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Effective image retrieval based on an optimized algorithm utilizing a novel WOA-based convolutional neural network classifier

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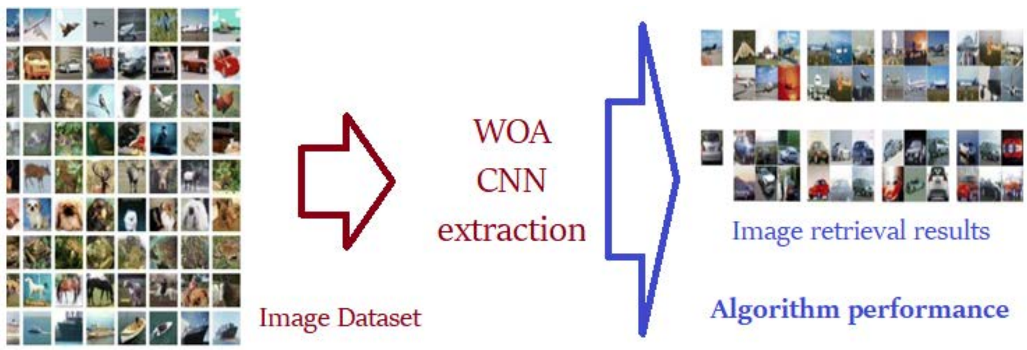
ABSTRACT



Traditional image retrieval from database based on available specific algorithms has drawbacks, including laborious image annotation, poor feature extraction, an inability to handle complicated queries, longer processing times, and less precise results. The study of CBIR is a current area in image processing. The most effective and efficient method for identifying and extracting images or patterns is deep learning. Finding the ideal CNN hyper-parameter value is a significant challenge, and using nature-inspired methods and the Whale Optimization Algorithm (WOA), it is possible to identify the ideal capability (NIAs). With the help of the best feature extraction technique, this effort aims to efficiently retrieve photos. An MRFODE approach is utilized in the pre-processing of this study to eliminate the undesired data that was present in the dataset. Feature extraction is used to extract features like texture and colour after pre-processing. Here, the statistical and colour features are referred to as image intensity-based colour features, while the texture feature is classified as a grey-level co-occurrence matrix. K-means clustering is used to group these features into groups for label creation. The features are classified using a unique WOA-based convolutional neural network, and were optimized using an MRFODE. The performance assessed based on sensitivity, specificity, precision, recall, retrieval, and recognition rate utilized a novel deep learning technique for CBIR using a CNN optimized through WOA. The WOA applied in two levels of CNN at the convolutional layer and fully connected later on to the CIFAR10 dataset provide better performance results compared to other reported models.

Keywords: Image Retrieval, Convolutional Neural Network, Whale Optimization Algorithm

INTRODUCTION

Digital images have become increasingly important in recent years for the representation and dissemination of graphical information. As a result, massive databases have been built and used for a variety of purposes, including the development of multimedia encyclopedias, identifying criminal activity, and geographic information systems. Digital images are a viable medium for the storage and description of the temporal, spatial, physical, and spectral components of information in several fields, including biomedical and satellite imaging.[1] Deep learning is an important framework for developing machine learning models.[2] CNN model performance is very good for image classification and recognition.

CNN: The data in the input layer is processed by the convolutional layer with the help of filters/kernels to generate feature maps which signify the raw features.[1,3] The pooling layer performs a downsampling operation, reducing the feature map's dimensionality. The processed features from the ReLU units are supplied to the fully connected layer which enables the classification of the data. The output layer generally consists of the

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soft-max approximation which facilitates the multiclass classification. The simple architecture of CNN is depicted as follows in figure 1.

