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Hyperparameter optimization of convolutional neural network using grey wolf optimization for facial emotion recognition

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ABSTRACT

Facial emotion recognition (FER) is a challenging task in computer vision with wide applications in areas such as human-computer interaction, security, and healthcare. To improve the performance of convolutional neural networks (CNN) in FER, a novel approach combining CNN with grey wolf optimization (GWO) was proposed to optimize key hyperparameters. The CNN-GWO model was fine-tuned by adjusting hyperparameters such as the number of convolutional layers, kernel size, number of filters, and learning rate. This model was evaluated using the CK+ dataset and achieved an accuracy of 90.97%, demonstrating its competitive performance compared to existing methods. The optimized hyperparameters included three convolutional layers, 35 filters, a kernel size of 5, a learning rate of 0.045990, a dropout rate of 0.4988, and a max pooling size of 3. These results confirm that GWO is effective in optimizing CNN for FER tasks, providing an efficient solution to enhance model accuracy. This approach shows promising potential for future FER applications, highlighting GWO as a valuable optimization technique for CNN architectures.

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1. INTRODUCTION

Facial emotion recognition (FER) has been extensively studied in recent decades due to its wide applications in human-computer interaction, mental health monitoring, and security. Among the various techniques used for FER, convolutional neural networks (CNNs) have emerged as one of the most effective methods due to their ability to extract spatial features from facial images automatically. CNNs classify emotions by analyzing facial visual patterns such as smiles, furrowed brows, or mouth shapes. However, one of the significant challenges in implementing CNNs for FER is determining the optimal combination of hyperparameters, such as kernel size, the number of filters, and the learning rate. These hyperparameters are critical in ensuring high model accuracy while preventing overfitting or underfitting.

Traditionally, researchers have relied on conventional hyperparameter optimization methods such as Grid Search and Random Search to fine- tune CNNs [1]. Grid Search systematically evaluates every possible combination of hyperparameters within a predefined range, ensuring a thorough search. However, this approach becomes computationally impractical as the number of hyperparameters increases, leading to an exponential growth in combinations and requiring extensive computational resources. On the other hand, Random Search selects hyperparameter values randomly from the predefined space, making it faster than Grid Search. However, this method is inefficient because it relies on chance and often fails to find the optimal solution, especially when dealing with an ample hyperparameter space.

Researchers have increasingly turned to metaheuristic optimization algorithms to overcome these limitations, which efficiently explore the solution space without evaluating every possible combination. One such algorithm is the grey wolf optimizer (GWO), which mimics the hunting behaviour of grey wolves and operates based on a structured social hierarchy. In GWO-based optimization, the alpha, beta, and delta wolves lead the search, directing the rest of the pack towards optimal solutions. This mechanism allows GWO to balance exploration and exploitation, efficiently navigating large hyperparameter spaces without exhaustive computations. In each iteration, the wolves adjust their positions based on the guidance of the top three wolves (alpha, beta, and delta), accelerating the search process and making it more efficient than traditional optimization methods. Furthermore, GWO has the advantage of adaptability, allowing it to handle different data structures and characteristics. This algorithm makes it particularly suitable for optimizing CNNs in various datasets, including CK+48, which exhibits unique facial expression variations.

By leveraging the strengths of GWO, this study aims to optimize CNN hyperparameters to enhance FER performance. The proposed method seeks to improve classification accuracy while reducing computational complexity compared to conventional approaches. This research contributes to the ongoing advancements in metaheuristic optimization for deep learning applications, demonstrating the potential of GWO in solving complex hyperparameter tuning problems in CNN-based FER models.

2. RELATED WORKS

Researchers have also explored various methods for optimizing hyperparameters in CNNs. For example, they applied Random Search for object recognition [2] and Bayesian Optimization for medical image recognition [3]. Although Grid Search is still widely used, researchers have noted its inefficiency in several cases [4]. Metaheuristic approaches such as particle swarm optimization (PSO) have been applied to image classification [5], while genetic algorithm has been used for facial recognition [6]. Researchers have also used hyperband to accelerate optimization in emotion recognition [7] and combined Simulated Annealing with CNN for plant disease detection [8]. They have applied Differential Evolution for medical image segmentation [9], Tree-structured parzen estimator (TPE) for visual pattern recognition [10], and Multi-Objective Optimization for object detection in traffic images [11].

