Deep Features Selections with Binary Marine Predators Algorithm for Effective Classification of Image Datasets

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Abstract

The paper proposes a method for improving the accuracy of image classification by combining CNNs and the Binary Marine Predators Algorithm (BMPA). The CNNs used in the study, ResNet 50 and AlexNet, were trained on ImageNet and used to extract features from the images in the dataset. Features are taken from layers (avg_pool) in ResNet 50 and (drop7) in AlexNet. These features were then fed into the BMPA algorithm, which selected the most relevant features and removed irrelevant ones to improve the classification process. The proposed method is said to be efficient, capable of achieving higher classification accuracy, and able to select the best features. The authors believe that this approach could be applied to a variety of other image classification tasks. It is important to note that the effectiveness of this method should be evaluated on a range of datasets and compared to other state-of-the-art methods.

Keywords: Convolution Neural Networks; Marine predators algorithm; Feature selection; Classification.

1. Introduction

The Marine Predators Algorithm (MPA), which was developed by Afshin Faramarzi et al. in 2020, is a heuristic algorithm inspired by the hunting behavior of ocean predators. The algorithm mimics the motion of predators when pursuing prey, using two techniques: Brownian motion and Lévy motion [1]. The algorithm divides the hunting process into three distinct stages - searching, approaching, and attacking - to evaluate the progress of both predator and prey. The MPA algorithm takes into account factors such as taxing flight and Brownian locomotion to assess the progression of predators and prey during each stage [2].

Feature selection is a technique that aims to eliminate redundant features from the original feature set, particularly when working with large datasets [3]. Its objective is to select relevant and essential features that improve classification accuracy. The two primary methods for choosing a feature filtering approach are wrapper methods [4][5].

Deep learning is a subfield of machine learning that utilizes artificial neural networks and transfer learning techniques. Deep learning algorithms can learn from supervised, semi-supervised, or unsupervised [6]. However, to achieve reliable results, deep learning algorithms typically require large amounts of data. Currently, convolutional neural networks (CNNs) are the most effective deep learning approach for image classification tasks [7]. The CNNs are usually pre-trained on a large and diverse set of general image data before being fine-tuned for a specific task. Some of the popular pre-trained CNNs include VGGNet [8], ResNet [9], MobileNet [10], Inception [11], and Xception [12]. In this paper, the ResNet 50 and AlexNet CNNs were employed for the image classification task. The study presents a novel approach that combines the Binary Marine Predator Algorithm (BMPA) optimization with convolutional neural networks (CNNs) to identify the most relevant features. The ResNet 50 and AlexNet CNNs, which have been pre-trained on a large number of images, are used to extract the features. By

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leveraging the strengths of both CNNs and BMPA algorithm optimization, the proposed method efficiently identifies the most significant features. The resulting features are then used to categorize the dataset using support vector machine (SVM) classification.

The main contribution of the study recognition of the fact that image datasets used for classification have many features that affect classification accuracy. Application of dimensional reduction and feature selection using various metaheuristic algorithms, such as the Marine Predators (MPA) algorithm, after converting the continuous space to a discrete space. Utilization of two pre-trained convolutional neural networks (CNNs), ResNet 50 and AlexNet, to extract features from dataset images. Features are obtained from layers (avg_pool) in ResNet 50 and (drop7) in AlexNet and input into the binary marine predator (BMPA) algorithm. Implementation of the BMPA algorithm to select the most relevant features and remove irrelevant features to improve the classification process. High efficiency and the ability to achieve higher classification accuracy and select the best features are the unique features of the proposed method.

This study is limited by potential biases in several aspects, such as the selection of features, the choice of convolutional neural network models, and the hyperparameters used in BMPA and SVM classifiers.

The essay is structured into six sections. Section 1 introduces the topic while Section 2 discusses the related work. Section 3 details the methodology utilized in the study. In Section 4, the proposed technique is presented and explained in detail. The study's results and findings are analyzed in Section 5. Finally, Section 6 provides concluding remarks.