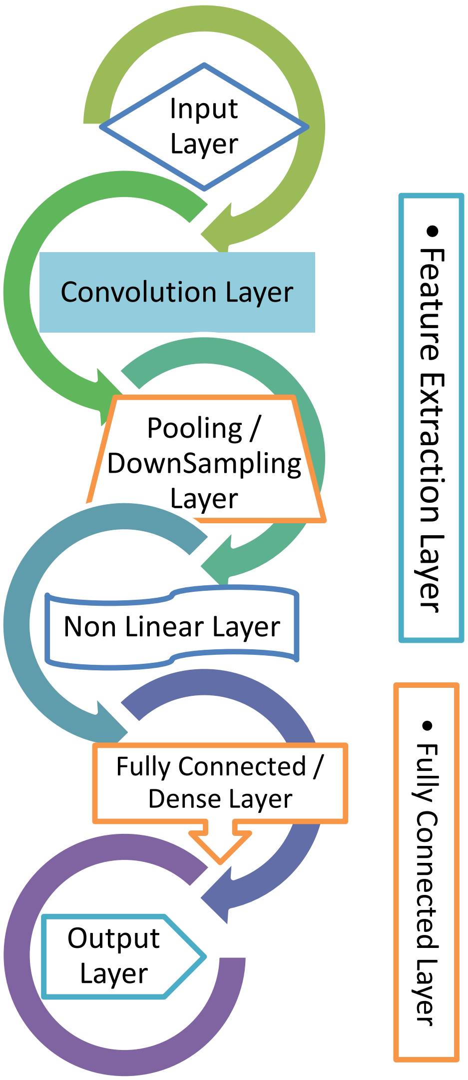


Figure1: CNN Model

CBIR: The word content-based indicates that the search evaluates the picture's contents rather than the metadata connected with the image, such as keywords, tags, or descriptions. Colours, forms, textures, and any other information obtained from the image itself may be referred to as "content" in this context. CBIR is useful because searches that rely solely on metadata rely on the quality and completeness of annotations.[4]

Nature-Inspired Algorithms

NIAs are meta-heuristic algorithms with the exceptional capacity to handle optimization problems in a limited setting. The majority of these issues are NP-hard and cannot be solved with typical deterministic methods. NIAs are a great tool for addressing difficult optimization issues and have been used to solve a variety of them.

Whale Optimization Algorithm

WOA is an NIA that imitates the behaviour of humpback whales.[5] WOA has been hybridized with various machine learning algorithms like SVM, ANN, etc.[6–8] WOA consists of the following two phases.[5]

I. Encircling Prey (Exploration Phase) and,
II. Bubble-Net Attacking (Exploitation Phase)

The WOA is mathematically written as follows.

$$\vec{A} = \overrightarrow{2a}\,.\,\vec{r} - \vec{a} \qquad (1)$$

$$\vec{C} = 2\,.\,\vec{r} \qquad (2)$$

$$\vec{D} = |\,\vec{C}\,.\vec{X}*(t) - \vec{X}(t)| \qquad (3)$$

$$\vec{X}(t+1) = \vec{X}*(t) - \vec{A}\,.\vec{D} \qquad (4)$$

$$\vec{D} = |\,\vec{C}\,.\vec{X}rand - \vec{X}\,| \qquad (5)$$

$$\vec{X}(t+1) = \vec{X}rand - \vec{A}\,.\vec{D} \qquad (6)$$

$$\vec{D'} = |\vec{X}*(t) - \vec{X}(t) \qquad (7)$$

$$\vec{X}(t+1) = \vec{D'}.e^{bl}.\cos(2\pi l) + \vec{X}*(t) \qquad (8)$$

The above equations from 1 – 8 have symbols and are explained as follows.

$\vec{a}$ is a linear variable used to iterate from 2 to 0
$\vec{r}$ is a random vector from 0 to 1
b is a constant
l is a random number
$\vec{A}$ and $\vec{C}$ are the coefficient vectors
$\vec{D}$ is the optimum solution
t is the current iteration
$\vec{X}*$ is an optimum solution vector
X is a positional vector

The eq. 3 and 4 indicate the behaviour of the encircling prey, eq. 5 and 6 explain the search for prey methods, and 7 and 8 make the behaviour of whales using bubble-net attack.

Herein, a WOA based CNN method is reported for the image retrieval and the results obtained from this methods have been deliberated at length.

Literature Review

Various approaches for combining NIAs with ANN have been proposed. These hybrid algorithms outperformed classic classification techniques for both binary and multiclass.[9] A comparative analysis of the optimized neural network (NN) and individual algorithms such as ANN, SVM, and GA is presented.[10] provides another comparison of the standard NN, WOA-Elman NN, and chaotic WOA-Elman NN models. CNNs with deep architecture usually deploy a fully connected layer with some associated.

