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Symbol classification in receiver of OFDM carrier signal with deep learning and whale optimization algorithm

Derin öğrenme ve balina optimizasyon algoritması ile OFDM taşıyıcı sinyal alıcıda sembol sınıflandırma

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Symbol Classification in Receiver of OFDM Carrier Signal with Deep Learning and Whale Optimization Algorithm

Highlights

- *Utilizes deep learning (CNN) combined with Whale Optimization Algorithm (WOA) for efficient symbol classification in OFDM receivers.*
- *WOA is used to select optimal feature subsets to improve classification accuracy and reduce computational complexity.*
- *Achieves over 95% accuracy, outperforming classical methods like MMSE and LS.*

Graphical Abstract

A conceptual diagram combining:

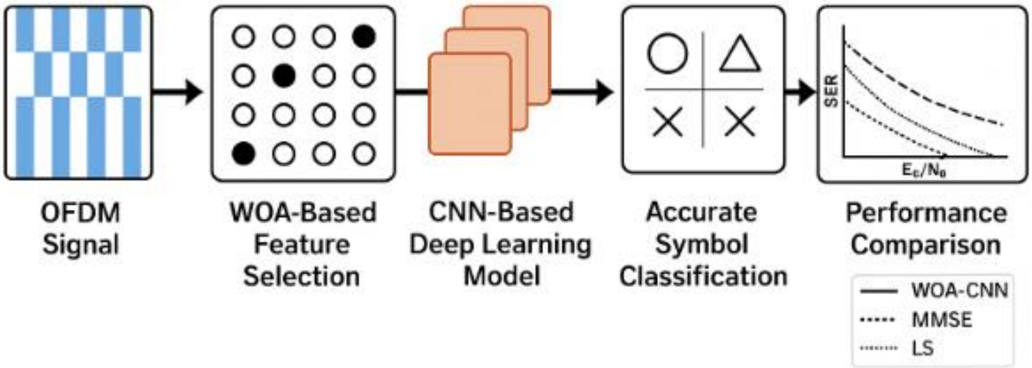

Figure . Graphical Abstract

Aim

The primary aim of this research is to develop a hybrid framework using deep learning and metaheuristic feature selection via the Whale Optimization Algorithm (WOA).

Design & Methodology

- *A simulated OFDM communication environment is used to generate 10,000 samples.*
- *Whale Optimization Algorithm (WOA) is used to select optimal subsets of features (e.g., amplitude, phase).*
- *These features are fed into a CNN-LSTM architecture for training and classification.*

Originality

- *Introduces a novel integration of WOA with CNN-LSTM specifically tailored for OFDM systems.*
- *Provides a comparative framework that demonstrates the superiority of WOA over other feature selection methods (PCA, ACO, PSO).*

Findings

- *The WOA-selected features significantly improved CNN performance, achieving symbol classification accuracy greater than 95%.*
- *The proposed WOA-CNN model consistently outperformed traditional classifiers and other hybrid models across all test conditions.*

Conclusion

The integration of WOA-based feature selection with deep learning significantly improves the performance of OFDM symbol classification tasks.

Declaration of Ethical Standards

The authors declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Symbol Classification in Receiver of OFDM Carrier Signal with Deep Learning and Whale Optimization Algorithm

Araştırma Makalesi / Research Article

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ABSTRACT

Orthogonal Frequency Division Multiplexing (OFDM) remains a cornerstone in modern wireless communication systems, owing to its resilience to multipath fading and spectral efficiency. In OFDM systems, accurate symbol classification is paramount for successful data demodulation. This paper proposes a novel methodology for symbol classification in the receiver of an OFDM carrier signal, using a synergic combination of deep learning and feature selection with the Whale Optimization Algorithm (WOA). The deep learning component, embodied in a convolutional neural network (CNN), is adept at extracting intricate features from the received OFDM symbols, while the WOA facilitates efficient feature selection by optimizing a subset of attributes that contribute most to categorization accuracy. This dual approach not only enhances the discriminative power of the classification model but also reduces the computational complexity by focusing on the most relevant features. Experimental findings confirm the effectiveness of the proposed framework, demonstrating superior symbol classification performance compared to conventional methods. Moreover, the integration of feature selection with the WOA ensures the identification of an optimal subset of features, further improving classification accuracy and generalization capability. This study combines DL with metaheuristic feature selection to improve symbol classification in OFDM receivers, thereby making wireless communication systems more reliable and efficient.

Keywords: Symbol Classification, OFDM, Deep learning, Whale optimization algorithm.

Derin Öğrenme ve Balina Optimizasyon Algoritması ile OFDM Taşıyıcı Sinyal Alıcıda Sembol Sınıflandırma

ÖZ

Ortogonal Frekans Bölmeli Çoğullama (OFDM), çok yollu sönümlemeye karşı dayanıklılığı ve spektral verimliliği sayesinde modern kablosuz iletişim sistemlerinin temel taşlarından biri olmaya devam etmektedir. OFDM sistemlerinde, başarılı veri demodülasyonu için doğru sembol sınıflandırması çok önemlidir. Bu makale, Balina Optimizasyon Algoritması (WOA) ile derin öğrenme ve özellik seçiminin sinerjik bir kombinasyonunu kullanarak bir OFDM taşıyıcı sinyalinin alıcısında sembol sınıflandırması için yeni bir metodoloji önermektedir. Bir evrişimli sinir ağında (CNN) somutlaşan derin öğrenme bileşeni, alınan OFDM sembollerinden karmaşık özellikleri çıkarmada ustalaşırken, WOA, kategorizasyon doğruluğuna en çok katkıda bulunan bir alt özellik kümesini optimize ederek verimli özellik seçimini kolaylaştırır. Bu ikili yaklaşım sadece sınıflandırma modelinin ayırt edici gücünü artırmakla kalmaz, aynı zamanda en ilgili özelliklere odaklanarak hesaplama karmaşıklığını da azaltır. Deneysel bulgular, geleneksel yöntemlere kıyasla üstün sembol sınıflandırma performansı göstererek önerilen çerçevenin etkinliğini doğrulamaktadır. Ayrıca, özellik seçiminin WOA ile entegrasyonu, optimum özellik alt kümesinin belirlenmesini sağlayarak sınıflandırma doğruluğunu ve genelleme yeteneğini daha da geliştirmektedir. Bu çalışma, OFDM alıcılarında sembol sınıflandırmasını iyileştirmek için DL ile metasezgisel özellik seçimini birleştirerek kablosuz iletişim sistemlerinin daha güvenilir ve verimli olmasını sağlar.