2. Related Work

This section discusses a comparison with related works. This paper proposes a computer-aided diagnosis system for detecting abnormal brain images using a modified pre-trained AlexNet and an extreme learning machine, optimized by the chaotic bat algorithm, which achieved state-of-the-art performance [13]. This research proposes the use of deep learning with neural networks like AlexNet, ResNet18, and SqueezeNet to automatically detect road cracks [14]. This research proposes an improved image classification method based on AlexNet, which adds a deconvolution layer and reduces the number of parameters and parameter proportion of the full connection layer [15]. Facial emotion recognition is a crucial aspect of intelligent human-computer interaction. This study proposes a ResNet-50-based feature extraction method for facial emotion recognition, which outperforms current models in terms of detection performance [16]. Bolt loosening in large-scale steel structures can reduce load-carrying capacity, safety, and durability. This study proposes a method based on time-frequency diagrams and a CNN (ResNet-50) using vi-bro-acoustic modulation signals to identify multi-bolt loosening conditions, which outperforms traditional methods and eliminates the influence of operational noise on identification accuracy [17]. Medical imaging relies on segmentation to extract salient features, which is typically done using deep convolutional neural networks (CNNs). This study compares the performance of pre-trained models, including VGG-19 and ResNet-50, to training from scratch, finding that properly fine-tuned pre-trained models can achieve comparable results with less computational time and labeled training data [18].

3. Methodology

3.1 Marine Predators Algorithm (BMPA)

MPA is a modern, nature-inspired metaheuristic primarily inspired by foraging strategies, specifically the Brownian and Lévy movements of ocean predators. MPA considers both predator and prey as a search factor since the prey itself is a predator when it forages for its food [19].

3.1.1 MPA Modeling.

MPA is one of the metaheuristics algorithms. This method is based on population. In this algorithm, the first solution is distributed uniformly in the first experiment [20]:

$$X_0 = X_{min} + rand\ (X_{max} - X_{min}) \tag{1}$$

Where X_0 represents the initial positions, which are spread at random within the search space based on their upper and lower bounds, denoted by X_{max} and X_{min}, respectively, $rand$ is a random number between [0,1].

Fitness for all predators is calculated next to prey initializing since the highest predator has the best fitness value. By the theory of survival of the fittest, the higher predator is better at foraging, so the higher predator is used to build a matrix called the $Elite$. The $Elite$ matrix $(n \times d)$ can be formulated as [21]:

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$$Elite = \begin{bmatrix} X_{1,1}^{I} & X_{1,2}^{I} \dots & X_{1,d}^{I} \\ X_{2,1}^{I} & X_{2,2}^{I} \dots & X_{2,d}^{I} \\ \vdots & \vdots & \vdots \\ X_{n,1}^{I} & X_{n,2}^{I} \dots & X_{n,d}^{I} \end{bmatrix} \tag{2}$$

Where iterates n times to construct the matrix and X^{I} represent the best predatory vector. n and d denote the figure of the search area and dimensional agents, respectively.

The $prey$ is a matrix of the same dimension as the $Elite$ matrix, and through this matrix, the predator positions are updated. The $prey$ $(n \times d)$ is shown:

$$prey = \begin{bmatrix} X_{1,1} & X_{1,2} \dots & X_{1,d} \\ X_{2,1} & X_{2,2} \dots & X_{2,d} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ X_{n,1} & X_{n,2} \dots & X_{n,d} \end{bmatrix} \tag{3}$$

The MPA approaches divide the total number of iterations evenly into three stages, which represent the complete optimization process [22].

First stage: the velocity of prey is higher than the predator, the high-velocity ratio ($v \geq 10$)

$$while\ Iter < \frac{1}{3}\ Max\_Iter$$

$$\overrightarrow{stepsize}_i = \overrightarrow{R_B} \otimes \left(\overrightarrow{Elite}_i - \overrightarrow{R_B} \otimes \overrightarrow{prey}_i\right) \qquad i = 1, \dots \dots, n \tag{4}$$

$$\overrightarrow{prey}_i = \overrightarrow{prey}_i + p \cdot \vec{R} \otimes \overrightarrow{stepsize}_i \tag{5}$$

Where $p = 0.5$ and $\overrightarrow{R_B}$ is a vector containing random numbers based on a Normal distribution representing Brownian motion, R is a vector of uniform random numbers in [0,1].

Two stages: Has an equal velocity of prey and predator, high-velocity ratio ($v = 1$).

$$while\ \frac{1}{3}\mathrm{Max\_Iter} < Iter < \frac{2}{3}\mathrm{Max\_Iter}$$

For the first semi of the population:

$$\overrightarrow{stepsize}_i = \overrightarrow{R_L} \otimes \left(\overrightarrow{Elite}_i - \overrightarrow{R_L} \otimes \overrightarrow{prey}_i\right) \qquad i = 1, \dots, \frac{n}{2} \tag{6}$$

$$\overrightarrow{prey}_i = \overrightarrow{prey}_i + p \cdot \vec{R} \otimes \overrightarrow{stepsize}_i \tag{7}$$