In some architecture, there is an addition of the soft-max regression to make it suitable for multi-class classification,[11] focused on learning activation functions by combining basic activation functions. The feature extraction layer of the CNN consists of filters/kernels which help in generating the feature maps, indicating the various possible features present in the data. The number of these filters is usually tuned up manually. NIAs can contribute to deciding the number of filters to make the system more robust and accurate. But there have been no significant advancements in employing NIAs to the feature extraction layer The other parameters such as window size, stride, filter values, etc. also need to be adjusted as per the need of the application. NIAs can come in handy for selecting the optimal values of these parameters also.

A hybrid deep learning technique utilizing GA to optimize the weights of the FCL of the CNN has been proposed by A. Trivedi et.al.[12] A detailed review of the transfer learning approaches has been given SJ Pan et.al.[13] Lopes et al.[14] utilized pre-trained CNNs as feature extractors for detecting tuberculosis and achieved encouraging results. VGG-16 model comprises of total 16 layers, of which 13 are convolutional and three are fully connected.[15] This model's features need to be reshaped. 'Reshape,' provided by the TensorFlow API.[16] The features extracted from the chest x-ray images using new Fractional Multichannel Exponent Moments (FrMEMs) descriptors, and feature selection is made MRFODE.[17]

H. Etefagh et.al.[18] used group-based meta-heuristic techniques for addressing early convergence problems and balancing exploitation and exploration. Yin et al.[19] experimented with classification for brain-tumour image classification as compared with GA, brainstorm optimization and Firefly algorithms.

The review of the current approaches mentioned above revealed some significant problems with image retrieval, including high computational complexity, inaccurate feature extraction and classification, longer computation times, higher costs, semantic gaps, reliability, and inefficient image retrieval. The process of picture retrieval has been studied in the past using various algorithms, but the old method has some drawbacks, including inefficient feature extraction, human image annotation, and poorer accuracy. To solve these problems and improve accuracy and dependability, a median filter preprocessing technique is applied. The use of a trained classifier for the classification of specific features to get the pertinent data makes image retrieval efficient.

METHODOLOGY

The application of the image retrieval and classification approach to categorise photographs that are present in a database is covered in this section. The images are initially pulled from a dataset as input for pre-processing. Then, characteristics are retrieved to create the optimal colour and texture features by utilising MRFODE and WOA.

The first step in image processing or retrieval is pre-processing. The input photos are taken from the database and pre-processed to improve efficiency. The pre-processing method reduces the image dimensions while removing image noise.

The process of extracting features from input data and converting them into a set of features involves separating the accurate data from a vast array of databases and obtaining the pertinent and illuminating features.

K-means clustering is employed in this clustering strategy. The clustering algorithm k-means is frequently employed. Images in the database are labelled concerning colour, size, and shape using clustering techniques. The complete database's image collection is labelled using extracted characteristics, and each image's classification depends on the labelling outcome. To improve the picture retrieval process, optimization of the collected features is carried out using an optimized algorithm. For classification procedures including an activation update, the k-means clustering method is employed.

A novel deep learning approach has been proposed using a CNN optimized through WOA with addition of optimization at the feature extraction phase of the CNN model.

In our work, this classifier is used to combine the advantages of WOA and CNN techniques. The classification strategy is better because it uses the train feature matrix to obtain class values for each picture feature. As shown in the metrics below, our innovative classifier obtains higher precision and recall values. The optimal features are divided into train and test features for processing, and the labelled k-means clustering results are also regarded as train and test labels. The classifier analyses these inputs to retrieve the appropriate images.