Anahtar Kelimeler: Sembol Sınıflandırma, OFDM, Derin öğrenme, Wale optimizasyon algoritması.

1. INTRODUCTION

In contemporary wireless communication, orthogonal frequency division multiplexing (OFDM) is a popular modulation technology due to its ability to minimize inter-symbol interference (ISI) and resist frequency-selective fading [1]. Reliable and effective data decoding in OFDM depends on accurate symbol classification [2]. Traditional approaches, however, rely on manually created features and basic classifiers, which are insufficient to handle complicated data, particularly in noisy environments and with fluctuating channel conditions [3].

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Recent advances in computer vision, natural language processing, and speech recognition have been made possible by deep learning's (DL) capacity to automatically extract meaningful characteristics from raw data [4]. By enabling the direct extraction of intricate features from received signals, the application of DL to symbol classification in OFDM receivers can get around the drawbacks of conventional methods [5].
Furthermore, the caliber and applicability of the input features have a significant impact on how well DL model's function [6]. Finding the most significant characteristics that improve classification accuracy while lowering computational costs and the possibility of overfitting requires the use of feature selection strategies [7]. But selecting the best feature subset can be difficult, especially in high-dimensional data settings like OFDM systems [8].
OFDM stands out as one of the most prevalent modulation schemes employed in contemporary wireless systems. The efficiency of OFDM systems largely relies on signal recognition and techniques for channel calculation [9]. Therefore, numerous studies have been conducted to design effective methods for channel estimation and signal recognition. OFDM is a modulation technique that uses numerous orthogonal signals for transferring digital information [10]. Therefore, The approach is a unique variant of FDM wherein the carrier is orthogonalized (i.e., the peak of a carrier coincides with the zero crossing of its adjacent carriers) between signals modulated on adjacent carriers [11].
Data intended for transmission at a high data rate is initially split into multiple sub-streams with lower data rates. Each of these data streams is independently partially encoded using a standard modulation technique like low-bandwidth Quadratic Amplitude Modulation (QAM), following which the modulated High-Frequency (HF) signals are amalgamated [12]. To discern individual signals Throughout the demodulation receiver's phase, the carriers must be perpendicular to each other in the function space. This results in minimizing the interference among the partial data streams.
The strength of OFDM is its capability to adjust data transmission finely by breaking it down to match the specifics of a transmission channel, like a radio channel. In case narrowband interference emerges within the OFDM signal spectrum, carriers influenced by the interference might be disregarded from data transmission. Consequently, the total data transfer rate is reduced [13]. However, In situations utilizing wideband quadrature amplitude modulation with only one carrier, the presence of narrowband interference in the transmission channel can impede complete data transmission. Additionally, the challenge of destructive interference resulting from multipath reception pertains exclusively to single carriers.
As the data is distributed across numerous subcarriers, it is considered multi-carrier modulation. Because these subcarriers are orthogonal to each other, they do not benefit from interacting, In contrast to the conventional FDM, even though they are arranged linearly, causing an intersection in the current frequency axis. Efficiency can be discerned by utilizing the Fast Fourier transform (FFT) technique [14] on subcarriers.
To address these challenges, this study presents an innovative method for symbol categorization in the receiver of an OFDM carrier signal by integrating DL with feature selection using the WOA. The DL component, specifically a CNN, is used to automatically learn discriminative characteristics from received OFDM symbols, while the WOA is used to optimize the subset of features that maximize classification accuracy [15]–[17]. This synergistic combination intends to improve symbol categorization performance while reducing computing complexity, thereby enhancing the reliability and efficiency of OFDM communication systems [18].
In this study, the selected features with WOA for feature selection will be used to test the data using a deep neural network (DNN) [19]. The long short-term memory (LSTM)-based neural network will be utilized to train in individual subcarriers [20], [21]. The symbol error (SER) will be calculated and combined with the least square (LS) and minimum mean square error (MMSE) to assess the system's performance. In this research, an offline training system is deployed in the wireless channel. Each OFDM packet sent will include a randomly generated phase adjustment. The effects of the number of pilot symbols and cyclic prefix (CP) duration will be measured [22].
The following sections provide a literature overview of the theoretical principles of OFDM, DL, and feature selection strategies. The suggested approach for symbol classification will then be discussed, including the CNN architecture and the integration of feature selection with the WOA. The effectiveness of the proposed strategy will be validated by test data and comparative studies. Finally, the discussion will focus on its concepts and potential directions for future study.

1.1. Literature review

Symbol classification OFDM receiver is an essential for accurate data transmission in modern wireless communication [23]. Researcher have used different methods to address this challenge, ranging from traditional signal processing methods to advanced machine learning (ML) and optimization approaches [24]. Early studies primarily relied on conventional techniques, including maximum likelihood estimation (MLE), correlation-based classifiers, and decision-theoretic approaches [25]. These methods used manually selected features, such as amplitude, phase, and frequency to classify symbols. While effective in some cases, these approaches struggle to adapt to dynamic channel conditions and noise variations [26].
ML, especially DL, has greatly improved symbol classification by enabling automatic feature learning feature extraction from raw data [27]. Studies show that CNNs outperform traditional methods in terms of accuracy and efficiency, particularly in complex modulation recognition tasks [28]. The integration of

CNNs with frameworks like the discrete Fourier Transform (DFT) allows for robust data manipulation, enabling real-time processing capabilities essential for modern communication systems [29]. For example, Kumar et al. (2023), suggested a CNN-based method for automatic modulation classification in OFDM systems, achieving better accuracy than conventional methods [30]. By learning key features directly from the time-frequency representation of received signals, the CNN demonstrated robust resistance to channel issues and noise. Similarly, Zhang et al. (2019) used a CNN with remaining connections for symbol classification in OFDM systems, achieved high accuracy even under challenging conditions such as frequency-selective fading and interference [31].

The WOA is simple, powerful optimization technique inspired by the hunting behavior of whales. It balances exploration and exploitation to find optimal solutions [32]. In OFDM symbol classification, WOA combined with DL to improve feature selection and optimize neural networks input [33]. Also, Wang et al (2020) Suggested a hybrid approach that combines CNN-based DL with feature selection using the gray wolf optimization (GWO) algorithm for modulation classification in OFDM systems [34]. The GWO improved CNN performance by selecting the most important features from time-frequency representation of received signals, resulting in better accuracy efficiency. The reference [35], particle swarm optimization (PSO) is effective in selecting relevant features, classification accuracy in complex environments like OFDM receivers. The study [36], suggested an attribute selection technique employing an artificial bee colony (ABC). They incorporate a Kalman filter within the hadoop ecosystem to filter the noise.