GWO has proven effective in various optimization problems. Researchers have found that GWO delivers competitive results in multiple contexts [12]. Other studies have shown that GWO improves CNN performance in 3D object recognition [13] and skin cancer detection [14]. Researchers have also used GWO to optimize neural networks for EEG signal classification [15] and enhance CNN performance in agricultural image classification [16] as well as network intrusion detection [17]. GWO has been used for hyperparameter optimization in CNN for satellite image classification [18], and a hybrid approach combining GWO and PSO has been applied in facial image classification [19]. Additionally, GWO has been used in medical image segmentation [20] and plant disease detection [21].

Although these studies have shown promising results, further research is needed to explore the application of GWO in facial emotion recognition using the CK+48 dataset. CK+48 is widely used in FER research because it provides clear variations in facial expressions and high-quality images covering seven main emotion categories: anger, disgust, fear, happiness, sadness, surprise, and neutral. However, CNN hyperparameter optimization for emotion recognition on this dataset has not been extensively explored, particularly using GWO as an optimization method. This research aims to bridge this gap by exploring how GWO can effectively optimize CNN hyperparameters in facial emotion recognition tasks using the CK+48 dataset. In this study, researchers will test various hyperparameter combinations such as kernel size, the number of filters, and learning rate to find the optimal configuration. Additionally, this research will evaluate the impact of varying the number of wolves in the GWO algorithm on CNN model accuracy. This study is expected to provide better guidance on using GWO for deep learning model optimization on datasets with unique characteristics like CK+48, and to expand the application of GWO in deep learning model optimization across various fields.

3. METHODS

3.1. Pre-processing

This section aims to enhance the quality of facial images before the feature extraction process. Facial images with various emotional expressions undergo a lighting normalization process to reduce noise and excess information caused by lighting variations. Lighting normalization adjusts the pixel intensity values across the image, increasing the contrast and sharpness of facial features. As a result, the facial images become more consistent and ready for feature extraction without being affected by lighting discrepancies. Block diagram of the proposed facial emotion as shown in Figure 1.