Feature Extraction from the VGG-16 model and MRFODE

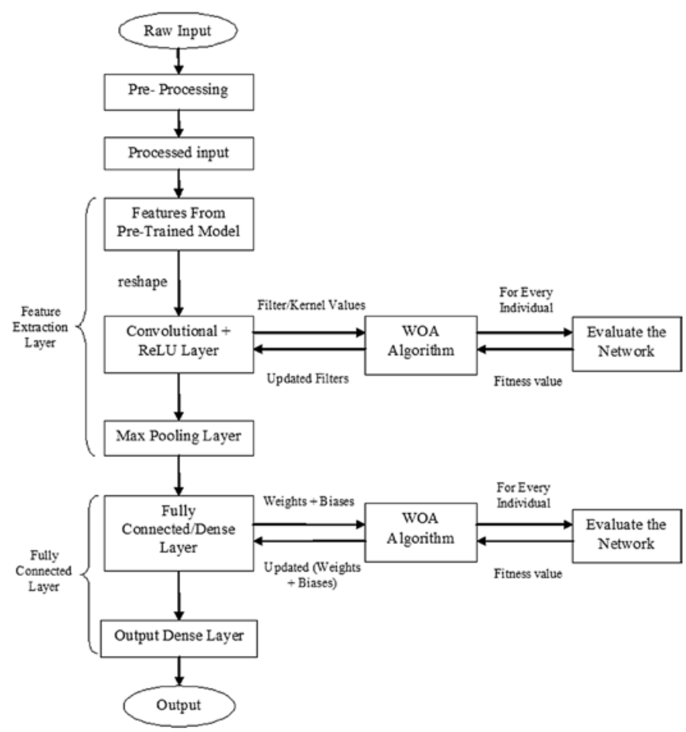


Figure 2: CNN model with WOA

Figure 2 describes the basic CNN model with the Whale Optimization Algorithm.

VGG-16

VGG-16 is a convolutional neural network that is 16 layers deep. Out of these, 13 are convolutional layers and 3 are fully connected layers used as a pre-trained model for feature extraction.

Enhanced MRFO based on DE as feature selection (MRFODE)

The modified Manta-Ray Foraging Optimization (MRFO) is based on Differential Evolution (DE) as a feature selection method.

The MRFO simulates the behaviours of three foragings, including cyclone foraging, Chain foraging, and somersault foraging. The mathematical modelling of Differential evolution (DE) is one of the most popular.

The extracted features using the FrMEMs and implemented an enhanced version from the MRFO based on DE, which is called MRFODE presented by M. Elaziz et.al.[17] The developed method begins by extracting the features from the input images, using FrMEMs. Then MRFODE generates a set of N agents; each of them is a solution for the Feature Selection problem. After that, the fitness value for each agent is computed, which indicates the quality of the selected features corresponding to the ones in the Boolean version of each agent. The best agent that has the best fitness value is determined and used in updating the position of agents using the operators of the traditional MRFO. Then, the terminal condition is checked. Finally, stop updating or repeating the process.

Optimization at the feature extraction layer and dense layer

The paradigm for optimizing the filter values at the feature extraction layer and weights at the dense layer is quite similar. The filter values and weights are arranged one after the other and are passed onto the WOA algorithm for parametric optimization. During individual fitness calculation, these weights are passed onto the module that contains the replica of the model, and the individual weights get copied onto that replica for accuracy/fitness calculation.

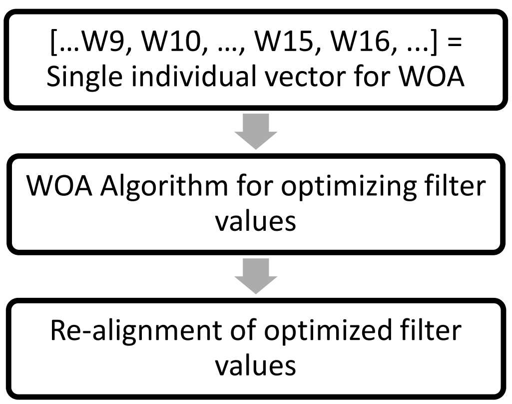


Figure 3: Optimization process of feature extraction

WOA algorithm and Objective Function

Here, the individual vector is n-dimensional, where the parameters are longer in n-dimensional space rather than in single space. By these, the WOA algorithm would align with the CNN model. The objective function uses the forward network for the evaluation of similarity. The similarity can be calculated as follows.

$$SI = \sqrt{\sum_i [\mathrm{vexp}(i) - \mathrm{vcal}(i)]^2} \qquad (9)$$

Where vexp is the expected output and vcal is the calculated output

Results and Analysis

The performance results of the suggested technique on the dataset are covered in this section. To compare the suggested method to other methods already in use, a comparative analysis of the proposed dataset is employed. The CIFAR10 dataset is used to evaluate the performance measures.