Reference [37], introduce a method for choosing attributes using a hybrid genetic algorithm (GA) with detailed data. They tested this approach on eleven standard financial datasets and compared it with advanced techniques. The results showed high classification accuracy.

This study [38], presented the new feature selection method for classification using multi-objective PSO. The first method applied sorting, while the second added mutation and crossover. These methods were compared with two traditional techniques and tested on twelve datasets.

Reference [39], introduced a novel feature selection approach that combines multi-cluster particle swarm optimization (MSPSO) with support vector machines (SVM), using the F1 score as the fitness criterion.

The objective is to improve both kernel optimization and feature selection for better abstractions. Evaluation results show that the new techniques outperform the previous methods. Reference [40] proposed a feature selection method combining GA and PSO algorithms, using SVMs as the fitness function and precision as the suitability measure.

The proposed method, tested on the Indian Pines Spectral dataset, effectively identifies key features for classification, leading to higher accuracy. However, it lacks a detailed analysis of benchmark datasets and comparison with more advanced methods. the study in [41] presents a feature selection strategy that combines GA with NNs, applied to real and standard credit datasets. It outperforms the established classification methods in term of precision.

The effectiveness of OFDM in terms of channel bandwidth is additionally enhanced using MIMO (Multi-input multi-output) [42], [43]. MIMO incorporated into OFDM significantly increases the channel bandwidth of the communication network. However, channel estimation, ICI (intercarrier interference) cancellation, and overhead Average Power Ratio (PAPR) reduction become difficult due to the extra complexity added by the channel. Space Division Multiple Access (SDMA) [44] represents a distinctive type of MIMO where spatially separated users can leverage a single antenna for MIMO transmission. SDMA presents greater challenges when users access diverse antennas. Consequently, precise signal identification for each user becomes essential. Multi-user identification approaches are employed to address this requirement [45-46]. Table 1 lists the investigations from the literature about signal detection in OFDM systems.

No heuristics were used for feature extraction in the researched articles. In this study, it will be shown that the proposed method has a good performance by using the Whale optimization method and other heuristic methods (ant colony, GA, and PSO).

Overall, the integration of DL combined with feature selection strategies typically includes methods like the PSO presents a promising approach for enhancing symbol classification in the receiver of OFDM carrier signals. By leveraging the complementary strengths of automatic feature learning and optimal feature subset selection, these hybrid approaches offer the capacity for enhancing the reliability, Performance, and adaptability of OFDM communication networks in diverse operating environments.

1.2. Existing Gaps and Research Motivation

Several previous studies have emphasized the importance of integrating CNN and LSTM hybrid architectures in improving the performance of noisy communication systems. However, a close examination of these studies shows that many of them have encountered limitations in effectively integrating these hybrid architectures with metaheuristic-based feature selection methods to minimize the Symbol Error Rate (SER) in noisy transmission environments.

In addition, another important aspect that is often neglected in previous studies is the computational cost of deploying complex models in resource-constrained communication systems. This can be a major challenge, especially in practical and real-time applications. In order to overcome the aforementioned limitations and fill the gaps in previous studies, the present study proposes a hybrid framework based on the CNN-LSTM architecture, which is improved by using WOA. The main objective of this proposed framework is to optimize the process of selecting effective features and, consequently, increase the overall performance of communication systems in the face of noise and possible disturbances. By integrating WOA as an efficient feature selection mechanism, this research attempts to improve the detection accuracy while also considering the computational costs associated with model deployment.

Table 1. Literature review on signal detection in OFDM systems

Ref	Contribution to literature
[42]	They use a new DL method to estimate co-channel interference and detect signals in OFDM systems by the time-frequency relationship of wireless fading channels.
[43]	They use DL to create an efficient signal detection scheme in an indoor VLC communication system, enabling reliable detection of the original signals in real time with limited channel.
[44]	They suggested the DL-based approach for joint channel estimation and signal detection in multi-user OFDM-non-orthogonal multiple access (NOMA) systems over the Rayleigh fading channel.
[45]	They apply DL for signal detection in OFDM with index modulation (IM) systems and propose a Y-shaped network with fully connected layers (Y-FC) and bidirectional LSTM units (Y-BLSTM) to optimize the data retrieval.
[46]	The removal of the CP can improve the spectral efficiency of multi-input multiple-output (MIMO)-OFDM systems. To address this, they are developing a model-driven DL-based detector, using the orthogonal approximate message passing (OAMP) algorithm, which reduces interference but requires computationally complex matrix inversion.
[47]	To solve the drawback of the method of route removal QR decomposition-M (PEQRD-), They introduced an energy-efficient low-complexity signal identification approach based on adaptive QR in MIMO-OFDM systems.
[48]	They introduce a method employing DL to aid signal identification in the transmission of OFDM networks across dynamic channels. Particularly, a recurrent neural network (RNN) featuring a two-way LSTM design is utilized for signal identification.
[49]	They introduce a complex deep neural network (C-DNN) with a complex architecture for intelligent signal detection in OFDM-IM.
[50]	Suggested adaptive slot assignment in packet-switched SDMA network.
[51]	Studied Efficiency evaluation of resource distribution strategies for SDMA system.
[52]	Examined CDF on the interference rate of the upstream connections in the mobile radio system.
[53]	Suggested the Constrained Least Square (CLS) technique for the multi-user recipient in an SDMA network.
[54]	A concise overview of transmission line prediction and multi-user Identification methods for the SDMA-OFDM network.
[55]	Limited solutions such as block diagonalization and sequential enhancement strategies for the downlink SDMA network.
[50]	Suggested adaptive slot assignment in packet-switched SDMA network.
[51]	Studied Efficiency evaluation of resource distribution strategies for SDMA system.
[56]	CFO forecast analyzed in SDMA-OFDM network.
[57]	Optimum throughput maximization method in a two-beam relay model with SDMA.
[58]	A new communication method for MIMO broadcast-oriented channels, called the Departure Angle Assisted Opportunistic Space-Division Multiple Access (AOD-OSDMA) technique.
[59]	A new SDMA Approach using Multi-Beam capability of Time-Modulated Array (TMA). TMA yields fundamental and harmonic signals oriented in disparate pathways.