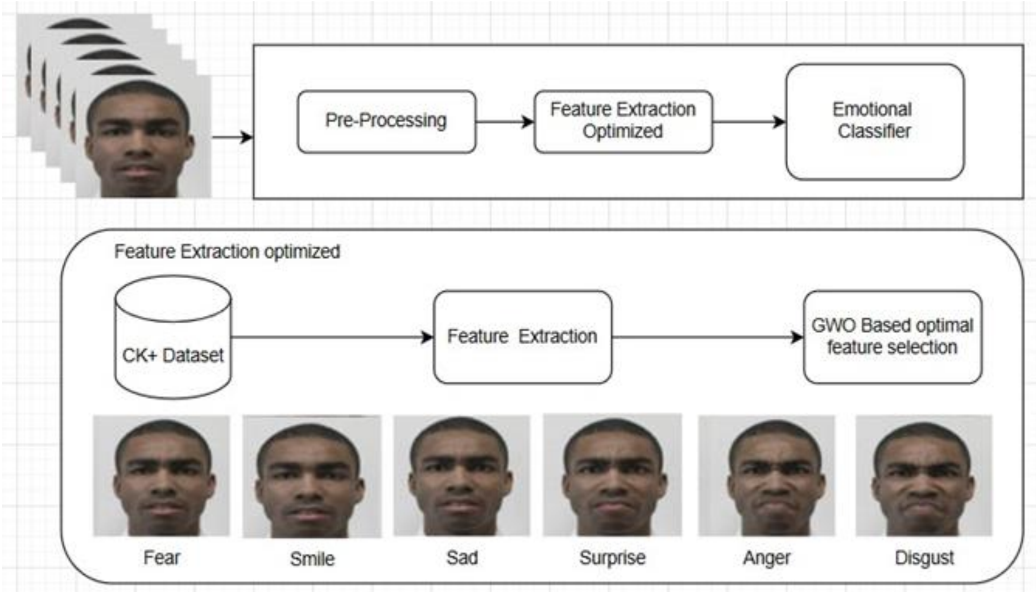

Figure 1. Block diagram of the proposed facial emotion

3.2. Feature extraction

This section extracts key facial features such as the eyes, nose, mouth, and other relevant areas using standard methods. This feature extraction represents facial characteristics that can serve as a basis for emotion recognition. Standard feature extraction methods typically involve simple filters or edge detection techniques, enabling quick detection of facial areas or contours. These basic features represent general facial characteristics and provide the model with initial helpful information for subsequent stages, particularly in distinguishing between different facial expressions.

3.3. Optimal feature selection using grey wolf optimization (GWO)

The basic structure of the CNN for feature extraction and classification begins with convolutional layers responsible for extracting features from facial images. These layers contain multiple filters (kernels) that automatically learn to detect visual patterns such as edges, textures, and corners. Each filter slides across the entire image, producing an output in the form of a feature map represented by the following:

$$O_{ij} = \sum_m \sum_n I_{i+m,j+n} \cdot K_{m,n} \quad (1)$$

where O_{ij} is the output value at position $i + m, j + n$ is the pixel value in the input image, and K is the kernel that learns to detect specific patterns. After convolutional layers, pooling layers reduce the feature map size, often using Max Pooling or Average Pooling, which takes the highest or average value from a region, helping decrease data dimensions and computational complexity. Following several convolutional and pooling layers, the output is flattened into a single vector and passed to fully connected layers, combining all extracted features to produce the final output, representing the probability of each emotion class.

CNN weights are initially set randomly or by other methods. In the CNN-GWO approach, the GWO algorithm is integrated to optimize these weights, aiming for the most optimal weight configuration for accurate classification. GWO is a metaheuristic optimization algorithm that mimics the hunting behavior of grey wolves in nature. Here, the wolf population represents different configurations of CNN weights and biases, with the best wolf designated as α, followed by β and δ, who assist α in guiding other wolves towards the “prey” (i.e., the optimal weight configuration).

The GWO process begins with initializing the wolf population, where each wolf represents a specific weight configuration for the CNN. The best wolves, α, β, and δ, guide other wolves towards the prey, updating their positions based on the optimal coordinates of α, β, and δ. The position update of the wolves is determined by the following equations:

$$D = |C \cdot X_{best} - X| \quad (2)$$

$$X_{new} = X_{best} - A \cdot D \quad (3)$$

where X_{best} is the position of the best wolf, X is the current position, and A and C are coefficients adjusted during each iteration to control movement intensity towards the optimal position. Each wolf's position is updated by calculating three new positions influenced by distances from α, β, and δ. These positions are calculated as follows:

$$X_1 = X_\alpha - A_1 \cdot |C_1 \cdot X_\alpha - X| \quad (4)$$

$$X_2 = X_\beta - A_2 \cdot |C_2 \cdot X_\beta - X| \quad (5)$$

$$X_3 = X_\delta - A_3 \cdot |C_3 \cdot X_\delta - X| \quad (6)$$

The final position of the wolf is calculated by averaging these three positions:

$$X_{new} = \frac{X_1 + X_2 + X_3}{3} \quad (7)$$

After each iteration, each wolf's position is evaluated based on the CNN's objective function (loss function), with the wolves that reduce error retained as the best positions, guiding further iterations.
The objective function in CNN-GWO aims to minimize classification error or the CNN loss function, such as cross-entropy for classification tasks. This function is represented by:

$$Loss = -\sum_i y_i \log(\hat{y}_i) \quad (8)$$

where y_i is the actual label and $\hat{y}_i$ is the predicted probability for each class GWO works to minimize this loss, finding the optimal weight configuration that enhances CNN accuracy. After GWO completes the optimization of CNN weights, the CNN-GWO model is ready for final classification. The input image goes through optimized CNN layers, producing an output with probabilities for each emotion class, and the class with the highest probability is selected as the predicted emotion. Through GWO optimization, the CNN operates more efficiently with weights refined gradually, reducing classification errors and increasing accuracy in recognizing facial expressions.