For the second semi of the population:

$$\overrightarrow{stepsize}_i = \overrightarrow{R_B} \otimes \left(\overrightarrow{R_B} \otimes \overrightarrow{Elite}_i - \overrightarrow{prey}_i\right) \qquad i = \frac{n}{2}, \dots, n \tag{8}$$

$$\overrightarrow{prey}_i = \overrightarrow{Elite}_i + p \cdot CF \otimes \overrightarrow{stepsize}_i \tag{9}$$

where

$$CF = \left(1 - \frac{Iter}{\mathrm{Max\ \_}Iter}\right)^{\left(\frac{2\,Iter}{\mathrm{Max\ \_}Iter}\right)} \tag{10}$$

Third stage: It is deemed as prey velocity is lower than the predator, high-velocity ratio ($v = 0.1$).

$$while\ Iter < \frac{2}{3}\mathrm{Max\_Iter}$$

$$\overrightarrow{stepsize}_i = \overrightarrow{R_L} \otimes \left(\overrightarrow{R_L} \otimes \overrightarrow{Elite}_i - \overrightarrow{prey}_i\right) \qquad i = 1, \dots, n \tag{11}$$

$$\overrightarrow{prey}_i = \overrightarrow{Elite}_i + p \cdot CF \otimes \overrightarrow{stepsize}_i \tag{12}$$

Where $Iter$ is the current iteration, $\otimes$ represents the multiplication on entry wise and Max_Iter is the maximum one.

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By observing the nature of predators in the surrounding environments, we note that sharks ordain more than 80% of their time nearer $FADs$. As for the residual 20%, the sharks will gather a long jump of different dimensions to find an environment with other distribution of prey. The impact of $FADs$ is expressed mathematically as:

$$\overrightarrow{prey_i} = \begin{cases} \overrightarrow{prey_i} + CF\left[\overrightarrow{X_{min}} + \vec{R} \otimes \left(\overrightarrow{X_{max}} - \overrightarrow{X_{min}}\right)\right] \times \vec{U} & if \quad r \leq FADs \\ \overrightarrow{prey_i} + [FADs\ (1 - r)\} + r]\left(\overrightarrow{prey_{r_1}} - \overrightarrow{prey_{r_2}}\right) & if \quad r > FADs \end{cases} \tag{13}$$

where environmental effect $FADs$ on predator is 0.2, U is the binary vector at 0 and 1, r is the random number in [0,1], symbols $r_1 and\ r_2$ represent the random indexes of the prey [23].

```
Start
Initialize search agents (Prey) populations i = 1, ... , n
while the criteria for termination were not met
Calculate the fitness , build Elite Matrix and accomplish memory saving
if Iter < 1/3 Max_Iter   then
   Find the current  prey_i  based on Eq. (5)
else
     if 1/3 Max_Iter < Iter < 2/3 Max_Iter   then
 if   i = 1, ... ... , n/2   then
   Find the current   prey_i   based on Eq. (7)
else
   Find the current   prey_i   based on Eq. (9)
end if
else
 Find the current   prey_i   based on Eq. (12)
end if
end if
end for
Accomplish memory save and Elite update
Apply the effect of FADs and update based on Eq. (13)
End while
End
```

Figure 1: The pseudo-code of the MP algorithm.

3.2 Binary Marine Predators Algorithm (BMPA)

The scientists sophisticated the basic MPA algorithm by transforming the search algorithm from continuous to discrete. The features are selected by the MPA binary algorithm that uses binary values of either 0 or 1. The solutions are grouped in binary form based on the basal MPA algorithm[12].

3.3 CNN Model

In this section, the ResNet 50 and AlexNet models are technically shown. Layer (avg_pool) was used in ResNet 50 and layer (drop7) in AlexNet, and the BMPA algorithm was used on the features obtained from these layers. Schematic representations of CNN architectures are shown in Figures (2 & 3).

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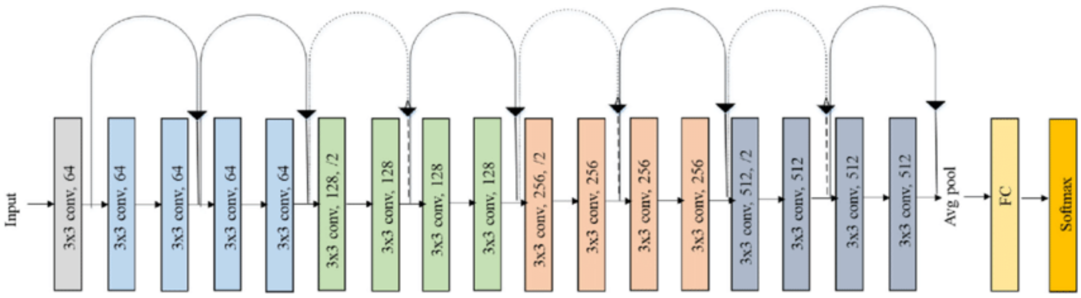

Figure 2: The architecture of ResNet 50.