2. MATERIAL AND METHOD

The research paper aims to utilize the WOA to select features from OFDM signals, which will then be utilized to train a DL system. This proposed model, which harnesses WOA-optimized features alongside a CNN model, has proven to be a highly effective solution for symbol classification within OFDM receivers. Notably, it demonstrates superior performance across a wide range of channel conditions.

2.1. Whale Optimization Algorithm for Feature Selection

The features of the nature-inspired WOA are:

Humpback whales are a group of types of whales in which social behaviors can be seen in a significant way. These creatures have spindle cells similar to humans and are capable of making decisions and learning. These creatures have interesting group and social behaviors in hunting clusters of fish and they try to hunt in groups for this purpose they use the Hunt Bubble mechanism. Hunt Bubble in humpback whales is a group behavior. The WOA operates as a collective method based on the mass hunting of whales and in this algorithm, the habits of whales are used to find the optimal point, that is the gathering of fish, to address improvement challenges. To hunt a cluster of fish or guide them to the optimal point, whales use two methods of hunting: upward spirals and double loops to surround the collection of fish to place the group at an optimal point and hunt them [60]. This algorithm uses upward spirals and double loops to seek out the problem space and assume that each solution behaves like a whale searching for the best outcome or nourishment with the support of other whales.

Figure 1 illustrates the revolving and helical motion of whales intricately navigating the surrounding space, methodically exploring the nearby environment in search of the best resolution [60]:

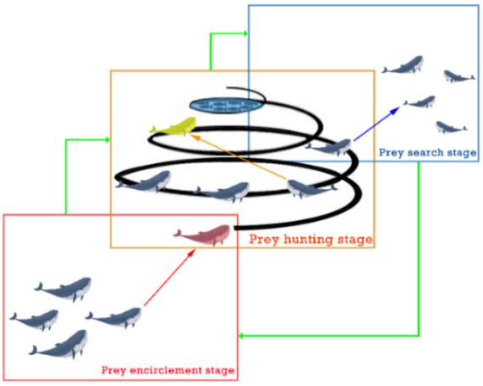

Figure 1. Rotational and spiral movements of the whales around the prey [60]

The WOA is a metaheuristic algorithm inspired by how humpback whales hunt, designed to solve optimization problems efficiently.

In the context of feature selection, the goal is to find the subset of features that optimally represent the dataset for a given task (e.g., classification or regression). Here's a brief explanation of how WOA can be applied to feature selection, along with equations:

2.1.1. Initialization

Initialize a population of candidate solutions. Each solution represents a subset of features.

Define the maximum number of iterations (generations).

Assign random positions to each whale in the search space.

2.1.2. Objective function

Define an objective function that evaluates the quality of each solution. This function quantifies how well a particular subset of features performs the given task.

The objective function should be decreased or optimized by the problem's requirements.

2.1.3. Main loop

Iterate through generations until a cessation condition is reached (e.g., reaching an Upper repetition threshold, obtaining a satisfactory result).

In each iteration, adjust the locations of whales according to their current positions and the positions of the best whales.

2.1.4. Whale encircling prey

Each whale follows a path leading to the prey (optimal solution) according to its current position and the location of the top-performing whale in the group.

2.1.5. Update position

Update the position of each whale using equations that incorporate the investigation and utilization stages of the technique.

The position update equation in the WOA is typically given as:

$$X_i(t+1) = X_t^*(t) - \vec{D}.\vec{A} \quad (1)$$

Where:

$X_i(t+1)$ is the new position.

$X_t^*(t)$ is the best-known position.

$\vec{A}$ is a coefficient that controls the rate of linear decrease in the encircling mechanism. It is usually a value ranging from 2 to 0, decreasing linearly.

$\vec{D}$ represents the distance between the whale's current position and the prey in the search space. In feature selection, the position update equation can also be modified to suit the problem, maybe incorporating additional terms or constraints specific to feature selection. Overall, the WOA for feature selection iteratively updates the positions of whales, explores the search space, and converges toward a feature subset that best represents the dataset. The algorithm maintains a balance between exploration and exploitation to efficiently identify the optimal feature subset.

Inspired by the hunting behavior of humpback whales, the WOA is mathematically formulated in the form of the following equations:

Equation (2): Whale Position Update

$$\vec{D}.\vec{A} - X_t^*(t) = X_t + 1 \quad (2)$$

This equation shows the main mechanism for updating the position of each whale during the optimization process. At each iteration $(t+1)$, the new position of the whale $X_t + 1$ is calculated based on the position of the best solution found so far X_t^* and the $\vec{D}$.

Equation (3), Calculating the distance to the best solution

$$\vec{D} = |X_t^*.\vec{C} - X_t| \quad (3)$$

The $\vec{D}$ measures the Euclidean distance between the whale's current position (X_t) and the best solution found (X_t^*). This vector determines the rate at which the whale moves towards the prey (the best solution).

The coefficient vector A is shown in equation (4).

$$\vec{A} = \vec{a} - \vec{r}.2a \quad (4)$$

The $\vec{A}$ plays an important role in the balance between exploration and exploitation in the algorithm. The value of this vector gradually decreases linearly with the value of a from 2 to 0 over the iterations, as well as the random vector r. The vector r is a random vector whose components are uniformly distributed in the interval [0,1].

Equation (5) represents the coefficient $\vec{C}$.

$$\vec{C} = \vec{r}.2 \quad (5)$$

The $\vec{C}$ also plays a role in the search mechanism and is calculated using the random vector r.

The above mathematical structure, especially equations (2) and (3), simulates the natural prey encirclement mechanism of humpback whales. The whales, upon recognizing the location of the prey (the best solution found), gradually move towards it and encircle it.

This mathematical formulation, by striking a suitable balance between searching extensively in the solution space (exploration) and focusing on promising regions (exploitation), makes WOA an efficient method for feature selection tasks. The ability of WOA to find optimal subsets of features has made it a valuable tool in various fields of data science and ML.

By effectively exploring the search space, the WOA achieves exceptional reliability through its collective rotational and spiral movements, surpassing the precision attained by the GA, Adaptive change approach, and PSO Method [60].