Experimental Setup

The experiments are carried out on a system with an Intel I5 processor @ 3.60 GHz with 8 GB RAM. Models are implemented using Python 3.7 and the entire model is designed using TensorFlow Library.

Results and Discussion

The accuracy and root mean square loss for the CIFAR10 dataset was evaluated with a pre-trained model VGG-16, MRFODE, pre-trained VGG-16 + CNN + WOA and pre-trained VGG-16 + MRFODE + CNN + WOA, and is shown in table 1.

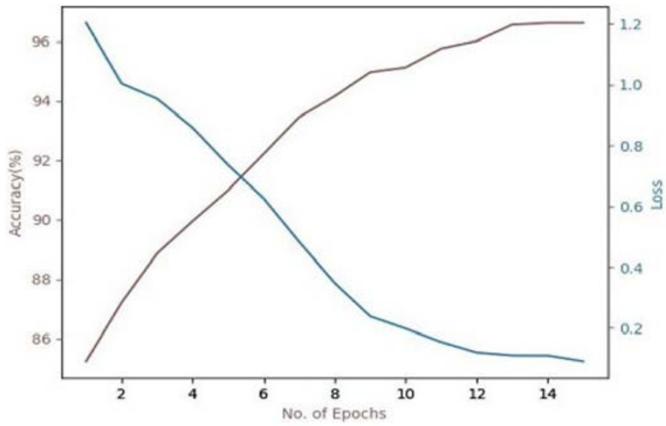
Table 1: Precision, recall, and F1-score

Model Name	Precision	Recall	F1-Score
VGG16	0.972	0.962	0.967
MRFODE	0.981	0.979	0.977
Basic CNN	0.967	0.954	0.962
VGG16 + CNN + WOA	0.989	0.983	0.988
VGG16 + MRFODE + CNN + WOA (proposed)	0.987	0.989	0.981

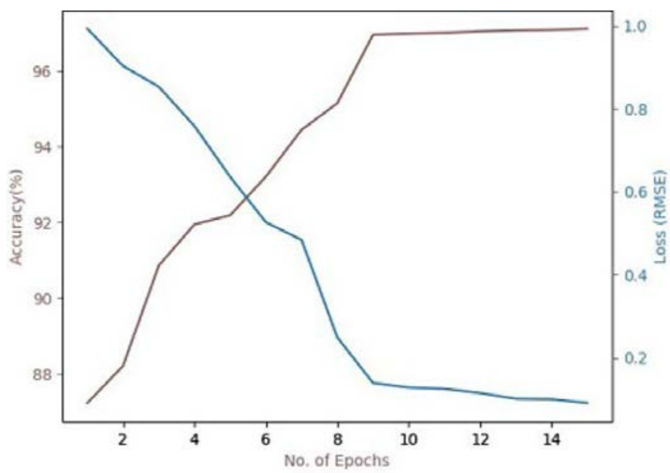
Table 2: Fitness value for MRFODE and WOA

Fitness Value	MRFO	MRFODE	WOA
Mean	0.034	0.028	0.035
STD	0.003	0.007	0.003
Best	0.029	0.019	0.031
Worst	0.036	0.036	0.038

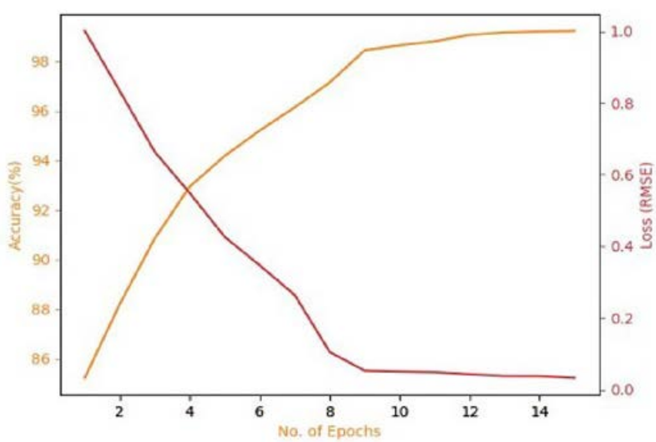
The proposed MRFODE has the smallest fitness value overall the mean, STD, Best, and Worst values in the CIFAR10 dataset shown in table 2. It provides better results according to the mean and the Best value, while, the traditional MRFO achieves the better values of STD and Worst. These results indicate that the proposed algorithm has a high ability to balance the error of classification by selecting the most relevant features, as well as, and, selecting the smallest number of features.