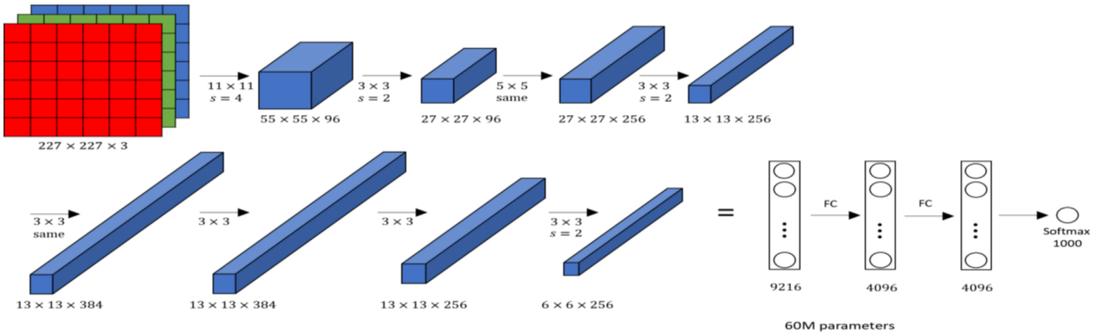

Figure 3: The architecture of AlexNet.

The residual network has many variations, namely ResNet-16, ResNet-18, ResNet-34, ResNet-50, ResNet-101, etc. The architecture of this network is intended to enable large quantities of convolutional layers to work efficiently. The basic idea of ResNet is to use jump links which are often referred to as short links. These connections work by hopping over one or several layers to form abbreviations between these layers[24]. The introduction of these short links was intended to solve the pervasive problem of gradient fading faced by deep networks. ResNet 50 is a 50-layer deep convolutional neural network. This architecture consists of fully connected convolutional, pooling, and fully connected layers. The input size is 224 x 224 x 3, which is predefined[25]. The network is considered a DAG network because of its complicated layered architecture and because the layers have inputs from multiple layers and give outputs from multiple layers[9].

The AlexNet architecture consists of eight layers: five convolutional layers and three fully connected. With 60 million parameters, AlexNet had a huge problem with overfitting[26]. To reduce hyper allocation data augmentation and dropout were used. Dropout: Using a predetermined probability, the neurons are 'turned off in this way[27]. As a result, each iteration uses a different sample of model parameters, forcing each neuron to have more robust features that can be applied to other random neurons. However, dropout lengthens the amount of training time required for the model to converge[28].

4. The proposed algorithm

The proposed method combines binary marine predator (BMPA) algorithm optimization with convolutional neural networks (CNN). To extract features, a different kind of CNNs called ResNet 50 and AlexNet that has been pre-trained on millions of images is employed. Features are extracted from the image collection using ResNet 50 and AlexNet. The last two layers of ResNet 50 and AlexNet are removed so that the image can be passed through the rest of the network to get its feature vector. After feature extraction with CNN, the features are taken from layer (avg_pool) in ResNet 50 and layer (drop7) in AlexNet to apply the feature selection to use only those features from the most contributing classification. The features are fed into the BMPA algorithm to identify the most relevant features and eliminate the associated and noisy features. These features are then passed to an external classifier to classify the images as an SVM classifier. This proposed method improves classification performance by excluding irrelevant features and selecting relevant features. Classification becomes more efficient and computationally stable.

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Start

1. Input images datasets

2. Initialize the CNN model (ResNet 50, AlexNet) parameters, including weights and biases.

3. Decode the best search agent into the CNN model parameters.

4. Extract the features from the decoded CNN model. Extract ResNet 50 features from (avg_pool) and AlexNet features from (drop7).

5. Insert the features extracted from the CNN layers into a Marine Predator Algorithm (MPA).

6. Initialize the population of search agents using the MPA.

7. Evaluate the fitness of each search agent by training the Marine Predator Algorithm and calculating the accuracy on a validation set.

8. Update the position of each search agent using the MPA update rules.

9. Repeat steps 4 and 5 until the stopping criterion is met (e.g., a maximum number of iterations is reached).

10. Decode the best search agent into the CNN model parameters

11. Extract the features from the Marine Predator Algorithm and use them to train an SVM classifier.

12. Test the trained SVM classifier on a separate test set and evaluate its performance.

13. Use the final CNN-MPA -SVM model to classify new images.

Figure 4**:** The pseudo-code of the proposed algorithm

5. Datasets and Results

To validate the efficacy of the proposed classification algorithm, three distinct classification problems were chosen.