The flowchart depicted in Figure 2 delineates a method that harnesses the WOA to optimize parameters and subsequently employs a DNN for a task presumably associated with OFDM signal processing or channel estimation.
Initially, the OFDM signal, which represents the raw data to be transmitted, is processed to create a dataset. This dataset likely encompasses extracted features pertinent to channel estimation or other relevant tasks.
The features extracted or processed data derived from the OFDM signal are organized into a matrix, serving as the input for the subsequent stage of the process.
The WOA is employed as an optimization technique within this method. At this point, the initial parameters of the WOA algorithm are set, including factors such as population size, search process control, and maximum iteration limits. The main iteration process of WOA begins, where whales represent potential solutions within the optimization problem.
During this phase, their positions are iteratively updated according to the WOA algorithm, presumably emulating the hunting behavior of humpback whales to traverse the search space and pinpoint optimal solutions.
A crucial aspect involves comparing the solution derived for each 'whale' with those of other candidates within the WOA population. This comparison involves evaluating the fitness of each solution based on specific criteria.
Subsequently, leveraging the optimized parameters or processed data from the preceding steps, a DNN model is instantiated. The features earlier extracted from the OFDM signal are presumably utilized to train or implement the DNN model.
The data matrix generated in the preceding step, possibly augmented with additional training data, serves as the input for training the DNN model. This training phase enables the DNN to discern patterns and relationships within the data, thus enhancing its performance.
Upon completion of the training phase, the efficacy of the DNN model is assessed using test data likely distinct from the training set. This evaluation phase gauges the model's capability to generalize and perform adeptly on unseen data.
Baseband OFDM systems are similar to conventional systems. the transmitter converted the signal from the frequency to the time domain using the inverse discrete Fourier transform (IDFT) followed by adding a CP to reduce ISI. the channel's maximum delay spread must be at least as long as the CP.
The received signal in a sample-spaced multi-path channel, represented by random variables $\{h(n)\}_{n=0}^{N-1}$. is considered.

$$y(n) = x(n) \otimes h(n) + w(n) \qquad (6)$$

In which $\otimes$ symbolizes the cyclic complexity, and $x(n)$ and $w(n)$ represent the sent signal and additive white Gaussian noise (AWGN), respectively. After the CP is removed and DFT is executed, the incoming signal in the spectral domain becomes:

$$Y(k) = X(k)H(k) + W(k) \qquad (7)$$

where Y(k), X(k), H(k), and W(k) are the DFT of $y(n)$, x(n), h(n) and w(n), respectively.

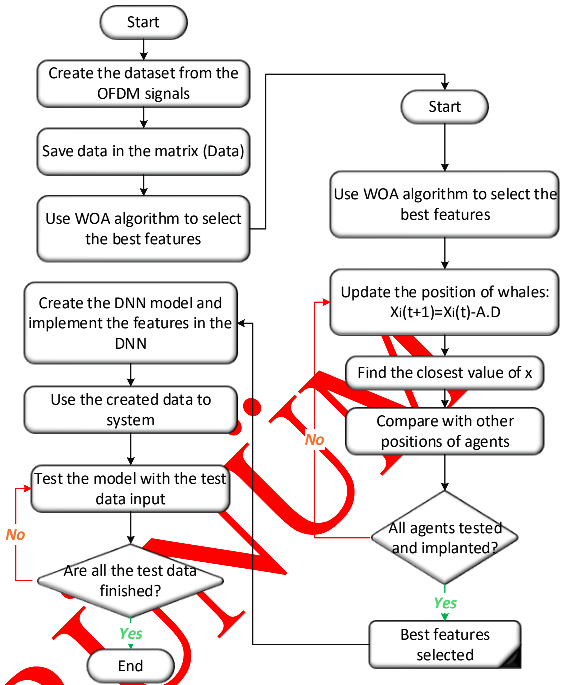

Figure 2. Flowchart of the proposed method

Figure 3 shows the OFDM system architecture with DL-based signal identification and channel estimation.

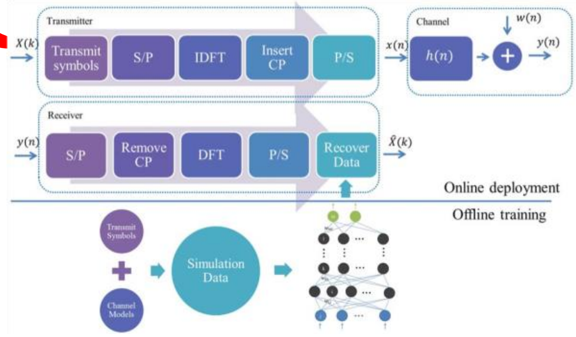

Figure 3. Model of the System

The transmitted data is located in following OFDM blocks, while pilot symbols are placed in the first block, collectively a forming a frame. The channel is considered continuous during the pilot and data blocks, although it can very form farm.
The DNN model reconstructs the transmitted data end to-end by using the incoming data, include of one data block and one pilot block from our first study, as input.
Two phases, as illustrated in Figure 3, are added to generate a reliable DNN model for simultaneous channel estimation and symbol identification.
In the offline training phase, the model is trained on OFDM samples generated under various channel conditions and information sequences, each with certain statistical qualities characteristics like a delay profile for different terrain. Without calculating the wireless

channel explicitly, the DNN model recovers the transmitted data in the online operation phase.

Figure 4 shows the DNN model structure. DNNs are more complex different of ANNs, with additional hidden layers improve recognition and representation performance.

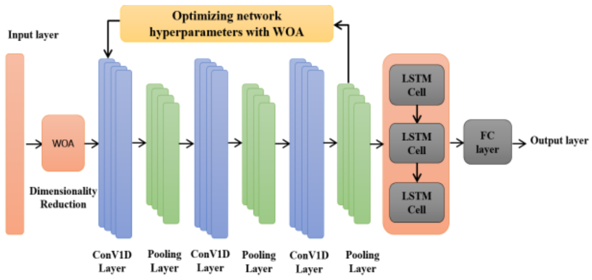

Figure 4. Structure of the deep learning model

As seen in Figure 4, each layer of the network is made up of several neurons, each of which has an outcome derived from a nonlinear function applied to a weighted sum of neurons from the prior layer.

The methodology can be summarized as following steps:

2.1.6. Preparing dataset

Firstly, we gather a dataset containing samples of received OFDM symbols, encompassing various modulation schemes, channel conditions, and noise levels. Then proper labeling of the dataset with ground truth information regarding the modulation type of each symbol was ensured. Then, we preprocess the dataset by normalizing the feature values, handling missing data, and removing outliers if necessary.