(a). MRFODE



(b). VGG16 + CNN + WOA



(c). VGG16 + MRFODE + CNN + WOA (Proposed)

Figure 4: Accuracy and Loss curves (a) MRFODE (b) VGG16 + CNN + WOA (c) VGG16 + MRFODE + CNN + WOA

Figure 5: Sample images of the CIFA10 Dataset

Figure 6: Top 6 retrieved images of 4 query images

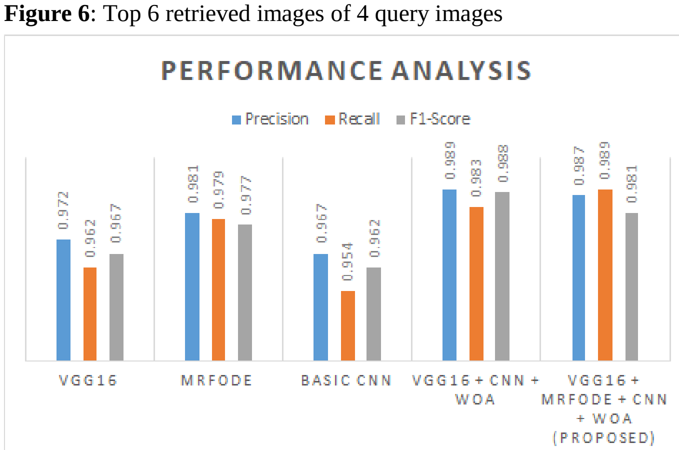


Figure 7: Performance Analysis

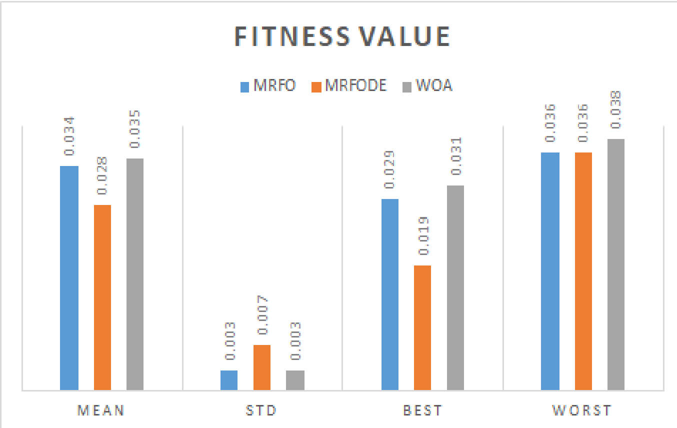


Figure 8: Fitness Value

Figure 7 exhibits the performance values of the methods and figure 8 describes the fitness value of the proposed method. It is indicating the proposed method shows higher precision and recall values.

CONCLUSION

Data pre-processing, feature extraction, and feature optimization are all included in the suggested method. Pre-processing is carried out to remove inaccurate data. Depending on the image intensity, texture and colour are retrieved from features. By using k-means clustering, these features are arranged into labels. Finally, the WOA-CNN was trained to maximize the collected features and then retrieve the appropriate images.

This paper covers a proposed method for finding the optimal structure of deep CNN for CBIR on CIFAR10. The results indicate better results in applying the proposed VGG16 + MRFODE + CNN + WOA model. We conclude that our strategy contributes to CNN being more robust and successful at image identification and retrieval.

In the future, this suggested method could be applied to the greater than 2L datasets that would be used in big data analytics. We want to use additional recently suggested swarm-intelligence algorithms to optimize the structure of CNN. There is enormous potential for furthering this study by adapting our approach to additional pattern recognition tasks such as traffic sign identification, handwritten character recognition, gait recognition, medical picture categorization.

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CONFLICT OF INTEREST STATEMENT

Authors declare that there is no academic or financial conflict of interest towards publciation of this work.

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