomposed modes. Three frequency components were used because they were sufficient to represent the main spectral content of the signals; additional modes did not improve classification performance significantly in initial tests. This parameter selection ensures that the MVMD effectively extracts meaningful features for subsequent 1D CNN and BiLSTM processing. OFDM modulated signals containing each frequency information were arranged in parallel with the 1DCNN architecture and the features in the signals were determined. These signals were then implemented into the BiLSTM architecture and incorporated into the memory structure. In addition, it is an undeniable fact that the BiLSTM architecture is effective against the vanishing gradient problem [20].

When the studies conducted with the data set used in this study are examined, Chong et al. obtained as an average of 91.4% accuracy was achieved in classification [17]. It also shows that simulation results are approximately 5% to 10% higher than visual geometry group, ResNet, recurrent neural network and multi-scale feature extraction and content-aware reassembly network in the same study. The experimental results demonstrate the efficacy of the proposed model in identifying Orthogonal Frequency Division Multiplexing (OFDM) signal types under varying noise conditions. The model achieved a success rate exceeding high accuracy level at the challenging 0dB noise level and an impressive accuracy at the 16dB noise level. This suggests the model's robustness and adaptability to different noise scenarios, showcasing its reliability in practical 5G communication environments. This outcome is proof that modulated signals in the environment can be easily classified. The classification of the signals in the environment indicates that a new security layer can be added for DMZ with safety communication channel.

Although the proposed model demonstrates high classification accuracy across different SNR levels, the generalization capability of the model may vary when applied to the different signal characteristics.

Conclusion

This study focused on determining digital modulation types. Applications of deep learning models for classifying signals separated into different frequency components were discussed. In the study, the robustness of the proposed model was systematically examined under various SNRs. It provided a comprehensive understanding of the classification performance of ODFM signals at different noise levels. Experimental results demonstrated remarkable accuracy, which was particularly notable at 16dB SNR, consistently achieving Cohen's kappa values exceeding 98%. This validation performance underlined the strong ability of the proposed model to accurately distinguish modulation types, demonstrating its superiority over a comparative study using the same dataset. These findings are evidence of an important step towards improving security, especially within the Demilitarized Zone. While the proposed method may contribute to enhancing the security of the DMZ in practical scenarios, no formal threat model or adversarial analysis was conducted in this study. Therefore, the security-related statements are presented in a cautious manner, and the approach is described as potentially adding a layer of protection rather than guaranteeing improved security.

Future studies may include improving these results by developing a new security layer in software. This effort involves integrating a specifically designed hardware architecture to identify various modulated OFDM signals and different signal characteristics. This research will enable not only to contribute to theoretical advances in deep learning for signal classification, but also to facilitate the practical implementation of robust security solutions in real-world scenarios.

Ethics committee approval and conflict of interest statement

There is no need to obtain permission from the ethics committee for the article prepared.

There is no conflict of interest with any person / institution in the article prepared.

Authors' Contributions

Kasım Ö.: Study conception and design, visualization, analysis, interpretation of data, drafting of manuscript, conceived the original idea, supervised the project and critical revisions.

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