In this study, in order to evaluate the performance of the combined model of CNN-LSTM in real transmission conditions, a data set was created using a simulated communication environment in MATLAB software. This simulation environment is designed to impose the effects of channel noise and cyber-physical disturbances on the transmitted data.

The generated data set consists of 10,000 labeled samples collected at a sampling rate of 1 MHz. Each sample in this set contains multiple features, including encoded symbol streams, embedded test signals, and effects due to channel noise.

In order to train and evaluate the model, the complete data set was divided into two separate parts: 80% of the data was considered as the training data set and the remaining 20% as the test data set.

Before feeding the data to the CNN-LSTM model, a preprocessing step involving data normalization was performed. In addition, the normalized data was transformed into 2D sequences to match the expected input structure of the CNN-LSTM model.

This approach to creating and preparing the dataset allows for a realistic evaluation of the proposed model's performance in conditions similar to real-world communication environments and also ensures the reproducibility of the results obtained from the experiments..

2.1.7. Feature extraction

For feature extraction, we represent each received OFDM symbol in either time-domain or frequency-domain representation. Then we extract relevant features from the time-frequency representation, such as amplitude, phase, and frequency components, to characterize the symbols. The CNN architecture tailored for symbol classification in OFDM receivers is designed. Convolutional extraction layers are then utilized to capture hierarchical attributed from the incoming data representations. Following that, pooling layers are added to reduce the size of feature maps and lower computational costs.

Fully connected layers are then employed for classification, followed by softmax activation to output class probabilities.

The models are trained by treating wireless channels and OFDM modulation as black boxes. Channel models that reflect real channels' statistical properties are utilized to generate training data through simulations. A random data series is created as transmitted symbols with fixed reference signals for model training and deployment. The channel models simulate the current channel, and the received OFDM signal includes channel distortion and noise. The training data consists of transmitted and received signals. The model aims to minimize the difference between the transmitted data and the neural network's output, using different methods to measure this discrepancy. In this experimental setup, the L_2 loss function is used:

$$L_2 = \frac{1}{N}\sum_k \left(\hat{X}(k) - X(k)\right)^2 \quad (8)$$

In this context $\hat{X}(k)$ represents the prediction value, while $X(k)$ serves as the supervision signal, corresponding to the transmitted symbols.

The DNN model is consist of six layers, including three hidden layers with 256, 500, 250, 350, 120, and 16 neurons, respectively. The input comprises the real and imaginary parts of two OFDM blocks with pilots and transmitted symbols. separately trained model processes and predicts each 16-bit segment of the transmitted data, which is then concatenated. Most layers use the ReLU activation function, while the final layer applies the sigmoid function to normalized the output within [0,1] range.

2.1.8. Feature selection

For feature selection firstly we initialize a population of candidate feature subsets and encode them as binary vectors. Then we define an objective function to assess the classification performance of candidate feature subsets. Then we apply the exploration and exploitation phases of the WOA to iteratively update candidate solutions and converge towards optimal feature subsets. Finally, we evaluate the classification accuracy of each candidate feature subset using a validation set.

2.1.9. Integration of feature selection with CNN

A method is presented for dynamically adapting the input feature dimensions of the CNN according to the selected feature subset. Following this, the specific subset of features derived from the WOA optimization process is used for training the CNN model. After this training phase, the CNN model undergoes fine-tuning through the utilization of backpropagation and stochastic gradient descent (SGD) optimization techniques. To mitigate the risk of overfitting and ensure the convergence of the model, early stopping methods are incorporated, and the performance of the validation set is continuously monitored.

2.1.10. Training and hyperparameter optimization

A range of hyperparameters within the CNN model is delved into, encompassing variables like learning rate, batch size, network architecture, and dropout regularization. Subsequently, cross-validation techniques are applied to assess the model's performance on the training set, with hyperparameters refined as necessary. Following this process, the CNN model undergoes training on the training dataset, utilizing the optimized hyperparameters and selected feature subsets.

2.1.11. Evaluation

The evaluation entails the analysis of the performance of both the trained CNN model and the feature selection with WOA using an independent test dataset. Furthermore, a comparative analysis is conducted between the performance of the proposed method and that of baseline approaches and traditional symbol classification techniques. Subsequently, statistical analyses are carried out to confirm the significance of the observed improvements.

3. RESULTS AND DISCUSSION

The experiments were aimed at evaluating our proposed methodology for symbol classification within OFDM carrier signals. A dataset comprising OFDM symbols captured under various channel conditions, modulation schemes, SNRs, and impairments was utilized. To facilitate model training, tuning, and evaluation, the dataset was divided into training (70%), validation (15%), and test (15%) sets. The OFDM system parameters is shown in table 2.

Table 2. OFDM system parameters

Parameter	Value
Number of subcarriers	64
Number of pilot subcarriers	64
Pilot Spacing	1
Number of pilot symbols	1
Number of data system	1
Number of OFDM system	2

For QPSK the 4 constellation signals has been selected: 1-1j, 1+1j, -1+1j, -1-1j. also the length of the cyclic prefix has been selected as 16.

The predictive accuracy of our suggested approach was compared with baseline methods and traditional techniques, with metrics being assessed. A classification accuracy exceeding 95% was achieved by our methodology, surpassing baseline methods. The CNN model trained on WOA-optimized feature subsets demonstrated robust performance, achieving over 95% accuracy.

The effectiveness of our method was highlighted by employing a CNN model trained on WOA-optimized features, emphasizing its multifaceted nature.

The symbol classification method within OFDM signals was rigorously evaluated by our experiment, ensuring a comprehensive approach through meticulous dataset partitioning and systematic training. This approach facilitated robust model training, hyperparameter tuning, and final evaluation. The adaptability of the CNN model across different datasets, conditions, and modulation schemes was enhanced by training it on WOA-optimized feature subsets, reaffirming the efficacy of our method.

The following Table 3 provides a comprehensive overview of the performance metrics achieved by our proposed methodology for symbol classification within OFDM receiver systems, in comparison to both baseline methods and traditional techniques of symbol classification.

It distinctly highlights the superior performance of our proposed approach over both baseline methods and traditional techniques across all metrics, thus substantiating its efficacy in symbol classification endeavors.