4. RESULTS AND DISCUSSION

This study evaluates the effectiveness of the CNN-GWO approach in the FER task using the CK+48 dataset, which consists of seven emotion categories: anger, disgust, fear, happiness, sadness, surprise, and neutral. The CNN-GWO model was designed to optimize CNN hyperparameters using the GWO algorithm, aiming to improve the model's performance in classifying facial emotions while avoiding issues such as overfitting and underfitting. GWO plays a crucial role in dynamically adjusting model parameters, including the number of convolutional layers, number of filters, kernel size, and learning rate, allowing the model to achieve optimal accuracy.

GWO is a metaheuristic-based optimization algorithm that mimics the hunting behaviour of grey wolves in the wild. In this algorithm, wolves are categorized into three hierarchical levels: α, which acts as the leader in the search for the best solution; β, which serves as an advisor in exploration; and δ, which assists in the exploitation of the search space. This social structure enables GWO to navigate the hyperparameter search space more efficiently than conventional methods. Several key hyperparameters of the CNN were optimized within specific ranges to ensure the model achieved the best configuration, as shown in Table 1.

Table 1. List of hyperparameter

Hyperparameter	Range
num_conv_layers	[1, 10]
num_filters	[16, 64]
filter_size	[3, 9]
activation_function	[0, 1, 2] (0: relu, 1: tanh, 2: sigmoid)
batch_size	[8, 256]
epochs	[5, 100]
learning_rate	[0.0001, 0.1]
dropout_rate	[0.1, 0.8]
max_pooling_size	[2, 5]

The CNN-GWO model demonstrated a significant improvement in accuracy over 15 optimization iterations. In the initial phase (Iterations 1-4), the model's accuracy ranged between 83% and 89%, indicating that GWO was exploring various parameter combinations to determine an effective initial configuration. In Iteration 5, the model reached a peak accuracy of 91%, demonstrating that GWO successfully identified an optimal hyperparameter combination that enabled CNN to achieve its best classification performance for facial emotions. However, in Iterations 6-9, a slight decrease in accuracy below 90% was observed, indicating that the GWO algorithm was still exploiting and validating the best configuration. After Iteration 10, the model began to stabilize, with accuracy consistently ranging between 88% and 89%, suggesting that the model had reached an optimal configuration that no longer required significant adjustments. As illustrated in Figure 2, the accuracy progression shows rapid improvement in the initial iterations, followed by minor fluctuations, and eventually stabilizes after Iteration 10.

Hyperparameter optimization using GWO significantly impacted the model's performance. By identifying the optimal hyperparameter combination, CNN-GWO achieved higher accuracy than conventional CNN methods without optimization. Additionally, this approach helps prevent overfitting and underfitting by adaptively adjusting the dropout rate, batch size, and learning rate. GWO also accelerates model convergence by selecting the most effective parameter combinations, allowing the model to reach optimal results faster than traditional optimization methods. Another advantage is training efficiency, as using the GWO algorithm reduces the need for manual experimentation in hyperparameter selection. Upon completing the optimization process, CNN-GWO identified the following optimal configuration, as presented in Table 2.