Dataset 1: Star-Galaxy Classification Data

The images were captured by the in-house 1.3m telescope of the observatory situated in Devasthal, Nainital, India. The original images captured were 2kx2k in size which was reduced to 64x64 cutouts from the images to isolate the sources in a single image. For labeling the images, image segmentation was used to identify the sources in the image, and finally, the center coordinates of the found sources were queried with the SDSS database to give a label corresponding to each 64x64 cutout. Finally, the cutouts were saved in different directories according to the label suggested by the SDSS query search. https://www.kaggle.com.

Dataset 2: Identification of Pseudo papilledema

It is known as pseudo papilledema when one or both optic discs are abnormally elevated without the retinal nerve fiber layer being edematous. The optic disc swells with papilledema, on the other hand, because of a rise in intracranial pressure. The data set consists of three classes - Normal pseudo papilledema & Papilledema. https://www.kaggle.com.

Dataset 3: Mosaic Images for YOLO

The dataset contains images from the Pascal VOC Dataset, taken 4 at a time and augmented using the mosaic strategy. The images are combined into one single image with 4 tiles or subsections, each containing an image. The labels folder contains all the box labels for the objects in the images in a YOLO annotation style and the dimensions of the boxes are scaled according to the mosaic image. https://www.kaggle.com.

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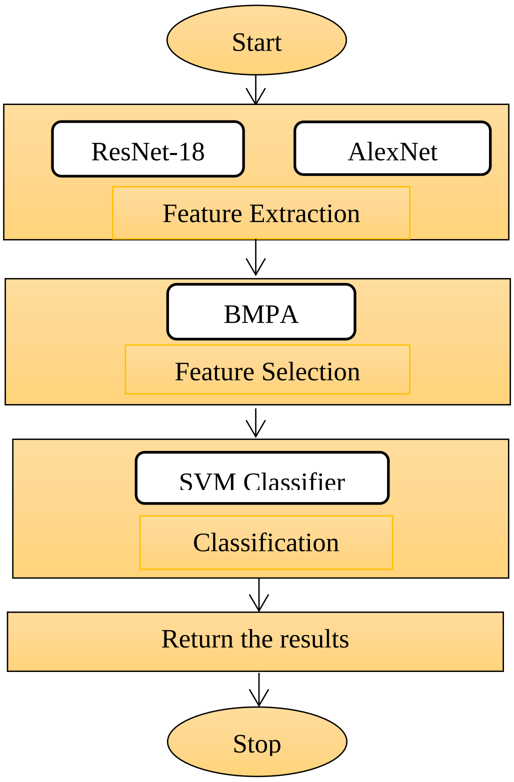

Figure 5: Flowchart showing the strategy we proposed.

Table 1: Comparison the Accuracy of the dataset.

Datasets	Algorithms	ACC of the testing dataset
Dataset1	ResNet 50	83.7793
	Proposed approach	86.4548
Dataset2	ResNet 50	94.8780
	Proposed approach	95.3654
Dataset3	ResNet 50	96.1905
	Proposed approach	96.1905

Table 2: Comparison of the Accuracy of the dataset.

Datasets	Algorithms	ACC of the testing dataset
Dataset1	AlexNet	79.9331
	Proposed approach	82.5251
Dataset 2	AlexNet	94.6341
	Proposed approach	93.4146
Dataset 3	AlexNet	96.1905
	Proposed approach	96.1905

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Table 3: Comparison of the Feature Selection of the dataset.

Datasets	Algorithms	Feature selection (FS)
Dataset1	ResNet 50	2048
	Proposed approach	685
Dataset2	ResNet 50	2048
	Proposed approach	807
Dataset3	ResNet 50	2048
	Proposed approach	21

Table 4: Comparison of the Feature Selection of the dataset.

Datasets	Algorithms	Feature selection (FS)
Dataset1	AlexNet	4096
	Proposed approach	1291
Dataset2	AlexNet	4096
	Proposed approach	1022
Dataset3	AlexNet	4096
	Proposed approach	7

6. Conclusion

The paper introduces a method for enhancing classification accuracy through the use of ResNet 50 and AlexNet CNNs and the BMPA algorithm. Initially, features are extracted from an image dataset using ResNet 50 and AlexNet, and then the BMPA algorithm is used to filter the extracted features to keep only the relevant ones. The filtered features are then fed into an SVM classifier for classification. The results presented in Tables (1-4) demonstrate an improvement in classification accuracy and a reduction in the number of features used.

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