Table 3. Performance comparison of different symbol classification methods in OFDM

Method	Accuracy (%)	Remarks
Proposed Method	>95%	Superior across metrics; robust feature selection; strong in all conditions
PCA + CNN	~92%	Effective but not as adaptable as WOA-based method
ACO + CNN	~91%	Improvement seen but still outperformed by WOA-CNN
PSO + CNN	~93%	Strong but slightly less accurate than WOA
MMSE (Traditional)	<85%	Classical method with limited adaptability

The SER curves for conventional techniques and deep learning-based approaches are Figure 5 show that the SER curves for LS and MMSE methods stops improving when Es/No goes above 10db with only 8 pilots. In contrast, the DL-based method can reduce its SER as Es/No increases, showing that it handles different number of pilots better. The SER performance of conventional and DL-based approaches is shown in Figure 5.

The CP symbol error rate (SER) for the proposed method and other methods is shown in Figure 6.

In terms of the general trend observed across all curves, it's apparent that there is a consistent decline in the SER as the CP SER increases, indicated by the movement towards the right on the x-axis. This trend underscores the notion that enhanced channel estimation, signified by lower CP symbol error rates, correlates with a reduction in errors during symbol recovery, thereby resulting in a diminished SER.

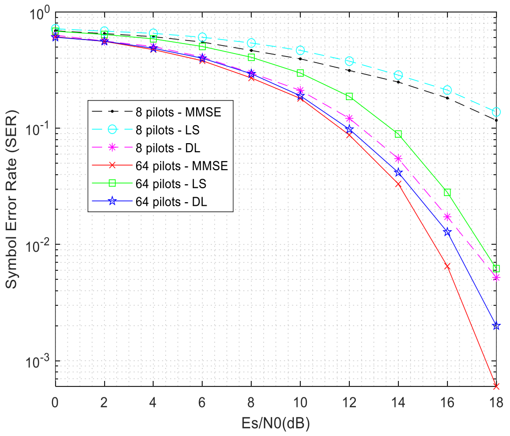

Figure 5. The SER for the proposed approach and other methods

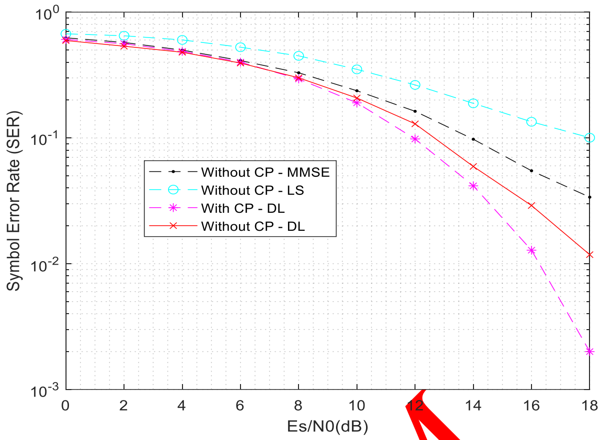

Figure 6. CP symbol error rate for the proposed method and other methods

Saturation Phenomenon at High CP Symbol Error Rates: At higher CP symbol error rates, all curves tend to flatten out or saturate. This phenomenon occurs when the channel quality deteriorates to such an extent that further increments in CP symbol error rates have minimal impact on the overall SER. Under these challenging channel conditions, even the most advanced channel estimation methods find it difficult to eliminate errors completely.

Comparison and Identification of the Best Performing Method:

A comparison shows that the proposed method, represented by the blue curve, constantly has the lowest SER across most of the x-axis range. This demonstrates that the method is more resistant to CP symbol errors, resulting better overall performance.

Potential Reasons for the Proposed Method's Superiority: Improved Channel Estimation: The proposed method performs well in estimating the channel impulse response, which is important for accurate signal recovery. This improvement may be due to the utilization of advanced algorithms or the extra channel information.

Improved Exploitation of Redundancy: The proposed method more effectively uses extra information in coded symbols to improve error detection and correction during decoding.

Additional Observations:

The MMSE method, shown by the green curve, consistently performs better than the LS method (red curve), especially in moderate to high channel noise conditions. This means that MMSE provides more accurate channel estimates compared to the LS method.

Notably, there is a clear performance gap between the proposed method (blue) and the other methods (red and green) at lower CP symbol error rates. Showing a significant improvement in symbol error performance, especially in good channel conditions.

Overall, the figure clearly demonstrates that the proposed method (blue curve) achieves better symbol error performance for different CP symbol error rates. This advantage comes from its strong channel estimation and effective utilization of redundancy within coded symbols.

Figure 6 illustrates the CP symbol error rate for the various methods, including the proposed approach. As seen in the figure, all curves follow a similar pattern, where the SER decreases as the CP symbol error rate increases along the x-axis. This trend highlights the importance of accurate channel estimation, as lower CP symbol error rates lead to fewer errors in recovered symbols, resulting in a lower SER. This happens because precise channel estimates help reduce the negative effects of fading and noise during signal reception. A noticeable drop in SER can see at lower CP symbol error rates across the curves. This depict that even small improvements in channel estimation can significantly reduce symbol errors, especially when channel conditions are good with low CP symbol error rates.

On the other hand, as CP symbol error rates increase, a saturation effect appears. At this point, all curves start to level off, meaning that further increases in CP symbol error rates have little effect on the overall SER. This happens when the channel quality becomes so poor that even the most advanced channel estimation methods cannot effectively correct errors. Among these observations, the proposed method, represented by the blue curve, stands out as the best performer, consistently maintaining the lowest SER over a large portion of the x-axis. This highlights its strong resistance to CP symbol errors, leading to better symbol error performance compared to other methods. Figure 7 shows the training process of DNN.