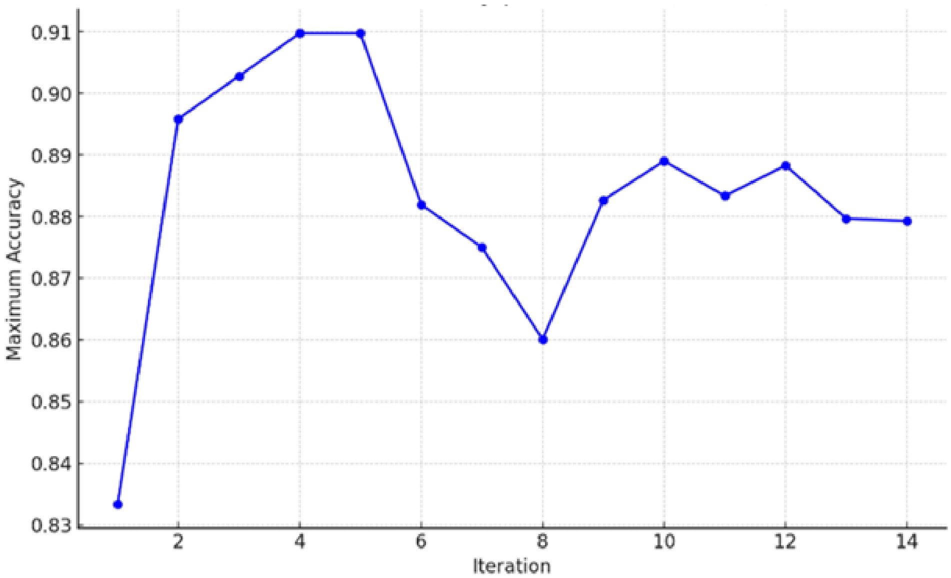

Figure 2. The maximum accuracy per iteration

Table 2. Optimal results of the CNN-GWO model

Hyperparameter	Optimal value
num_conv_layers	3
num_filters	35
filter_size	5
activation_function	tanh
batch_size	56
epochs	57
learning_rate	0.004599
dropout_rate	0.4988
max_pooling_size	3
optimizer	Adagrad
Highest Accuracy	90.97%

With this optimal configuration, the CNN-GWO model achieved the highest accuracy of 90.97%, demonstrating that the metaheuristic-based optimization method can significantly enhance CNN performance in FER tasks. This approach improves model accuracy and enhances training efficiency and model stability over time. The results in Table 2 confirm that the CNN-GWO model successfully identifies the best hyperparameter settings, outperforming conventional tuning methods. These findings suggest that GWO can be an effective alternative for hyperparameter optimization in various deep-learning classification tasks.

The results of this study are compared with previous research on Facial FER using the CK+ dataset. The CNN-GWO model achieved an accuracy of 90.97%, which is competitive with existing methods. As presented in Table 3, Sun and Akansu [22] achieved an accuracy of 90.98%, showing nearly identical performance to CNN-GWO, with only a marginal difference. Similarly, Ahmed obtained an accuracy of 91%, slightly outperforming the CNN-GWO model. However, compared to other studies, such as [23] (88.5%) and [24] (89.92%), the CNN-GWO model demonstrated superior accuracy. These results indicate that metaheuristic-based optimization using GWO effectively fine-tunes CNN models to achieve a performance level that is on par with the highest-performing models while surpassing several conventional approaches.

Table 3. The comparison of accuracy performance with existing approaches

Author	Accuracy (%)
Sun and Akansu [22]	90.98
Yi *et al.* [23]	88.5
Sonmez and Albayrak [24]	89.92
Ahmed [25]	91
CNN+GWO (Proposed)	90.97

The performance comparison in Table 3 highlights the effectiveness of the CNN-GWO approach, demonstrating its ability to achieve accuracy comparable to state-of-the-art methods. Despite the slight difference between CNN-GWO and Ahmed’s model (91.00%), the CNN-GWO method provides the advantage of automated hyperparameter tuning, making it a more efficient approach for optimizing deep learning models. Additionally, Table 3 confirms that CNN-GWO outperforms several traditional CNN-based models, such as those proposed by [23], [24], further emphasizing the robustness of metaheuristic optimization in FER tasks.

One of the main advantages of the CNN-GWO model is its ability to automatically optimize hyperparameters, significantly reducing the need for manual tuning. Unlike traditional approaches such as grid search, which require an exhaustive search over possible hyperparameter combinations, GWO dynamically explores the search space and converges toward an optimal configuration in fewer iterations. This capability allows the model to achieve high accuracy while generalizing unseen data. Additionally, the adaptive adjustment of key parameters, such as dropout rate, learning rate, and kernel size, ensures that the model is neither overfitting nor underfitting, which are common challenges in deep learning-based FER tasks. Another notable advantage is that GWO is highly adaptable and can be extended to different datasets and architectures, making it a promising alternative for optimizing CNN models beyond FER applications.