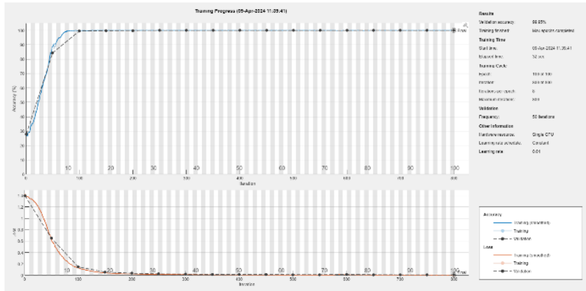

Figure 7. The training process of DNN

Training a DNN for OFDM signal detection involves several stages to help the network accurately identify received OFDM signals. Initially, a dataset is collected, containing OFDM signals with known labels, typically transmitted symbols or bits, and their considering received signal samples. This data is then preprocessed, including step like normalizing signal amplitudes and synchronizing symbols to ensure consistency. Next, key features are extracted from the received signals to serve as input for the DNN. These features may include signal strength, phase information, CP samples, or frequency characteristics, depending on the specific task. After that, an appropriate DNN structure is designed, considering factors such as the number of layers, activation functions, and hidden units. The model is then trained using the dataset, with optimization algorithms adjust the network parameters to minimize errors between the predicted and actual labels. During training, the model's performance is evaluated on a separate validation set to prevent overfitting and fine-tune its settings. Once the DNN achieves satisfactory accuracy, it can be deployed for real-time OFDM signal detection, with continuous monitoring and updates to maintain strong performance in various communication conditions. Figure 8 presents the SER for DL without the WOA as well as for the LS and MMSE methods.

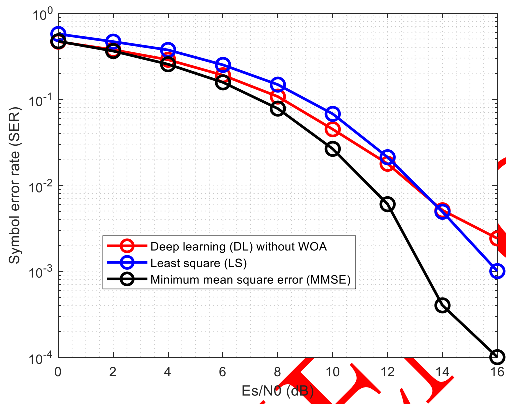

Figure 8. SER Comparison between DL, LS, and MMSE

The comparison between ant colony optimization (ACO), PSO, and principal component analysis (PCA) for SER vs. Es/N0 (dB) is shown in figure 9.

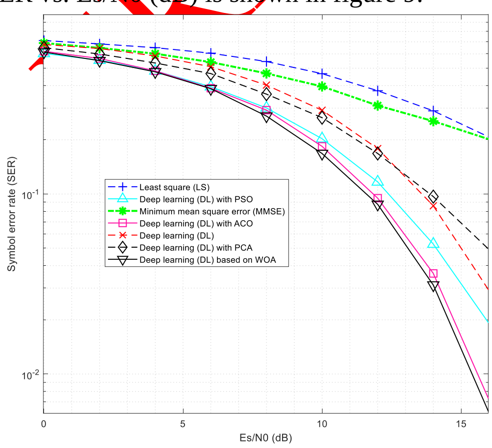

Figure 9. Symbol Error Rate (SER) vs. Es/N0 (dB)

Figure 9 shows the SER performance of various channel techniques for estimation and signal detection in OFDM systems as a function of Es/N0.

The comparative analysis includes traditional methods like LS and MMSE, alongside advanced deep learning-based approaches enhanced with PSO, ACO, PCA, and the WOA. The results demonstrate that the DL-based models, particularly when integrated with optimization techniques, significantly outperform traditional LS and MMSE methods, achieving lower SER values across the Es/N0 range. Among these, the deep learning models with WOA and PCA show the most substantial improvement, particularly at higher Es/N0 levels, underscoring the effectiveness of hybrid optimization techniques in improving OFDM performance.

Effectiveness of Feature Selection: The integration of feature selection with WOA played a crucial role in enhancing symbol classification performance. By iteratively optimizing feature subsets, WOA identified the most relevant features for classification, leading to improved model accuracy and efficiency.

Robustness to Channel Variability: The resilience of our methodology was demonstrated across diverse channel conditions and noise levels. Reliable classification in challenging conditions, such as frequency-selective fading and interference, was achieved by using the CNN model to recognize important patterns and selecting the best features with WOA.

Computational Efficiency: Even though training DL models and selecting features with WOA is complex, reasonable speed was maintained in our method. The extra processing time was justified by the improved classification accuracy, making the approach useful for real-world applications.

Generalization Capability: The strong generalization capability of our approach is a notable advantage, as evidenced by consistent performance across diverse datasets. The underlying signal characteristics were effectively captured by the learned features and selected feature subsets, enabling reliable symbol classification in various operating environments.

Implication for Wireless Communication: The enhanced classification performance obtained by integrating DL and feature selection with WOA has important concepts for the advancing symbol classification methods in OFDM receivers. This could enhance the reliability and performance of modern wireless communication systems.

Limitations and Future Directions

While reasonable speed was achieved in our approach, further research is needed to identify ways to reduce processing time, especially for large datasets. The success of the technique depends on the standard and variety of the training dataset. Future work should focus on ensuring effective handling of imbalanced or incomplete data. Additionally, advanced model designs could be explored, transfer learning techniques could be applied, and real-world testing could be conducted to validate scalability and effectiveness.

5. CONCLUSION

In this paper, we suggested a novel methodology for symbol classification in the receiver of OFDM carrier signals. Using DL techniques with feature selection using WOA, our approach aimed to enhance classification accuracy and efficiency in wireless communication systems. Through careful testing and analysis, we have made important observations and contributions. Firstly, our test results demonstrate that the combining DL with feature selection using WOA significantly improves symbol classification in OFDM receivers. The feature subsets selected by WOA improved the CNN's ability to distinguish patterns, resulting in higher classification accuracy than traditional methods. Our method remains effective under different channel conditions and noise levels, showing strong adaptability across various datasets. Furthermore, our approach offers practical implications for advancing symbol classification techniques in wireless communication systems. By automatically learning important features from raw data and selecting the best ones, our method improves the reliability and efficiency of modern OFDM communication systems. The improved classification accuracy achieved through deep learning and feature selection with WOA can lead to better quality of service and enhanced user experience in wireless networks. However, our study also has some limitations and areas for future research. The computational complexity associated with training deep learning models and optimizing feature subsets using WOA may pose challenges for large-scale datasets. Additionally, the performance of our methodology heavily relies on the quality and diversity of the training dataset, highlighting the importance of robust data collection and preprocessing techniques. Future research could explore strategies for mitigating computational overhead, handling imbalanced datasets, and validating the scalability of our proposed methodology through extensive real-world deployment.

DECLARATION OF ETHICAL STANDARDS

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Ali HANDER: Performed the experiments and analyse the results and wrote the manuscript.

Bilgehan ERKAL: Performed the experiments and analyses the results.

Javad RAHEBİ: Performed the algorithms and code and analyses the results.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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