Despite its strengths, the CNN-GWO model has some limitations. A key limitation is the fluctuation in accuracy observed between Iterations 6 and 9, where performance briefly dropped below 90% before stabilizing. This variation, as shown in Figure 2, suggests that while GWO effectively explores the hyperparameter space, it may temporarily settle on suboptimal configurations before refining its search further. Additionally, while the optimization process successfully identifies an optimal configuration, it does not guarantee global optimality, as better configurations may still exist. Another limitation is that the CNN-GWO model has only been tested on the CK+ dataset. Since CK+ is relatively tiny and contains well-posed facial expressions, further validation on more extensive and diverse datasets, such as FER2013 or RAF-DB, is necessary to assess the model’s robustness in real-world applications. Furthermore, the computational cost of running GWO-based optimization is higher than traditional CNN training since multiple iterations are required before reaching convergence.

An unexpected finding in this study was the sharp increase in accuracy at Iteration 5, where the model reached its highest accuracy of 91%. This sudden performance spike indicates that GWO identified an optimal hyperparameter configuration early in the optimization process. However, the subsequent fluctuations in later iterations suggest that the algorithm continued refining parameters to validate and stabilize its selection. The final accuracy range of 88% to 89% in later iterations, as illustrated in Figure 2, suggests that the model reached a balanced configuration, ensuring stability in classification performance. This trend contrasts with conventional training methods, where accuracy increases gradually without significant fluctuations. The iterative nature of GWO highlights its ability to balance exploration and exploitation, leading to a more refined tuning process.

This study demonstrated that the CNN-GWO approach is an effective optimization strategy for enhancing CNN performance in FER tasks. By dynamically adjusting key hyperparameters such as the number of convolutional layers, number of filters, kernel size, learning rate, and dropout rate, the GWO algorithm enabled the CNN model to achieve an optimal balance between accuracy and generalization. The proposed model achieved a peak accuracy of 90.97%, positioning it competitively with state-of-the-art methods while surpassing several conventional CNN models, as highlighted in Table 3. The findings underscore the importance of automated hyperparameter tuning in deep learning, as it significantly reduces the need for manual experimentation while improving model efficiency and performance. The implications of this research extend beyond FER, suggesting that metaheuristic-based optimization techniques can be applied to various other deep learning classification tasks that require fine-tuning of model parameters. Despite its advantages, the CNN-GWO model has certain limitations, including the observed accuracy fluctuations during optimization and the need for validation on more diverse datasets beyond CK+. Future research should explore the scalability of CNN-GWO on larger datasets such as FER2013 or RAF-DB to assess its robustness in real-world scenarios.

Additionally, integrating GWO with other optimization techniques, such as Bayesian Optimization or Differential Evolution, could enhance its efficiency and accuracy. Moreover, investigating the impact of ensemble learning by combining multiple CNN-GWO models may provide insights into further improving FER performance. In conclusion, the results confirm that GWO is a promising optimization technique for CNN-based FER models, with potential applications in various fields requiring high-accuracy emotion recognition, such as healthcare, human-computer interaction, and psychological assessment.

5. CONCLUSION

The CNN-GWO approach has been applied to the task of FER using the CK+ dataset. Optimization of key hyperparameters, such as the number of convolutional layers, filter size, number of filters, and learning rate, resulted in a highly competitive model performance. The optimal hyperparameters obtained include three convolutional layers, 35 filters, a kernel size of 5, the tanh activation function, a batch size of 56, 57 epochs, a learning rate of 0.045990, a dropout rate of 0.4988, and a max pooling size of 3, with the Adagrad optimizer. With this configuration, the model achieved its best accuracy of 90.97%, demonstrating the effectiveness of the GWO technique in tuning CNN hyperparameters for FER tasks. These results indicate that GWO can significantly enhance CNN performance in FER by efficiently identifying the optimal hyperparameter configuration, leading to an effective and efficient model. The CNN-GWO model exhibited performance comparable to or slightly lower than the best existing methods, confirming GWO's potential as a promising optimization technique for future emotion recognition applications.

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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